Outcome Matrix based Phrase Selection

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Abstract

This article presents a method for using outcome matrices for social phrase selection. An outcome matrix is a computational representation of interaction often used to represent a social decision problem. Typically an outcome matrix lists the potential actions that a robot or agent might select and how the selection of each possible action will impact both the agent and their interactive partner. Here we examine the possibility of replacing the social actions listed in a matrix with phrases that could be spoken by the robot. We show that doing so allows one to utilize several tools from interdependence theory and game theory.

Introduction

Social psychologists define interaction as influence—verbal, physical or emotional—by one individual on another (Sears, Peplau, & Taylor, 1991). This definition of interaction centers on the influence individuals have on one another. Hence, one's representation of interaction must also include information about the actions each individual is considering, the influence that the selection of a pair of actions would have on each individual, and information about who is interacting.

Outcome matrices contain all of this information (Wagner, Creating and Using Matrix Representations of Social Interaction, 2009). An outcome matrix not only identifies the individuals interacting but also contains information about the actions available to both individuals and the influence that results from the selection of each pair of actions. If we allow a social action to include verbal statements then outcome matrices can serve as a method for deliberating over distinct verbal phrases and gauging how these phrases will impact both the agent and the human. Moreover, this approach allows one to use tools from interdependence and game theory for phrase selection (Kelly & Thibaut, 1978).

This article examines the use of outcome matrices as a method for phrase selection. We assume that the intelligent agent has at their disposal a limited set of known phrases. These phrases serve as the agent's universal set of actions. From this set, a subset of appropriate phrases is selected based on the agent's perceptual recognition of the environment. Stereotyping is used to create a further subset of the remaining phrases. This final set of phrases is incorporated into the outcome matrix representation.

An outcome matrix explicitly represents little information related to common ground. In fact, the only mutual understanding that the robot and the human are assumed to have is rudimentary knowledge of how a selected phrase would influence both individuals. We argue that the robot's use of outcome matrices for the selection of phrases does in fact ground the phrase with respect to its influence on both individuals. Put another way, our method does not assume or argue that the robot has any understanding of what the phrases mean. Rather, their value during an interaction is completely determined by the outcome values within the matrix at that time. Hence the phrases are grounded in these outcome values and common ground is established when these outcome values are mutually recognized.

This article does not examine the problem of creating or understanding human-robot dialog. Rather we simply present a method by which a robot can select a phrase, whether spoken or otherwise, resulting from an interaction with a person. The key contribution of this paper is to present phrase selection as a form of social action selection, thereby suggesting that the phrase selection problem is a decision theory problem which can be represented as an outcome matrix. Moreover, use of the outcome matrix representation leaves at our disposal the various tools from interdependence theory. For example, the outcome matrix's position in the interdependence space can be calculated and the resulting values can be used to influence the selection of a phrase or the robot can transform the matrix to reflect include its own internal disposition. We examine the use of these interdependence theory tools in greater detail below.

Related Work

Many researchers have examined human-robot dialog. Much research has been devoted to developing robots that learn the words for objects in an environment (Chauhan & Lopes, 2010)(Iwahashi, Sugiura, Taguchi, Nagal, & Taniguchi, 2010). Others have focused on specific portions of dialog such as adjectives (Petrosino & Gold, 2010) or spatial language (Skubic, Perzanowski, Schultz, & Adams, 2002). Investigations of timing and turn-taking are plentiful (Chao & Thomaz, 2010) (Spiliotopoulos & etal, 2001). Scheutz et al. developed an architecture that expressed and verbally responded to a human's affect(Scheutz, Schermerhorn, & Kramer, 2006).

Representations for interaction have a long history in social psychology and game theory (Kelly & Thibaut, 1978)(Osborne & Rubinstein, 1994). Interdependence theory, a type of social exchange theory, is a psychological theory developed as a means for understanding and analyzing interpersonal situations and interaction (Kelly & Thibaut, 1978). The term interdependence specifies the extent to which one individual of a dyad influences the other. Interdependence theory is based on the claim that people adjust their interactive behavior in response to their perception of a social situation's pattern of rewards and costs. Thus, each choice of interactive behavior by an individual offers the possibility of specific rewards and costs—also known as outcomes—after the interaction. Interdependence theory represents interaction and social situations computationally as an outcome matrix (Figure 1). An outcome matrix represents an interaction by expressing the outcomes afforded to each interacting individual with respect each pair of potential behaviors chosen by the individuals.

Independent versus Dependent matrices

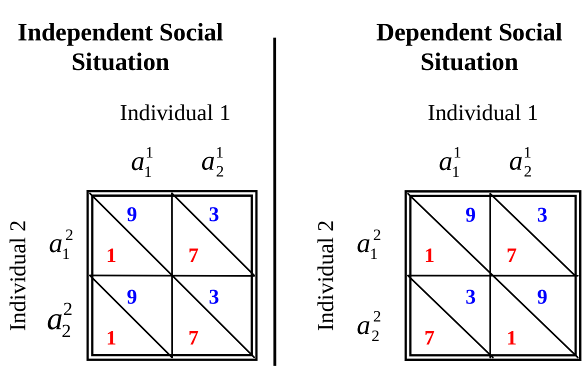

Figure 1. An example of an independent situation is depicted on the left and an example of a dependent situation is depicted on the right. In the example of an independent situation,, the action selection of the second individual does not have an effect the outcome received by the first individual. In the dependent example, on the other hand, the action selection of the second individual results in a gain or lose of 6 units of outcome (a measure of utility) by the first individual.

Representing Interaction

The outcome matrix is a standard computational representation for interaction (Kelly & Thibaut, 1978). It is composed of information about the individuals interacting, including their identity, the interactive actions they are deliberating over, and scalar outcome values representing the reward minus the cost, or the outcomes, for each individual. Thus, an outcome matrix explicitly represents information that is critical to interaction. Typically, the identity of the interacting individuals is listed along the dimensions of the matrix. Figure 1 depicts an interaction involving two individuals. In this article the term individual is used to indicate either a human or a social robot or agent. We will focus on interaction involving two individuals—dyadic interaction. An outcome matrix can, however, represent interaction involving more than two individuals. The rows and columns of the matrix consist of a list of actions available to each individual during the interaction. Finally, a scalar outcome is associated with each action pair for each individual. Outcomes represent unitless changes in the robot, agent, or human's utility. Thus, for example, an outcome of zero reflects the fact that no change in the individual's utility will result from the mutual selection of that action pair.

Because outcome matrices are computational representations, it is possible to describe them formally. Doing so allows for powerful and general descriptions of interaction. The notation presented here draws heavily from game theory (Osborne & Rubinstein, 1994). A representation of interaction consists of 1) a finite set N of interacting individuals; 2) for each individual $i \in N$ a nonempty set A^i of actions; 3) the utility obtained by each individual for each combination of actions that could have been selected (Gibbons, 1992). Let $a_j^i \in A^i$ be an arbitrary action j from individual i's set of actions. Let $\left(a_j^1, \ldots, a_k^N\right)$ denote a combination of actions, one for each individual, and let u^i denote individual i's utility function: $u^i\left(a_j^1, \ldots, a_k^N\right) \to \Re$ is the utility received by individual i if the individuals choose the actions $\left(a_j^1, \ldots, a_k^N\right)$. The term O is used to denote an outcome matrix. The superscript $-i$ is used to express individual i's partner. Thus, for example, A^i denotes the action set of individual i and A^{-i} denotes the action set of individual i's interactive partner.

Phrases as Outcome Matrix Actions

Verbal statements can have a powerful influence both on one's self and on one's interactive partner. As mentioned

Using Context and Stereotypes to refine the set of Phrases

Universal Set of Phrases	Context Subset	Partner Subset
1 "I can assist with the axe" 2 "I can assist with the baton" 3 "I can assist with a stethoscope" 4 "How can I help you?" 5 "Do you want coffee?" 6 "Yes" 7 "No?"	1 "I can assist with the axe" 2 "I can assist with the baton"	1 "I can assist with the axe"

Image example from experiment

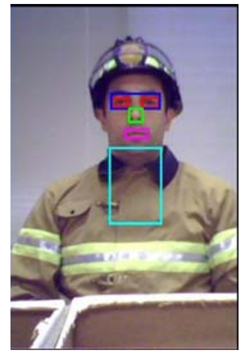

Figure 2 The figure above depicts the iterative refinement of set of phrases based on context and stereotyping. The robot begins with a universal set of phrases (left). Recognition of tools in the environment refines the possible set of phrases to be applicable to the context involving the tools located. Next, perceptual features related to the stereotype of a fire fighter are recognized. These features refine the set of phrases down to a single phrase.

an outcome matrix acts as a computational representation of interaction. The information contained within an outcome matrix explicitly represents the decision problem faced by the agent or robot. We argue that this decision problem often involves selecting the most appropriate verbal statement. In this case we consider the robot to have a set A^i such that $a_j^i \in A^i$ is a verbal statement. The selection of the verbal statement $a_j^i \in A^i$ will result in outcome (o^i, o^{-i}) for the robot and its partner. The robot selects the statement based only on the outcome values. Still, the outcome values themselves may be influenced by many different factors, such as the context or characteristics of the interactive partner.

The robot or agent thus has a finite, but possibly large, set of phrases representing the actions available to it. This universal set of phrases, A^U, includes all possible phrases available to the robot in all contexts and with all partners. At this point we do not offer insight as to how the robot generates or constructs such a set. Learning phrases from interactions with others seems to be the most obvious route. Keep in mind, however, that for this process to be viable, the robot must also learn the outcome values for such phrases. Simply learning the phrase itself would not be of value.

Refining the Set of Phrases

Social scientists claim that interaction is function of both interactive individuals (A and B) and the context (C), formally $f(A, B, C)$ (Rusbult & Van Lange, 2003). With respect to interactive phrase selection, the robot must have a process for down selecting the set of possible phrases to those phrases available for a given partner in a given context. In the section that follows we describe such a process.

We propose that the context and interactive partner operate by selecting subsets of a universal set of phrases. The robot begins with a universal set of phrases representing all phrases it has available. At startup, the robot surveys its environment generating a context vector, v_c, which includes perceptual information related to the robot's context. The context vector and the universal set of phrases are used as input to a function that produces a subset of phrases available in that particular context.

Next or possibly concurrently, the robot generates a partner feature vector, v_p, that includes perceptual information related to the robot's interactive partner. The partner feature vector and the context related subset of phrases are used as input to a function generated a further subset of phrases.

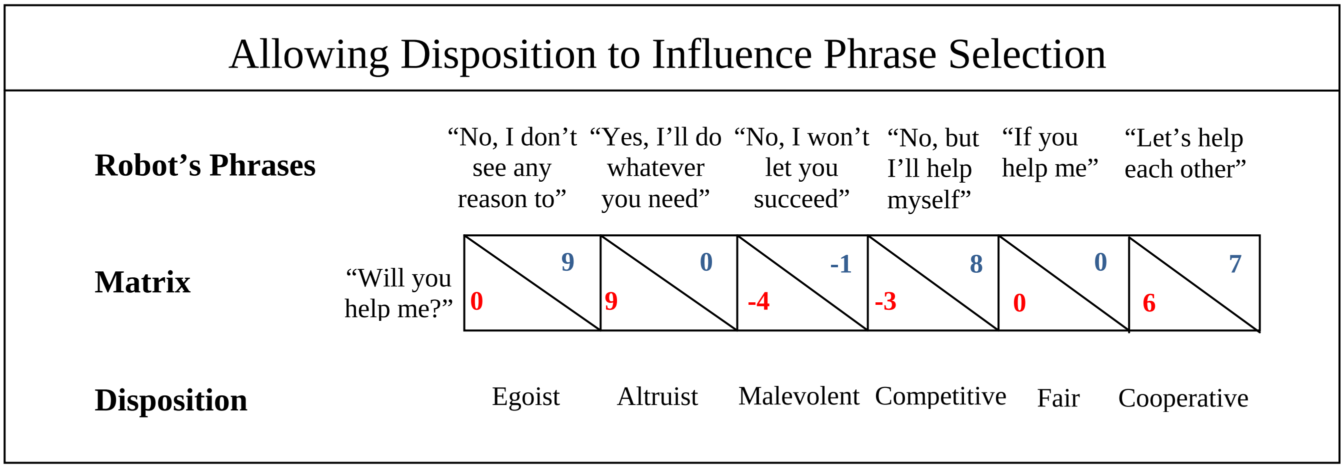

Figure 3 The figure above depicts a situation in which the human asks the question, "Will you help me?" The robot has several different potential phrases to choose from. Below the matrix underneath each potential robot phrase, the robot disposition that would choose that phrase is listed. For example, a malevolent disposition would choose the phrase "No, I won't let you succeed."

Stereotypes and stereotyping allow for the learning of categories of individuals. Sears, Peplau and Taylor define a stereotype as an interpersonal schema relating perceptual features to distinctive clusters of traits (Sears, Peplau, & Taylor, 1991). A stereotype is a type of generalized model of one's partner used to represent a collection or category of individual partner models. The creation of stereotypes requires the creation of these generalized partner models. Moreover, to be useful, techniques must exist which are capable of matching a new interactive partner's perceptual features to an existing stereotype. In previous work we developed algorithms for stereotype building and for matching a new partner to an existing stereotype (Wagner, Extended Abstract: Using Stereotypes to Understand One's Interactive Partner, 2010).

With respect to phrase selection, the use of stereotypes allows the robot to match collections of phrases to the particular categories of people. Figure 2 presents an example in which we have used this process of refining the set of phrases. In this example the robot begins with seven phrases in the universal set. The robot recognizes particular objects in the environment. These objects map to a particular subset of the universal phrase set. Next, the robot uses the perceptual characteristics of the person to create a feature vector. This feature vector is used to select a stereotype. The selected stereotype includes information related to which phrases remain viable during the interaction. The ordering of the refinement steps is not important; either the subset based on the stereotype or on the context may be performed first.

Allowing Disposition to influence Phrase Selection

Disposition refers to a natural tendency or predilection towards doing something or acting in a particular way. We can imbue the robot with a particular type of disposition by having it prefer one type of action selection strategy over another. Outcome matrices afford several simple action selection strategies. The most obvious method is to choose the action that maximizes the robot's own outcome. This strategy is termed *max_own*. A robot's use of the *max_own* strategy over the course of many interactions results in egoistic disposition—the robot tends to do what is best for itself without regard to others. Alternatively, the robot may select the action that maximizes its partner's outcome, a strategy termed *max_other*. A robot's use of the *max_other* strategy results in an altruistic disposition. Yet another action selection strategy is for the robot to select the action that maximizes the sum of its and its partner's outcome (*max_joint*). The use of this strategy results in a cooperative disposition. The *min_diff* action selection strategy, on the other hand, selects the action that minimizes the difference in outcome between the robot and the human, resulting in a fair or just disposition. Outcome matrices afford many other simple action selection strategies (see (Wagner, The Role of Trust and Relationships in Human-Robot Social Interaction, 2009) for other examples).

Figure 3 depicts an example in which the robot is asked a question. Six different phrases are available as a response. For this example, the robot's disposition uniquely determines the phrase that the robot selects. If the robot's disposition is malevolent, then the robot chooses the *min_other* action selection strategy resulting in the selection of the phrase "No, I won't let you succeed". If the robot's disposition is competitive then the robot selects the *max_diff* action selection strategy resulting in the selection of the phrase "No, but I'll help myself". Figure 3 depicts several other examples.

Interdependence Space Information

In previous work, we presented a situation analysis algorithm that calculated characteristics of the social situation or interaction (such as interdependence) when presented with an outcome matrix (Wagner & Arkin, Analyzing Social Situations for Human-Robot Interaction, 2008). The interdependence space is a four-dimensional space which maps the location of all interpersonal social situations (Kelley, Holmes, Kerr, Reis, Rusbult, & Van Lange, 2003). A matrix's location in interdependence space provides important information relating to the interaction. The interdependence, correspondence, and symmetry dimensions may be of particular importance for phrase selection. The interdependence dimension measures the extent to which each individual's outcomes are influenced by the other individual's actions in a situation. In a low interdependence situation, for example, each individual's outcomes are relatively independent of the other individual's choice of interactive behavior (Figure 1 left for example). A high interdependence situation, on the other hand, is a situation in which each individual's outcomes largely depend on the action of the other individual (Figure 1 right for example). Correspondence describes the extent to which the outcomes of one individual in a situation are consistent with the outcomes of the other individual. If outcomes correspond then individuals tend to select interactive behaviors resulting in mutually rewarding outcomes, such as teammates in a game. If outcomes conflict then individuals tend to select interactive behaviors resulting in mutually costly outcomes, such as opponents in a game. Symmetry refers to the balance of control that one individual has over another's outcomes. In a symmetric situation both individuals have equal ability to impact the other person's outcomes. In an asymmetric situation, on the other hand, one individual has significantly more control over the other person's outcomes. Our results showed that by analyzing the interaction, the robot could better select interactive actions (Wagner & Arkin, Analyzing Social Situations for Human-Robot Interaction, 2008).

Analysis with respect to the interdependence space, which we call situation analysis, is another source of potentially valuable information for phrase selection. In this case, the interaction's location in interdependence space could serve to influence characteristics of the phrase, such as tone, that is selected. For example, in an asymmetric situation the person in control may select a more demanding stance in the conversation. The person being controlled would likely assume a less demanding stance. Figure 4 presents examples of changes in tone that occur when the situation is located at different areas of the interdependence space.

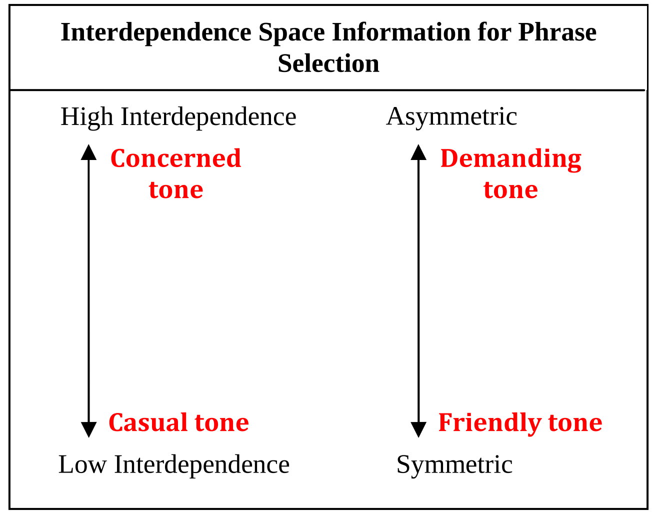

Figure 4 Examples of how the tone of a phrase might be influenced by changes in interdependence space dimension. For example, as the interdependence space dimension goes to asymmetric the tone of the phrase could become more demanding.

Summary and Conclusions

This article has presented a method for using outcome matrices for social phrase selection. Typically outcome matrices represent a social decision problem in which both individuals select among different social actions. In the work presented here these social actions are replaced with phrases. Each phrase in the matrix includes outcome values indicating the change in influence that speaking the phrase would have on both agents. A method by which a universal set of phrases can be reduced to a subset appropriate for the context and the interactive partner has also been outlined. We have discussed a technique for using stereotypes to select phrases based on categories of individuals, the inclusion of disposition in phrase selection, and the use of interdependence space information.

Many of the methods that have been presented are preliminary in the sense that they have yet to be fully tested on an implemented system. Additionally, it is unclear if and how well this approach would scale to more dynamic and complex social systems. The described system, for instance, relies on a predetermined set of phrases. Learning of new phrases might be accomplished by directly copying statements made by the human and incorporating these statements into the robot's universal set of phrases. Instantaneous phrase construction is not addressed and would likely be an important and necessary part of a system tasked with managing open ended dialog. Still, it is a potentially interesting question, how far the described system would go towards realistic dialog with a human. Even a partial system may allow the robot to interact in a more realistic manner.

Potential applications of the system might include a social robot that augments its existing social behavior with occasional phrases. Future work will focus on scalability and the development of applications based on a limited set of phrases.

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