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GENERATIVE PARALLAX SIMULATION: TOWARD M&S FORMALISMS FOR CREATIVE PROBLEM SOLVING

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ABSTRACT

We propose using models of creative cognition to rethink simulation modeling so that creativity in early phases of model-based problem solving is enhanced rather than stifled. Normative uses of simulation focuses mostly on convergent thinking, yet creative problem solving requires divergent thinking while addressing ambiguity and uncertainty in problem formulation. We introduce Generative Parallax Simulation (GPS) as a strategy and present a generic and abstract specification for its realization. GPS is based on an evolving ecology of ensembles of models that aim to cope with ambiguity, which pervades in early phases of model-based science and engineering. A meta-simulation study for GPS is conducted to better understand its dynamics as a creative evolutionary system. Besides its contributions as a modeling and simulation methodology in support of creativity, GPS provides a fertile and useful domain as an application testbed for parallel simulation.

1 INTRODUCTION

Advances in multimodel formalisms (Zeigler and Oren 1986, Fishwick and Zeigler 1992) and exploratory modeling techniques (Davis and Bigelow 2000) resulted in significant improvement in dealing with uncertainty and computational productivity in complex system analysis. However, as the use of simulation becomes pervasive in science and engineering, users are moving from comparably well-understood and safe territory of computational productivity to more ambiguous domain of discovery, creativity, and innovation (Schneiderman 2007).

In this article, we adopt the view that creativity is the production of novel and useful ideas (Amabile 1996), while innovation, as an extension of creativity,is the successful implementation, adoption, and transfer of creative ideas (West and Farr 1990). The challenge examined in this paper involves capabilities of advanced simulators and environments that foster discovery and innovation by supporting early phases of creative scientific problem solving. By leveraging models of *creative cognition* (Sawyer 2008), we delineate types of computational support needed to improve creativity and suggest design principles for next generation simulation theory and methodologies. Furthermore, GPS views novelty as an emergent phenomena and therefore harnesses the principles of self-organization, as well as science of complexity, for simulation technology development to enhance discovery in model-based science and engineering.

Whereas conventional simulation methodologies are powerful in prediction and optimization, they are not intended to support exploration and foresight activities for creative novelty (Yilmaz, Davis, Hu, Miller, Hybinette, Oren, Reynolds, Sarjoughian, and Tolk 2008). Creative processes often involve a broad idea generation phase from different perspectives, followed by an evaluation and selection stage. Since creativity requires novel yet useful solutions, appropriate trade offs between constraints and flexibility is needed over the problem representation to make creative leaps. The effectiveness of simulation systems that support creative discovery will rely heavily on their ability to start behaving robustly across large number of possible hypotheses, constraints, and propositions, followed by narrowing toward limited range of conditions that are found to be plausible in terms of explaining extensible set of attributes. Development of such next generation simulation systems will require progress addressing at least the following three questions:

- When does discovery involve exploitation of a problem space, and when does it involve exploring alternative the problem representations?
- What is appropriate trade off between constraints and flexibility in supporting incremental and iterative extension of the model space to explain expanding set of mechanisms and attributes of the phenomena of interest?

- How can models and theories of creative cognition help us rethink simulation modeling so that creativity is enhanced rather than stifled?

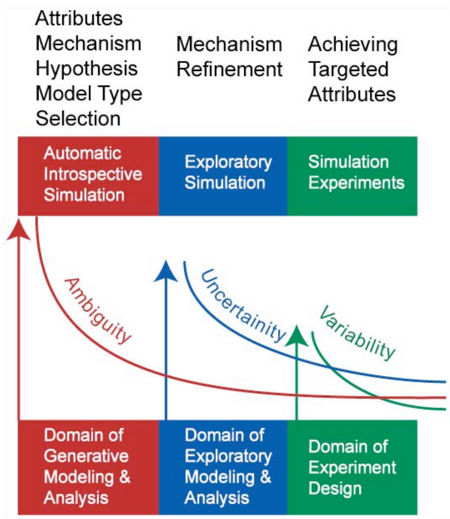


Figure 1: Generative and Exploratory Simulation

Proposed concepts and preliminary exploration are moving us toward answers. In Figure 1, this is shown as the domain of generative modeling and analysis, which precedes exploratory analysis and computational experimentation. The proposed approach is novel in how it uses the complexity paradigm (Miller and Page 2007), as well as principles of evolutionary dynamics (Nelson 1995) and self organization (Holland 1998)in the context of simulator design to develop computational discovery aids that support creative problem solving. To demonstrate the proposed concepts, we use model-based scientific study of biological systems as a motivating scenario. For clarity, we restrict discussions to problem solving in the biological domain, where uncertainty is ample. Further, our initial focus is on problems requiring deeper insight into causal mechanisms responsible for biological phenomena. Nevertheless, the ideas presented are generalizable. A major thrust of GPS is that by automating (large parts of) generating and exploring simulation models, we can enhance creativity and dramatically enhance the generation of foresight into epithelial morphogenesis, our motivating scenario. Achieving measurable scientific progress will motivate extension of the approach into other domains. Following the success of earlier work on Symbiotic Adaptive Multisimulation (Mitchell and Yilmaz 2009), we leverage principles of complex systems thinking in simulator design to propose GPS as a method based on adaptive evolutionary ecologies of ensembles of models.

2 MOTIVATION

The motivating scenario described herein aims demonstrating the need for a new class of models that are more effective in providing new insights and foresight into what mechanisms explain how and why natural (biological) or artificial systems behave as they do when faced with a changed environment or intervention.

2.1 Scientific Problem Solving with Computational Models

Figure 2 depicts the space of models used in biological research. Like much of biology, epithelial morphogenesis, is complex and a great deal remains obscure. Even when studying a single epithelial cell-line, such as Madin-Darby canine kidney (MDCK) cells, use of two different experimental conditions can change the mix of phenotypic attributes observed. It is as if we are observing the biological system from two different perspectives.

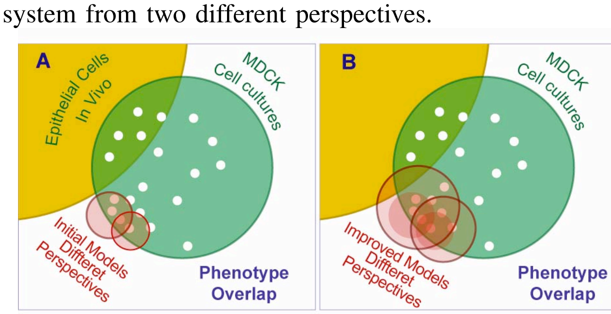


Figure 2: Phenotype Overlap of Different Model Systems

Figure 2 demonstrates phenotype overlap of different model systems. Each circle represents a set of relevant, measurable phenotypic attributes, viewed from related perspectives: epithelial cells within an animal model, MDCK cell cultures, and two somewhat different validated models of MDCK cells (Grant, Mostov, Tisty, and Hunt 2007). The white spots within the MDCK phenotype illustrate specific, measurable attributes. The area of overlap between in vivo and MDCK cultures represents situations in which attributes and generative mechanisms are similar. The areas of overlap between the phenotypes of two in silico models and cultured MDCK cells: measurable properties of the analogue during execution are similar to corresponding measures of MDCK cultures. Each model is of a different perspective of the same system. In part B, after multiple rounds of revision and validation, the models in A have evolved. The larger area of overlap (interpenetration) means that a larger set of each models relevant phenotypic attributes (and generative mechanisms / operating principles) have been judged similar to a target set of MDCK counterparts. It may take multiple, somewhat different analogues to obtain broad coverage of in vitro attributes.

The task of discovering abstract, atomic, cell-level operating principles for in vitro morphogenesis requires multiple models and, perhaps, multiple experimental contexts in which those multiple models live. Initial success has been achieved (Grant, Mostov, Tisty, and Hunt 2007, Kim, Park, Yu, Mostov, Matthay, and Hunt 2007) through the serial development of models, adding and removing various operating principles, executing the model, and falsifying against validation data from the referent. The fundamental method being employed is: a) hypothesize and implement operating principles, which can stand in for biological mechanisms, b) execute those implementations, c) determine a fine-grained falsification for the systemic behavior of the implementation, and d) modify, add, or remove operating principles and iterate. This method is a basic exploration of the forward and inverse maps from generator to phenomena and vice versa. This genotype/phenotype mapping is the most basic multi-scale nature of the research. It is based on falsification of the sequentially, iteratively developed models, not simply positive validation. The model validates only when it can no longer be falsified.

3 GENERATIVE PARALLAX SIMULATION: BASIC CONCEPTS

Development of simulation methods that support creative problem solving requires leveraging principles that explain emergence of creativity. The perspective examined in this work is the creative cognition world-view of creativity that focuses on bottom-up idea generation and evaluation strategies that enable optimal combinations of explorative and exploitative modes of scientific inquiry.

3.1 Background on Creative Problem Solving

To improve creativity and discovery in model-based science and engineering, advanced simulation technologies can be extended to provide facilities and opportunities that go beyond its conventional experimentation capabilities. Principles of creative problem solving help establish the role of evolutionary dynamics in generating novelty.

- As indicated in (Gero and Kazakov 1996), evolution is creative in the sense of generating surprising and innovative solutions.
- Analogous to creative and innovative problem solving, evolutionary mechanisms improve solutions iteratively over generations (Gero and Kazakov 1996).
- Ambiguity and lack of clarity about knowledge about existing relations between the requirements for ideal solution and forms that satisfy these requirements (Rosenman 1997) are useful opportunities for creativity.
- Exploring a search space in an effective and efficient manner and ability to explore alternative search spaces by redefining the problem representation are critical in creative problem solving. To the extent that evolutionary mechanisms that do not have considerable freedom to vary their representations are clearly not creative (Gero 1996).
- Creativity requires transfer of knowledge and use of metaphor (Holland 1998) and analogical reasoning across disciplines (Goldberg 1999). Hence, evolutionary dynamics coupled with ecological perspective that favors transfer is more likely to be creative.

3.2 An Abstract Model of Creative Cognition

The examination of creative cognition models reveal three main components that interact with each other to produce useful novelty: Domain, Generator, and Evaluator. We define a high-level reference model (see Figure 3) to delineate each component along with its role in the reference model.

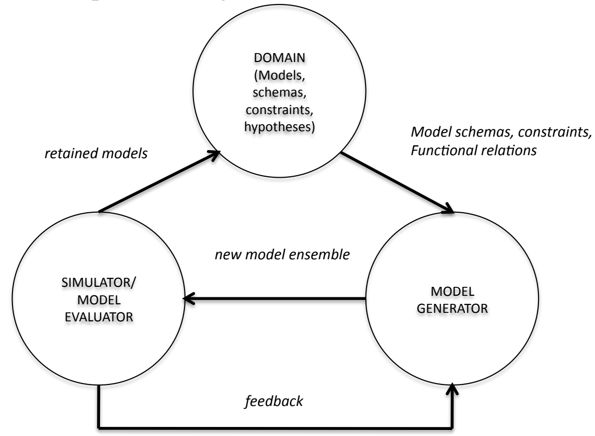


Figure 3: Generate and Explore Reference Model

Domain: The domain embodies the ensemble of plausible models (problem formulations), hypothesized mechanisms that are believed to represent the processes of the referent, constraints (e.g., experimental conditions, range of values of known variables), empirical regularities being tested, and schemas (e.g., meta-models) used to specify models.

Generator: Generation phase of the creative cognition process can be based on any number of the novelty generation actions. As such, to be successful in improving creative insight into problem, a simulation platform and its underlying mechanisms need to be aware of principles and operators underlying the process of generating creative novelty. Sawyer (2008) discusses and illustrates four major operators that are often observed in creative outcomes (Sawyer 2008):

- *concept elaboration* - extending existing concepts (e.g., models) through new features and constraints to obtain more specialized concepts.
- *concept combination* - requires integration of two or more concepts to obtain a new novel concept.
- *concept transfer* - involves establishing a metaphor through analogy to reuse a collection of related concepts in a new context.
- *concept creation* - refers to invention of new concepts that do not exist in the problem domain

Evaluator: Generated models are simulated to determine their fitness in terms of their ability to mimic the behavior of the referent and generating the empirical regularities dictated by the testable consequences of examined hypotheses. Models with high fitness in improving creative insight and coverage of examined attributes (e.g., regularities) are retained. The fitness of a model depends on model's ability to produce expected outcomes that may span from quantitative validation metrics to more qualitative measures such as relational or distributional equivalence, or similarity in observed patterns in data. The fitness measure should also take into account the relational fitness of the model to rest of the models (e.g., nonredundancy) in covering the hypotheses space. The feedback provided back to the generator improves its effectiveness in selecting the model generation operators through a learning mechanism.

3.3 Abstract Specification of the Structure and Dynamics of GPS

To formalize GPS, we define the structure of the domain of models as a graph of ensembles, $G = (V,R)$, where V is the set of nodes, and each node $v \in V$ denotes an ensemble of models, and R is the set of relations depicting affinity (e.g., similarity in terns of function and form) between the ensembles. Each ensemble E has a neighborhood $N(E)$, which refers to a connected subgraph of G containing E. For our purposes, each ensemble contains a collection of metaobjects, each one of which specifies the schema of a corresponding model. Figure 4 depicts the structure of graph of ensembles. The strength of relations (e.g., $w(i,k)$ or $w(k,i)$) between ensembles signify the degree of accuracy (fitness) of models in the source ensemble with respect to objective of the target ensemble.

To evolve model schemas and their metaobjects, we need an encoding scheme. Although the encoding of a schema depends on the purpose of the study and aspects that will be evolved during the process of generative simulation, for simplicity and purpose of demonstration, we assume that each schema is a binary sequence of length n from the space

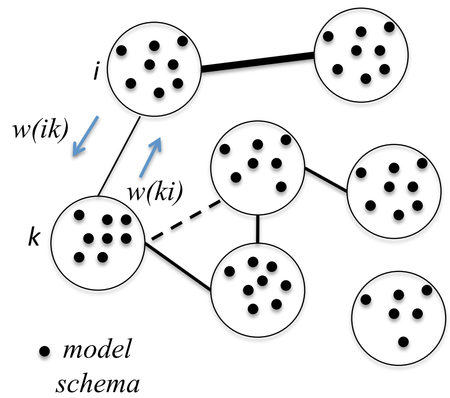


Figure 4: Graph of Model Ensembles

$\{0,1\}^n$. We denote the set of schemas with S and define a population function, P, as

$$P : V \rightarrow S \tag{1}$$

The population function can be extended via a neighborhood function $N : V \rightarrow 2^V$, which returns for a given node $x \in V$, all nodes, $y \in V$ in G, where $(x,y) \in R$. Hence, $P(N(E))$, where $E \in V$, returns all schemas contained in the neighboring ensembles. One can however also access schemas within a given ensemble by taking neighborhood equal to a specific ensemble. At any given round of generation, T, the schema population of the neighborhood of an ensemble, E, is given by $P(N(E),t)$. Similarly, the population of a specific ensemble is defined as $P(\{E\},T)$, and the number of schemas in ensemble is $N = N_{E;T}$.

Evaluation - Model fitness: Given the above specification of the population, we need to define evolutionary aspect of the ensemble. Three major factors are of interest in our domain. First, models that exhibit behavior similar to expected phenotype behavior need to be favored, as they generate sufficiently valid behavior, provided that the degree of accuracy exceeds a given minimum threshold. Second, those models that have divergent mechanisms with sufficient level of validity can facilitate discovery of novel mechanisms and should be retained. Finally, those models that demonstrate success in generating regularities and constraints imposed by neighboring ensembles should be favored as they are able extend their usefulness and scope. Such models that can satisfy the constraints of multiple phenotypes and therefore relate to schemas from more than one ensemble have larger impact. The *accuracy* function for a given ensemble v is defined as $F_a : S \rightarrow [0,1]$. $F_a(s)$, where $s \in S$, returns the accuracy of the model with schema s within the ensemble v. The performance is the degree of similarity of the schema to expected behavior designated by the phenotype. The *extent* function, $F_e : N(E) \times S \rightarrow [0,1]$, measures the degree of relevance of the schema with respect to ensembles in $N(E)$. The total fitness of the schema s in ensemble E is the weighted sum of its validity and extent:

$$f(s) = \alpha_a F_a + \alpha_e F_e \tag{2}$$

where $\alpha_a + \alpha_e = 1$. Adjustment of these parameters enable examination of alternative population evolution strategies to suggest effective and efficient methods for discovering models that are qualified to explain selected set of phenotypes.

Generation: The fitness functions specify how the schemas in the ensemble will be judged. The generation of schemas is defined using a general scheme using *transformation operators*. A transformation operator is defined as a function $t : S^m \rightarrow S$ for some integer m. The generative simulation system has a collection of operators, $R = \{t_i, i = 1, 2, \ldots, J\}$, that mimic alternative forms of form and structure generation. *Elaboration* involves refinement of a schema and is similar to mutation operation with $m = 1$, while *combination* is analogous to crossover operation, with $m = 2$. Each transformation operator, t_i, is associated with a weight, w_i, that determines frequency of its application. The generation of new schema involves a stage of selection of schemas, followed by a process of interaction for creation of new schemas. At each round, schemas with fitness scores less than predefined threshold are dropped. The remaining population in $P(\{E\}, t)$ representing ensemble E is replaced with a new interim population ϕ consisting of schemas in $P(\{E\}, T)$ with different frequencies. Using the conventional GA fitness proportionate parent selection mechanism, we compute for each schema its probability of selection: $\frac{f(s)}{\sum_{j \in E} f(j)}$. The expected number of copies of each schema (metaobject) in the interim population is then given by $\frac{f(s)}{\overline{f}}$, where $\overline{f} = \frac{1}{N} \sum_{j \in E} f(j)$ is the average fitness of the population. The frequency of each schema is therefore approximately proportional to its total fitness. The interaction between selected schemas proceed as follows. A schema is selected from the interim population ϕ. A transformation operator t_j is selected with a probability proportional to its weight w_j. If the arity of the transformation operator is m, then the remaining $m - 1$ schemas are randomly selected from the the interim population ϕ. Following the application of the transformation operator the produced schema is included in the new population: $P(\{E\}, T + 1)$. The interaction process is repeated N times to generate a new full population.

Transfer: Given the set of edges, $R \subseteq V \times V$ of the ensemble graph, G, each edge (E_i, E_j) is associated with two components: w_{ij} and w_{ji}. These components, shown in Figure 4 as the strength of relations, are positive integers that define transfer rates from from E_i to E_j and E_j to E_i, respectively, and $Q = \sum_j m_{ij} \leq N$. Each schema s in the ensemble has a propensity to transfer $\mu(s)$, which is a monotonic function of the change of fitness over k iterations. Initially, m_{ij} for each ensemble i is set to a low value. These transfer rates, which emulate conceptual transfer and analogy-based discovery, may change over time. Learning takes place as information about the fitness of copied and transferred models is gathered. If models that are transferred from E_i to E_j improve their average fitness, the transfer rate for migration from E_i to E_j is updated to increase number of transfers; otherwise, the transfer rate is decreased. At each round of evaluation, for every (E_i, E_j) in the model ensembles graph, the population in ensemble i is scanned to locate K schemas with $\mu(s) \geq \gamma_{transferThreshold}$ and from these schemas a subset of size proportional $\frac{m_{ij}}{Q}$ schemas are selected for transfer to E_j.

4 Meta-simulation of GPS

Preliminary experiments are conducted to better understand the operating regime and parameter ranges that improve integrated differentiation in a hypothetical model space. To this end, we present a agent-based meta-simulation study of evolving ensembles of model schemas. Meta-simulation is defined as a simulation study of a simulation methodology for the purpose of better understanding its behavioral dynamics and patterns that emerge as a result of sensitivity to parameters, which are related to creative cognition model discussed above.

4.1 Conceptual Model for GPS Simulator

As shown in Figure 5, the collection of models is comprised of four ensembles, each constituting a quadrant of the grid. Each ensemble contains a set of model schemas. A model schema is specified as a binary vector of length 40. Each element (i.e., bit) of the vector depicts a trait that a model belonging to associated ensemble representing one of the four perspectives or aspects involved in the hypothetical abstract problem. In comparison to the motivating scenario examined in section 2, each ensemble represents a separate targeted attribute.

Each bit in the vector representing a trait is interpreted as a component (e.g., axiom, indicators for existence or lack of a variable, low or high levels of values for a specific variable). Ideally, in realistic problems, a set of components is used as primitive blocks to construct solutions through an evolutionary design mechanism to generate problem representations and configurations to facilitate discovery of novel and useful solutions.

4.2 Meta-simulation Parameters

Those schemas that score well with respect to selection threshold against the objective function are qualified for

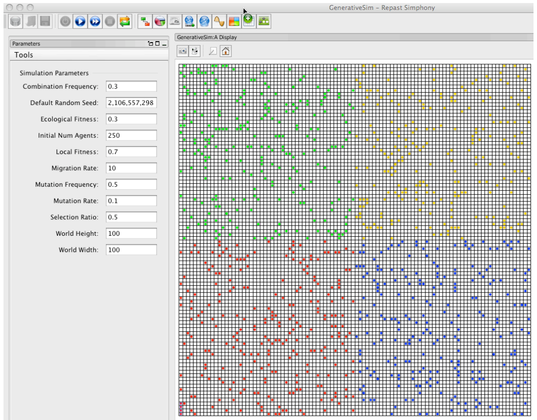


Figure 5: Initial State of the Meta-simulation

retainment and are transferred to the next generation. The parameters of the simulation and their influence on the evolution of model ensembles are defined as follows.

- **Local and Ecological Fitness**: These parameters refer to accuracy (i.e., α_a) and extent (i.e., α_e) parameters of the abstract specification, respectively. For instance, in our hypothetical problem, the overall fitness of a schema in ensemble a is defined in terms of accuracy and extent parameters: $F = \alpha_a O_a + \frac{1}{3}\alpha_e(O_b + O_c + O_d)$. While O_a depicts the fitness of a schema in its local context, where it is originally defined, the remaining part of the formula facilitates retention of those that are able to migrate to and succeed in other ensembles .
- **Combination Frequency**: Variation and transformation of schemas take place by either elaboration (update of its own traits) or transfer from other schemas. Combination frequency defines the probability at which combination operator that transfers traits (e.g., components) is selected. Exchanging traits across multiple schemas is a prerequisite for inducing variability and inheritance of solutions that are successful in multiple domains.
- **Mutation (Elaboration) Frequency and Rate**: The mutation frequency is the probability that the transformation operation selected during the generation phase involves elaboration or update of its own components. The rate parameter defines the probability of mutation for a single component during the scan of the components of the section of the binary vector that belongs to ensemble from which the schema is originated.
- **Selection Ratio**: This parameter (i.e., β) controls the degree of receptivity of the evaluator. From a given set of N schemas in an ensemble, βN schemas are selected as fit solutions to induce a selective pressure toward the evolution of fitter solutions. This is similar to parent selection process in evolutionary computation with genetic algorithms.
- **Migration Rate**: This parameter controls the number of schemas that are transferred from a source ensemble to a target ensemble. At each time step, a number of schemas designated by migration rate are selected and transferred to a neighboring ensemble. The purpose of transfer is to control the rate at which traits and components are exchanged across ensembles. Increased transfer rates are expected to improve extent and scope of models and facilitate their interpenetration.

4.3 Qualitative Analysis of Results and Discussion

To study the behavior and sensitivity of GPS to above parameters, a meta-simulation is performed to observe emergent patterns pertaining to interpenetration of models across distinct, yet related, targeted attributes (i.e., 4 quadrants). While capability of a model to increase its fitness and survivability in a new context after its transfer is an indicator for its usefulness and extent, dominance of one type of model across all contexts may be an indicator for lack of differentiation. The failure to achieve balance between differentiation and integration results in decreased adaptiveness, diversity, and hence robustness of the model ensemble to address future attributes and empirical observations. Just like a controller that is rich and diverse in terms of its possible actions is resilient in the presence of unforeseen perturbations in its environment, sufficiently differentiated ensemble of models is more likely to adapt when new attributes or phenotypes are introduced.

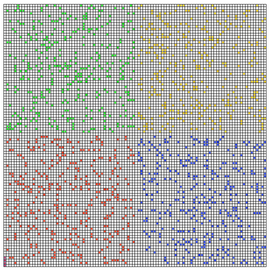
To better understand and discuss the behavior of generative ensemble of models as a creative evolutionary system, we examine emergent patterns under various environmental conditions and evolutionary dynamics defined by model migration (transfer) rate, selection ration, degree and importance of ecological fitness, and frequency of the use of schema combination.

4.3.1 Migration Rate

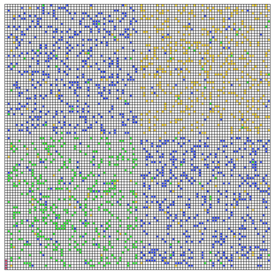
The migration rate between ensembles is defined in terms of the number of schemas that are selected randomly from the new population for transfer to a related ensemble. Figure 6 demonstrates emergent patterns as the number of transferred schemas increase.

4.3.2 Ecological Fitness

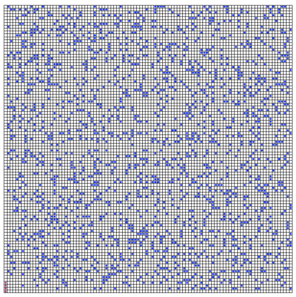
To improve interpenetration of model schemas and induce diversity and resilience, evolution of existing schemas require consideration of not only fitness against the constraints



(a) Migration Rate = 0

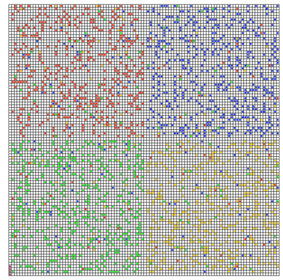


(b) Migration Rate = 10

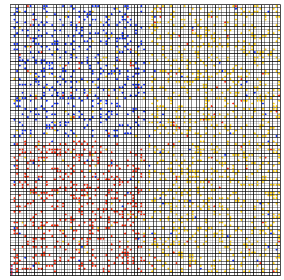


(c) Migration Rate = 40

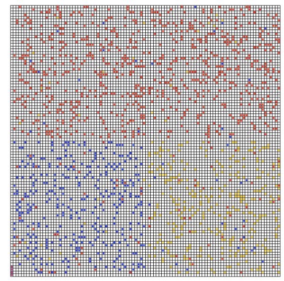
Figure 6: Impact of Migration Rate on Schema Diffusion



(a) Ecological Fitness = 0.0



(b) Ecological Fitness = 0.3



(c) Ecological Fitness = 0.9

Figure 7: Impact of Ecological Fitness on Schema Diffusion

of the local ensemble, but also its neighboring domains. The expectation is that schemas that exhibit high fitness in their local environment are more likely to survive and sustain when they are transferred to neighboring ensembles, if relational fitness is factored in. Figure 7 presents distribution of schemas under different levels of ecological fitness. As expected, in part (a) the diffusion and interpenetration of schemas is significantly restrained since schemas that are favored in their local context fail to survive when they are transferred to a new context.

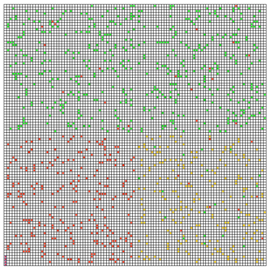
4.3.3 Combination Frequency

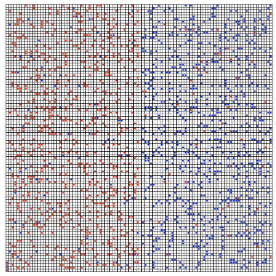
Schema combination is a powerful transformation operator that facilitate achieving creative leaps, especially when remote meaningful and useful associations are made. Concomitantly, increased frequency of combination of schemas is expected to restrain diversity.

4.3.4 Summary and Evaluation of Qualitative Analysis

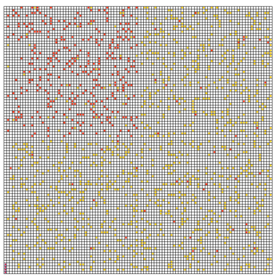
As depicted in the above sections, although there is further need to study interaction between different parameters, preliminary results confirm expectations about the role of combination frequency, knowledge transfer, significance of ecological perspective, and intensity of selective pressure on the degree of integrated differentiation of emergent landscape of models. The demand for interpenetration is based on the expectation that those models that can co-exist in the same ensemble to explain the desired phenotypic property may suggest alternative explanations for the same phenomena, and hence as a corollary improve discovery process. Yet, complete random and disordered allocation of models with significantly disparate schemas makes it difficult to establish coherent explanation and analysis of the phenomena and its phenotypic properties.

Observations with this simplified abstract model suggest use of moderate migration rates to avoid global uniformity, where a single model type survives to explain all phenotypic properties, resulting in not only lack of interpenetration and mobility of schemas, but also differentiation across distinct phenotypes. At first glance, having a single model that can explain all targeted attributes seems to be powerful, yet lack of differentiation is less likely to cope with new empirical regularities and environmental perturbations. Experimentation related to sensitivity to selective pressure reveals that non-critical and constraint free environment is likely to lead pseudo-random distribution of models leading significant entropy and disorder that lacks integrated differentiation. Optimal levels of of differentiation and interpenetration are observed at medium levels of selective pressure. We also observed that ecological fitness levels that are slightly higher than medium levels improve interpenetration, while improving overall global integration. Finally, high degrees of combination frequency as compared





(a) Combination Freq. = 0.3 (b) Combination Freq. = 0.5



(c) Combination Freq. = 0.9

Figure 8: Impact of Combination Frequency on Schema Diffusion

to elaboration inhibits interpenetration, while significantly increasing global uniformity.

5 CONCLUSIONS

In this article, we present various strategies, methods, and desiderata to support creative model-based problem solving and to facilitate evaluation of plausible models early in the foresight phase. Using the metaphor of traditional research cycle, where hypotheses are formulated from a body of knowledge and their testable consequences are tested against empirical evidence, models are viewed as plausible hypotheses, and successful models are evolved to facilitate explaining multiple phenotypic properties. We used a motivating scenario to demonstrate the utility of viewing solution to a scientific problem as an evolving ecology of collection of ensembles of models. Theories of creativity and creative cognition are overviewed and considered to facilitate rethinking the use of models to enhance creative problem solving in model-based science and engineering. Multiplicity and parallel simultaneous exploration using ensembles of models brings not only effective and efficient search of useful and novel models, but also, via subtle variation among models, enables discovery of multiple competing mechanisms embodied by models. Furthermore, through differentiation and multiplicity of models, it is expected that the discovered solution will be robust against perturbations in the environment. That is, despite falsification of subset of models, multiple ensembles of models can continue to sustain and evolve, with increased ability to generate empirical regularities and phenotypic properties that are unforeseen a priori, but rather presented later.

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