DEUX: An Attribute-Guided Framework for Sociable Recommendation Dialog Systems

†Yu Li ‡Shirley Anugrah Hayati §Weiyan Shi §§Zhou Yu

†Department of Computer Science, University of California, Davis ‡University of Pennsylvania §Department of Computer Science, Columbia University †yooli@ucdavis.edu, ‡sahayati@upenn.edu §{ws2634, zy2461}@columbia.edu

Abstract

It is important for sociable recommendation dialog systems to perform as both on-task content and social content to engage users and gain their favor. In addition to understand the user preferences and provide a satisfying recommendation, such systems must be able to generate coherent and natural social conversations to the user. Traditional dialog state tracking cannot be applied to such systems because it does not track the attributes in the social content. To address this challenge, we propose DEUX, a novel attribute-guided framework to create better user experiences while accomplishing a movie recommendation task. DEUX has a module that keeps track of the movie attributes (e.g., favorite genres, actors, etc.) in both user utterances and system responses. This allows the system to introduce new movie attributes in its social content. Then, DEUX has multiple values for the same attribute type which suits the recommendation task since a user may like multiple genres, for instance. Experiments suggest that DEUX outperforms all the baselines on being more consistent, fitting the user preferences better, and providing a more engaging chat experience. Our approach can be used for any similar problems of sociable task-oriented dialog system.

1 Introduction

In recent years, research in recommendation dialog systems have received increasing interest. They commonly focus on two approaches: task-oriented dialog systems or free-form dialog systems with more diverse interactions. Traditional task-oriented recommendation dialog systems collect information by asking questions with predefined slots and limited values (Zhang et al., 2018; Sun and Zhang, 2018; Christakopoulou et al., 2018; Lee et al., 2018). While the response is controllable, such systems can only provide limited and rigid responses, which could neglect the user experience in the conversation. On the other hand, with the increasing demand for engaging personal conversational assistants, an ideal recommendation dialog system should be natural and sociable to gain trust and favor from the users (Hayati et al., 2020).

To address the rigid response problems in task-oriented recommendation systems, previous studies have developed free-form recommendation dialog systems that enable more diverse social interactions and better user experiences (Li et al., 2019a; Kang et al., 2019; Chen et al., 2019; Liu et al., 2020). These systems do not use predefined slots and make recommendations without slot filling. As a result, they suffer from understanding user preferences correctly and updating the dialog states accurately. Therefore, it is important to combine the strength of the two approaches to build controllable sociable recommendation dialogue systems.

However, it is challenging to track traditional dialog states in free-form recommendation dialogs because (1) the on-task content and the social content are intertwined in the conversation and (2) new attributes could be introduced in the so-
Table 1: Comparison between our framework DEUX and traditional dialog state tracking (DST).

| Characteristics               | DEUX | DST |
|-------------------------------|------|-----|
| Tracking user’s preference    | ✔    | ✔   |
| Tracking system’s preference  | ✔    | ✗   |
| Multiple slot values          | ✔    | ✔   |

cial content. For example, in a movie recommendation setting, the system needs to accomplish the recommendation task with on-task responses, such as asking for a user’s favorite genre. Meanwhile, to make the conversation more sociable, the system also needs to respond to the user with social content, such as commenting on a movie. These social content introduces new movie titles and their related attributes (e.g., genres and actors) and drives the conversation forward. Thus, it is difficult to define specific dialog states and update dialog policies in these free-form dialog systems. As a result, although these systems can generate fluent responses, they are often redundant and inappropriate.

To address these challenges, we propose DEUX, a novel attribute-guided framework to create better user experiences while accomplishing the recommendation task. DEUX has a module that keeps track of the attributes (e.g., favorite genres, actors, etc.) in both user utterances and system responses. Instead of providing a response solely based on the attributes already mentioned in the context, we also have a system attribute predictor module to predict the preferred attributes in the next system response. Finally, the response is conditionally generated on the predicted preferred attributes, leading to a more controllable generation compared to the existing free-form recommendation dialog systems.

As shown in Figure 1, our response is more engaging and consistent than the responses of both a task-oriented system and an existing free-form recommendation dialog system.

Our main contribution is as follows. We introduce a new definition of attribute tracking in the sociable recommendation task. Our attribute tracking has two main differences with the dialog states in traditional task-oriented dialog systems as shown in Table 1. Unlike traditional dialog states which only focus on the user’s preference, DEUX includes attributes in previous system responses. These additional attributes are about system preferences because the system should also introduce its own opinion and new attributes in sociable recommendation tasks. On the other hand, while traditional dialog states also track attributes on the system’s side, that tracking is only used when the dialog system requests the user’s preference. Then, instead of limiting only one value for one slot type, we have multiple values for the same slot type. For instance, the slot type of movie genre may contain actions, comedies, and dramas at the same time.

Note that a complete recommendation dialog system includes a dialog system that interacts with the user to collect user preferences and a recommender system that converts user preferences into queries and retrieves movies from a database. In this work, we focus on the dialog system, so any off-shelf recommender systems can be easily plugged into our framework. The advantage of such modular approach is that the dialog system and recommender system can be improved separately.

We evaluate our framework on INSPIRED, a sociable movie recommendation dialog dataset that contains human-human conversations with rich social content (Hayati et al., 2020). Human evaluations suggest that DEUX outperforms multiple competitive baselines on different metrics.

2 Related Work

Early research in recommendation dialog systems has utilized task-oriented slot-filling approach. In their conversations, the systems ask questions about user preference to fill in the predefined slots and later select items for recommendation (Zhang et al., 2018; Sun and Zhang, 2018; Christakopoulou et al., 2018; Lee et al., 2018). This method has explicit dialog states because the number of slot types and values is limited. Therefore, they mostly use fixed template-based response generation where the variables are filled in by the generator, resulting in rigid sentences and monotonous conversations.

Recently, to make the conversation more natural and engaging, researchers have shifted toward free-interaction recommendation dialog systems (Li et al., 2019a; Kang et al., 2019; Moon et al., 2019; Chen et al., 2019; Zhou et al., 2020; Hayati et al., 2020). Li et al. (2019a); Kang et al. (2019) develop free-interaction recommendation dialog systems on human-to-human multi-turn movie recommendation dialog datasets. Moon et al. (2019) create a recommendation dialog dataset with parallel attributes in the knowledge graph. Chen et al. (2019); Zhou et al. (2020) integrate the recommender system and the dialog system to incorporate the knowledge from recommender system into
These approaches mostly build the recommender system and the dialog system together. Meanwhile, our approach focuses on the dialog system and any off-shelf recommender system can be plugged into our framework following Hayati et al. (2020). Rather than using a sentiment classifier to detect user preference for a certain attribute as in Hayati et al. (2020) and Li et al. (2019a), for each turn in the conversation, we represent the user preferences as a set of attributes of user preferences from both user utterances and system responses. Furthermore, we predict the attributes that could appeal to the user in the next system response so that we can track the status in the dialog system.

In traditional task-oriented dialog systems, dialog state tracking predicts belief state which contains limited domains, slot types, and slot values in the dialog history (Henderson et al., 2013; Mrkšić et al., 2017; Rastogi et al., 2018). These works only focus on the dialog state tracking module. Recent improvements built on top of the transformer and pre-trained language models (Devlin et al., 2019; Liu et al., 2019; Radford et al., 2019; Yang et al., 2020). Lately, Hosseini-Asl et al. (2020) have obtained state-of-the-art results of dialogue state tracking on Multi-Domain Wizard-of-Oz dataset (Budzianowski et al., 2020). Our framework is also developed on top of large scale pre-trained language models. However, we track not only the information in the user’s dialog history, but also the attributes that the system delivers in the previous system responses. Since attributes could exist in both on-task and social content, our framework leads to a better combination of the social content and on-task content during the response generation.

To interleave the on-task content with the social content in dialog systems, Yu et al. (2017); Papaioannou et al. (2017) build hybrid dialog systems that combine a task-oriented model and a social model. In these studies, a selector is designed to choose an appropriate output from one of the systems (Yu et al., 2017) and a connector to combine two responses (Zhao et al., 2018). Li et al. (2019b) proposes a hierarchical intent annotation scheme that divides on-task and off-task content in the dataset and trains a model handling both types of content in non-collaborative tasks. Compared with these efforts, we track the attributes in the history instead of classifying the user and the system’s intents. DEUX’s approach is appropriate for recommendation task since the system can provide both on-task and social content containing attributes, and finally make a recommendation based on these attributes. Combining both attributes and intents will be an interesting future work.

3 Our Approach: DEUX

We demonstrate the overall architecture of DEUX, our framework for recommendation dialog system, in Figure 2. To enable easy replacement with any off-shelf recommender system, we decouple the system into separate modules: attribute tracking (section 3.1), system attribute predictor (section 3.2) and response generator (section 3.3). For each turn, the attribute tracking module pre-
dicts user’s attribute tracking and system’s attribute tracking at current turn. Then the system attribute predictor module predicts the system’s attribute tracking at next turn. Finally, the response generator module generates the next response conditionally on predicted attributes. Suppose we have a recommendation dialog corpus with $N$ turns, as shown in the dialogue context box in Figure 2:

$$D = \{(U_i, E^{usr}_i, E^{sys}_i, T^{usr}_i, T^{sys}_i, Y_i)\}_{i=1}^{N}$$

where $\forall (U_i, E^{usr}_i, E^{sys}_i, T^{usr}_i, T^{sys}_i, Y_i) \in D$, and $C_i = (U_1, \cdots, U_N)$ represents the dialog history consisting utterance at $i$-th turn. $E^{usr}_i$ is a set of attributes which user mentions in the dialog history. $E^{sys}_i$ is a set of attributes that system mentions in the dialog history. $T^{usr}_i$ and $T^{sys}_i$ are the attribute tracking in user utterances and system responses. $Y_i$ represents the system responses.

### 3.1 Attribute Tracking

Given the dialog history at each dialog turn $i$, the goal of this module is to predict the attribute tracking $T^{usr}_i$ and $T^{sys}_i$. Specifically, we aim to extract the attributes that a user prefers in both user utterances and system responses. Then the system will recommend the item that can meet the preference. We use a positive or negative label to categorize attributes in the attribute tracking. A positive attribute means the user prefers a recommendation that is related to this attribute while a negative attribute means the user has relatively low interest to this attribute. $T^{usr}_i$ and $T^{sys}_i$ can be denoted as:

$$T^{usr}_i = \{(e^{usr}_{i,j}, l^{usr}_{i,j}) | e^{usr}_{i,j} \in E^{usr}_i, l^{usr}_{i,j} \in \{\text{pos, neg}\}\}$$

$$T^{sys}_i = \{(e^{sys}_{i,j}, l^{sys}_{i,j}) | e^{sys}_{i,j} \in E^{sys}_i, l^{sys}_{i,j} \in \{\text{pos, neg}\}\}$$

where $j$ is the number of attributes in $E_i$.

In our architecture, to detect positive attributes in the dialog history, we first use a public named-entity recognition tool from Liang et al. (2020) and regular expressions to extract all the movie-related attributes (e.g., movie genres, movie titles and person’s names). Then we build a classifier on top of BERT (Devlin et al., 2019) to predict the label for each attribute due to BERT’s predominant performance on text classification tasks. This process can be formally denoted as:

$$[T^{usr}_i, T^{sys}_i] = \text{ET}([C_i, E^{usr}_i, E^{sys}_i])$$

where ET represents the entity tracking module.

### 3.2 System Attribute Predictor

This module aims to predict the appropriate attributes that the system could mention in the response. Therefore, the system can actively drive the conversation forward as well as provide satisfying recommendation. Specifically, its input consists of user’s attribute tracking $T^{usr}_i$, system’s attribute tracking $T^{sys}_i$ and the dialog history $C_i$. Then, it predicts the system’s attribute tracking $T^{sys}_{i+1}$ at next turn.

As mentioned above, the system attribute tracking module consists of attributes in previous system responses and their sentiment labels. Meanwhile, the relations between these attributes, such as the relation between the actors and the movies, are mainly from the recommender system. Since we only focus on the dialog system, our module for predicting the system attribute consists of these three steps:

1. We replace the attributes in current turn attribute tracking with placeholders as the multi-slots.
2. Then, we build a system attribute predictor model that takes a set of placeholders as input and generates a set of positive placeholders in the predicted system attribute tracking.
3. Finally, we use the plugged recommender system to replace the placeholders with relative attributes and output the final predicted system attribute tracking.

Our system attribute predictor model is adapted from the generative pre-trained language model (GPT-2) (Radford et al., 2019). We fine-tune our model with delexicalized text. During training, we concatenate dialog history and indexed positive placeholders as the input. Meanwhile, in the output, because there could be placeholders that are not in the input dialog history, we substitute all the placeholders that have not been observed in the dialog history with a special “new_attribute” token. Later, we replace all the “new_attribute” tokens and placeholders with the attributes of the
recommended items provided by the plugged recommender system. We formulate the process in this module as:

\[ T_{i+1}^{sys} = \text{Rel}(\text{SEP}(\text{Del}([C, T_{i+1}^{attr}, T_{i+1}^{sys}]))) \]  \hspace{1cm} (5)

where Del is the delexicalization process and Rel is the relexicalization process, SEP represents the system attribute predictor model.

3.3 Response Generator

Our final module aims to produce a response that is conditioned on the predicted system attribute tracking for the next turn by using the output from the system attribute predictor. More concretely, we calculate the attribute difference between the current system attribute tracking and the next system attribute tracking \( \Delta T_{i+1}^{sys} \) as:

\[ \Delta T_{i+1}^{sys} = \{ e_{i,j} | e_{i,j} \in T_{i+1}^{sys}, e_{i,j} \notin T_{i}^{sys} \} \]  \hspace{1cm} (6)

Attributes in \( \Delta T_{i+1}^{sys} \) are considered to be the appropriate attributes that should be in the system response. Thus, we concatenate the dialog history \( C_i \) and \( \Delta T_{i+1}^{sys} \) as the input of the response generator:

\[ Y_i = \text{RG}([C_i, \Delta T_{i+1}^{sys}]) \]  \hspace{1cm} (7)

where RG is the response generator module. We fine-tune the BlenderBot model on INSPIRED dataset as our response generator. We choose BlenderBot as our base because it is the state-of-the-art model for open-domain chatbot (Roller et al., 2020).

3.4 Data Preprocessing

To automatically annotate the positive and negative labels for each attribute in attribute tracking, we extract all the attributes and movie recommendations in the dialogs. Then we search for every recommended movie, its genres, actors, and directors in the movie database.

If the recommended movie has a relation to an attribute which is mentioned in the previous dialog history, we annotate this attribute as a positive attribute. Otherwise, we annotate the attribute as a negative attribute. Note that there are commonly multiple recommended items through the conversation in a free-form recommendation dialog dataset. This is because in a sociable recommendation dialog, the user discloses more favor and disfavors.

As the system elicits more information of user preferences, users may reject the movie recommendation and ask for a different movie. This changes a positive attribute to negative for the next recommendation. As a result, the same attribute could have different labels in different dialog turns. Thus, we need annotate the attributes in the dialog history every turn rather than the system’s internal state, which means the annotation should be considered with the dialog context together.

4 Experiments

4.1 Dataset

We evaluate on INSPIRED, a newly released dataset of movie recommendation dialogs (Hayati et al., 2020). It contains 1,011 human-human conversations with 10.73 average turns with concrete success measures. The dialogs are collected in natural setting where human recommenders are informed with sociable strategies and make recommendations to the seeker who is looking for a movie recommendation. Thus, the dialogs contain diverse social interactions from both recommenders and users, including movie discussions, chit-chat, and encouragement. The dataset is also already automatically annotated with movie attribute placeholders (movie titles, actors, and genres), and we use this information for our model.

INSPIRED contains 1,011 conversations, but there are over 17,000 movies in our movie database. Since our response generator is conditional on the predicted attributes in the system response, we exploit data augmentation to alleviate the sparse data issue when we train the response generator. Specifically, we first extract all the attributes in the dialog, we then search for the relations between all the attributes in a same dialog. To augment the dataset with more movies, we replace the attributes in a same dialog with another set of attributes which have same relations in the database. Finally, we expand INSPIRED dataset to 10,000 conversations with different attributes so that the augmented dataset can include more movies.

4.2 Baselines

For our baselines, we choose the following dialog models:

**INSPIRED Bot** This is the strategy-based model from Hayati et al. (2020). It utilizes two separate Transformer-based GPT-2 language models
and heuristics to obtain recommendations from off-the-shelf recommender system\(^2\).

**BlenderBot**  We fine-tune the BlenderBot model (Roller et al., 2020) with augmented INSPIRED dataset as our second baseline. This serves as a baseline for social chatbot since we are not adding recommender system to this baseline.

**Hybrid**  Following Yu et al. (2017), we build a hybrid dialog system by combining the BlenderBot (Roller et al., 2020) and our system. Since there is no intent label in this work, we use the prediction of the system attribute predictor as a proxy for selecting a chitchat content or an on-task content. When the output of the system attribute predictor is empty, we choose the response from the BlenderBot baseline. Otherwise, we choose the response from our response generator. We compare DEUX with this model to explore the ability of generating social content in our response generator.

**DEUX-Usr**  This is our ablated model where we only consider the attributes from user utterances in both attribute tracking module and system attribute predictor module. We build this model to examine contributions of considering attributes in previous system responses.

### 4.3 Implementation Details

We implement our attribute tracking module on pre-trained language model BERT (Devlin et al., 2019) and add the placeholders in INSPIRED as special tokens. We truncate input dialog history to 512 tokens. Our system attribute predictor module is developed upon medium size GPT-2 (Radford et al., 2019). Except for the same placeholders tokens, we also add a set of special tokens indicating new attributes in the next system attribute tracking. Sequences longer than 1024 tokens are truncated in system attribute predictor. Experiments for our approach use default hyperparameters for BERT and GPT-2 in Huggingface Transformers (Wolf et al., 2020). Our response generator and all the baselines use 2.7B BlenderBot model (Roller et al., 2020), we fine-tune BlenderBot with Adafactor (Shazeer and Stern, 2018) and conduct nucleus sampling during testing. All the models are implemented on two NVIDIA titan RTX GPUs. Since we mainly focus on the dialog systems, we use the same recommender system with INSPIRED Bot baseline in all our dialog systems. We use ParlAI framework (Miller et al., 2018) to implement our code for building the model.

### 4.4 Metrics

We adopt automatic evaluation for separate modules and human evaluation for the whole system. We have more number of human evaluation metrics than automatic metrics since sociable chat is a subjective task. We choose to use perplexity and token accuracy which are the default automatic metrics in ParlAI.

#### Automatic Metrics

We calculate the accuracy and F1 scores of the placeholders in the predicted next system attribute tracking to measure the performance of attribute tracking predictors, we also calculate the per-token accuracy of the placeholders in the system attribute tracking\(^3\). To evaluate the performance of the response generator, we report perplexity which measures the system response quality.

#### Human Evaluation

In most previous works of recommendation dialog systems, human evaluation often consists of assessing the utterances generated by the systems, e.g. in terms of their consistency with previous dialog history utterances. Such assessment may not be sufficient to show the practical usefulness of the recommendation dialog system. Jannach and Manzoor (2020) found that about one third of the generated responses are not meaningful in the given context. To alleviate this problem in the human evaluation, we evaluate our system and other baselines with crowd-workers on Amazon Mechanical Turk.

We hire 58 workers on Amazon Mechanical Turk platform; each worker is assigned the task to be a movie seeker and interact with all the chatbots to get movie recommendation. Workers are required to use consistent movie preference to interact with all the chatbots. We randomize the order of the chatbots to avoid unfair evaluation. After chatting with each bot, workers are required to finish a post-survey and score each chatbot on four metrics in a 5-point Likert scale:

- **Consistency**: focuses more on the logical consistency between the system response and the dialog history.

\(^2\)https://www.themoviedb.org/

\(^3\)These metrics are the accuracy of placeholders instead of attributes because we can fill in the placeholders with attributes by any recommender system.
Table 2: Results from human evaluation; we test all the baseline bots against DEUX with **p < 0.01, *p < 0.05.

| Model       | Consistency | Naturalness | Engagingness | Sociability | Length |
|-------------|-------------|-------------|--------------|-------------|--------|
| INSPIRED Bot | 3.40        | 3.29**      | 3.51         | 3.74        | 8.64   |
| BlenderBot  | 3.40        | 3.55        | 3.67         | 3.86        | 10.86  |
| Hybrid      | 3.43        | 3.55        | 3.53         | 3.72        | 9.62   |
| DEUX-Ur      | 3.25*       | 3.43**      | 3.34**       | 3.69        | 9.69   |
| DEUX        | 3.64        | 3.79        | 3.78         | 3.86        | 11.91  |

4.5 Results and Discussion

**Naturalness:** Unlike consistency, naturalness is used to explore how human-like the systems’ language generation quality.

**Engagingness:** One goal of the sociable movie recommendation system is to keep engaging with users. Here, we evaluate if the user would like to continue chatting with the system.

**Sociability:** Our goal in this work is to combine on-task content and social content in the movie recommendation task. Sociability is used to evaluate if the bot has good social content in the responses and if the user considers the bot as friendly.

We also report the dialog length and the success rate of good recommendation. In the post-task survey, we ask the users if the chatbot recommends a movie and if the recommended movie fits their preference. To guarantee the quality of our human evaluation result, we ask these same questions before and after the task to filter out bad workers. If the answers are different, we drop the results. We provide more details of human evaluation in Appendix A.

Table 3: Automatic evaluation results of attribute tracking predictor. **Token Acc.** : token accuracy of system attribute tracking & **Acc.** : accuracy of system attribute tracking

| Model | Token Acc. | Acc. | F1 |
|-------|------------|------|----|
| DEUX-Ur | 0.55     | 0.34 | 0.46 |
| DEUX  | 0.78      | 0.48 | 0.63 |

Table 4: Automatic evaluation results of response generator. The automatic evaluation results of INSPIRED Bot is from Hayati et al. (2020).

| Model       | Perplexity ↓ |
|-------------|--------------|
| INSPIRED Bot | 8.93         |
| BlenderBot  | 8.95         |
| DEUX        | 7.42         |

The result from automatic metrics are shown in Table 3 and Table 4. Table 3 presents the results of two different attribute tracking predictors. We observe that our attribute tracking predictor outperforms the baseline which only considers the attributes in user utterances on all the metrics. This result shows that in the movie recommendation task, tracking the attributes in previous system responses can contribute to the improvement of the system attribute tracking module’s performance. From Table 4, we observe that DEUX achieves a lower perplexity, indicating that our method has a better generation quality compared to INSPIRED Bot and BlenderBot. This indicates that using the attribute information in the response generator improves the quality of the system response.

For our human evaluations studies, 58 users participate in our user study. Each user chats with all chatbots. Table 2 shows human evaluation results of different recommendation chatbots. We can see that DEUX outperforms all the baselines on all metrics. Users rate DEUX as the most consistent and natural bot, indicating it has better response quality than other baselines. DEUX also maintains longer and more engaging conversations. This suggests that users are more willing to chat with DEUX for a longer time. DEUX also has a sociability score as high as the BlenderBot; this indicates that DEUX contains diverse social interactions.

Compared to DEUX-Ur which only tracks attributes in user utterances, DEUX receives significantly higher average consistency score. It suggests that system responses in DEUX are more consistent with the dialog history since it also tracks the attributes in previous system responses. We also notice that DEUX has significantly higher engagingness score than DEUX-Ur. It indicates that the attribute tracking module in the system side improves the sociability of the bot.

If we look more into the details of the task success in Figure 3, DEUX always recommends a movie compared to other baseline bots. BlenderBot has the highest number of users (27.59%) who re-
| (A) Usr: User | Sys: BlenderBot | (B) Usr: User | Sys: DEUX |
|-------------|---------------|---------------|------------|
| Sys: Hello! How are you doing? | Sys: What kind of movies do you enjoy watching? | ... | ... |
| Usr: Do you know any animated movies? | Usr: I really like horror, but I was thinking for tonight with the kids maybe an action movie? | ... | ... |
| Sys: Yes, I am a fan of cartoons. | Sys: I would like to recommend Avengers: Endgame. | ... | ... |
| Usr: I enjoy animated movies from Japan. | Usr: You know what, we have seen it. | ... | ... |
| Sys: Alladin came out last year and it was a good movie. | Sys: That is a great choice. have you watched any of the other action movies yet? | ... | ... |
| (C) Usr: User | Sys: DEUX-Usr | (D) Usr: User | Sys: DEUX |
| Usr: Who is your favorite actress? | ... | Usr: I like horror movie | ... |
| Sys: I really like Sandra Bullock | Sys: I recommend the movie Antlers | ... | ... |
| Usr: Can you recommend a movie with her? | Sys: I have not heard of that, who is the star? | ... | ... |
| Sys: I would like to recommend Like a Boss? | Sys: Keri Russell | ... | ... |
| Usr: She is not in that. | Usr: Is she a new actress? I haven’t heard of her. | ... | ... |
| Sys: What type of movies do you like? | Sys: Have you heard about Tom Cruise? | ... | ... |
| Usr: Movies starring Sandra Bullock. | Usr: Yes of course. | ... | ... |
| Sys: I am recommending: Gravity | Sys: They were cast together for Mission Impossible. | ... | ... |

Table 5: Examples of human-machine dialogs in human evaluation. Attributes in the utterances are bolded.

Figure 3: Percentage of users who reported in the post-task survey that the bot never recommends a movie or the bot recommends a movie but it does not fit the user preferences.

Influence of our attribute tracking module. In Example 5A, we can see how the user mentions that “animated movies” as their preferred movie genre, rejects the first recommendation, and requests for another one. Then, the BlenderBot is requesting the user’s movie preference again (the last line in Ex. 5A) even though it should have provided another animated movie. This is because the BlenderBot doesn’t track the attributes in the dialog so that it can ask repeated questions.

In Example 5B, DEUX has similar context where the user asks for an “action movie” and refuses the first recommendation. DEUX extracts action movies instead of horror movies as the positive attribute and predicts the “action movies” to be in the next system attribute to track. Then, DEUX asks the user about what action movies the user has watched, which is consistent with the history.

Now, let us look at the conversations with DEUX-Usr (Ex. 5C) and another conversation with DEUX (Ex. 5D) to explore if tracking the attributes at the system side helps. In Example 5C, the system says that “Sandra Bullock” is its favorite actress. However, it recommends a movie without this actress in the following turn since it does not track the attributes in its own response. After the user mentions the same actress again in the user utterance, the system recommends an appropriate movie (“Gravity”) with “Sandra Bullock” in it. Meanwhile, in Example 5D, there are three attributes in previous responses. DEUX tracks that “Keri Russell” is acting in “Antlers”. Later, it suggests an

4.6 Analyses of Human-Machine Dialogs

We show four examples of human-machine dialogs from our human evaluation in Table 5. First, we compare the conversations generated by the BlenderBot baseline (Ex. 5A) and the conversations generated by DEUX (Ex. 5B) to explore the
actor, “Tom Cruise”, and then generates a natural response which recommends a movie (“Mission Impossible”) where both “Tom Cruise” and “Keri Russell” starred. These observations indicate the contribution of system attribute tracking in recommendation dialog systems for a consistent response.

5 Conclusion and Future Work

In this paper, we present DEUX, a novel attribute-guided framework for sociable recommendation dialog systems. It tracks attributes in the conversation from both user’s and system’s sides. Thus, our framework can generate more consistent and natural responses compared to previous methods. While DEUX can be applied to any recommendation dialog tasks, we evaluate it on a movie recommendation dataset. DEUX outperforms the existing dialog systems in both automatic metrics and human evaluation.

Looking forward, a future direction would be to incorporate the dialog policies or strategies in our attribute-guided framework. By integrating the strategies with our attribute tracking slots, we hope that the dialog system can produce better social content and task-oriented content. Another interesting direction would be to expand the framework to consider other attributes of the recommended item, such as the movie plots which have more complex characteristics compared to current attributes.

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A Human Evaluation Details

Figure 4 shows the instruction we give to the Amazon Mechanical Turkers in the human evaluation task. Figure 5 shows the questions in the pre-survey, questions are designed for two purposes: first, these questions help Turkers think about related topics they may discuss in the movie recommendation conversations thus they can provide consistent answers in all the conversations. Second, the multiple choice question about movie genres is used to check the quality of the evaluation: we ask a same multiple choice question in the post-survey, if the answers are different, we think the Turker fails to provide consistent answers and remove the result. Figure 6 shows the interface of the interaction task, we assign our system and other four baselines in random order, Turkers are asked to interact with one chatbot and finish the survey shown in Figure 7 about the chatbot performance. Figure 8 shows the post-survey questions, it includes a quality checking question mentioned above and an open question to collect additional feedback. Every Turker can only do the task once, we collect human evaluation results from 90 people on Mechanical Turk. We remove 32 Turkers who fail the quality check questions.
Evaluation Task

For this task, you will be chatting with another user.

Please complete the pre-task survey, then chat with the other user for approximately 5 minutes.

Finally, you will complete a post-task survey.

Begin Task

Figure 4: Screenshot of the human evaluation task instruction.

Pre Task Survey

What kind of movies do you like? *
- Action movies
- Horror movies
- Mystery movies
- Comedy movies
- Documentary movies
- Drama movies
- Sci-fi movies

Please list at least one of your favorite movies. *

Please list at least one of your favorite actors. *

Please list at least one of your favorite directors. *

Figure 5: Screenshot of the pre-survey.
Instructions

1. Chat naturally as to a friend, talking about your movie history, preference, and/or your partner’s movie recommendation.

2. When a bot recommends a movie, you can type in [accept] to accept the recommendation, or you can continue the chat if you don’t get a good recommendation.

3. If the response is bad and you can’t continue the chat, you can type in [quit] to end the chat.

4. Please don’t game the task by replying short and meaningless sentences. Discuss more about the movies (what you like, acting, experience, etc.)

5. You can click Complete Chat when you finish the chat.

CyanBot

CyanBot: Hello
You: Hi
CyanBot: How are you today?
Type response here...

Figure 6: Screenshot of the interaction task interface.
Post Task Survey Cyan Bot

Did Cyan Bot recommend a movie to you? *

- Yes
- No

If Cyan Bot recommended a movie to you, does the movie recommendation fit your personal preferences? *

- Cyan Bot recommended a movie and it fits my personal preferences.
- Cyan Bot recommended a movie but it doesn't fit my personal preferences.
- Cyan Bot didn't recommend a movie.

How consistent was the conversation? 1 (many inconsistent statements) -- 5 (very consistent) *

- 1
- 2
- 3
- 4
- 5

How natural was the conversation? 1 (many unnatural statements) -- 5 (very natural) *

- 1
- 2
- 3
- 4
- 5

How engaging was the conversation? 1 (not engaging at all) -- 5 (very engaging) *

- 1
- 2
- 3
- 4
- 5

How sociable was your partner? 1 (not sociable at all) -- 5 (very sociable) *

- 1
- 2
- 3
- 4
- 5

Figure 7: Screenshot of the survey after finishing every interaction task.
Figure 8: Screenshot of the post-survey.