

# Exploiting Objects as Artifacts in Multi-Agent Based Social Simulations

## (Extended Abstract)

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### ABSTRACT

In this study a recent evolution and learning model for artifacts is extended to address the ability of artificial social agents to realize their goals by adapting the exploitation of dynamic artifacts in dynamic environments over time. An implemented case study is provided incorporating the model into the multi-agent simulation of the Village EcoDynamics Project developed to study the early Pueblo Indian settlers from A.D. 600 to 1300. The dynamic landscape used for settling and farming is abstracted as an artifact and agents learn to adapt its exploitation over time by employing individual, social and population learning strategies. Comparing various strategies revealed learning through social networks while evolving the extent of the network as the best adaptive strategy. The results are consistent with archeological records as a wider margin is observed between social and non-social learners during periods known for the highest landscape variability. In addition, learning through social networks outperforms learning via cultural beliefs which is expected given the heterogeneity of the landscape.

### Categories and Subject Descriptors

I.2.11 [Computing Methodologies]: Distributed Artificial Intelligence—*Intelligent Agents, Multi-Agent Systems*;  
I.6.3 [Simulation and Modeling]: [Applications]

### General Terms

Human Factors, Design

### Keywords

Artificial social agents, Cognitive models, Learning and adaptation

## 1. INTRODUCTION

Researchers across the cognitive sciences acknowledge the vital role played by tools or artifacts in the evolution of societies. The artifact concept has recently been introduced in multi-agent systems (MAS) as an abstraction to represent the reactive functional system components made available

**Appears in:** *Proceedings of the 14th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2015), Bordini, Elkind, Weiss, Yolum (eds.), May 4–8, 2015, Istanbul, Turkey.*

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to agents [4]. With multi-agent based simulation (MABS) identified as one of the primary application areas to benefit from the abstraction, the artifact theory was extended to include evolution and learning [2]. Artifacts represented in terms of functional attributes with predefined domains were embedded in a MABS where agents could evolve their exploitation through individual learning and collaborative learning from a cultural belief space. In this study we increase the adaptive capabilities of the agents by introducing communication via dynamic social networks and providing additional learning strategies for exploiting dynamic and heterogeneous artifacts. An existing MABS that constitutes a significant part of a broader study of the history of the American Southwest is utilized as a case study.

## 2. ARTIFACT EXPLOITATION

In order to learn and evolve artifact exploitation, an artifact is reduced to a set of functional attributes each of which has a predefined real-valued domain. An agent learns use actions for exploiting an artifact by evolving functional attribute value combinations. A use action  $ua$  is defined as:  $ua \triangleq \langle V, r, y \rangle$  where  $V = \{v_1, \dots, v_n\}$  specifies a selected value for each of the artifact's  $n$  functional attributes,  $r \in \mathbb{N}$  denotes the social network radius for social learning agents that evolve the extent of their social network and  $y \in \mathbb{R}$  indicates a score attributed to the use action once its applied and evaluated.

**Individual-Strategy** Individual learners use a genetic algorithm (GA) with a real-valued representation for pool solutions  $V$ , contrary to the binary representation in Mokom and Kobti [3]. Genetic operators include roulette wheel for selection, crossover and mutation realized with the real-valued mutation of the Breeder GA. To support adaptation for dynamic artifacts, the fitness score obtained after evaluating a performed action is used to update all equivalent pool solutions.

**Social-Strategies** Dynamic social networks are supported by allowing agents to modify their network members and possibly evolve the network radius. A GA is used with an additional value for evolving the radius:  $W = \{w_1, \dots, w_{n+1}\}$ . Social learners evolve a single-solution pool with influence from better network members. Agents that enter the world during the evolutionary process initiate learning with influence from their nearest neighbor.

**Cultural-Strategies** A cultural algorithm (CA) is used to support agents learning from a cultural belief space which maintains situational knowledge (best examples) and normative knowledge (favorable attribute value ranges). The population space is implemented with a single-solution pool GA and agents are influenced by either type of belief space knowledge or a combination of both.

**Strategy-Combinations** Agents can combine any of the learning strategies.

**Evolving-Strategies** Agents can evolve the strategy combinations. This is realized with a binary representation GA where each solution represents the employed strategy or combination of strategies. Agents that evolve strategies are equipped with the GA for strategy evolution and a separate algorithm (GA or CA) for each possible strategy. The agent generates a strategy then employs its algorithm for choosing an action.

### 3. CASE STUDY: ARTIFACTS IN THE VILLAGE MULTI-AGENT SIMULATION

In the Village MABS of the Village Eco-Dynamics Project [1], agents represented as households are mobile, enter and leave the world through marriages (new households) and deaths respectively and can farm for maize, hunt for protein, gather water and wood. The landscape is divided into cells (114,210 in VEP IIN) and agents are presumed to know the soil productivity of every cell over time. As such agents automatically select productive areas to settle and farm upon. A time step in the simulation is a year with four seasons: spring, summer, fall and winter. Agents consume maize during all seasons however they plant in the spring and harvest in the fall. Agents self-evaluate and will plant additional plots or move when necessary. The MABS is implemented using the Repast Simulation Toolkit.

Artifact exploitation is incorporated into the MABS by abstracting the landscape as an artifact (LANDSCAPE). Agents are stripped of all tasks except farming and LANDSCAPE is represented with five functional attributes: the average elevation, the average slope, the average direction of slope, the average depth to bedrock and the average proportion of its biomass consisting of any subspecies of big sagebrush prior to any agricultural clearing. Known in the current simulation the fitness score of a use action is essentially the agent's harvest and agents die when their maize storage is depleted. Agents always plant in their settled cell and will generate use actions if they need to plant in additional cells or move. Since a use action's values will not necessarily be identical to those in a particular cell, agents use a simple distance measure function to average over all attribute values and select the cell that is closest to the generated values.

### 4. EXPERIMENTS AND RESULTS

All experiments begin with 600 randomly generated agents randomly placed on the landscape and each given access to LANDSCAPE. Agents use the various learning strategies to select a cell to settle on, farm upon or move. Results track the survival count of agents and aggregate them over the four study periods of the archeological Pecos classification currently used by the Village Ecodynamics Project researchers. They are *Basketmaker III (A.D. 600-900)*, *Pueblo I (A.D.*

*750-900)*, *Pueblo II (A.D. 900-1150)* and *Pueblo III (A.D. 1150-1280)*. For all experiments the simulation begins in year A.D. 600 and runs through 1280. Experiments are conducted for no learning, individual learning, social learning with random and learned radius, cultural learning with situational, normative or both influences, various strategy combinations and random strategy selection or evolved strategies.

Results reveal social learning with learned radius as the best adaptive strategy, with strategy combinations that include it performing better than others that do not. Social learning outperformed learning from the cultural belief space. Individual learners were shown to be poor performers and agent survival when evolving strategies exceeded choosing strategies at random.

### 5. CONCLUSIONS

This study presents a model usable by MABS agents for adapting the exploitation of dynamic artifacts in dynamic environments through various learning strategies. The model was incorporated into the existing Village MABS where agents represented as households exploited the dynamic and heterogeneous landscape as an artifact towards their objective of farming for survival over time. The revelation of social learners evolving their network radius as the best adaptive strategy is consistent with archeological findings since the widest gaps between social and non-social learners are observed during the *Pueblo II* and *Pueblo III* phases. These phases are identified as periods when the landscape showed high variability. The superiority of learning from the network over the belief space can be explained by the heterogeneity of the landscape and the poor performance of individual learners demonstrates that social strategies can be valuable in dynamic environments. The study revealed that with just a few essential functional attributes represented, the model can be used to gain insight into a social complex system.

### 6. ACKNOWLEDGEMENTS

This work is made possible by grants from NSERC Discovery No. 327482 and National Science Foundation No. DEB-0816400. The authors would like to thank Kyle Bocinsky, Stefani Crabtree and Dr. Tim Kohler from Washington State University for their valuable discussions.

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