Towards Socially Intelligent Agents with Mental State Transition and Human Utility

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Abstract

Building a socially intelligent agent involves many challenges, one of which is to track the agent’s mental state transition and teach the agent to make rational decisions guided by its utility like a human. Towards this end, we propose to incorporate a mental state parser and utility model into dialogue agents. The hybrid mental state parser extracts information from both the dialogue and event observations and maintains a graphical representation of the agent’s mind; Meanwhile, the utility model is a ranking model that learns human preferences from a crowd-sourced social commonsense dataset, Social IQA. Empirical results show that the proposed model attains state-of-the-art performance on the dialogue/action/emotion prediction task in the fantasy text-adventure game dataset, LIGHT. We also show example cases to demonstrate: (i) how the proposed mental state parser can assist agent’s decision by grounding on the context like locations and objects, and (ii) how the utility model can help the agent make reasonable decisions in a dilemma. To the best of our knowledge, we are the first work that builds a socially intelligent agent by incorporating a hybrid mental state parser for both discrete events and continuous dialogues parsing and human-like utility modeling.

1 Introduction

Recently, there has been remarkable progress in language modeling with large-scale pre-trained models (Vaswani et al., 2017; Devlin et al., 2019; Radford et al., 2019). Such models are used to build either general chatbots (Zhang et al., 2020) or task-oriented dialogue systems (Peng et al., 2020). While most of these systems have been able to generate fluent sentences, there are two major challenges towards building socially intelligent agents. First, considering language is a communication channel that bridges the agents’ minds, few existing work (Adhikari et al., 2020) can track such mental states that represent their understanding of the surrounding environment. Second, it is under-explored for teaching agents to make a rational and responsible decision in a dilemma, i.e., when all available options satisfy the physical or causal constraints. In specific, humans tend to have a common preference described by the utility function related to individual values, common sense, and social awareness. For example, one would prefer to mop up the floor after spilling the food rather than stepping on it to mess it up.

Psychologist Nicholas Humphrey believes that it is social intelligence, rather than quantitative intelligence, that defines humans (Ganaie and Mudassir, 2015). From one perspective, social intelligence is reflected by an individual’s Theory of Mind (ToM) (Premack and Woodruff, 1978), i.e., capability to understand others’ thoughts and sense their emotions. Such capability is based on one’s wider understanding of the social environment. From another point of view, individuals choose the best action according to their preferences under environmental constraints. In rational choice theory (Hechter and Kanazawa, 1997), we make decisions to maximize the expected utility, i.e., the expected value of a reward to a person (Browning et al., 1999). This work, based on the ToM and rational choice theory, aims to teach agents to speak and act in a socially intelligent way.

To overcome the aforementioned challenges, we first present a hybrid mental state parser that converts both continuous dialogue observation and discrete action history into a graphical representation of the agents’ mind. Initialized with the location and object description, the topology of the graph is updated through the interaction history to track the evolving process of an agent’s belief about surroundings and other agents. Then, we propose to incorporate a utility model that is pre-trained on Social IQA (Sap et al., 2019) dataset to bring in the social common sense. We perform experiments on a large-
scale crowd-sourced text-adventure game LIGHT (Urbanek et al., 2019). Empirical results show that our model with the mental state parser and utility achieves the highest performance that aligns with human annotation among existing transformer-based ranking models. Moreover, case studies further demonstrate that the mental state provides extra context information, while the utility model helps agents make rational decisions.

Our contributions are two-fold. First, we propose a novel hybrid mental state parser that tracks both explicit environment changes caused by agents’ actions and the implicit mental state updates triggered by agents’ dialogues. Second, we initiate to apply human utility defined by social common sense into dialogue generation and decision making. Our methodology can be generalized to a wide range of interactive social situations in socially-aware dialogue systems (Zhao, 2019), virtual reality (Lai et al., 2019), and human-robot interactions (Yuan and Li, 2017).

2 Related Work

2.1 Text-based Game Playing

Most recent works in dialogues only study the statistical regularities of language data, without an explicit understanding of the underlying world. The virtual embodiment was proposed as a strategy for language research by several previous works (Brooks, 1991; Kiela et al., 2016; Gauthier and Mordatch, 2016; Mikolov et al., 2016; Lake et al., 2017). It implies that the best way to acquire human semantics is to have the agent learn through experience in a situated environment. (Urbanek et al., 2019) introduce LIGHT as a research platform for studying grounded dialogue, where agents can perceive, emote, and act when conducting dialogues with other agents. (Ammanabrolu et al., 2020) extend LIGHT with a dataset of "quests", aiming to create agents that both act and communicate with other agents in pursuit of a goal. Instead of guiding the agent to complete an in-game goal, our work aims to teach agents to speak/act in a socially intelligent way. Besides the LIGHT, there is also other text-adventure game frameworks, such as (Narasimhan et al., 2015) and TextWorld (Côté et al., 2018), but no human dialogues are incorporated in them. Based on the TextWorld, there are recent works (Yuan et al., 2018; Yin and May, 2019; Adolphs and Hofmann, 2019; Adhikari et al., 2020) on building agents trained with reinforcement learning.

2.2 Theory of Mind

(Premack and Woodruff, 1978) defined Theory of Mind (ToM) as the ability to impute mental states to oneself and to others. ToM is thus impossible without the capacity to form such "second-order representations" (Dennett, 1978; Pylyshyn, 1978; Ganaie and Mudasir, 2015). The ability to make inferences about what other people believe in a given situation allows one to predict what they will do. As a crucial social skill, ToM enables humans to navigate social situations ranging from simple conversations with friends to complex negotiations in courtrooms (Apperly, 2010; Gordon and Hobbs, 2017). It is well developed in most neurotypical adults, but can be influenced by age, culture, or developmental disorders. To model the agent’s state of mind for dialogue generation, a previous study (Dinan et al., 2019) designs a memory network capable of retrieving knowledge, reading and conditioning on it, and finally generating natural responses. More recently, (Adhikari et al., 2020) propose a graph-aided transformer agent (GATA) that infers and updates latent belief graphs during planning to enable effective action selection by capturing the underlying game dynamics. Inspired by GATA, we employ a hybrid graphical method for agents’ mental state tracking, building the foundation towards modeling deeper levels of ToM. However, GATA is not designed for dialogues and our method is more flexible to encode both explicit environmental changes caused by agents’ actions and implicit mental state updates triggered by agents’ dialogues.

2.3 Human Utilities

When teaching agents to speak and act in a socially intelligent way, an approach considering human utilities should be adopted. The concept of utility was initially defined as a measure of pleasure or satisfaction in economics and ethics that drives human activities at all levels. It is based on the rational choice theory (Abella, 2009). In the theory, human decision making could be viewed as a two-step procedure. First, we select a feasible region based on financial, legal, physical, or emotional restrictions we are facing. Then we make a choice based on the preference order (Allingham, 2002; de Jonge, 2012). Similarly, in the field of intercultural research, Shalom H. Schwartz developed the theory of basic human values. A set of 19 basic individual
values are identified and serve as the guiding principles in the life of a person or group (Schwartz, 2012; Cieciuch and Davidov, 2012), as shown in Figure 1. To learn a utility or value function, we refer to the dataset Social Intelligence QA (SOCIAL IQA) (Sap et al., 2019). SOCIAL IQA contains 38k multiple-choice questions regarding the pragmatic implications of everyday social events. It collected commonsense questions along with correct and incorrect answers about social interactions, making it suitable to train a ranking model representing common social preference or utility.

3 Problem Formulation

We first briefly introduce the game environment LIGHT, followed by the mental state modeling and utility formulation.

LIGHT (Urbanek et al., 2019) is a large-scale crowdsourced fantasy text-adventure platform for studying grounded dialogues. Figure 3(a) shows a typical local environment setting, including location description, objects (and their affordances), characters and their personas. Agents can talk to other agents in free-form text, take actions defined by templates, or express certain emotions (Figure 3(b)). Agents could be role-played by either humans or machines. Our task is to build an agent to speak and act in LIGHT in a socially intelligent manner. To achieve this goal, we model the agent’s mental state transition and incorporate human utility. The mind model is proposed to depict the agent’s belief about the underlying states of the text world. Meanwhile, the utility model is designed to learn human preference in common social situations.

3.1 Mental State Modeling

Our goal is to construct and maintain the mental states among the theory of mind in dialogues. With the mental state grounding on the details of the local environment, the agent could simulate and reason the evolutionary status of the world and condition its speaking and actions. A graphical representation of the mental state is proposed, as illustrated in Figure 2. All the agents, persona descriptions, objects and their descriptions, and setting descriptions are represented as nodes, which will change as the game location switches. The state of mind is described by the relational edges between these nodes. The mental state is updated with the observed dialogue history or actions, e.g., King gives the scepter to the servant will result the servant is carrying the scepter. Such graphical representations are largely distributed among the theory of minds and they are updated in the following mental states:

- **Level 0**: Physical world
- **Level 1**: A’s belief and desires; B’s belief and desires
- **Level 2**: A’s belief in A’s mind, B’s mind in B (self-conscious); B’s belief in A’s mind and A’s belief in B’s mind.

Note that our model only stays in the Level 1 due to the dataset limitation.

3.2 Human Utility Modeling

We assume that the agent in the fantasy world would make near-optimal choices to maximize its
utility. We denote the available alternatives to be a set of \( n \) exhaustive and exclusive utterances or actions \( A = \{a_1, \ldots, a_i, \ldots, a_n\} \). The utility function \( u(\cdot) \) describes the common preferences over the alternatives. For example, if \( a_i \) is more preferred than \( a_j \), then \( u(a_i) > u(a_j) \).

Our formation of human utilities takes the following two factors into consideration: (i) the task, speech, act or agent’s emotion prediction, and (ii) the mental state constraints. As an example, since some actions could be impossible physically (one cannot drop an object if the agent is not carrying the object), the decision making process becomes a problem of maximizing the utility function that is subject to some constraints from the mental state, \( i.e., u(a|c) \), where \( c \) represents the context or constraints. Usually, we cannot find an analytical form of the utility function. However, what matters for preference ordering is which of the two options gives the higher expected utility, not the numerical values of those expected utilities.

4 Algorithms

The overall architecture of our proposed agent model is illustrated in Figure 3. For each scenario, a setting description (Figure 3(a)) is provided by the LIGHT environment, which can include a description about the location, object affordances, agents’ personas, and the objects that agents are carrying, wearing, or wielding. The free-form conversations, actions and emotions are logged during the communication as the observation history (Figure 3(b)). To begin with, a mental state parser will parse the setting descriptions into graph representation and initialize the agent’s mental state (step 1 and 2). Besides the mental state updating, the parser also outputs an action mask that is aimed to rule out actions that are physically or causally impossible to take (step 3). A graph encoder (step 4) and a text encoder (step 5) will convert the mental state graph \( G_t \) and the dialogue observation \( O_t \) into vector representations, respectively. The same text encoder will be used to encode the candidates \( C_t \) (step 6). In step 7, the context vectors are combined by a bi-directional attention aggregator, and each candidate is assigned a score with a Multi-layer Perceptron (MLP) (step 8). The action mask is then applied to get the feasible candidates under the current state-of-mind constraints (step 9). In step 10 and 11, the top three candidates from the last step will be fed into the utility model and re-ranked. Finally, the selected utterance/action/emotion is executed by the agent (step 12) and returned to the environment. Upon receiving the response from other agents in the environment, the new observation will be again parsed and used to update the agent’s state of mind, and the cycle repeats. In the following, we will describe each component in more detail.
4.1 Mental State Modeling (Steps 1-2)

Figure 4 describes the architecture of the mental state parser. The initial mental state graph $G_0$ is constructed by a rule-based parser from the setting description $O_0$ and the graph is encoded by function $f_e$ to a hidden state that is later used for graph update. At game step $t$, the mental state parser parses relevant information from observation $O_t$ and update the agent’s mental state from $G_{t-1}$ to $G_t$. Considering that observations $O_t$ typically convey incremental information from step $t - 1$ to $t$, we generate the graph update $\Delta g_t$ instead of the whole graph at each step

$$G_t = G_{t-1} \oplus \Delta g_t, \quad (1)$$

where $\oplus$ is the graph update operation. The graph update can be discrete and continuous, and there have been studies on the pros and cons of each updating method (Adhikari et al., 2020). The discrete approach may suffer from an accumulation of errors but benefit from its interpretability. The continuous graph model needs to be trained from data, but it is more robust to possible errors. In this work, we propose a hybrid (discrete-continuous) method for updating the agent’s state of mind by considering the characteristics of the LIGHT environment: since actions in LIGHT are template-based, it is more appropriate to adopt a discrete method for parsing; meanwhile, since utterances are challenging to be encoded into discrete representations, we apply a continuous update method instead.

4.1.1 Discrete Graph Definition & Update

We define the discrete mental state graph as $G \in \{0, 1\}^{R \times N \times N}$, where $R$ is the maximum number of relation types and $N$ is the maximum number of entities. To update the graph, we further define $\Delta g_t$ as a sequence of update operations of the following two atomic types:

- **ADD(src, dst, relation)**: add a directed edge, named relation, from node src to node dst.
- **DEL(src, dst, relation)**: delete a directed edge, named relation, from node src to node dst.

LIGHT defines various actions including get, drop, put, give, steal, wear, remove, eat, drink, hug and hit, and each taking either one or two arguments, e.g., give scepter to servant. Every action could be parsed as one or a sequence of update operators that act on $G_{t-1}$. For example, actor performing “give object to agent” can be parsed into DEL(actor, object, carrying) and ADD(agent, object, carrying). A full list describing how actions are parsed is shown in Appendix. Note that actions in LIGHT could only be executed when constraints are met, so we also generate an action mask according to the current mental state.

4.1.2 Continuous Graph Definition & Update

Besides the actions taken by the agents, their utterances could also have an implicit impact on the state of the underlying world. By following (Adhikari et al., 2020), we use the recurrent neural network as the operation $\oplus$ to update the mental state with the utterances from agents. We define the continuous mental state graph as $G \in [-1, 1]^{R \times N \times N}$, which is a real-valued adjacency tensor,

$$\Delta g_t = f_\Delta(h_{G_{t-1}}, h_{O_t}), \quad h_t = \text{RNN}(\Delta g_t, h_{t-1}), \quad G_t = \text{MLP}(h_t). \quad (2)$$

The function $f_\Delta$ aggregates the information from the previous mental state $G_{t-1}$ and observation $O_t$ to generate the graph update $\Delta g_t$. $h_{G_{t-1}}$ denotes the representation of $G_{t-1}$ from the graph encoder. $h_{O_t}$ is the output of the text encoder. $h_t$ is a hidden state acting as the memory, from which we decode the new mental state $G_t$ using a MLP. For the recurrent operator, we could either use LSTM (Hochreiter and Schmidhuber, 1997) or GRU (Cho et al., 2014a). More details on the graph encoder and text encoder we applied are revealed in the section 4.2.
4.2 Action Selector (steps 4-11)

Conditioned on the agent’s mental state, the action selector chooses the optimal candidate based on the prediction task (i.e., utterance, action or emotion). The selector consists of five components: a graph encoder (Figure 3(4)) to convert the state-of-mind graph to a hidden state vector; a text encoder (Figure 3(5, 6)) to encode the dialogue history and text candidates; an aggregator (Figure 3(7)) to fuse the two context representations; a general scorer (Figure 3(8)) to assign a score to each candidate; and a utility model (Figure 3(10)) to re-rank the candidates based on human utility.

1. Graph Encoder. We use relational graph convolutional networks (R-GCNs) (Schlichtkrull et al., 2018) to encode the graph representation of mental states. The R-GCN is adapted from normal graph convolutional networks so that it could embed the relation edge information.

2. Text Encoder. We use a BERT (Devlin et al., 2019) encoder to convert the text-based dialogue history into a vector representation; We also use the same encoder to encode the text response candidates.

3. Aggregator. A bi-directional attention layer (Yu et al., 2018; Seo et al., 2016) is adopted to fuse the information from the mental state and the contextualized text hidden state. The co-attention allows the agent to focus on the memory part that has been mentioned in the dialogue.

4. Scorer. The full context representation vector is concatenated with each candidate and an MLP layer with softmax activation generates a score for each of them.

5. Utility Ranker. After all the candidates are ranked, we select the top three candidates and then re-rank them according to the proposed utility model. We use the T5 Transformer model (Raffel et al., 2019) pre-trained on Unified QA (Khashabi et al., 2020) and fine-tuned on Social IQA (Sap et al., 2019) to model the human utility. Figure 5 shows example question-answer pairs in Social IQA dataset.

5 Experiments

We conduct experiments on the LIGHT dataset and compare our model with state-of-the-art methods, which are based on two variants of BERT models. Ablation study is carried out to justify our model design, and case study is performed to demonstrate how the proposed model could help the agent ground upon the environment details and make decisions in dilemmas.

5.1 Experimental Setup and Implementation

LIGHT dialogues are split into train (8539), valid (500), seen test (1000), and unseen test (739) as the dataset is released. The unseen test set consists of dialogues collected on a set of scenarios that have not appeared in the training data, which can be used for evaluation of the model generalization capability. We use the history of dialogues, actions, and emotions to predict the agent’s next turn. Note that the original paper leverages the annotation of the object affordances and environment states to manually filter out actions with no affordance (e.g., one can not drop an object if the agent is not carrying it), while we provide all action candidates to demonstrate our model’s capability of reasoning available actions automatically from its understanding of the world state. We encourage the readers to refer to the original paper (Urbanek et al., 2019) for details about the LIGHT dataset.

We describe the implementation details of our proposed model. The mental state graph is initialized with the environment description (i.e., task name, setting name and descriptions), the agent’s name and persona that is being played, the partner...
agent’s name, the objects’ descriptions, the objects in the room, the objects being carried/wore/wielded by the agent. An example setting string for the utterance prediction is included in Appendix A.1. The setting string is parsed by regular expression, spaCy (Honnibal and Montani, 2017) coreference parser (Clark and Manning, 2016) and dependency parser (Honnibal and Johnson, 2015), resulting in the initial mental state graph as shown in Figure 6.

![Figure 6: Initial mental state graph parsed from an example setting string in Appendix A.1. The nodes of objects’ descriptions are omitted to save space.](image)

For the functions $f_e$ and $f_d$, we use two-layer MLPs with tanh (Karlik and Olgac, 2011) and ReLU (Agarap, 2018) activations. The Text Encoder is a pre-trained BERT (base-uncased) model (Wolf et al., 2020) followed by a linear output layer. The Graph Encoder is an R-GCN with six layers and a hidden size of 64. We also adopt the highway connections between consecutive layers for faster convergence and 3-basis decomposition to reduce the R-GCN parameters and prevent overfitting. We use a GRU (Cho et al., 2014b) with a hidden size of 64 as the graph update operator.

### 5.2 Baseline Models

Two BERT-based models proposed in the original LIGHT paper are used as strong baselines, which have kept the state-of-the-art performance on this task.

**BERT Bi-Ranker** uses the BERT pre-trained language model to produce a vector representation for the context and a separate representation vector for each candidate. The representation is obtained by passing the hidden state corresponding to the [CLS] token from the last layer to an additional linear layer. Each candidate is assigned a score by the dot product between the context embedding and the candidate embedding.

**BERT Cross-Ranker** concatenates the context string with each candidate and feeds the string to the BERT model instead. Each candidate is scored by computing a softmax function over the additional linear layer. The cross-ranker allows the model to attend to the context when encoding each candidate, building a context-dependent representation of each candidate. However, it is much more computationally expensive than the Bi-Ranker since the Bi-Ranker can cache the candidates for reuse.

### 5.3 Results and Analysis

Table ?? shows the results, where our model outperforms the state-of-the-art models by a large margin. To understand the results, we first compare between mental state graph designs of using discrete, continuous, and our proposed hybrid parser. We find that the hybrid mental state parser performs the best among the three according to almost all metrics, mainly because it aggregates the soft update from the dense dialogue and the hard constraints from the sparse actions. The discrete mental state parser constructs an interpretive graph based on the setting and only uses actions to update the graph. Therefore, it did not incorporate the rich information that comes from the dialogue history. While the continuous mental state parser updates the graph implicitly with the dialogues and shows a better result than the discrete one on dialogue prediction, it misses the hard constraints introduced by the less frequent actions and performs worse on action prediction task.

![Figure 7: Intermediate mental state for the agent servant in the dialogue example of Figure 3. Only critical relation types between nodes are shown for illustration purpose and the darkness of the edges represent the relation strength.](image)
| T5 config                     | test accuracy |
|------------------------------|---------------|
| T5-small                     | 43.3          |
| T5-base                      | 43.5          |
| T5-large                     | 43.7          |
| T5-small pretrained on Unified QA | 46.1  |
| T5-base pretrained on Unified QA | 46.4  |
| T5-large pretrained on Unified QA | 46.6  |

Table 1: T5 Model Accuracy on Social IQA dataset.

Then, with the ablation study of our proposed action mask (hybrid mental state vs. hybrid+mask), we prove the effectiveness of it for improving action accuracy by $\sim 1\%$. Figure 7 shows an example illustrating how the mental state could help agent ground on the surrounds. We can see a very weak relation of the type “carrying” between the agent King and the object crown. Thus the King should not be able to give the crown to others at this time step. Even our model does not rely on annotated action constraints during the action predicting, the action mask can be reasoned from such a mental state, which helps rule out actions that are physically or causally impossible.

Lastly, we analyze the results after introducing the utility model. Table ?? shows that when we directly use the T5 utility model, the overall performance of the proposed model actually drops. Case study shows even when the top candidate is predicted correctly after applying the hybrid mental state model and action mask (step 9 in Figure 3), the agent could make a mistake after the utility model re-ranks the top three candidates. Appendix A.2 shows an example when we try to use the utility model alone to predict the agent dialogue. We find that rephrasing the dialogue context in a third-person view could help the utility model in the LIGHT task. Other tricks include restricting the length of the dialogue context and excluding persona descriptions. These tricks actually make the input format look more similar to the examples in the SOCIAL IQA, as shown in Figure 5. Moreover, the fine-tuning results of T5 transformer on Social IQA are shown in Table 1. Using a larger size of T5 transformer did help increase the performance on the Social IQA dataset but the improvement is negligible.

6 Conclusion

This paper introduces the mental state parser and utility model to build a socially intelligent agent. We explore using a hybrid discrete-continuous graph parser to provide grounded context information to the agent. The utility model pretrained from the SOCIAL IQA dataset brings common social preference to help the agent make decisions. The model is proved to have a better performance than the state-of-the-art models. In the future, we have a plan to build a dataset to study the implicature in conversation and model deeper levels of Theory of Mind based on it.
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