Towards Deception Detection in a Language-Driven Game

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Abstract

There are many real-world scenarios where agents must reliably detect deceit to make decisions. When deceitful statements are made, other statements or actions may make it possible to uncover the deceit. We describe a goal reasoning agent architecture that supports deceit detection by hypothesizing about an agent's actions, uses new observations to revise past beliefs, and recognizes the plans and goals of other agents. In this paper, we focus on one module of our architecture, the *Explanation Generator*, and describe how it can generate hypotheses for a most probable truth scenario despite the presence of false information. We demonstrate its use in a multiplayer tabletop social deception game, *One Night Ultimate Werewolf*.

1. Introduction

Intelligent agents do not always operate in cooperative environments. Oftentimes an agent must make correct inferences given deliberate deceit from adversarial human participants. The agent must infer this information based on observable behavior (i.e., actions and speech), with the adversarial goal as a latent variable. In this work, we consider a particular problem domain in which humans often intentionally conceal information through deception.

Specifically, we describe a component of our agent architecture that reasons over observations of game actions to hypothesize about each player's plans and goals. Our group's prior work has shown that such an agent can successfully predict squad members' goals in a military domain (Gillespie et al. 2015). We extend that work by demonstrating the ability to generate hypotheses for the actions and goals of deceptive agents based on observations of their speech.

While we describe the entire agent architecture in Section 2, our focus in this paper is on the Explanation Generator module, which allows the agent to hypothesize the possible actions and goals of other participants. Section 3 introduces the social deception game we use, One Night Ultimate Werewolf. Section 4 presents our approach for designing a knowledge base that models possible actions in our problem domain, with Section 5 providing analysis of our findings. We have performed a case study of the current system, but have not yet performed a rigorous empirical evaluation. We examine related work in Section 6 and present future research directions in Section 7.

2. Agent Architecture

Our agent interprets and responds to its environment via a five-step goal reasoning process (Molineaux et al. 2010; Aha 2015). This process allows an agent to dynamically refine its goals in response to unexpected external events or opportunities, and enact plans to accomplish those goals. The agent's decision cycle (Figure 1) has five primary components: *Natural Language Classifier*, *Explanation Generator*, *Plan Recognizer, Goal Selector*, and *Plan Generator*.

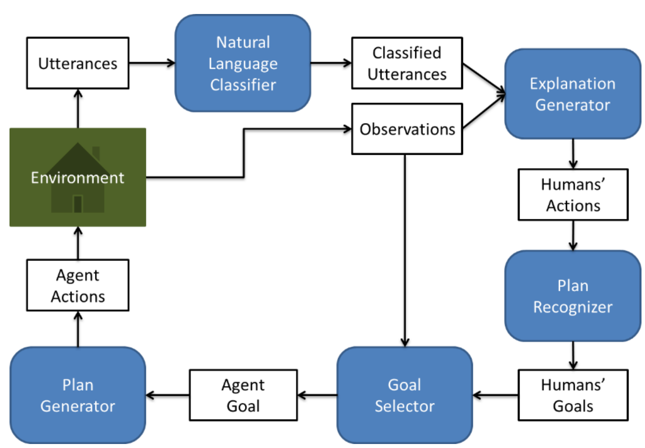

Figure 1: Decision cycle of the goal reasoning agent

This paper focuses exclusively on how the Explanation Generator generates hypotheses for the actions of human players based on observations of their conversational utterances. Gillespie et al. (2015) use a similar agent architecture and provide a more detailed description of the other four components.

3. One Night Ultimate Werewolf

The domain we examine is a tabletop social deception game called *One Night Ultimate Werewolf* (Bezier Games 2016). We chose this game because players interact using unconstrained natural language, have a variety of goals, work under hidden information, and actively engage in deception.

In the game, players are randomly assigned *roles* that place them into three competing factions with conflicting goals: *Villagers*, *Werewolves*, and the *Tanner*. Initially each player knows only their own role. We constrained the game to five players and eight possible roles (i.e., five roles will be assigned and three will be unused), with some roles granting special abilities. The roles (and the maximum number of players with that role in each game) we use are *Werewolf* (2), *Mason* (2), *Generic Villager* (2), *Seer* (1), and *Tanner* (1). The Werewolf roles are part of the *Werewolves faction*, the Tanner is part of the *Tanner faction*, and all remaining roles are part of the *Villagers faction*.

The game proceeds as follows:

1. **Role assignment**: Each player receives a *role card* with an assigned role printed on it. After viewing his or her role, the player then places the card face down in front of them and may not view their card again. The remaining three roles are placed face down on a table within reach of all players.
2. **Special abilities**: An external moderator oversees this portion of the game:
   a. The moderator instructs all players to close their eyes.
   b. The moderator instructs all Werewolves to open their eyes, identify the other Werewolves (if any), and close their eyes. If only one Werewolf opens their eyes, they may look at one of the unused role cards.
   c. The moderator instructs all Masons to open their eyes, identify the other Masons (if any), and close their eyes.
   d. The moderator instructs the Seer to open their eyes. The Seer may look at the role card of one other player or two of the unused role cards. The Seer then closes their eyes.
   e. The moderator instructs all players to open their eyes again.
3. **Information gathering**: The players have several minutes to attempt to gather information about the other players. There is no turn taking; players can speak as much or as little as they wish. Similarly, there are no constraints on what is discussed or the vocabulary used.
4. **Shooting phase**: Each player chooses one other player to "shoot" and players announce their choices simultaneously. The player who is shot by the most other players "dies". In the event of a tie, all players tied for the most shots die.
5. **Declaring winners**:
   a. If the Tanner dies, the Tanner wins (regardless of which other players die). Otherwise, the Tanner loses.
   b. If at least one Werewolf dies, the Villagers faction wins (regardless of the Tanner's fate). Otherwise, they lose.
   c. If neither the Tanner nor any Werewolves die, the Werewolves faction wins. Otherwise, the Werewolves lose.

Players know their own role and, depending on the special ability of that role, may have more information as well. The Werewolves and Masons know information about other members of their faction; the Seer may know the role of any one other player; and a lone Werewolf or the Seer may know either 1 or 2 unused roles. Players with the Generic Villager role have no special abilities, so they have less information than do other players.

4. Explanation Generation

Our agent's Explanation Generator uses DISCOVERHISTORY (Molineaux and Aha 2015), which searches a hypothesis space to find explanations of the current and past game state. This module uses environmental observations, including representations of statements made by players, to generate possible explanations for what has occurred in the environment (i.e., actions and external events that must have occurred). Each explanation contains, in part, the agent's hypothesis as to what actions each other entity (e.g., humans, robots, or other agents) in the environment has performed. DISCOVERHISTORY's search is constrained by the requirement that observations received must be explained by those actions. At the beginning of each game, DISCOVERHISTORY begins with a set containing a single, trivial explanation. As observations are received, the Explanation Generator iteratively refines this set. At each step, the generated explanation set includes the most probable explanations (i.e., based on the likelihood of actions and events contained in each explanation) that are consistent with all past observations.

The observations received by DISCOVERHISTORY in the One Night Ultimate Werewolf domain consist of a list of facts about utterances made by the players. The source of this data is natural language utterances taken from games of werewolf played by human participants (e.g., "*I think you are a werewolf.*" or "*Did you look at anyone's role?*"). Utterances are classified along nine dimensions, and the classifications are input to DISCOVERHISTORY. The nine classification tasks are: *Phrase-purpose* (i.e., general type of utterance); *Phrase-address-type* (i.e., size of group the utterance was addressed to); *Phrase-addressee* (i.e., whether an utterance was directed at a specific player); *Phrase-subject* (i.e., the subject matter discussed in the utterance); *Phrase-target-person* (i.e., the player being discussed in the utterance); *Phrase-target-role* (i.e., the role being discussed in the utterance); *Phrase-target-role-group* (i.e., the subgroup of roles being discussed in the utterance); *Phrase-target-position* (i.e., the unused role card being discussed); and *Phrase-negated* (i.e., whether an utterance was positive or negative). Gillespie et al. (2016) provide more information about the classification tasks and their possible labels. Additionally, each utterance also contains two other pieces of information: *Phrase-speaker* (i.e., who spoke the utterance) and *Phrase-responds* (i.e., whether the utterance was in response to another utterance). For our initial case study, we use human-labelled test data as input rather than the output of the Natural Language Classifier (i.e., to remove any errors the Natural Language Classifier might introduce).

4.1 Action Modelling

For an agent to play One Night Ultimate Werewolf, it requires a *model of the game rules* and a *model of possible actions*. The game rules include, for example, the following background information:

1. A limited number of each type of role can be active in any game (i.e., some roles are unused).
2. Each role starts the game with role-specific knowledge.
3. Each Werewolf knows the identity of the other Werewolf (if any).
4. If a second Werewolf is not active, each Werewolf knows one unused role.
5. The Seer knows the role of one other active player, or two inactive roles.

The action model provides a mechanism for the agent to interpret the various utterances as speech actions. We use a modified version of PDDL+ (Fox and Long 2006) to model actions. Each action is defined by parameters, a logical precondition (i.e., what must be true for the player to perform this action), and set of effects (i.e., what utterance the player will speak). Additionally, each action also identifies its performer for purposes of ascribing actions to individual players. The domain model we created has both deceptive and non-deceptive actions; thus, multiple actions can result in the same utterance (i.e., one action where a player says something truthful and one where they say something deceitfully). The difference between a truthful and deceitful action is a result of their differing preconditions. For example, the utterance "*Bob is a werewolf!*" could be a result of a player revealing knowledge that they know, asserting a belief with no knowledge of its accuracy, or lying to divert attention. The following action model describes an action where the player truthfully reveals a role:

```
(:action reveal-player-role
 :performer ?self
 :parameters (?p - person ?r - role)
 :precondition (and (eq (self) ?self)
                    (person-observed-role ?self ?p ?r)
                    (create phrase ?ph (get-phrase-symbol))
               )
 :effect (and (set (phrase-purpose ?ph) claim)
              (set (phrase-address-type ?ph) everyone)
              (set (phrase-subject ?ph) starting-role)
              (set (phrase-target-person ?ph) ?p)
              (set (phrase-target-role ?ph) ?r)
              (set (phrase-speaker ?ph) ?self)
         )
)
```

In contrast, the following action model describes an action where the player is being deceitful:

```
(:action divert-with-false-role
 :performer ?self
 :parameters (?p - person ?r - role)
 :precondition (and (eq (self) ?self)
                    (not (person-observed-role ?self ?p ?r))
                    (create phrase ?ph (get-phrase-symbol))
               )
 :effect (and (set (phrase-purpose ?ph) claim)
              (set (phrase-address-type ?ph) everyone)
              (set (phrase-subject ?ph) starting-role)
              (set (phrase-target-person ?ph) ?p)
              (set (phrase-target-role ?ph) ?r)
              (set (phrase-speaker ?ph) ?self)
         )
)
```

These two models differ both in the type of the action (i.e., *reveal-player-role* and *divert-with-false-role*), which could be used to determine intent, and the preconditions (i.e., not observing a person's role), which require the player to have certain information. To use the revealing action, the player must have actually observed Bob's role, meaning the player is either another Werewolf (i.e., the Werewolves observed each other) or the Seer (i.e., the Seer observed a role card).

A player could lie for multiple reasons. For example, a Werewolf player might lie to try to divert suspicion to avoid being shot by other players. A Tanner might lie to create suspicion, to appear to be a Werewolf and be shot. The Explanation Generator does not attempt to determine this motivation; that is left to the Plan Recognizer. It attempts to determine only which actions are consistent with the available information (i.e., the utterances that have been spoken thus far). In modeling deception for the Explanation Generator, it is challenging to provide an adequate set of actions to reason over all possible behaviors and goals of participants. The model must be general enough to accommodate a majority of possible game states, specific enough to allow recognition of typical strategies used by players, and must permit efficient reasoning. A larger set of more specific actions may better encode possible game states, but also cause processing time for DISCOVERHISTORY to become intractable.

The foundation for encoding game knowledge lies in PDDL+ events and actions corresponding to opening game moves. In general, each game role performs a specific predetermined action before gameplay begins. All roles share one common action, which is the action of observing one's own role. Other roles carry additional actions (e.g., Werewolves observe whether there is another Werewolf in the game).

Certain static parameters of the game of Ultimate Werewolf can be encoded into the set of actions as constraints. In any game, the number of possible instances of a particular role is known (i.e., based on the game configuration). If three players claim to be the Seer, at least two must be lying since there is at most one Seer, and possibly all three are lying (e.g., the Seer role is unused or another player is the Seer).. We introduce this constraint in the PDDL+ actions by including fluents that model these class instantiation limits. By introducing these limits in the initial PDDL+ event of a player observing their own role, all subsequent events that occur due to these initial observations are therefore constrained by our role-limiting fluents.

4.2 Preliminary Case Study

We present as a case study the explanation generated from a sequence of utterances in a game. We denote the five players in the game *person1*, …, *person5*. In this game, our agent is an impartial observer. We observe the following series of utterances:

- **Person3**: *I am the Seer*
- **Person5**: *There's only one Werewolf in the game*
- **Person1**: *How do you know?*
- **Person5**: *Because I am the actual Seer*
- **Person3**: *And you saw the Seer?*
- **Person5**: *I am the Seer*
- **Person1**: *I was also the Seer*

There can only be one Seer per game. Therefore, given the above utterances, we have a conflict where three players are claiming to be the Seer, so at least two of them must be lying. Using these utterances as input to DISCOVERHISTORY gives us one possible explanation:

```
0. (ASSUME-INITIAL-VALUE (PERSON-STARTING-ROLE PERSON1)
   VILLAGER TIME 1)
1. (ASSUME-INITIAL-VALUE (PERSON-STARTING-ROLE PERSON5)
   SEER TIME 1)
2. (ASSUME-INITIAL-VALUE (PERSON-STARTING-ROLE PERSON3)
   WEREWOLF TIME 1)
3. (VILLAGER-EXAMINES-STARTING-ROLE PERSON1 TIME 3)
4. (SEER-EXAMINES-STARTING-ROLE PERSON5 TIME 3)
5. (WEREWOLF-OBSERVES-UNUSED-WEREWOLF PERSON3 TIME 3)
6. (WEREWOLF-EXAMINES-STARTING-ROLE PERSON3 TIME 3)
7. (TIME-PASSES 0.1 TIME 37)
8. (TIME-PASSES 0.1 TIME 121)
9. (WEREWOLF-CLAIMS-SEER PERSON3 PERSON3 PHRASE2 TIME
   136)
10. (TIME-PASSES 0.1 TIME 154)
11. (HYPOTHESIZE-ONE-ACTIVE-ROLE WEREWOLF PERSON5
   PHRASE7 TIME 169)
12. (TIME-PASSES 0.1 TIME 187)
13. (REVEAL-PLAYER-ROLE PERSON5 SEER PERSON5 PHRASE9 TIME
   202)
14. (TIME-PASSES 0.1 TIME 220)
15. (REVEAL-PLAYER-ROLE PERSON5 SEER PERSON5 PHRASE14
   TIME 235)
16. (TIME-PASSES 0.1 TIME 253)
17. (DIVERT-WITH-FALSE-ROLE PERSON1 SEER PERSON1 PHRASE32
   TIME 268)
18. (TIME-PASSES 0.1 TIME 286)
```

This explanation assumes that *person5* is the actual Seer (line 1), while *person1* is a Villager (line 0) and *person3* is a Werewolf (line 2). The remaining lines describe the actions performed by each player that resulted in the observed utterances. This explanation is consistent with the states of the game. However, it is not the only possible explanation. Note that *person5* (the actual Seer), makes an observation that there is only one Werewolf in the game. Intuitively, this naturally lends credence to their claim of being a Seer. However, if it was later revealed that the Werewolf statement was false, then the most plausible explanation may conclude that *person5* is not the actual Seer. The above explanation provides the agent with the most likely hypothesis given the currently available information and allows it to use the explanation to make strategic decisions, but does not preclude further refinement of the explanation as more information becomes available.

5. Analysis

An initial analysis of the agent's explanation generation performance over five game logs allows us to make several key observations. The hypothesis space over which DISCOVERHISTORY must search is large. Care is needed to balance action generality and specificity. Adding ambiguity to the search domain results in exponential growth of the space to search over. For any action with a slot for the role, the branching factor is then the number of possible roles in the game. Fortunately for Ultimate Werewolf, this is not a significant concern due to the limited number of players and roles.

While collecting experimental data we observed that even players with roles that should not require deception (e.g., Villagers) actively engage in deception and omission. Since nearly all players engage in deception, it becomes more important to identify when they are being deceptive and why they are being deceptive. We can imagine a game state where all players tell the truth. Thus, there are no inconsistencies and each utterance further constrains the space, simplifying search. We can also imagine a game where every utterance is a lie. Our agent, as well as a human player, would perform poorly since no truthful information is available to generate hypotheses. Real-world games lie somewhere between these two extremes. Assuming that an individual human player's memory of all prior game utterances is imperfect, their ability to consistently lie diminishes over time. However, our agent does not suffer from this problem (at least not the ability to remember, but perhaps pruning is necessary to trim the search space) and therefore should have an advantage in its ability to resolve inconsistencies from earlier in the game.

Aside from the rate of lying, we hypothesize that as the number of utterances increases, accurate inferences on which players are being truthful quickly collapses the state-space into something manageable by the Explanation Generator. Therefore, we believe that the action model developed here can be used as a basis for a larger set of real-world scenarios. This hypothesis matches our observations in the limited amount of games that we have analyzed so far, but we plan to evaluate performance in a larger-scale environment as part of future work.

6. Related Work

Our work focuses on deceit detection in a game where the players often engage in deception. Deception detection in conversational games has been approached using textual cues (Zhou and Sung 2008) (e.g., word selection, utterance duration, utterance complexity), vocal cues (Chittaranjan and Hung 2010) (e.g., pitch, pauses, laughter), and visual cues (Raiman et al. 2011) (e.g., head and arm movements). In contrast, our system uses logical inference to detect deception. These systems are designed to classify players as truthful or deceptive, and use that information to identify players with deceptive roles (e.g., werewolves).

Network analysis has been used to identify groups of players with similar patterns of behavior (Yu et al. 2015). The statements made by each player are used to determine their attitudes toward other players (e.g., a positive attitude if they regularly defend another player or a negative attitude if they regularly accuse another player) and players are clustered based on their attitudes. The underlying assumption is that deceptive players will have positive attitudes toward other deceptive players while having negative attitudes toward other players. In our domain, even the most common roles (e.g., Werewolf, Mason, Generic Villager) have at most two players with those roles. If a player knows of another player with the same role (i.e., using a special ability), they often avoid displaying a positive attitude toward that player since it can arouse suspicion.

Pearce et al. (2014) examine multiagent social planning scenarios that possibly involve deception. Their system reasons over agent goals to allow a particular agent to achieve its goals by reasoning over other agent's beliefs and goals. The target agent may aim to manipulate other participants' belief states to achieve its aim. Our system can be viewed as a more generalized version of this, as our agent roles are an unknown, thus giving our reasoning engine an additional layer of uncertainty. However, we have not yet tested this conjecture.

Meadows et al. (2014) study social cognition by developing an agent that can understand simple fables. An Explanation Generator is used to reason over the agent's beliefs and goals, but again, the roles of agents are static and known a priori, giving the system a simpler domain to reason over.

Azaria et al. (2015) have developed an agent that can identify deception, convince other players of the deception, and avoid raising suspicions about their own behavior. The agent participates in a simplified social deception game where a single pirate has to deceive three non-pirates to steal treasure. The primary differences between their work and our own are that their game uses structured sentences rather than free text, the game is less complex (i.e., fewer roles and player goals), and their system is focused on identifying deception rather than a player's plan or role.

Vázquez et al. (2015) have studied the reaction of human players when a robotic player participates in a social deception game. The robot has the appearance of autonomy but is actually controlled by an unseen human. Although this differs from our own goal of an autonomous player, it demonstrates that humans are open to playing social deception games with robotic participants.

Toriumi et al. (2016) describe the AI Wolf contest, a competition to create AI agents that play Werewolf. The primary difference between AI Wolf agents and our agent is that their AI Wolf agents use a set of predefined actions to play the game rather than using unstructured natural language. A primary contribution of our work is that utterances are interpreted and used to generate hypotheses for probable actions. The other major difference is that our agent is a game observer rather than an active participant, although that is a goal of future work.

7. Conclusions and Future Work

We described our architecture for an agent that uses domain specific knowledge to reason about the plans and goals of humans. In this paper, we focus on one module of this architecture, the Explanation Generator, and examine its ability to abduct world state information given observations of participants. These observations came in the form of human-coded propositions. We chose not to rely on the natural language processing module of the system to prevent bias from potential noisy encodings. We plan to integrate our explanation generator described in this paper with the natural language module in the future. While other systems have used a similar approach in a military domain (Gillespie et al. 2015), in this paper we chose to examine a social deception game because it posed several interesting challenges, including less constrained language, deception, and ambiguity.

The DISCOVERHISTORY algorithm outputs plausible explanations for the current world state by reasoning over observations of game players. We did not perform a thorough quantitative analysis of the agent, but our case study and qualitative analysis of the resulting explanations shows promise. Given complex observations from all players involved, our agent can generate reasonable and logically consistent explanations for the current game state.

Our principal area of future work is to integrate DISCOVERHISTORY with the other components of the agent architecture and evaluate the agent's overall performance. Additionally, we plan to allow the agent to observe games of Ultimate Werewolf and make predictions about player roles, identify deception, and learn the motivations of individual players. Finally, we plan to transition the agent from a passive bystander to an active participant in a game of Ultimate Werewolf.

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