STAR: A Schema-Guided Dialog Dataset for Transfer Learning

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Abstract

We present STAR, a schema-guided task-oriented dialog dataset consisting of 127,833 utterances and knowledge base queries across 5,820 task-oriented dialogs in 13 domains that is especially designed to facilitate task and domain transfer learning in task-oriented dialog. Furthermore, we propose a scalable crowdsourcing paradigm to collect arbitrarily large datasets of the same quality as STAR. Moreover, we introduce novel schema-guided dialog models that use an explicit description of the task(s) to generalize from known to unknown tasks. We demonstrate the effectiveness of these models, particularly for zero-shot generalization across tasks and domains.

1 Introduction

A long-standing challenge in computer science is to develop algorithms that can interact with human users via dialog in natural language (Turing, 2009; Kim et al., 2019). Of particular interest is task-oriented dialog, wherein a user interacts with a system to achieve some goal (e.g. making a doctor appointment). The system should understand the user’s requests and assist them by taking the appropriate actions (e.g. searching a database or replying to the user). In recent years, supervised learning approaches to this problem have become particularly popular (Gao et al., 2018), because they can potentially learn complex patterns without relying on hand-crafted rules. While such data-driven methods already demonstrate impressive performance in open-domain dialog (Zhang et al., 2019; Adiwardana et al., 2020; Roller et al., 2020), task-oriented dialog models face the additional difficulty of transferring skills to tasks and domains that were not present in the training data. To address this issue, we present the Schema-guided Dialog Dataset for Transfer Learning (STAR) dataset, a collection of realistic, task-oriented dialogs, that is especially designed to test and facilitate the transfer of learned patterns between tasks.

Unlike open-domain dialogs, task-oriented dialogs are accompanied by a set of steps that are necessary to complete the task. These steps are typically known a priori and thus do not have to be learned from the data. In fact, for practical applications it is desirable that we could make modifications to this logic without having to discard large parts of the dataset. The ideal sequences of steps that a dialog would follow to complete the task can be arranged in a graph (see Figure 1 for a flow chart that summarizes the graph). Together with the utterances or actions that are associated with the nodes of this graph, we hence call this a task schema, or simply schema. Note, that what we call ‘schema’ is similar to the ‘task specification’ of (Bohus and Rudnicky, 2009), but distinct from the ‘schemas’ that only define slots and intents of a task as used by Rastogi et al. (2019).

In a typical supervised model that is trained to, say, predict the next system action for a task-oriented dialog, the schema of the training tasks is implicitly captured by the learned model parameters. This makes generalizing to a new task difficult, as the implicitly memorized schema will no longer be appropriate (Mehri et al., 2019). With STAR we provide explicit schema representations for each task and thereby enable models to condition on the schema (see §5).

To collect STAR we use a Wizard of Oz setup (Kelley, 1984), where the system’s role is played by a human ‘wizard’. Based on our pilot studies, we found that the quality of crowd-sourced dialogs depends strongly on (i) the details of how crowd workers are briefed, (ii) that they have an idea of what they are contributing to with their work, (iii) how varied and interesting they perceive
the task to be, and (iv) on the incentive structure for receiving payments.\(^1\) We refined our approach through extensive internal testing and four rounds of pilot studies.

Our aim is to create an ecologically valid dataset (de Vries et al., 2020) with the following four attributes, which we believe are crucial for a dataset to be of high quality:

1. **Realistic, variable user behavior.** Realistic dialog rarely strictly follows the ideal path, but is interrupted by small talk, changes of the user’s mind, and references to events that happen in the user’s environment. In STAR we capture these behaviors.

2. **Progression of difficulty.** We collect three kinds of dialogs: (a) happy where the dialog progresses along one of the paths in the schema, (b) unhappy where the user adds complexity to the task (changing their mind, small talk, etc.), and (c) multi-task where the user engages in a complex dialog spanning multiple domains and tasks (e.g., restaurant, flight, hotel, ride). The progression of difficulty allows better assessment of dialog models and potential for transfer learning across levels of difficulty.

3. **Consistency on the system side.** The behavior of a task-oriented dialog system should be largely deterministic and not subject to the whims or personality of the wizard. In particular, we encourage wizards to follow the given task schema(s) as closely as possible.

4. **Explicit knowledge base queries.** A large part of developing a dialog system is the implementation of application programming interface (API) calls, such as knowledge base queries. In STAR we represent our dialogs as a three-party interaction wherein the system acts as the intermediary between a user and a knowledge base (user $\leftrightarrow$ system $\leftrightarrow$ knowledge base). Thus, models have to learn when to query the knowledge base, what the query should be, and how to explain the returned knowledge base item to the user.

With this paper, we contribute (i) a novel, high-quality dataset of 127,833 utterances and knowledge base queries across 5,820 task-oriented dialogs in 13 domains that admits the above-mentioned properties (with caveats, see §4), (ii) a novel, scalable crowd-sourcing setup to collect arbitrarily large datasets of the same quality as STAR, and (iii) novel schema guided dialog models that use the explicit task schemas we provide to generalize to unseen tasks. The code for the latter setup, all collected (anonymised) data, and all modeling code is freely available under https://github.com/RasaHQ/STAR.

2 Related Work

2.1 Dialog Datasets

While STAR shares some aspects with existing datasets, to our knowledge it is the first that admits all of the properties listed in the Introduction (see Table 1 for an overview). For example, similar to the dataset of the Fourth Dialogue State Tracking Challenge (DSTC4, Kim et al. (2017)) and its successors, STAR is composed of human-human dialog, yet provides much richer annotation. Furthermore, similar to the Microsoft Frames dataset (El Asri et al., 2017) we make knowledge base queries explicit. STAR, however, covers 13 domains and encourages a consistent system behavior, while Frames does not do so and only covers
Table 1: Comparison of dataset statistics and characteristics.

|                  | MultiWoZ | MetaLWoZ | Frames | Taskmaster | SGD    | STAR |
|------------------|----------|----------|--------|------------|--------|------|
| Number of dialogs| 8,438    | 37,884   | 1,369  | 13,215     | 16,142 | 5,820|
| Number of domains| 7        | 47       | 1      | 6          | 16     | 13   |
| Number of tasks  | 7        | 227      | 1      | 6          | 16     | 24   |
| Total number of turns | 115,434 | 432,036  | 19,986 | 274,647    | 329,964| 127,833|
| Average turns / dialog | 13.46   | 11.40    | 14.60  | 21.99      | 20.44  | 21.71|
| Average tokens / turn | 13.13   | 8.47     | 12.60  | 8.62       | 9.75   | 11.20|
| Ensure system consistency | x       | x        | x      | x          | x      | x    |
| Real-time data collection | x       | ✓        | ✓      | ✓          | ✓      | ✓    |
| Difficulty progression | ✓       | ✓        | ✓      | ✓          | ✓      | ✓    |
| Explicit KB queries | ✓        | x        | ✓      | ✓          | ✓      | ✓    |

RavenClaw (Bohus and Rudnicky, 2009) disentangles the task specification and the dialog engine for rule-based task-oriented dialog systems. STAR shares a similar motivation and aims to extend to explicitly disentangle the task schema in neural, data-driven models. Hybrid Code Networks (Williams et al., 2017) incorporate task-specific constraints to avoid illogical system actions (e.g., requesting known slots) in neural models. Recently, several attempts have been made to use intermediate annotations (e.g., belief state, dialog acts) to explicitly incorporate structure in neural dialog models (Mehri et al., 2019; Chen et al., 2019; Peng et al., 2020). Furthermore, the SGD dataset by Rastogi et al. (2019) mentioned in §2.1 comes with explicit slot and intent annotations that serve as an inductive bias for their model.

3 Data Collection Method

We collect our annotated dialogs from Mechanical Turk (Crowston, 2012), using ParlAI (Miller et al., 2017).

3.1 Stages

We run our data collection in 4 stages to prepare and evaluate workers effectively, and to maximize the quality of the dialogs. In Stage I and Stage III, workers are asked to watch video tutorials and answer questionnaires to qualify for Stage II and Stage IV, respectively. In Stage II and Stage IV, workers are paired up to produce single-task and multi-task dialogs, respectively. The estimated earnings and bonuses increase with each stage. Workers are made aware of this fact during Stage I to encourage them to go through all four stages.

To enter Stage I, we require workers to have a minimal approval rate of 98%, a minimum of 10 approved assignments, and a US-based Mechanical Turk.

2Only half of the Taskmaster-1 dataset has been collected via real-time human-human conversations. The other half—“Self-Dials”—have been completely written by a single crowd worker, who is assuming the user and wizard role, each.

3For the worker’s reward payments and bonuses, please refer to Appendix B.
Turk account. To succeed in the questionnaire (see Appendix D.1), workers have to answer 10 questions about the video with no more than 6 hints. Of the 210 workers that attempted the Stage I tutorial, 162 (77%) succeeded.

In every assignment of Stage II, workers are paired up as “users” and “AI Assistants” (wizards), and assigned a particular scenario. A scenario consists of instructions for the user (see §3.2), instructions for the wizard, and a specialized knowledge base interface for the wizard to handle the particular task(s) at hand (see §3.3). All scenarios in Stage II concern one task at a time, e.g. only organizing a party or only making a doctor appointment (see §4 for a list of tasks). Out of the 162 workers who entered Stage II, 74 continued into Stage III.

The Stage III video tutorial prepares workers for multi-task dialogs in Stage IV (see Appendix D.2 for the questionnaire). Of the 74 workers who got the qualification to enter Stage III, 72 attempted to pass it and all of them progressed to the final Stage IV.

3.2 User’s Interface

We want to cover a wide range of user behaviors. Therefore, we design the user’s interface (see Appendix A) to encourage the worker to make the dialog more realistic, i.e. to occasionally engage in small talk, refer back to earlier parts of the dialog, change their mind, or use negation.

Therefore, during the dialog, users not only receive messages from the AI Assistant (wizard), but also from the “MTurk System bot”, which instructs them to, e.g., change their mind about something, interrupt the dialog with chitchat, or refer back to an earlier stage of the dialog.

These in-dialog instructions come in three flavors. Sometimes, the instruction is direct and vague, such as “Either tell a joke, or try to engage in some small talk with the AI Assistant”. Other times, the instruction is direct and specific, such as “Change your mind about either the apartment size and/or ask for the balcony to be on the east side instead of the south side”. Finally, some instructions describe things that happen in the user’s environment, such as “You get a text from your hotel: The water pipe broke and – regrettably – they cannot accommodate you tonight”.

Most in-dialog instructions are generated from templates that contain multiple placeholders for specifics (e.g. the new balcony side) and reasons (e.g. the broken water pipe). Thus, turkers almost never see the same in-dialog instruction set more than once.

In Stage IV, most instruction sets merely point out the topics that the user should touch on and provide some example names or locations for them to work with, as this leads to a particularly broad range of behaviors (see Appendix E for some examples).

3.3 Wizard’s Interface

In contrast to the user, we want the wizard to behave in a consistent and structured manner. Therefore, we design the wizard’s interface such that they are encouraged to use predefined replies whenever possible, and to not rely on any other sources of information than those provided by the interface. Most importantly, wizards are instructed to always (when possible) follow a flow chart representation of the task’s schema (as shown in Figure 1), which we use to condition our models on particular tasks (see §5).

In the multi-task dialogs (Stage IV), wizards can switch between up to five tasks by selecting the corresponding tab on the left side of the screen (orange rectangle in Figure 2). We refer to the results of these queries as knowledge base items (red rectangle in Figure 2). The knowledge base items are not visible to the user, and thus the wizards have to describe them when required by the schema.

To reply, wizards enter a query into a text box (magenta rectangle in Figure 2). They are then presented with a ranked list of suggested responses that they can pick from (blue rectangle). If no sug-
gestion fits what they need to say, they can either change the search query or use a custom reply. The latter should only be necessary in situations where the user shows unexpected behavior, and thus the schema cannot provide guidance.

The response suggestions work by classifying the intent of the wizard’s input, conditional on the selected task and knowledge base item. For the classification we use 24 instances of the recently proposed DIET architecture by Bunk et al. (2020), one for each task. Every intent is then linked to a response string template, which in turn is filled with the information from the selected knowledge base item (if any).

From a typical wizard turn we thus collect (i) which task the wizard is considering, (ii) the knowledge base query (optional), (iii) the selected knowledge base item (optional), (iv) the reply text entered, and (v) the selected response text and action label. See Appendix C for details on the data format.

Together, the schema flow charts, knowledge base forms, and response suggestions provide a framework for wizards to make their behavior consistent and structured, even when dealing with erratic users.

4 The STAR Dataset

Our dataset covers 24 tasks in the 13 domains, with a total of 127,833 turns in 5,820 dialogs (i.e. 22 turns per dialog on average). Of these, 4,152 (71.3%) are single-task dialogs, and 1,668 (28.7%) are multi-task dialogs. Of the 4,152 single task dialogs, 2,688 follow a happy path, i.e. the user is not instructed to do anything that is not accounted for by the schema. A detailed list and description of the tasks, as well as detailed turn statistics can be found in Appendix A.

We focused our data collection design choices around grounding dialogs in knowledge base queries, and providing an explicit mechanism that encourages consistent system actions, which are paramount for real-world conversational assistants. Furthermore, we required that our dialogs are created in real-time by two humans, and ensured that only workers that are comfortable with our task setup progress to the more advanced multi-task dialogs.

Our goal of high variability of the user’s behavior is difficult to quantify, but one indicator that users are more creative than in other datasets is the size of the vocabulary used. Specifically, users in STAR employ 6507 distinct dictionary words to express themselves (here we do not count entities). This is 3.6 times as large a vocabulary as users in MultiWOZ use. Even when we take into account that STAR covers almost twice as many domains, this indicates more complexity on the user side.

Evaluating the consistency of the wizard’s behavior is even more challenging, because we did not annotate user intents in the dataset, which makes it more difficult to assess whether the next wizard action is consistent given the user’s utterance. For example, we have observed that when users begin the dialogue with, say, the second piece of information that the wizard should collect according to the schema, wizards often continue asking for the third piece of information even though they should technically ask for the first (if that was not also given by the user). Other inconsistencies can occur later in the dialogue, but with increasing history length it becomes less and less clear if two dialogue states should be considered the same or not. We can, however, see if wizards generally ask questions in the right order at the beginning of a single-task dialog. Table 8 in Appendix A shows how many dialogs begin with questions in the expected order. Here, skipping questions or asking questions twice is allowed, since users might provide more than one (or no) piece of information at a time. On average, in 91% of all single-task dialogs the wizards follow the correct order of actions at the beginning of the dialog. Since this is not the only possible source of inconsistencies, we think that our data collection setup should be improved to enforce system consistency further. However, this number also suggests that a large portion of the data is consistent and can be used to train supervised learning algorithms.

An essential feature of task-oriented dialog is its history dependence, i.e. the next system action hinges on what has been said or decided in multiple previous turns, as this sets it apart from question answering settings. To assess the history dependence of STAR, we train a transformer-based response selector (Bunk et al., 2020) with ConveRT word embeddings (Henderson et al., 2019) for predicting the next wizard utterance with a varying number of preceding dialog turns that the model has access to. The results, presented in Figure 3, indicate that system actions depend on 5 to 10 turns of history, which highlights the complexity of our collected dialogs.
STAR allows us to train models which are conditioned on a task-specific schema. Rather than relying on a model to implicitly learn the steps required to complete a task (e.g., ask for a name, then ask for a phone number), we instead propose to explicitly provide this information through the task-specific schemas. We hypothesize that such models will better generalize to tasks that are unseen at training time. In this Section, we present baseline models for next action prediction and response generation, both with and without conditioning on the schema.

5.1 Schema Representation

The schema is a graph, wherein each node is associated with text that either describes a system or user action. For example, the schema in Figure 4 can be constructed from the flow chart of Figure 1. Each bullet point in the flow chart becomes a node in the graph, and every node would be associated either with a system response template or with text describing the user’s anticipated input (e.g., ‘No’). The complete translation of Figure 1 into a schema is given in Appendix C.

While collecting STAR, we designed the instructions and the task-specific flow charts to encourage that the wizard’s actions are deterministic. As such, if we accurately determine our current position in the schema graph (i.e., the state of the dialog), the next system action can be determined by following the single outgoing edge. For example, if we consider a dialog (corresponding to the schema in Figure 4) wherein the system has requested the user’s name and the doctor’s name – we know that our current position in the graph is doctor-ask-doctor-name and therefore the next system action should be doctor-ask-day.

We manually construct the schema graphs by considering the flow charts and a few example dialogs. While we believe this graph-based representation of the schema to be derived naturally from the formulation of the flow charts, it is by no means the only possible representation of the schema. We consider the schema representation to be an attribute of the models rather than of the dataset. As such, we anticipate that future work will propose improved representations of the schemas, which may involve manually constructing schemas for the 24 tasks or devising an automatic data-driven mechanism of extracting schema representations.

5.2 Next Action Prediction

We introduce both schema-free and schema-guided BERT baselines for next action prediction on STAR. For the schema-free model, we begin by encoding the dialog history using the BERT-base model (Devlin et al., 2018). We use the pooled representation, denoted $h_{CLS}$ as the latent representation of the dialog history. This representation is passed through a linear layer (parameterized by $W$ and $b$) to produce a probability distribution over the set of possible actions:

$$P_{clf} = \text{softmax}(W h_{CLS} + b).$$

The schema-guided model augments the BERT classifier by conditioning it on the aforementioned schema graph. The schema-guided models use the schema to produce a probability distribution over the set of actions, $P_{scm}$. This probability distribution is then combined with $P_{clf}$ to produce the final distribution over the set of actions. To produce $P_{scm}$ we begin by encoding the dialog history, $h_{CLS}$. Next, we produce a latent representation for each node in the schema by using BERT to encode the associated text. We denote the latent representations of the nodes as $K = \{\kappa_1, \kappa_2, \ldots, \kappa_n\}$, such that $\kappa_i$ is the latent representation of the $i$-th node. For each node, we consider the corresponding next action to be the action label of the subsequent node (e.g., in Figure 4, the next action for the hello node would be ask-name). We represent the set of next actions as $V = \{v_1, v_2, \ldots, v_n\}$ such that
\(v_i\) is the one-hot representation of the next action corresponding to the \(i\)-th node. Given \(h_{CLS}\), \(K\) and \(V\), we compute:

\[
P_{scm} = \text{softmax}(h_{CLS}^T K) \cdot V
\]

STAR includes dialogs where the user exhibits behavior that forces the wizard to deviate from the task schema. To account for this, \(P_{scm}\) is combined with \(P_{clf}\) by computing \(\rho_{scm}\) and using it to combine the two probability distributions. We compute \(\rho_{scm}\) by passing \(h_{CLS}\) through a linear layer (defined by \(W_h\) and \(b_h\)):

\[
\rho_{scm} = \sigma(W_h^T h_{CLS} + b_h),
\]

\[
P_{\text{fin}} = \rho_{scm} P_{scm} + (1 - \rho_{scm}) P_{clf}
\]

where \(\sigma\) denotes the logistic sigmoid function.

### 5.3 Generation

We fine-tune GPT-2 (Radford et al., 2019) for the task of response generation on STAR. We carry out response generation experiments both with and without the schema. In the schema-free model, we fine-tune GPT-2 to produce the response conditioned on the dialog history. During inference, we sequentially decode until the end of sentence token is generated.

We augment the GPT-2 model to condition on the schema representation. To do so, we use the aforementioned schema-guided BERT classifier (pictured in Figure 5) to produce a probability distribution over the set of next actions. We then use the top 3 predicted next actions\(^6\) to produce a schema-augmented dialog context. Concretely, given a dialog history \(H\), we use the schema-guided next action classifier to predict the top 3 actions, \(a_1, a_2\) and \(a_3\). For each of these actions, we identify the corresponding system response template, \(t_1, t_2\) and \(t_3\). We then concatenate the history and the response templates to produce the schema-augmented dialog context: \(H; t_1; t_2; t_3\), where \(;\) denotes a separator token. GPT-2 is then fine-tuned to generate the ground-truth response conditioned on this schema-augmented dialog context.

The schema-guided next action classifier uses the explicit schema representation to predict the next actions and our schema-guided response generation model uses the templates corresponding to the predicted next actions. As such, our schema-guided response generation model explicitly uses the schema graph to determine the next system action. We hypothesize that this will result in better performance, particularly when transferring to unseen tasks or domains.

### 6 Experiments

Here we demonstrate how to use the STAR dataset for the tasks of next action prediction and response generation. Furthermore, we carry out zero-shot transfer learning experiments to assess our models’ performance on unseen tasks and domains.

Unless otherwise specified, we carried out the following experiments in three stages: (i) happy, (ii) unhappy, and (iii) multi-task. For each stage, we trained the models on 80\% of the data from the current stage and all data from the previous stages. We tested models on the remaining 20\% of data from the current stage. We forego the use of
Figure 5: Schema-guided next action prediction model as described in §5.2 in Equations 1 - 4.

6.1 Next Action Prediction

In next action prediction, the task is to predict the next system action conditioned on the dialog history. For every response, we provide a single ground-truth action. We evaluate our models on this task using the weighted F-1 score. The results shown in Table 2 demonstrate that the BERT classifier outperforms the schema-augmented BERT model. While this is a negative result, it should be noted that the schema is intended to facilitate transfer learning and the fact that it does not yield performance improvements when evaluating on seen tasks and domains does not invalidate its effectiveness.

6.2 Response Generation

Response generation is the task of generating the system response conditioned on the dialog history. Through the schema and the suggested response templates, STAR was designed to contain consistent and deterministic system behavior. As a result, it is suitable to evaluate with word-overlap metrics since the one-to-many problem (Zhao et al., 2017) is less prevalent. We evaluate response generation with three metrics: (i) BLEU-4 (Papineni et al., 2002), (ii) IEM (in-domain exact match), which measures the rate of exact matches between the hypothesis and domain-specific reference responses (i.e., excluding 'Hello', 'Goodbye', etc.),...
Table 3: Results of the generation prediction experiments for the three stages. Note that the results are not comparable across the three stages, since the latter stages were trained on more data.

| Model                  | Happy | Unhappy | Multi-task |
|------------------------|-------|---------|------------|
|                        | IEM   | BLEU    | Entity F-1 | IEM   | BLEU    | Entity F-1 | IEM   | BLEU    | Entity F-1 |
| GPT-2                  | 42.93 | 58.60   | 75.85      | 46.63 | 61.44   | 78.21      | 35.18 | 61.35   | 76.42      |
| GPT-2 + schema         | 44.17 | 58.96   | 77.89      | 47.03 | 60.39   | 79.45      | 50.43 | 61.35   | 76.42      |

Table 4: Results of the zero-shot task and domain transfer experiments for next action prediction. The column denoted $H$ refers to the experiments with only the happy dialogs, while $H+U$ denotes the use of both the happy and unhappy dialogs.

| Experiment      | Model          | $H$ F-1 | $H+U$ F-1 |
|-----------------|----------------|---------|-----------|
| task transfer   | BERT           | 36.45   | 36.89     |
|                 | BERT + schema  | 36.77   | 37.15     |
| domain transfer | BERT           | 34.84   | 35.63     |
|                 | BERT + schema  | 37.20   | 35.71     |

Table 5: Results of the zero-shot task transfer experiments for response generation.

| Model                  | IEM   | BLEU    | Entity F-1 |
|------------------------|-------|---------|------------|
|                        |       |         |            |
| GPT-2                  | 4.76  | 15.23   | 48.22      |
| GPT-2 + schema         | 5.17  | 15.49   | 52.12      |
| Happy + Unhappy        | 8.61  | 14.57   | 47.45      |
| GPT-2 + schema         | 8.79  | 15.15   | 51.63      |

Table 3: Results of the generation prediction experiments for the three stages. Note that the results are not comparable across the three stages, since the latter stages were trained on more data.

and (iii) Entity F-1 (Wen et al., 2016) which measures the weighted F-1 for entities in the response (e.g., ‘2 pm’).

The results of the generation experiments are shown in Table 3. Leveraging the schema leads to a performance increase, albeit less so for the unhappy dialogs, as one would expect (users in unhappy dialogs diverge from the schema). Leveraging the schema results in a significant performance increase in the multi-task setting, suggesting that explicitly conditioning on the schema (both through the next action classifier and through the response templates) is valuable for multi-task dialogs.

6.3 Other Tasks

STAR can be used for additional tasks, such as knowledge base query prediction (predicting the correct knowledge base keys, values and operators), schema prediction (predicting the schema of a task, given a collection of dialogs), and out-of-domain detection (detecting whether a user has made an out-of-domain request).

6.4 Zero-Shot Transfer

The variety of tasks and domains as well as the structured policy representation makes the STAR dataset ideal for zero-shot transfer learning experiments. For the tasks of next action prediction and response generation, we carry out two sets of transfer experiments: (i) using only happy dialogs and (ii) using both happy and unhappy dialogs. We also experiment with both task transfer and domain transfer. While there might be high overlap between tasks (e.g., `bank_balance` and `bank_fraud_report`) there is less overlap between domains (e.g., `hotel` and `flight`).

We train the model on $N-1$ tasks/domains and evaluate on the $N$-th. We repeat this for each task/domain for a total of $N$ times ($N = 24$ for task transfer, $N = 13$ for domain transfer).

The results in Tables 4-6 show that the use of the schema consistently results in performance improvement for zero-shot task and domain transfer. These preliminary results highlight the potential of using the schema as an inductive bias to help with model generalizability and task transfer. However, the zero-shot transfer experiments demonstrate that even the schema-guided models perform significantly worse on unseen tasks than it does on seen tasks. To mitigate this performance gap, future work should explore mechanisms of better leveraging the task-specific schemas to facilitate generalizability to unseen tasks and domains.

7 Conclusions

With this work, we make multiple contributions to the field of task-oriented dialog research. First, we presented STAR, a novel dialog dataset that we specifically designed to facilitate transfer learning experiments. Second, we introduced a new, scalable crowd sourcing paradigm to collect data of similar quality as STAR. In future work, this setup could be used to expand on STAR by collecting data for additional tasks, domains, or in languages other than English. Finally, we established baseline scores for next action prediction, response generation, and zero-shot transfer learning for the former two tasks. With this we demonstrated how task
| Model        | IEM | BLEU | Entity F-1 |
|--------------|-----|------|------------|
| GPT-2        | 8.14| 17.12| 48.18      |
| GPT-2 + schema | 8.39| 18.60| 50.23      |

| Model        | IEM | BLEU | Entity F-1 |
|--------------|-----|------|------------|
| GPT-2        | 8.77| 19.46| 50.43      |
| GPT-2 + schema | 8.82| 19.74| 53.02      |

Table 6: Results of the zero-shot domain transfer experiments for response generation.

Schemas can be used to improve transfer learning capabilities. We also outlined a variety of other experiments that STAR would be suitable for, and we look forward to seeing these experiments, as well as improvements upon our baseline scores, implemented in future publications.
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A Tasks

Table 7 shows the 24 tasks and their descriptions. Figure 6 shows the distribution of action counts for single- and multi-task dialogs, respectively. For multi-task setups, action counts double for the user and the wizard and exhibit a substantial increase in knowledge base queries, highlighting how difficulty and complexity increase when moving from a single-task to a multi-task setup, which typically cover 2-5 tasks.

Multi-task scenarios connect tasks as is shown in Figure 7. For the user, task instructions are sometimes given during the dialog, as shown in Figure 8.

Table 8 shows the fraction of single-task dialogs per task in which the wizards follow the prescribed order of questions at the beginning of the dialog.

B Worker payments

Here we summarize the payments and bonuses that workers receive for their work.

In Stage I, workers that use fewer than 9 hints to solve the questionnaire are paid $2 for participating in the tutorial, otherwise their assignment is rejected. In addition, successful workers are paid a bonus of $0.50 or $0.25 if they answer without using hints or with up to three hints, respectively.

In a second evaluation step, we consider workers for which both initially considered dialogs where acceptable, and who have submitted at least 10 assignments for each role (user and wizard). We manually read samples of their submissions and decide who are members of the top performing 10%, based on how well they followed their instructions and how creative they’ve been as a user. Those workers get paid a bonus amount of $0.40 per assignment.

The payment in Stage III is identical to that of Stage I, but the video is shorter and, therefore, the hourly salary is higher.

In Stage IV we pay $1.90 per HIT plus a bonus of $0.90 cents for particularly long instruction sets (they take about 20 minutes to complete). Once again, the top 10% of workers get paid a bonus of $0.60 per assignment.

C Data format

Each dialog is stored as a JSON file with the following structure.

```json
{
    "FORMAT-VERSION": 6,
    "dialogID": integer number of the dialog,
    "BatchID": string identifier for the collection batch,
    "CompletionLevel": string indicating possible disconnects,
    "Scenario": {
        "Domains": list of domains that this dialog can touch on,
        "UserTask": initial instructions given to the user,
        "WizardTask": instructions given to the wizard,
        "WizardCapabilities": list of capabilities of the wizard (see below),
        "Happy": boolean indicating if this scenario was happy,
        "MultiTask": boolean indicating if the wizard had more than one task capability,
    },
    "Events": list of events that constitute the dialog,
    "AnonymizedWizardWorkerID": string identifying the wizard worker,
    "AnonymizedUserWorkerID": string identifying the user worker,
    "UserQuestionnaire": list of questions and answers for the user at the end of the dialog,
    "WizardQuestionnaire": list of questions and answers for the wizard at the end of the dialog,
}
```

At the heart of the dialog file is the list of events. Events can be user utterances or the custom response of the wizard, but also one of the other things that we describe in Table 9. Apart from time stamp data, all events have an Agent and an Action field. Further information stored with the event depends on these latter two fields, as can be seen in Table 9.

The task schemas are also stored as JSON files. For example, the schema of the book_doctor_appointment task is:

```json
{
    "task": "book_doctor_appointment",
    "replies": {
        "hello": "Hello, how can I help?",
        "ask_name": "Could I have your name, please?",
        "doctor_ask_doctor_name": "What doctor would you like to see?",
        "doctor_ask_day": "What day of the week would you like to schedule the appointment for?",
        "doctor_ask_start_time": "At what time?
```
| Task name                          | Description                                                                 |
|-----------------------------------|-----------------------------------------------------------------------------|
| book_apartment_viewing            | Schedule an apartment viewing, given the name of the rental company         |
| apartment_search                  | Find an apartment to rent                                                   |
| bank_balance                      | Check the balance of a bank account (A).                                   |
| bank_fraud_report                 | Report suspicious behavior on your bank account (A).                       |
| book_doctor_report                | Make an appointment with a doctor                                          |
| followup_doctor_appointment       | Check instructions given by doctor upon last visit                        |
| hotel_reserve                     | Reserve a room in a hotel                                                  |
| hotel_search                      | Find a hotel                                                               |
| hotel_service_request             | Ask for a room service in a hotel                                          |
| schedule_meeting                  | Schedule a meeting                                                         |
| party_plan                        | Plan a party at a given venue                                              |
| party_rsvp                        | RSVP to a party of a given host at a given venue                           |
| plane_search                      | Find a flight between two cities                                           |
| plane_reserve                     | Book a flight, given its id                                                |
| restaurant_search                 | Find a restaurant                                                          |
| restaurant_reserve                | Reserve a table at a restaurant                                            |
| book_ride                         | Call a Taxi/Uber/Lyft ride to any destination                              |
| ride_change                       | Change details of a Taxi/Uber/Lyft ride that had been called earlier       |
| ride_status                       | Check the status of a ride you called earlier                              |
| spaceship_life_support            | Recover the spaceship’s life support                                        |
| spaceship_access_codes            | Get a repair robot to open a door for you                                  |
| trip_directions                   | Get walking/driving/transit directions between two locations (B).           |
| trivia                             | Play a game of trivia (C).                                                 |
| weather                            | Check the weather (forecast) in various cities                             |

Table 7: Descriptions of the 24 tasks. Particular challenges are introduced by (A) different options for what information the user can provide (security questions in case of forgotten PIN number), (B) repeated information retrieval from a single knowledge base item, and (C) a loop in the schema with a summary of events in that loop at the end.

Figure 6: Distribution of action counts for single task (left panel) and multi-task (right panel) dialogs.

time can you be at the clinic?",  
"doctor_ask_symptoms": "Could you describe your symptoms, please?",  
"doctor_inform_booking_unavailable": "Unfortunately {doctor_name:s} has no appointment available at {time:s}.",  
"doctor_inform_booking_available": "Alright, {doctor_name:s} is available at {time:s}. Can I book the appointment for you?",  
"doctor_inform_booking_successful": "Great, your appointment with {doctor_name:s} is booked for you!",  
"doctor_bye": "Thank you and goodbye.",  
"doctor_inform_nothing_found": "Unfortunately there is currently no doctor available.";
Figure 7: Co-occurrence of tasks. Each task is shown as a vertex in this graph. The more dialogs two tasks jointly appear in (based on the knowledge base queries in that dialog) the thicker the edge connecting these tasks. Some tasks do not appear together in any dialog and are therefore not connected. Vertex colors indicate the task domain. The relative frequency of the 13 domains is illustrated in the top left inset. The largest clique in this graph is \{restaurant_reserve, schedule_meeting, plane_search, hotel_service_request, party_rsvp\}.

"anything_else": "Is there anything else that I can do for you?",
"out_of_scope": "I am sorry, I don’t quite understand what you mean. I am only able to help you book an appointment with your doctor.",
"unavailable": "Unavailable",
"available": "Available",
"no": "No",
"yes": "Yes",
"query_check": "Query Check",
"query_book": "Query Book"
},
"graph": {
  "hello": "ask_name",
  "ask_name": "doctor_ask_doctor_name",
  "doctor_ask_doctor_name":
    "doctor_ask_day",
  "doctor_ask_day":
    "doctor_ask_start_time",
  "doctor_ask_start_time":
    "doctor_ask_symptoms",
  "doctor_ask_symptoms": "query_check",
  "available":
    "doctor_inform_booking_available",
  "unavailable":
    "doctor_inform_booking_unavailable",
  "yes": "query_book",
  "no": "doctor_ask_doctor_name",
  "query_book":
    "doctor_inform_booking_successful",
  "doctor_inform_booking_successful": "anything_else"
}

D Multiple-choice tests

To prepare workers for the Stage II and Stage IV tasks, we ask them to watch video tutorials and
answer the following questions during Stages I and III.

D.1 Stage I - Single Task

The Stage I video tutorial is available at https://youtu.be/L7QpscLPTFM. After watching the video, workers have to answer the following questionnaire with fewer than 9 hints.

1. As the user, when can you end the task? (Correct answer: (c))
   (a) I cannot. Only the assistant can do this.
   (b) As soon as the ‘Click here when you’ve accomplished your task(s)’ button is enabled.
   (c) When I have followed all the instructions, including those on the left panel and those that are given by the MTurk System Bot.

2. As the user, if you forget to follow an instruction from the MTurk System bot, what should you do? (Correct answer: (b))
   (a) Forget about the instruction since it is outdated.
   (b) Follow the instruction once I realise that I’ve overlooked it.
   (c) Tell the AI Assistant that I’ve missed an instruction.

3. As the user, what should you do if you need some information that was not given in the task instructions? (Correct answer: (a))
   (a) I can just make something up.
   (b) Give up.
   (c) I must avoid answering any questions about the missing information.

4. As the assistant, what should you do if the user begins a dialog, but doesn’t say what he/she wants? (Correct answer: (b))
   (a) I tell the user what task I can help her with.
   (b) I should just greet the user.
   (c) I should say that I cannot understand what he/she’s saying.

5. For the assistant, what of these things is the MOST important? (Correct answer: (b))
   (a) Being helpful to the user
   (b) Following the flow chart of the current task whenever possible
   (c) Making the conversation as short as possible
   (d) Making the conversation as long as possible

6. What does the request-optional box mean in the flow chart? (Correct answer: (a))
   (a) It represents information that I can use, but that is not absolutely required.
   (b) I can ignore this box if it doesn’t make sense here.

7. As an assistant, when should you use one of the suggested responses? (Correct answer: (a))
Table 8: Fraction of single-task dialogs per task in which the wizards follow the prescribed order of questions at the beginning of the dialog. Here, skipping questions or repeating them is allowed, as the user can provide multiple pieces of information at once or say something irrelevant. The fractions shown in the second column concern happy-path dialogs only, whereas the third column includes all single-task dialogs. The last column shows the number of actions that are checked for correct order. For example, in the plane_book task, the three actions “ask name”, “plane ask flight id”, and “query plane book”, must occur in that order.

| Task                          | Happy | All  | Number of Checked Actions |
|-------------------------------|-------|------|---------------------------|
| apartment_schedule            | 0.95  | 0.94 | 5                         |
| apartment_search              | 0.90  | 0.90 | 7                         |
| bank_balance                  | 0.97  | 0.97 | 3                         |
| bank_fraud_report             | 0.97  | 0.96 | 3                         |
| doctor_followup               | 0.98  | 0.98 | 4                         |
| doctor_schedule               | 0.90  | 0.90 | 6                         |
| hotel_book                    | 0.95  | 0.91 | 6                         |
| hotel_search                  | 1.00  | 1.00 | 5                         |
| hotel_service_request         | 0.66  | 0.66 | 6                         |
| meeting_schedule              | 0.94  | 0.94 | 6                         |
| party_plan                    | 0.77  | 0.77 | 6                         |
| party_rsvp                    | 0.67  | 0.67 | 7                         |
| plane_book                    | 0.97  | 0.94 | 3                         |
| plane_search                  | 1.00  | 1.00 | 4                         |
| restaurant_book               | 0.84  | 0.84 | 5                         |
| restaurant_search             | 0.99  | 0.99 | 7                         |
| ride_book                     | 0.98  | 0.95 | 4                         |
| ride_change                   | 0.92  | 0.92 | 4                         |
| ride_status                   | 0.90  | 0.90 | 3                         |
| spaceship_access_codes        | 0.88  | 0.88 | 5                         |
| spaceship_life_support        | 0.99  | 0.95 | 4                         |
| trip_directions               | 0.79  | 0.76 | 5                         |
| trivia                        | 1.00  | 1.00 | 2                         |
| weather                       | 1.00  | 1.00 | 2                         |
| mean                          | 0.91  | 0.91 |                           |

(a) Whenever possible - I only use custom responses if the situation is not accounted for in the flow chart
(b) Only if they fit exactly what I want to say

8. What does the “request type” form field mean? (Correct answer: (a))
(a) It is there to distinguish between checking if a booking is available or actually performing the booking
(b) It’s about the type of person I am dealing with
(c) The request type describes the topic that the user is referring to.

9. How does the ideal user behave? (Correct answer: (b))
(a) As a user, I should behave in a structured and consistent manner. Always friendly and concise.
(b) As a user, I should make the dialog more interesting and complicated (but follow instructions).
(c) Just follow the instructions.

10. How does the ideal AI Assistant behave? (Correct answer: (c))
(a) Just follow the instructions.
(b) As an AI Assistant, I should make the dialog more complex and be very creative - but follow the instructions.
(c) As an AI Assistant, I should behave in a structured and consistent manner. Always friendly and concise.
Agent | Action | Additional information
--- | --- | ---
User | utter | Text
User | complete | 
Wizard | request_suggestions | Text, PrimaryItem, SecondaryItem
Wizard | pick_suggestion | Text, Intent, IntentOptions, PrimaryItem, SecondaryItem
Wizard | utter | Text, PrimaryItem, SecondaryItem
Wizard | query | Constraints, API, PrimaryItem, SecondaryItem
Wizard | select_topic | Topic, PrimaryItem, SecondaryItem
Wizard | select_primary | PrimaryItem, SecondaryItem
Wizard | select_secondary | PrimaryItem, SecondaryItem
KnowledgeBase | return | Item, TotalItems, Topic
UserGuide | instruct | Text

Table 9: Information stored in dialog events. Each event contains an Agent and an Action field. Additional fields depend on the former two. The Text field contains a plain text utterance of the agent. The PrimaryItem and SecondaryItem fields contain JSON objects that describe the selected knowledge base item, and the knowledge base item that is selected for comparison. Both of these fields may be null. The Intent field is a label associated with the utterance that the wizard has selected. If the intent is custom, then the wizard used a free-form reply. The IntentOptions field is a list of suggested responses (given as intent labels) that the wizard could choose from. The Constraints field is a JSON object describing the constraints on the knowledge base query. Here, comparators may be expressed as python expressions, e.g. `api.is_greater_than(4)`. The API field is the name of the task that the event is related to. Finally, the Item field is a JSON object describing a knowledge base item and the TotalItems field is the number of knowledge base items that would also satisfy the specified constraints, or -1 if not applicable.

D.2 Stage III - Multi Task

The Stage III video tutorial is available at [https://youtu.be/dd0s2Sqox6g](https://youtu.be/dd0s2Sqox6g). After watching the video, workers have to answer the following questionnaire with fewer than 9 hints.

1. Which one of these three things has changed, compared to the single-task dialogs? (Correct answer: (a))
   
   (a) The number of flow-charts that the AI Assistant has to follow.
   (b) The fact that one plays either a user or an AI Assistant.
   (c) The design of the AI Assistant’s flow-charts.

2. Why is it important to use names (for places, airlines, etc.) that are given in the left-panel instructions (if any)? (Correct answer: (b))

   (a) Those names are better.
   (b) The AI Assistant may only be able to choose from a limited set of names, so if I come up with something random, the assistant cannot help me.
   (c) This is a complicated issue that has to do with machine learning.

3. As the user, what should you do if you need some information that was NOT given in the task instructions? (Correct answer: (a))

   (a) I can just make something up.
   (b) Give up.
   (c) I must avoid answering any questions about the missing information.

4. As the assistant, what should you do if the user begins a dialog, but doesn’t say what he/she wants? (Correct answer: (c))

   (a) I tell the user what task I can help her with
   (b) I should say that I cannot understand what he/she’s saying
   (c) I should just greet the user
   (d) Making the conversation as long as possible

5. For the assistant, what of these things is the MOST important? (Correct answer: (b))

   (a) Being helpful to the user
   (b) Following the flow chart of the current task whenever possible
   (c) Making the conversation as short as possible
   (d) Making the conversation as long as possible
6. If two or more topics are given, and you (as a user) are otherwise free to form the dialog, what would NOT be ok? (Correct answer: (c))
   (a) Jumping back and forth between topics.
   (b) Occasionally saying something that’s not really relevant to the conversation (smalltalk).
   (c) Covering only one of the given topics.

7. As an assistant, when should you use one of the suggested responses? (Correct answer: (a))
   (a) Whenever possible - I only use custom responses if the situation is not accounted for in the flow chart
   (b) Only if they fit exactly what I want to say

8. As an assistant, what should you do when the user changes tasks? (Correct answer: (b))
   (a) I switch to the corresponding task-tab and follow this task’s flow chart from the beginning
   (b) I switch to the corresponding task-tab and follow this task’s flow chart from the point that makes most sense, given what information I already have.
   (c) I use a free-form response.

9. How does the ideal user behave? (Correct answer: (b))
   (a) As a user, I should behave in a structured and consistent manner. Always friendly and concise.
   (b) As a user, I should make the dialog more interesting and complicated (but follow instructions).
   (c) Just follow the instructions.

10. How does the ideal AI Assistant behave? (Correct answer: (c))
    (a) Just follow the instructions.
    (b) As an AI Assistant, I should make the dialog more complex and be very creative - but follow the instructions.
    (c) As an AI Assistant, I should behave in a structured and consistent manner. Always friendly and concise.
E Example Dialogs

What follows are example dialogs from the three classes: happy, unhappy, and multi-task. Here, we only display the plain text utterances exchanged by the user and the wizard and the knowledge base items received by the wizard. We suppress the knowledge base queries and other annotation.

E.1 Single-Task, Happy

USR: I would like to make a service request for 6 am
WIZ: Could I get your name, please?
USR: Mark
WIZ: At what hotel are you currently staying?
USR: Old Town Inn room 359
WIZ: Right, please let us know your request now.
USR: I want to order medium rare steak and a glass of red wine
KB : RequestStatus: Request Confirmed, RoomNumber: 359, Time: 6 am, api_name: hotel_service_request
WIZ: Your request has been submitted successfully. A member of the service team will knock on the door of room 359 at 6 am!
USR: okay thanks
WIZ: Is there anything else that I can do for you?

E.2 Single-Task, Unhappy

USR: Hi i need a room at the Hilton please
WIZ: What hotel would you like to stay at?
USR: Ah actually my friend just told me Old Town Inn is better, i whant that one
WIZ: May I have your name, please?
USR: Yes its Mark,
WIZ: When are you arriving?
USR: Ah he was saying the Old Town is better in naother city, i just saw the Shadyside inn online and think its better, May7th to 23rd please
KB : Message: Unavailable, HotelName: Shadyside Inn, api_name: hotel_reserve
WIZ: I’m very sorry, but there is no room available at the Shadyside Inn for your requested dates.
USR: Oh no, this blog never let me down, its so great usually, can you check again?
KB : Message: Available, HotelName: Shadyside Inn, api_name: hotel_reserve
WIZ: Alright, the Shadyside Inn ticks all of your boxes, can I book this room for you?
USR: Ah, cant beleve this i just got invited to a wedding in LONDON, lol please change the dates to 15th-26th the following month
KB : Message: Unavailable, HotelName: Shadyside Inn, api_name: hotel_reserve
WIZ: I’m very sorry, but there is no room available at the Shadyside Inn for your requested dates.
USR: Oh, bad news all the way, ok thats it i guess
WIZ: Would you like to try searching for another Hotel?
USR: No thats it, thanks bye!
WIZ: Thank you and goodbye.

E.3 Multi-Task

USR: Hey, I need to change a ride I have already booked!
WIZ: Could you give me your name, please?
USR: Ben
WIZ: Can I get your booking ID, please?
USR: It is ride id 551.

WIZ: Sure, what can I change for you?

USR: I need to change the arrival time if possible. I won’t be ready for at least 20 more minutes.

KB : ChangeStatus: We are unable to change your trip., api_name: ride_change

WIZ: Unfortunately I wasn’t able to update your booking, sorry.

USR: Oh no! Well they might have to wait. Can you give me the status of the ride now please?

KB : RideStatus: Your ride is on its way., RideWait: 3 minutes away, api_name: ride_status

WIZ: Your ride is 3 minutes away

USR: Yikes! I am sick on my stomach and I think it is because of these meds Dr. Morgan gave me. Can you check if I was supposed to take this with food, or only water, or what?

KB : Message: You must take your medicine 2 times a day before meals., api_name: followup_doctor_appointment

WIZ: Your instructions are: You must take your medicine 2 times a day before meals.,

USR: Oh, I didn’t eat with it. I bet that is why I am sick now.

WIZ: Is there anything else that I can do for you?

USR: I will need to find a restaurant to go to dinner, so I will have something to eat before my next scheduled dose.

WIZ: What restaurant would you like to go to?

USR: I don’t have a real preference. I would like something in the North or South of town though.

WIZ: What cuisine are you looking for?

USR: I would like pizza or Italian. But I am open. Just anything but Chinese.

KB : id: 366, Name: The Porch, Cost: Cheap, TakesReservations: False, DoesDelivery: False, AverageRating: 2, Food: Pizza, AverageWaitMinutes: 31, OpenTimeHour: 7 am, CloseTimeHour: 9 pm, MaxPartySize: 9, Location: West, api_name: restaurant_search

WIZ: Any minimum rating that the restaurant should have?

USR: No, sometimes ratings are set up. You know people get their friends to do their Yelp and Google reviews.

KB : id: 219, Name: Legume, Cost: Moderate, TakesReservations: True, DoesDelivery: False, AverageRating: 5, Food: Steak, AverageWaitMinutes: 50, OpenTimeHour: 11 am, CloseTimeHour: 7 pm, MaxPartySize: 6, Location: North, api_name: restaurant_search

WIZ: I found Legume restaurant in the North side. There is an average wait time of 50 minutes and it is moderately priced.

USR: That is a wait. My aunt is diabetic. Can you search for something else with less of a wait time?

KB : id: 884, Name: The Porch, Cost: Moderate, TakesReservations: False, DoesDelivery: True, AverageRating: 5, Food: Italian, AverageWaitMinutes: 27, OpenTimeHour: 6 am, CloseTimeHour: 11 pm, MaxPartySize: 42, Location: North, api_name: restaurant_search

WIZ: The Porch Italian restaurant is in the North side. There is an average wait of 27 minutes and it is moderately priced.

USR: Ok. I will tell her to bring her sugar tablets just in case. But that should be acceptable.

WIZ: Is there anything else that I can do for you?

USR: You know what? I forgot that I saw Dr. Alexis last week too and have pills from her. Can you check those instructions for me? One might be with food and the other not. Who knows?

KB : Message: You must take your medicine 2 times a day before meals., api_name: followup_doctor_appointment

WIZ: Your instructions are: You must take your medicine 2 times a day before meals.,

USR: Ok, they have the same instructions, that’s a relief. I have enough to think about.

WIZ: Is there anything else that I can do for you?

USR: Is my ride still 3 minutes away? He hasn’t arrived here yet?

KB : RideStatus: Your driver is dropping off another passenger., RideWait: 9 minutes away, api_name: ride_status

WIZ: Your driver is dropping off another passenger and is 9 minutes away.

USR: Oh, ok. That actually works out. I am still on the toilet. Smh. I will definitely eat after I take it next time.

WIZ: Is there anything else that I can do for you?

USR: I just want to tell you that you have been most helpful to me today.

WIZ: Thank you and goodbye.

USR: Thank you so much!

WIZ: Goodbye. Enjoy your ride!
Selected Comments from Turkers

We received comments such as those below throughout the four stages of data collection. We also received emails with detailed constructive (though mostly positive) feedback that spans up to an entire page, which we do not share here. The primary negative feedback concerned partner disconnects during the dialogs and we intend to mitigate this in future projects.

“Thank you for doing such a nice job.”
- P. M.

“Will there be more hits posted? I love your hits!”
- S. K.

“I just wanted to take this opportunity to send out a warm thank you for the work you recently have posted. I hope the data you are getting will meet or excel your expectations and if there are any concerns or issues with dialog or extended conversations that you need, please don’t hesitate to contact me. Please stay safe during these times and I look forward to many more batches of work and working for you in the future. Thanks again, have a great day!”
- B. C.

“Thanks for everything! I’m loving participating.”
- T. R.

“I thoroughly enjoyed taking part in this study.”
- I. B. P.

“I loved doing your dialogs, they were so much fun and engaging.”
- N. W.

“Will there be any work today? Looking forward to the next round :)”
- L. H.

“I liked how clearly you explained the directions and that you made clear what your expectations were. The training videos were also very helpful, they made it easier for me to learn quickly and to be able to perform the HITs up to your standards. I also think the tests were helpful too because they really brought to my attention what was important in the video. For example, one of the test questions the early stage asked about whether the AI’s role was to bring the conversation back to the script or to make sure the customer was satisfied. The answer really let me know what my role would be, which I liked.

My only dislike was that during stage IV I occasionally had partners who were obviously working on more than one task at once, which led to long delays for simple responses. This became very frustrating when HITs would drag on for a long time due to inactivity from partners. I prefer to focus my full attention on each HIT, so I did become a bit impatient at times. However, I understand that there is only so much you can control so I do understand why this happens.”

- C. S.

“I would definitely like to work with you again in the future, I really enjoyed doing these tasks and can’t wait for future projects!”
- L. J.

“I enjoyed working on your project and am sorry to see it come to a close. I’d love to help out with future projects you might have. Please keep me in mind if you need a beta tester. I’d also be interested in reading about your research if/when you publish your findings. Thanks again for the HITs; it was a pleasure working for you guys.”

- A. F.