

Steps toward a possible theory of organization

Manoj Gambhir, Stephen Guerin,
Stuart Kauffman, Daniel Kunkle

Corresponding author:
Manoj Gambhir
RedfishGroup
624 Agua Fria St.
Santa Fe, NM 87501
manoj@redfish.com

Introduction

We anticipate a theory of organization to generalize the common structuring processes present in Rayleigh-Bénard convection, lasers, cellular slime molds, immune systems, genetic regulatory networks, neural systems, and social insect systems. A robust theory should also apply to systems of more commercial interest including firms, supply webs, financial markets, transportation systems, manufacturing production lines and consumer markets. This paper explores how Kauffman's Autonomous Agent might be used as a foundation for such a theory of organization and will use the context of a familiar computational model of an ant foraging system to demonstrate how the emergence and degradation of constraints simultaneously define the process of organization.

An Autonomous Agent (Kauffman, 2000), in brief, is a collectively autocatalytic system performing one or more thermodynamic work cycles that: (1) measures useful displacements from equilibrium from which work can be extracted; (2) discovers devices to couple to those energy sources such that work can be extracted; and (3) applies work to develop constraints to extract further work. A primary task in examining a given organization is to understand how the system is displaced from equilibrium and how work is extracted from these initial boundary conditions. This exercise is necessarily couched in

the language of thermodynamics and statistical physics. We are challenged to map this description not only to physically organizing systems, but to biological, social and computational instances of organization as well. Our aim is to make the mapping without the crutch of metaphor. We will appropriate the language and methods of statistical thermodynamics through the generalization of the thermodynamic processes of *heat* and *work* for definition in non-physical systems. Taking guidance from Atkins (1984), we can understand heat to be the *unconstrained transfer of energy* and its complement, work, to be the *constrained transfer of energy*. More generally, we might consider heat and work to be unconstrained and constrained processes. Consider a purely physical system where work was performed to create an initial concentration of a conserved quantity (eg. energy, mass, charge, linear momentum, angular momentum, etc.) in space. A diffusion process from thermal agitation can spontaneously arise to move the system to equilibrium absent constraint. This process of the unconstrained transfer of a conserved quantity is a heat process. Consider an alternative equivalent system comprised of a conserved quantity of computational entities (agents) performing a random walk in space. Beyond analogy, it is generally accepted that this agent system generates equivalent macroscopic dynamics that diffuse an average distance that scales with \sqrt{t} . In the ant model to be described below, the initial diffusion of random ant movement from a nest source is such a process — We describe this as a heat process in a non-physical system.

To consider non-physical representations of work, one can enumerate the degrees of freedom that characterize an agent's behavioral repertoire. In the ant model, an ant can potentially move to 8 neighboring spaces. Degrees of freedom are removed as an ant is informed by a pheromone gradient. As the ant movement is constrained by the pheromone field, we propose the idea that work is being done on the ant by the ant-pheromone field interaction.

Figure 1 depicts four phases of the typical evolution of the ant foraging model. It is an extension of the work of Guerin and Kunkle (2004) in which a simple agent-based model was constructed and the processes leading to structure formation, structure maintenance, and structure decay were studied. It was found that these three features—commonly observed in complex system agent-based models—could be explained in terms of ideas from equilibrium and non-equilibrium thermodynamics. For example, when a system forms an organization, it appears to move from a state of high disorder, or, in thermodynamic terms, high entropy, to a state of low entropy. The second law of thermodynamics contradicts such a change in an isolated system, and, in the simple ant system, it was observed that an initial increase in entropy might account for the eventual drop in entropy. Such increases in entropy, which enable the formation of organization, are the mainstay of non-equilibrium thermodynamics (Atkins, 1984; Prigogine, 1962, 1984; Haken, 2000; and Schneider and Kay, 1995; Swenson and Turvey, 1992). In the next section, measures of constraint and spatial entropy are defined as tools for examining the construction and destruction of constraints in this self-organizing system.

The ant model will currently be used for three purposes: 1) Exploring the parameter space of the model and produce a set of phase diagrams to show how its behavior changes with differing parameter values; 2) Introducing the concept of *useful work* done by the system and show how this is affected by changes in the behavioral rules and initial conditions of the model; 3) Discussing the work done by the system in the language of statistical thermodynamics.

Experimental Setup

The spirit of this model is an extension of the work of Parunak and Brueckner (2001), Kugler and Turvey (1987) and Gutowitz (1993). A basic simulation is set up as follows: A nest and some amount of food are placed in a space. All locations have zero levels of both food and nest pheromones. A conserved number of ants is placed in the system with varied spatial distributions. The system evolves as the ants move, drop pheromone, and transport food. An ant can hold one unit of food at a time and can take one of three actions: 1) move to one of eight adjacent locations (includes diagonal moves), 2) pick up a unit of food, and 3) drop a unit of food at a nest. At each time step some percentage of the pheromone present at each position “evaporates”, or is removed.

In some experiments, ants have directionality—they can only travel to their forward five positions instead of choosing from all eight adjacent positions. This local directionality—present regardless of the state of the system—is an example of a *context-free constraint* (Juarrero, 1999).

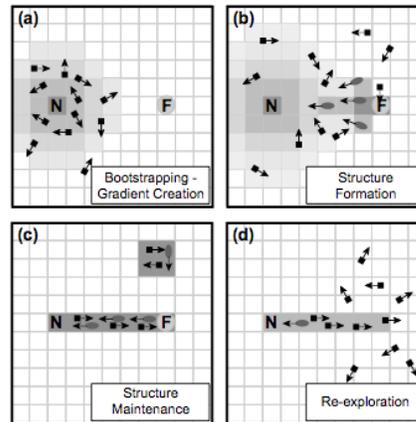


Figure 1. Typical evolution of the ant system. (a) *Bootstrapping – Gradient Creation*: Ants move randomly out from the nest, creating a gradient of nest pheromones. (b) *Structure Formation*: Some ants find the food and begin following the nest pheromones while dropping food pheromones that food-seeking ants begin to follow. (c) *Structure Maintenance*: A stable path of both food and nest pheromones is established. As shown in the upper-right corner, cycles that do not transport food can also form. (d) *Re-exploration*: Once all of the food has been transported to the nest the pheromones begin to evaporate and the ants disperse.

The direction of an ant is calculated after each step based on the previous and current positions. At time zero each ant chooses a random direction. In addition to this directionality, ants are given a behavior, in some experiments, that turns them around when they reach their goal—either the food-source or the nest. In the main set of experiments performed for this paper, the turnaround behavior and the ant directionality are successively turned off to observe the result on the ant-pheromone structure formed when the system reaches a steady state. The turnaround and directionality behaviors were originally included to make the system more efficient at reaching a structured steady state, but these behaviors constitute information about the environment and it is central to this paper to observe the macroscopic effect of removing this information from the microscopic actors.

Each time step, ants measure a local pheromone level then choose a direction to step. For example, for an ant with directionality, pheromone levels are read from the forward five positions. The probability of moving to position j is given by:

$$p_j = \frac{\mu_j^\alpha + \beta}{\sum_{n=1}^N \mu_n^\alpha + \beta} \quad (1)$$

where μ_j is the pheromone level at position j ; α is a scaling exponent; β is a random base; and the denominator represents the total pheromone level in all possible next positions. The scaling exponent α increases the probability that the next position will be the one with the greatest pheromone level, whereas the random base β has the opposite effect. Typical values used in our experiments were $\alpha = 3$, $\beta = 1$, and a maximum pheromone level of 511 at any one position. These parameters can be adjusted to tune the likelihood that an ant will explore for new food versus exploiting a found food source. The parameter β might be thought of as a temperature. By analogy to a physical system, when the temperature is high, each particle is highly agitated and the randomness of its motion is high. Any forces—e.g. electrostatic or gravitational—have to compete with this agitation for influence over the motion of the particles. Our β parameter effectively acts in the same way: high values of β can randomize the motion of the ants even in strong pheromone fields.

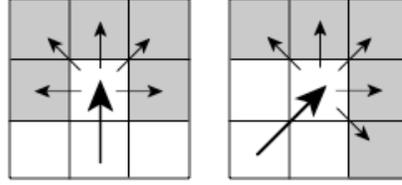


Figure 2. Examples of possible next steps (in gray) for an ant according to the last step taken. In this case, ants have fixed context-free constraints preventing backwards movement.

Constraint and Spatial Entropy Measures

It is in the initial conditions and the relevant behavioral rules of the ants and pheromones, that we find the propensity of the system to organize into structure.

As a system organizes, either through mechanisms of self-organization or through intervention by an external designer, components of the system are expected to lose degrees of freedom through the emergence of context-sensitive constraints (Juarrero, 1999). In this system, work is performed on the ants as they lose directional degrees of freedom when they are informed by the pheromone field. We measure this constraint in our model with a directional entropy. An ant that sees no pheromone gradient, which is an equal level of pheromone in all possible next positions, is said to be maximally ignorant with an ignorance level of 1. An ant that is constrained to move to one specific position on the next step would have an ignorance of 0. The Shannon entropy (Shannon, 1948a, 1948b) of the probabilities of moving to each of the possible positions on the next step defines the ignorance for each ant

$$S = \frac{-\sum_{n=1}^N p_n \log p_n}{\log N} \quad (2)$$

where p_n is the probability of moving to position n , and N is the number of possible next positions. The denominator is used to normalize the value to the range [0,1]. The ignorance of a group of ants is defined as the average ignorance of all ants.

Exploration of the parameter space of the model

With any model, it is important to know how the parameters affect the overall system behavior. In this section we look at the three main parameters governing the model: pheromone evaporation rate; number of ants; noise or 'temperature' parameter β . When several model runs are averaged over, we determine the effect of varying these parameters by looking at the following metrics:

Directional entropy (defined in the previous section, Experimental Setup).

Directional entropy can be considered a measure of how much work is being performed on an ant.

Mean-free-path of the ants. This is the average number of steps traveled by an ant between picking up and depositing a piece of food. A high mean-free-path value indicates that the ants are traveling large distances between picking up and depositing food; in this case, the system is unorganized—strong pheromone paths between food and nest have not yet been formed and the ants take many steps in moving between food and nest. Low values of mean free path indicate that the ants go almost directly from food to nest and back, without much deviation.

Number of food pieces picked up in a model run. The higher the number of pieces of food taken from food-source to nest over a run, the more efficient the system has become at performing this task. This is a measure of *useful work* performed.

The surface plots (figures 3 - 5) show the behavior of the system when the parameters are changed. A basic summary of these results is as follows: a low pheromone evaporation rate, a large number of ants, and a low temperature (though the temperature dependence is weak in figure 6) are required for organization to occur. Organization is measured in the plots by: low directional entropy; low mean-free-path (whose surface plot, though absent here, is very similar to that for the directional entropy); and a high number of food pieces collected. In each case, the organized state is seen as a transition to a trough or a peak in the surface defined over the parameter space. It can be seen that these transitions are fairly abrupt—the landscape is relatively flat but it rises or falls rapidly. We can think of these changes, from the unorganized state, as phase transitions.

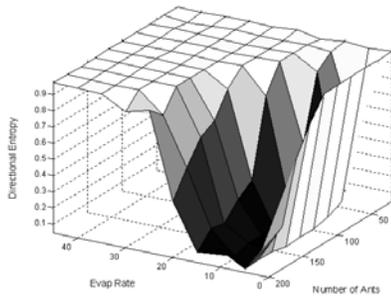


Figure 3 An exploration of the effect of evaporation rate and number-of-ant changes on the final average directional entropy of the colony.

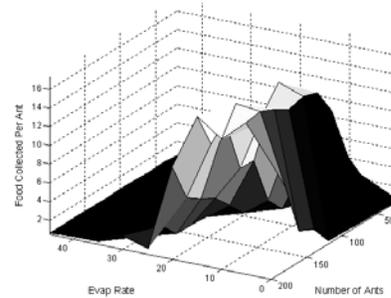


Figure 4 The effect of changing the pheromone evaporation rate and the number of ants on the total food collected per ant.

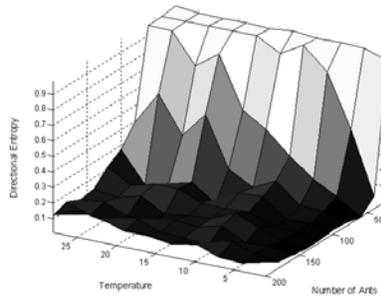


Figure 5 The effect of changing the temperature (noise parameter) and the number of ants on the average directional entropy.

The effect of the behavioral rules and initial conditions on the organization formed

An interesting question to ask of a dynamical system, such as our ant model, is: what happens to the final state of the system, and its evolution to this final state, when behavioral rule changes, or changes to the initial conditions, are made? We look here at several rule settings and initial conditions. As a baseline experiment, we turn off the ant pheromone and the directionality and turnaround behavior. In this case, we have a population of 'random' ants, similar to a non-interacting gas. The ants still pick up food at the food-source and deposit it at the nest, but, along the way, they neither sense nor deposit pheromone. The baseline experiment is numbered zero; the other experiments we perform are as follows:

Rule Changes: 1) Basic ants, 2) Basic ants with directional motion, 3) Basic ants with directional motion and turnaround behavior.

Initial Condition Changes: 4) All ants begin at the nest; all are food-seeking, 5) Ants begin randomly distributed; all are food-seeking, 6) Ants begin randomly distributed; half are food-seeking; half are nest-seeking.

The 'basic ant' indicated above is simply an ant with no directional behavior i.e. no directional rule or turnaround behavior when the ant reaches the food or nest. The three initial condition changes are all performed for ant systems in which the ants are equipped with their full set of rules i.e. directionality and turnaround. The purpose of these experiments is to begin to understand how much information—relevant to the construction of a stable and efficient final organization—is present in the initial conditions of the ants. As we add behavioral rules to the ants, the overall number of food pieces picked up increases—the system grows in efficiency at this task.

The results for the total number of food pieces picked up are, for each experiment:

Exp 0	Exp 1	Exp 2	Exp 3	Exp 4	Exp 5	Exp 6	Exp 7	Exp 8	Exp 9
4	8	2074	3367	4046	455	980	336	4608	2198

The previous section showed evidence that when the colony is efficient at food collection, the ants have low directional entropy and mean-free-path and are organized into a tight structure. It follows, therefore, that the addition of relevant, context-dependent, rules results in the formation of a tighter colony structure and a greater potential for the system to organize to perform the task of food collection.

Changes in the initial conditions also result in striking differences in the capability of the colony to self-organize. Two factors were identified as displacements from equilibrium in our model. First, the behavioral rule that changes the ant state between food-seeking and nest-seeking after touching a nest or food patch, creates concentration gradients of differentiated ant types with reciprocal sources and sinks at the nest and food. This system partitioning occurs even as the total ant distribution remains equipartitioned in the space. The second displacement from equilibrium occurs in some

experiments when ants are initially biased to be either all food-seekers and/or concentrated at the nest or food source. With all ants in their food-seeking state and beginning at the nest, the overall number of food pieces picked up is large (as expected, experiment 4) is close to experiment 3)). When the ants are initially randomly distributed, the ability of the colony to organize is significantly reduced—the total number of food pieces picked up is much smaller for experiments 5) and 6) than for 4).

Experiments 1), 5) and 6) share an interesting feature: despite the low number of food pieces picked up, the system does stabilize to a kind of structure—small clusters of ants form throughout the space. These clusters are composed of both nest- and food-seeking ants, one kind laying a pheromone trail attracting the other and, therefore, following the other. The result is a collection of tight loops and an organization that is totally inefficient at performing the task of food transportation. This loop formation is an example of useless, or pathological, self-organization.

In an attempt to investigate a rule change that might rid the system of this pathological behavior, we limit the total pheromone that each ant can deposit between visits to the food and nest. The ants are given 15 units of pheromone and can, therefore, take 15 steps before their pheromone has depleted. When a nest-seeking and food-seeking and become caught in a loop, it will not be long before the pheromone of the loop is no longer reinforced and the ants move away to discover other pheromone trails. We look at the following two cases: 7) Basic ants with limited pheromone, 8) Basic ants with directional and turnaround behavior and limited pheromone.

We also look at the system for ants which have directional behavior but which, instead of encountering a 3 cell 'wall' blocking their reverse path, encounter only one cell—the cell directly behind them. This softening of this constraint might be expected to result in more meandering ant behavior and, hence, less well-formed organization. Therefore, our final experiment is: 9) Basic ant with one cell directional and turnaround behavior. The number of food pieces gathered for these three experiments is as follows: 7) 336, 8) 4608, 9) 2198. The effect of limiting pheromone is to increase the effectiveness of the resulting colony at food collection—the directional entropies are also lower than for the unlimited pheromone counterparts. Experiments 7) and 8) should be compared with 1) and 3). Experiment 9) confirms our suspicion that the ants meander more when they are less constrained.

The results of the baseline experiment show that the case of no organization—the random ants are, by definition, incapable of forming structure—actually results in a greater overall amount of food picked up than the case in which ants drop and sense pheromone but they have no directionality. The reason for this is that the pheromone-sensing ants form the above-mentioned pathological organization—an organization that almost completely prevents them from performing the task of transporting food. In summary, the results show that the greater the number of structurally-relevant context free constraints the ants possess, the better the final organization is at the task of food collection and the less likely the system is to self-organize into a structure that hinders food collection. A further behavioral modification, limiting the total pheromone that can be deposited per ant, limits this 'useless' self-organization.

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