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An Artificial Laboratory Environment for Studying Distributed Decision Processes.

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Abstract

We examine the feasibility of using an adaptive systems approach for generating the non-linear and dynamic aspects of distributed decision processes. First, the issues that need to be considered in modeling agent interactions are discussed. We then present details of a computational prototype based on the interplay of agents and their actions. Our model represents agent decision making as an adaptive search activity. The agents in our model learn by using a system that rewards strategies that generate high payoffs and penalize strategies that do not.

Introduction

Distributed decision making tasks consist of either the resolution of conflicting viewpoints on how to achieve a common goal or objective (as in group decision making) or the resolution of conflicting goals or interests (as in negotiations). However, they are similar in that the final outcome or choice lies between the preferences of contending decision makers. Regardless of the type of motive involved, all distributed decision making processes are characterized by a fundamental property. Individual behaviors are adaptive, i.e. they change over time with respect to changes in the environment as well as other individual behaviors. As a result, the final outcome is dependent on the choices or preferences of individual behaviors. Modeling such processes is complex because the pattern that emerges from the interaction of the individual behaviors is often non-linear and dynamic. The goal of this research is to develop a computational model of distributed processes so as to study more complex phenomena such as coalition formation. In this paper, we discuss related modeling issues and present details of a prototype of negotiation behavior.

The development of a computational model of distributed decision processes is necessary for several reasons. It allows the researcher to keep track of the ongoing dynamics of the process. For example, while it is known that there is a general transition from competitive to cooperative behavior; enough is not known as to when and under what conditions do such transitions take place. This is perhaps due to the inability of existing experimental techniques to keep track of the process. Individual preferences are continually shifting and evolving over time. It is not always possible from only three data sets (before meeting, during meeting, and after meeting) to determine when and how exactly the change took place. Relying on process protocols typically could lead to coding problems. By creating an artificial laboratory environment, a computational model would help to keep experimental conditions constant and thereby provide a framework for the replication of studies.

Modeling Issues

There are two strategies for modeling distributed processes. The first entails a direct modeling of emergent behavior without considering individual agents. The problem with this approach is it assumes the existence of a widely accepted body of rules and protocols of interactions and preference choices. The second strategy referred to as the Bottom-Up approach relies on simulating individual agent behaviors; making them interact; and then observe the dynamics of interest. Our plan is to adopt the second strategy. Each agent will be modeled in the form of a simple rules of interaction and preference choices. To model agent interactions, the following issues need to be considered. They are:

1. Recognition of conflicting intentions of an agent

2. Recognition of favorable intentions of an agent

3. Resolution of conflicts

4. Taking advantage of favorable interactions

5. Enabling cognitive functions such as reasoning, learning, and memory in agents.

6. Measuring alignment and distance of preferences to common goal.

7. Enabling agents to communicate (e.g. based on a universal protocol).

8. Enabling different types of agents (e.g. based on hierarchy of power or based on purpose such as mediation or negotiation).

1. Medium of information exchange (i.e. the type of issues and their structure).

A Scheme for Coordinating Agent Plans

To simulate emergent behavior based on agent interactions, the model treats each agent decision process as an adaptive search activity. We consider an interactive process by which agents make offers and counter-offers until there is a compromise. The decisions of evaluating the opponent's offer and accordingly making a counter-offer was modeled using a genetic search procedure. Each agent's decision process considers the following factors:

1. Problem space scanning strategy

2. Cognitive capacities

3. Concession tactics

4. Opponent strategy

5. Time pressure

6. Agent preferences

7. Opponent preferences

8. Agent aspirations

9. Initial offer magnitude

10. Strategic postures

Different variants of agents were created based on various combinations of the above factors. For example, a rational agent is fully aware of opponent preferences. The prototype was able to predict and manifest several aspects of individual and dyadic behavior. Most of the predictions were consistent with results documented in the general literature.

Conclusions

Distributed decision processes involve complex agent interactions. The ability to generate such non-linear behavior might help us to understand aspects such as evolving strategies, shifting preferences, and coalition formations. We have presented a new approach which is a paradigm shift from the way researchers have studied distributed processes. The prototype used in this study represents each agent decision process as an adaptive search procedure. Simulation experiments reveal that it is able to generate fundamental patterns that have been documented in the literature. A validated computational model could serve as an artificial laboratory environment for analyzing and studying the separate or joint impact of different variables. The advantage of using such virtual environments is that it overcomes existing experimental limitations like the inability to keep track of shifting preferences and strategies. At the same time, it also helps to minimize confounding influences during experimentation.