Collaborative Intelligence in Living Systems: Algorithmic Implications of Evo-devo Debates

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ABSTRACT
This paper introduces the A-PR Hypothesis (Autonomy and Pattern Recognition) and explores the potential to develop next generation crowd-sourcing and recommender systems that apply *collaborative intelligence* principles to multi-agent distributed systems. If capacity for autonomy and pattern recognition marks the threshold when non-life becomes alive, and also characterizes the spectrum from grid computing, which consumes pre-defined resources, to crowd-sourcing menial tasks, to next generation crowd-sourcing for problem-solving, then unique players with unique capacities for pattern recognition and interpretation comprise a synergetic system where behavior of the whole is unpredicted by individual behaviors of its component agents.

Categories and Subject Descriptors
H.5.3. [**Information Systems**]: Collaborative Computing; I.2.11 [**Computing Methodologies**: Artificial Intelligence]: Multi-agent systems

General Terms
Algorithms, Design, Human Factors, Performance, Theory

Keywords
A-PR Hypothesis, Collaborative Intelligence, Complexity, Dyadic Model, Emergence, Innovation Networks, Multi-agent Systems, Self-organization, Sustainability, Bio-inspired Computing

1. INTRODUCTION
The A-PR Hypothesis, **A**utonomy and **P**attern **R**ecognition**,** distinguishes non-life from life, explaining how life continually self-organizes and adapts, and why evolution's arrow points, not necessarily toward complexity, but toward increased functional effectiveness. The A-PR cycle spirals from bacteria to humans as increasingly sophisticated pattern recognition is achieved. During its lifetime, each organism recognizes and interprets patterns differently. So too for problem-solvers and their ecosystems.

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2. THE A-PR HYPOTHESIS
Evolution manifests directionality via continual pattern recognition in the present state, without need for a goal state.

Autonomy. Individuals collaborate, maintaining their diverse roles and priorities as they apply their particular skills in a problem-solving ecosystem where individuals are not homogenized, as in consensus-driven processes, nor equalized through quantitative data processing, as in collective intelligence.

Pattern Recognition. Unique capacities for pattern recognition and interpretation characterize living systems and enable them to choose appropriate (or not) actions in context, driving evolution toward increased functional effectiveness [2]. The diagram below postulates the structure for a single A-PR cycle in a self-improving system through which non-life becomes alive.

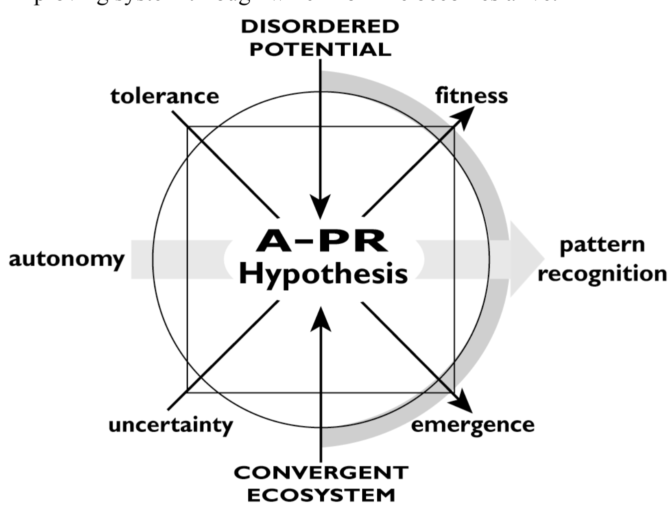

Figure 1. A-PR Cycle

The A-PR cycle occurs in iterative learning, self-improving systems. Artificial systems that mimic life's capacity to discriminate on its own behalf must be able to bootstrap themselves toward improved functionality by their choices. Although the starting condition is necessarily characterized by <u>uncertainty</u>, across a range of necessary prerequisite conditions tolerance spectra, when overlaid, must allow a "window of opportunity" for the emergence of a life-like system, whose fitness is tested in context. Selection for fitness computes the integrated synergy of interactions of the living organism (its smart, appropriate choices) with its environment, a persistent recycling into the uncertainty of the future. As the cycle repeats, life and intelligence bootstrap themselves as a single symbiotic system.

3. A-PR APPLICATIONS

There are many competing definitions of complexity. The A-PR Hypothesis defines complexity to qualify the cliché that "evolution's arrow points toward complexity," which is not always the case, and clarifies the real relationship between evolution's arrow and complexity. If life evolves toward increased functional effectiveness, how do we characterize the relationship between functional effectiveness and "effective complexity," or in semantic terms "meaningful complexity"? "Effective complexity" and "meaningful complexity" both require pattern recognition, in the first to determine utility, and in the second to interpret meaning. A utility function is an internal representation of the potential fitness consequences of behavior. But what is meaning? Meaning is here defined, not only as capacity to recognize utility in the me-here-now sense, but to see utility in the context of a broader value system, including future or potential utility, as well as utility for other agents or agendas. Utility, defined by a single pattern recognizer as "utility for me," becomes "meaningful" when shared by multiple pattern-recognizers with different utility profiles, each with capacity to resolve inputs from other agents and the larger ecosystem [4].

Emergence of a goal state, undefined *a priori,* characterizes breakthrough discovery, invention, and innovation. Genetic algorithms differ from natural evolution in that GA reproductive success of individuals depends on how well they meet externally imposed fitness criteria. In evolution fitness is a measure of reproductive success without referencing a predefined goal state. How can systems evolve "functionally effective" algorithms based, not on the pre-set goal of the programmer, but on agent pattern recognition in process, as in evolution? Autonomy and pattern recognition are key attributes through which living systems recognize and develop potential. There are many models in nature, from quorum-sensing in bacteria, to ants as more than collective intelligence systems of pre-programmed robots, to the theory of *facilitated variation* operating in our cells via weak linkage. All inform design of systems manifesting *collaborative intelligence* and extend our capacity to use crowd-sourcing beyond menial tasks to tap our uniqueness as pattern recognizers for interpretation to implement *collaborative intelligence*.

Five implications of the A-PR Hypothesis for understanding evolution's arrow have practical applications for computationally complex problems:

First, the A-PR Hypothesis aligns the blurry line between non-life and life with the blurry line between crowd-sourcing menial tasks and crowd-sourcing in a multi-agent intelligent system. Defining the boundary between non-life and life has long been a quandary for scientists. Nor is there consensus about how to define intelligence, which must include capacity for pattern recognition in order to assess the functional effectiveness of alternative options [3]. Darwinian evolution in non-living kaolinite clay, first postulated by chemist Graham Cairns-Smith, was experimentally confirmed in the laboratory, proving that Darwinian evolution is not a unique, defining attribute of living systems [1]. Crowd-sourcing menial tasks requires only the capacity to recognize individual utility. Each agent is detached from every other agent, performing in isolation, assessing utility for itself based on its own utility function. A sensor network would qualify. As crowd-sourcing tackles more complex tasks, agent inputs are increasingly differentiated from each other and integrated with the inputs of other agents. Beyond menial crowd-sourcing to crowd-sourcing solutions for complex problem-solving requires a bridge from utility (defined in a single unit processor) to making meaning (co-defined and co-evolving via interaction among multiple individual, non-identical processors, as in evolution) [4].

Second, traditional recommender systems analyze member profiles as targets, e.g. for marketing based on individual purchases or collaborative filtering that groups buyers with others who made similar purchases. On Amazon: "You purchased Book X; other Book X buyers also bought Book Y." In contrast, suppose member profiles could define unique roles for players in multi-player, game-like, problem-solving ecosystems where no two players are alike — multi-agent, complex systems where each autonomous agent is a pattern recognizer, interpreting signals in context, as in nature's ecosystems [4].

Third, exponential acceleration of technology innovation extends the acceleration of biological evolution. Neither is explained as a process where new variation is introduced randomly and selected non-randomly. Competing hypotheses about the origin and evolution of life suggest that nature has a range of non-random, pattern-recognizing, adaptive mechanisms that channel evolutionary directions. Evolvability, and the algorithmic implications of evo-devo debates, offer principles for a new collaborative computing paradigm that can increase the effectiveness of human teams as "evolving, multi-agent ecosystems," harnessing evolutionary principles to increase their *collaborative intelligence* [3].

Fourth, from micro-level cellular mechanisms to macro-level population genetics, evolution manifests a coordinated, multi-level Dyadic Model, comprising complementary competitive and collaborative mechanisms that next generation social networks could emulate in decision support systems for eco-sustainability.

Finally, living systems operate as innovation networks, manifesting principles of *collaborative intelligence*. Overemphasis on EVO, survival of the fittest algorithms, has caused us to neglect the role of DEVO, through which life's capacities for pattern recognition and self-organization drive evolution toward increased functional effectiveness.

4. REFERENCES

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