A GENETIC SIMULATION OF INFORMATION POLICIES AND AGENT LEARNING IN COMPLEX ENVIRONMENTS

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ABSTRACT

We study simulated adaptive responses through evolutionary models that yield insight into the interactions among information policies and environmental change. In medium and fast changing environments, we noted that policies that emphasized individual accountability and experimentation produced successful adaptations. In slow changing environments the simulations showed each policy's influence depends on the other policy setting which warrants caution in interpreting main effects.

INTRODUCTION

Organizational theorists have formalized well developed contingency theories that recognize interdependence of environment change and information policy [1][5]. Researchers have shown evolutionary simulations highlight how organizations apply information policies to support organization learning and adaptation. There is increasing recognition of the close association between organizational theories of adaptation and evolutionary processes that consider competition, imitation and knowledge sharing [2] [4]. Genetic models apply evolutionary mechanisms of variation, selection and fitness to study adaptive strategies in complex and changing environments.

Genetic algorithms and evolutionary programming evolve agent populations adapted to changing environments [3]. That is, given a set of environmental conditions, a genetic classifier produces adaptive responses to predict and anticipate change. Successful classifiers spawn offspring, through genetic crossover, where an offspring's resulting chromosomes represent a mixture of their successful parents' chromosomes. Genetic crossover involves sharing successful building block representing amassed agent knowledge. A changing environment requires new creative responses where agent communities must continually develops and tests new strategies. Interdependence between information policies and environment change results in continuous rounds of anticipating, sensing to developing novel organizations responses.

EVOLUTIONARY MODELING OF INFORMATION STRATEGIES

Agent communities apply information policies to support various strategies for adapting to environmental complexity. Information policies support adaptation by influencing agent explorations, assigning responsibilities, supporting hubs of agents and promoting knowledge sharing.

Sharing and Empowerment vs. Elitist Competition

Information policy may empower lower ranking agents by communicating and sharing knowledge from top agents. In contrast an information policy could instead limit sharing, promote competition and focus rewards and knowledge sharing only among top performing elite agents. The simulation model manages ranges of knowledge sharing through settings that reflect levels of genetic selectivity.

Exploit Internal Knowledge Vs Explore and Experiment

An information policy exploits internal success by preserving organizational knowledge. An information policy could also discount current knowledge and focus instead on exploring new knowledge. The simulation controls levels of exploitation and explorations by adjusting limits that, to various degrees, control a community's inclination to apply random mutations versus recombinant crossover.

Group Stability vs. Individual Accountability

Information policies may support qualitative organizational measures that promoting community stability by rewarding group performance. On the other hand information policy could focus on quantitative performance measurements that immediately hold individuals accountable for failures. The simulation controls community stability by directing a genetic replacement strategy for poor performers.

Fast Learners vs. Slow Learners

Closely related to the accountability policy is tolerance for slow learners. With a slow learners policy organizations provide more time and resources for poor performers to contribute to population adaptations. In contrast a policy favoring fast learners mean a limited tolerance for nonperformance, where new agents are evaluated and poor performers are quickly sacrificed.

COMPUTER SIMULATION

A C++ windows based simulation program, LISA (Learning Information System Adaptations) was constructed to conduct simulation experiments by first specifying the environment's rate of change: slow, moderate or severe change. Simulation experiments proceeded by specifying policy levels of information sharing (elitist vs. sharing), information focus (internal exploitation vs. external exploration), accountability (group vs. individual), and learning rates (fast learners vs. slow learners)

At the beginning of the simulation one hundred environmental entities (100 x 1024 bit strings) represent the businesses' environment where each entity is randomly assigned to either cooperate or defect. For simulation iterations, agents inspect each member of the environment which results in one hundred predictions of either cooperate or defect. An agent's fitness score is based on their resulting prediction accuracy.

During repeated learning cycles, and depending on the simulated rate of environmental change, an environmental entity may randomly switch sides where a previous defector now cooperates (or visa versa). For example, in a fast changing environment customers and suppliers often change affiliations and may or may not cooperate in the next cycle. In a slower changing environment environmental entities behave more consistently.

An experiment was conducted by systematically varying the environmental rates of change (three-levels), elitist selection (two-levels), information focus (two-levels), accountability (two-levels), and learning rate (two-levels). Each combination of factors was replicated four times with random initial populations of environmental entities and agents. Thus 192 simulation runs were conducted ((3*2*2*2*2) * 4 replications).

RESULTS

Among the 60 epochs, all experimental information policy combinations for the slow change environment resulted in successful population that predicted all environmental outcomes beyond random change. In contrast, for the medium and fast changing environments only four policy combinations (4/16) consistently produced successful populations where other combinations failed. Successful communities in the medium and fast changing environments all stress individual accountability with quick evaluations and favored experimentation over exploitation

A separate MANOVA analysis of the factor combinations for the slow environment revealed significant main effects. The best adaptation within the slow environment resulted from sharing, experimentation, group accountability and a tolerance for slow learners. The analysis however revealed a significant 4-way interaction among the factors.

DISCUSSION

In medium and fast changing environments, we noted that policies that emphasized individual accountability and experimentation produced successful adaptations. The findings are consistent with company surveys that report organizational adaptations improve with diverse innovations and experimentation. The findings are also consistent with empirical studies of enterprise adaptation to fast changing environments through rapid decisions, flexibility and boldness and by preserving knowledge within elite leadership, providing adequate support and time for learning and then replacing poor performers through retraining or "changing of the guard".

The second main finding of the simulation concerns large interaction among policies in slow changing environments. The simulations showed each policy's influence depends on the other policy setting which warrants caution in interpreting main effects. These finding are consistent with multiple contingency theories of information systems that suggest dynamic forces mutually interact in complex ways to amplify, reinforce, and dampen organizational learning effects [1].

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