

# Effect of Communication on Belief Dynamics in Multi-Agent Systems

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## Abstract

This paper presents the architecture of a multiagent society (MAS) designed to study the dynamics of belief change in natural and artificial societies. It also presents a hierarchical model for representation of beliefs and a multiagent domain called Multiagent Wumpus World (MWW) designed to test the capabilities of the proposed MAS. It also reports on a set of experiments designed to study the formation of false social beliefs. Our results indicate that more false beliefs are likely to be generated about objects/events whose presence is harder to confirm or disconfirm. We also discovered that this behavior is slightly enhanced when the agents are allowed to communicate with other agents, in which case, the false beliefs about the objects/events which are easier to confirm or disconfirm significantly decrease while about those objects/events which are harder to confirm remain higher.

## I. INTRODUCTION

Modeling and understanding the formation, propagation, and evolution of beliefs is crucial both to the success of distributed artificial intelligence (AI) systems as well as to improve our understanding of human and animal societies. The growth of multiagent systems research in artificial intelligence [1] has been paralleled by a growing realization among cultural scientists that the traditional verbal models are too imprecise to model belief dynamics while mathematical models are too rigid and unable to be scaled up [2]. As economist Scott Moss recently lamented, “in more than half a century since the publication of von Neumann-Morgenstern (194x), no significant progress has been made in the development of models that capture the process of interaction among more than two or three agents” [3]. The alternative that Moss and others propose is to build bottom-up algorithmic models of socio-cognitive processes. The key idea behind the agent-based social simulation (ABS) approach is to encapsulate each member of a population in a software module (called an *agent*) to build bottom-up models of human or animal societies. The ABS models focus on interactions between agents and, for the most part, abstract away the internal cognitive structure of the agents. Thomas Schelling, one of the early pioneers of the ABS approach, designed 1500 agents that lived on a 500 x 500 board [4]. The agent’s cognitive structure consisted of one simple inference rule, namely, if the proportion of your different colored neighbors is

above a tolerance threshold then move, otherwise stay. He showed that even populations with high tolerance end up living in highly segregated neighborhoods.

The ABS methodology illustrates that it is not necessary, or even desirable, to have a complete understanding of a social system before building computational models. Indeed, ABS systems are frequently used as theory exploration and development tools (similar to the way computer models are used as tools by AI and Cognitive Modeling researchers) because they allow theoreticians to visualize and fully explore the consequences of their models and to compare competing theories. The last few years, there has been an explosion in the development of ABS systems designed to simulate social systems from a variety of domains. Ignoring the complex internal cognitive structure not only allows ABS designers to design computationally tractable simulation systems but it also helps them show causal connections between the cognitive rules that agents use to make local decisions and social patterns that emerge at the population level—the highly desired, yet rarely achieved—identification of micro-macro links.

Few ABS systems, however, have been built to specifically model beliefs dynamics and the systems developed to date assumed overly simplistic models of individual cognition and knowledge representation. For instance, most existing ABS models of social belief change model agent-beliefs as a single bit and belief change involves flipping the bit from 0 to 1 or vice versa often to match the beliefs of the neighbors [5][6][7]. This severely limits these systems as they are unable to model most real world distributed systems applications. Complex patterns of shared beliefs such as those that characterize people’s cultural and religious beliefs are also not likely to emerge out of such systems because the ABS agents are not even able to represent them. Thus existing ABS systems cannot be used to explore or model belief dynamics in human societies.

Traditionally, artificial intelligence and cognitive modeling have studied how individuals form and modify complex belief structures [8][9][10] but have, for the most part, ignored agent interactions assuming single agents living unperturbed in closed worlds. Artificial intelligence research on *classical planning* illustrates this approach well [11]. Given the knowledge about current state of world, about goals that the

agent desires to achieve, and the generalized actions that the agent can take in the world, the planning problem is to compute an ordered sequence of action instances that the agent can execute to attain its goals. The classical AI planning research assumes that the planning agent is acting alone in the world so that the world does not change while the agent is figuring out what to do next because if that happens, the agent’s plan may not be executable any longer. If the world continues to change the agent may never be able to act as it will always be computing the plan for the changed situation. Abstracting away other actors allows AI researchers to eliminate additional sources of complexity to focus on complex reasoning processes that go on inside the heads of individuals and result in the rich knowledge structures such as plans. This has led to the development of successful game playing programs that work in environments with limited or no interaction with other agents. However, this approach is not useful for modeling the dynamics of cultural belief systems such as religious belief systems because they are by their very nature products of the interaction of a large number of agents.

Clearly, to simulate belief dynamics in human societies, we need to develop knowledge-rich agent-based social simulation systems (KBS) [12]. Agents in these systems must have rich knowledge representation and reasoning capabilities and they must be able to interact with other agents present in their environment. Such simulation systems must overcome computational tractability concerns without abstracting away the agent’s internal cognitive structure (as done by ABS systems) or ignoring interactions with other agents (as done by much of traditional AI & CM work)? Furthermore, to be able to tell us something about belief dynamics in human societies such agents in such systems must model the cognitive tendencies that people are known to possess. We believe that people’s ability to communicate, comprehend a message, and integrate the newly received information into their existing knowledge is crucial to understanding the formation, propagation, and evolution of beliefs. We have designed a knowledge-rich multiagent society, called CCI<sup>1</sup>, to model these processes. The challenge for any KBS system is that of overcoming the computational intractability problems to design an efficient system that can be run in real time. This paper argues that one promising approach for addressing this challenge is to develop synthetic computer games like environments that are rich enough to exercise the enhanced knowledge representation and reasoning capabilities of KBS agents yet they are not so complex to make the simulation intractable and the results impossible to analyze and understand.

## II. COMMUNICATING, COMPREHENDING, AND INTEGRATING (CCI) AGENTS

The CCI agents are goal directed and plan sequences of actions to achieve their goals. Some of the actions that they need to undertake to achieve their goals may be speaking

actions. An agent A may decide to send a message M to an agent B if it believes that sending B the message M will result in changing B’s mental state to cause it to perform an action C which can help A achieve one of its goals.

The CCI agents, similar to people [13], are comprehension driven i.e., they attempt to explain each piece of information their sensors detect. On observing an effect E, they search for a cause C that could have produced that effect.

Agents attempt to build accurate models of their environment by acquiring information about cause-effect relationships among various environmental stimuli. They store this information as cases [14]. Agents consult their case memory to form expectations about the future. If these expectations are violated, they attempt to explain the reasons for these violations and if they can find those explanations, they revise their world model. The CCI agents ignore the information received from others if they cannot find any justification for it.

We have designed the first version of a CCI society by embedding it into an artificial domain. Multiagent Wumpus World (MWW), shown in Figure 1, is an extension of Russell and Norvig’s [11] single agent Wumpus World.

	Smell glitter					Smell glitter		Smell	glitter
Smell glitter		Smell			glitter		Smell		
	Smell			Smell			Smell		Smell glitter
Smell	glitter		Smell glitter		Smell glitter	glitter		Smell	
	Smell	glitter		Smell	glitter		glitter		
		glitter				glitter		Smell	
	glitter		Smell glitter					glitter	
glitter		glitter		Smell	Smell				glitter
Smell		glitter	Smell	Smell			glitter		Smell
			glitter		Smell	glitter		Smell glitter	

Figure 1: A 10 x 10 version of the Multiagent Wumpus World (MWW) domain. This version has 10 agents, 10 Wumpuses, and 10 Treasures.

### A. Multiagent Wumpus World (MWW)

MWW has the same basic configuration as the single agent Wumpus World (WW). MWW is an  $N \times N$  board game with a number of wumpuses and treasures that are randomly placed in various cells. Wumpuses emit stench and treasures glitter. Stench and glitter can be sensed in the horizontal and vertical neighbors of the cell containing a wumpus or a treasure. Similar to the single agent WW, once the world is created, its configuration remains unchanged i.e., the wumpuses and

<sup>1</sup> Communicate, Comprehend, and Integrate

treasures remain where they are throughout the duration of the game. Unlike the single agent version, MWW is inhabited by a number of agents randomly placed in various cells at the start of the simulation. An agent dies if it visits a cell containing a wumpus. When that happens, a new agent is created and placed at a randomly selection location on the board.

The MWW agents have a causal model of their environment. They know that stench is caused by the presence of a wumpus in a neighboring cell while glitter is caused by the presence of treasure in a neighboring cell. Agents sense their environment and explain each stimulus they observe. While causes (such as wumpuses and treasures) explain themselves, effects (such as stench and glitter) do not. The occurrence of effects can only be explained by the occurrence of causes that could have produced the observed effects e.g., glitter can be explained by the presence of a treasure in a neighboring cell while stench can be explained by the presence of a wumpus in a neighboring cell. An observed effect, however, could have been caused by many unobserved causes e.g., the stench in cell (2, 2) in Figure observed in could be explained by the presence of a wumpus in any of the four cells:

- (1, 2)
- (3, 2)
- (2, 1)
- (2, 3)

1,3	2,3	3,3
1,2	smell 2,2	3,2
1,1	2,1	3,1

Figure 2: A part of the MWW.

An agent may have reasons to eliminate some of these explanations or to prefer some of them over the others. The MWW agents use their existing knowledge to select the best explanation. Agent's knowledge base contains both the game rules as well as their world model. A world model contains agent's observations and past explanations. The observations record information (stench, glitter, treasure, wumpus, or nothing) the agent observed in each cell visited in the past. The MWW agents use their past observations and game knowledge to eliminate some possible explanations e.g., if an agent sensing stench in cell (2,2) has visited the cell (1,3) in the past and did not find sense any glitter there, then it can eliminate "wumpus at (2, 3)" as a possible explanation because if there were a wumpus at (2, 3) there would be stench in cell (1, 3). Lack of stench at (1, 3) means that there cannot be a wumpus at (2, 3). Agents use their knowledge base to form expectations about the cells that they have not visited e.g., if the agent adopts the explanation that there is a wumpus in cell

(2, 1) then it can form the expectation that there will be stench in cells (1, 1) and (3, 1).

In each simulation round, an agent has to decide whether to take an action or not. Possible actions include:

- the action to move to the vertically or horizontally adjacent neighboring cell
- the action to send a message to another agent present in the same cell as the agent, and
- the action to process a message that the agent has received from another agent.

### 1) Hierarchical Belief Structure

Beliefs about the cells are incorporated into the knowledge base of the agents in a hierarchical fashion. The beliefs are classified into CERTAIN, ASSUMED, and EXPECTED. CERTAIN beliefs are those which the agent is sure about. For example, if the agent encountered a treasure in its path, it is sure that the four surrounding cells have glitter in them. ASSUMED beliefs are those which the agent is not very confident about. For example, if the agent encounters a glitter in its path, it is unsure of the source of the glitter, as the treasure could be in any one of the four neighboring cells of that cell. It then tries to explain this glitter by associating it with some treasure. If it finds none, it ASSUMES that one of the neighboring cells has the treasure and it EXPECTS to find glitter in the cells adjoining the ASSUMED treasure. While the agents have reason to hold ASSUMED and EXPECTED beliefs, they are not totally confident about them and are willing to modify these beliefs if experience suggests otherwise. The agents never accept any alterations to the CERTAIN beliefs.

The MWW agents are goal directed agents that aim to visit all treasure cells on the board. Agents create a plan to visit all treasure cells they know about. The plan must not include any cells that contain wumpuses in them. Each agent ranks all the cells by how confident it is of its knowledge about a cell. It has the highest confidence in the cells that it has already visited. Next are the cells whose neighbors the agent has visited and so on. Agents also rank cells by how urgently they need the information about that cell. The order in which the cells are to be visited determines the criticality e.g., if a cell is the next to be visited then finding information about that cell is assigned the highest priority while a cell that is not planned to be visited for another 10 rounds gets low priority. The agents then use an information seeking function that takes the two rankings (confidence and criticality) as inputs and decides whether the agent needs to communicate and if so which cell it needs the information about. If it decides to communicate and if another agent is currently present in the same cell then agent sends a request-for-information message to that agent.

The listening agent attempts to explain as to why the speaker sent it the message (e.g., was it sent to seek information or to distract me from traveling) and depending on that determination it may or may not decide to respond. If the

agent decides to respond, it will offer the information about the requested cell in exchange for information about a cell about which it needs information. If the speaker agrees to the exchange then the agents communicate information about the cells.

On receiving information about a cell, an agent has to decide whether to incorporate that information into its knowledge-base or not. If it decides to incorporate the new information then it has to decide how best to revise its existing knowledge. If the new information confirms what the agent already know about the cell then no revision is done. If, on the other hand, the information received from another agent is different from what the agent expects to find in that cell then it attempts to explain the reason for the contradiction. If it can find a possible explanation that it ignored in the past that supports the received information, then it adopts the new explanation and the new information and retracts its belief in the old explanation and expectation. If the agent does not have any information about that cell, it incorporates the received information as ASSUMED belief. Otherwise, the agent rejects the newly received information.

## 2) Formation of False Beliefs

Agents use symmetrical processes to form and revise beliefs in the presence of treasures and wumpuses. Thus agent models may contain false beliefs about the locations of the wumpuses as well the locations of treasures. However, while the agents prefer to travel towards a cell that they believe contains a treasure, they avoid cells that they believe contain wumpuses in them. This makes beliefs in the presence of wumpuses relatively harder to confirm or disconfirm than beliefs in the presence of treasures. The experiments described next were designed to investigate the impact that this asymmetry has on the patterns of false beliefs that the agents form.

## 3) Planning

Agents are required to generate paths which they would follow to achieve their goals, known as *plans*. The planning algorithm used is kept very simple as the focus is on belief dynamics. The agents are given a goal-cell to be reached when they are born. The agents simply include all the cells in the L-shaped path that leads them to the goal. This plan is revised if and when it suspects the presence of a wumpus in its previous plan. After one goal is reached, the agent then tries to confirm all the 'ASSUMED' treasures and 'EXPECTED' stenches it has recorded in its path. Thus, the agent tries to make its world model as accurate as possible.

## III. EXPERIMENTS AND RESULTS

We designed a 10 x 10 version of MWW with ten agents randomly placed at ten different locations. In the first set of experiments I designed three different versions of MWW:

- The 5x5 version has 5 wumpuses and 5 treasures

- The 10x10 version has 10 wumpuses and 10 treasures, and
- the 20x20 version has 20 wumpuses and 20 treasures.

I allowed the simulation to run for 300 rounds. At the end of that round I measured the following metrics:

- *Average agent age* is the average age of the ten agents that survive after round 300.
- *The average number of wumpus beliefs* is the average number of wumpus beliefs the surviving agents have
- *The average number of treasure beliefs* is the average number of treasure beliefs the surviving agents have
- *Average number of cells visited* is the average number of cells that 10 agent surviving at the end of round 10 have visited.

Figure 1 shows the results of Experiment I. The results for average age show that 10x10 world proves to be the most taxing for agents with average agent ages only being less than 30 rounds. Agents in 5x5 and 20x20 rounds, on the other hand, have much higher average ages. This is explained by the considering the average number of cells that the agents visit. Agents in the 5x5 world visit a larger number of cells while agents live longer in the 20x20 world by visiting fewer cells and by thus deciding to stay in their cells. Agents in the 10x10 world, however, visit more cells than in 20x20 world but they pay the price of this adventurism by having smaller average ages.

In the second experiment, then we adopted the 10x10 world and measured the proportion of false wumpus and treasure beliefs that the agents had at the end of round 100. The proportion of false wumpus/treasure beliefs is the proportion between the number of false wumpus/treasure beliefs that the agent has to the total number of wumpus/treasure beliefs that the agent possesses.

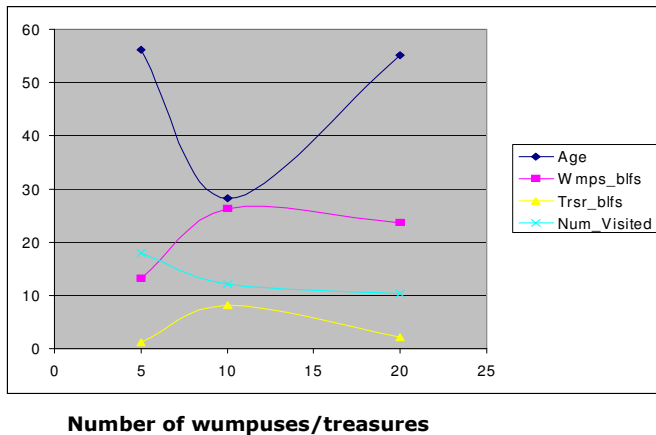


Figure 3: Results of Experiment 1. Each point is an average of 30 runs.

The results (Figure 4) show that after the initial drop, the proportion of false wumpus beliefs remains relatively unchanged regardless of how much the agents travel in the world. False beliefs in the presence of treasures, however, continue to decrease as agents with agent age. The agents who survive the length of simulation (100 rounds) have few, if any, false beliefs about treasures but on average 40% of their beliefs about the presence of wumpuses are false.

In the third experiment (Figure 5), we allowed the agents to communicate with other agents when they happen to meet in the same cell. The agents request information about the cells in their plan about which they are not sure of and they are about to visit. Criticality and confidence play a major role in the selection of this cell. The agents then offer information to the other agent.

The results show that communication affects false wumpus and treasure beliefs differently: the proportion of false wumpus beliefs remains almost the same as in the without-communication case while the proportion of false treasure beliefs decreases significantly.

#### A. Discussion

Owing to our planning strategy, which focuses on improving the accuracy of the world model, each agent tries to confirm as many treasures as possible and mark as many stenches as possible. Our results indicate that explanations that are harder to confirm and disconfirm are more likely to be generated by agents that attempt to explain their observations and revise these explanations in light of the evidence. This suggests that people should have more false beliefs about things that are harder to confirm or disconfirm. There is some evidence to suggest that that is the case. Bainbridge and Stark [15] made confirmability the core of their theory of religion to argue that religious beliefs are unconfirmable algorithms to achieve rewards that are highly desired by people yet cannot be obtained. Similarly, there is some evidence to suggest that

many false ethnic stereotypes people have are about things that are harder to confirm or disconfirm such as the sexual practices of the neighboring tribes. Our results also indicate that introducing the ability to communicate with other agents does not improve the condition of holding false beliefs about unconfirmable objects while it significantly reduces the false beliefs held about an object/event that is easier to confirm. This can be thought of as a traveler claiming that his city has good many skyscrapers and the listener then confirming it later when he visits that city.

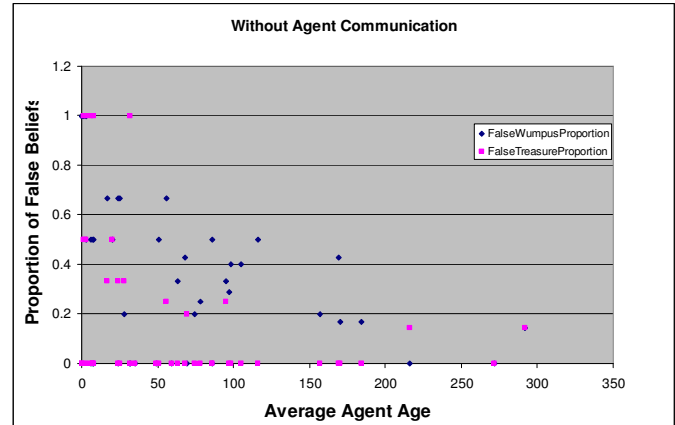


Figure 4: Results of Experiment 2, Without agent Communication

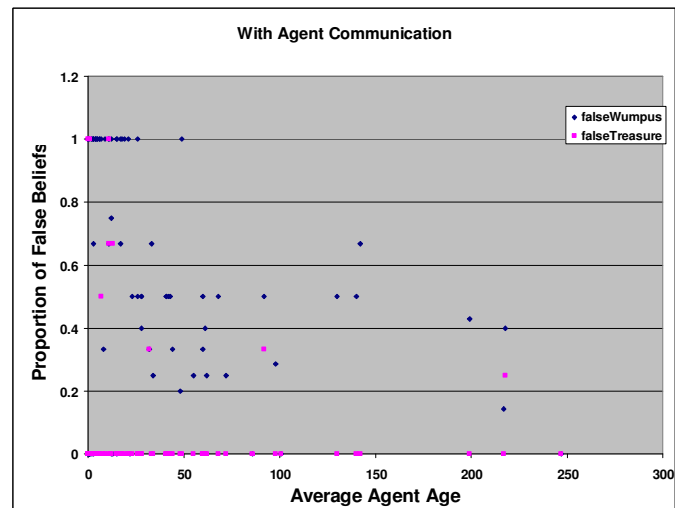


Figure 5: Results of Experiment 3, With agent Communication

## IV. CONCLUSION

This paper presents the architecture of a multiagent society designed to study the dynamics of belief change in natural and artificial societies. It also presents a multiagent domain designed to test the capabilities of the proposed systems. Preliminary results are encouraging as they indicate the potential for the use of the proposed society.

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