The "Fast and Frugal" Cognitive Architecture for Computational Social Simulations

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1. Introduction

Computational social simulations involving humans require models of human behavior but their behavior can be represented and modeled in many ways. The two dimensions of this challenge we are interested in are the degree of cognitive plausibility in the representation of the behavior of humans and the computational intensity involved.

We will define what we mean by cognitive plausibility and computational intensity. By cognitive plausibility, we mean that the observable behavior is based on models of cognition that are well received by the cognitive science and psychology community. By computational intensity we means how much of the computing resources required for the social simulation is involved in modeling the human decision-making process. We would, of course, like an approach that maximizes cognitive plausibility and minimizes computational intensity. However, neither of these dimensions is easily measured.

Recently, agent based models (ABM) have become a useful tool for modeling the behavior of many individual agents but researchers have not settled on a single tool for modeling human decision-making.

Social simulations often need models of hundreds to thousands of agents but research cognitive architectures such as ACT-R, Soar, and CLARION, are useful for studying individuals. They are usually considered too computationally intense for modeling hundreds or thousands of individuals. Another approach is an ad hoc representation of decision-making.

Here we describe our previous ad hoc approach, an alternative "fast and frugal" approach, and a comparison between our previous approach and the "fast and frugal" approach.

2. Our Previous (ad hoc) Approach

In a simulation involving thousands of herders and farmers interacting in East Africa, we use an ad hoc approach to the modeling of each agent's decision-making. In that system, our herder agents considered four factors in deciding where to move their herd each day. Those factors were the herd's need for water, need for vegetation, the potential for conflict, and the distance to the candidate location. These factors were evaluated for each possible next location in a single, multivariate polynomial of four terms with arbitrary scaling coefficients on each term as shown in Eq. 1.

$$Q = a*T + b*H + c*C + d*1/D \qquad \text{(eq. 1)}$$

where: Q is quality of parcel
T is thirst need
H is hunger need
D is distance to the parcel
a, b, c, & d are scaling coefficients

This approach generated reasonable behavior as judged by the anthropologists on our team and peer reviews of reported results in three venues (Kennedy et al 2010a; Hailegiorgis et al 2010; Kennedy et al 2010b). This approach is also reasonably fast even with thousands of agents, but it is not very cognitively plausible. There is evidence that people are not very good evaluators of multivariate polynomials and we do not want the community to suffer from the same plausibility challenges economics has. Therefore, we considered cognitive architectures used in cognitive science as likely to be more cognitively plausible and not too computationally intense.

3. The "Fast and Frugal" Approach

In 2007, Gerd Gigerenzer published a book discussing the research behind the concept of intuitive reasoning (Gigerenzer 2007). Although the book is primarily aimed at unconscious cognition, he also describes a "fast and frugal" heuristic for representing human decision-making and improving emergency room decisions, explaining judges' bail decisions, and implementing Simon's bounded rationality concept.

This approach to agent decision-making is a little different from the traditional rule-based approach. The approach considers the factors affecting a decision sequentially in the order of their importance. Each rule is focused a little differently from the standard approach of identifying the conditions in the environment necessary and sufficient to determine which possible action to take as stand alone rules. Here, the approach is to ask whether the agent has sufficient information to act. If so, act. If not, add consideration of the next factor. In other words, rather than saying humans weigh several factors simultaneously to make a decision, his research reports that humans rank order factors and consider the factors sequentially until they have enough information to act (explaining why car buying decisions could hinge on the number of cup holders).

In our previous model, our agents considered four factors and we adjusted the coefficients to tune the behavior to be appropriate. The new "Fast and Frugal" approach orders those factors to be ordered by importance. Our new model is:

1. If there is conflict nearby, then move away from the conflict.
2. If the need for water is critical, then move toward water.
3. Otherwise, move toward vegetation.

We handle the fourth factor, distance to the potential location, as part of the action side of the rules. The "move" command optimizes movement toward the current goal, either moving away from conflict, toward water, or toward vegetation.

This approach considers the same four factors as was done previously, but prioritizes the movement conditions explicitly rather than through the weights. Although the previous four-factor formula was more flexible, its range of possible actions was not cognitively plausible. The new approach is less flexible, but the flexibility has been traded for cognitive feasibility.

We have implemented the "fast and frugal" approach replicating the decision-making in our previous reports. The approach was implemented using the MASON system (Luke et al. 2005), a Java based simulation environment used in the previous studies.

4. Discussion

The aim of this work was to improve the credibility of our modeling of herder decision-making. Although we had a working model based on a four-factor formula, we looked for a more cognitively plausibly approach. After considering the research cognitive architectures, specifically ACT-R, Soar, and Clarion, we decided to implement a "fast and frugal" model of decision-making. The resulting behavior is expected to be more credible to anthropologists, available data and peer reviewers.

5. References

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