MODELING SELF-ORGANIZING SYSTEMS WITH SOCIAL INSECTS ALGORITHMS

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ABSTRACT. Self-organization is common in natural systems. This tutorial describes some of these systems, specifically from insect societies like in bees, termites or ant colonies. In a first part, a modeling process is explained. Objects and phenomena targeted by these methods are presented. Natural or social complex systems are the context of these objects and phenomena. Basic algorithms presented for example in [8] are given. These algorithms belongs to the class of swarm intelligence methods describing how a network of interacting entities can lead to emergent properties of the whole system. In a second part, more original applications are presented, based on extensions of these basic algorithms in order to model ecosystems, urban dynamics or to propose a decentralized method to distribute simulations over dynamical communication graphs.

KEYWORDS: *swarm intelligence, complex systems, ant colony optimization, self-organization, emergent properties*

1. Complexity and Self-Organization

Physic, Biology, Computer Science or Human Science give many examples of systems where the global behavior is the result of interactions between homogeneous or heterogeneous entities.

Our purpose is to model and to analyze social organizations inspired from these natural systems. Moreover, we want to highlight the essential role of space and so, how spatial interactions are the catalyst of emergent properties which appear in the formation of these complex systems.

On Figure 1, we describe a two-level model of spatial self-organizations with interactions in both directions between these two levels: the emergence of organizations from entities interactions but also the feed-back process describing how organizations are regulating their own entities.
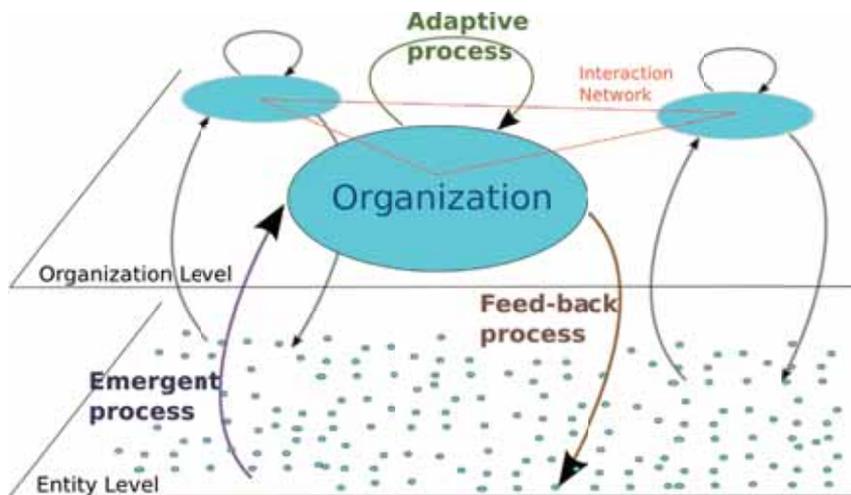
Figure 1: Complex spatial organizational model

In the following, we focuss our study on how building concrete algorithms to implement such phenomena involving adaptive complex systems. These algorithms are mostly belonging to swarm intelligence methods.

2. Swarm Intelligence

Swarm intelligence algorithms [7, 8, 15] find roots in various aspects of computer science development: from the evolution of the network architectures

that have led to distributed computing, but also from the evolution of software engineering that have led to distributed artificial intelligence paradigm.

Swarm Intelligence is based on such distributed solvers expected to interact together. In this approach, there is no plannication of any kind of master solvers, splitting a problem in smaller ones and then assemblying the sub-solutions of each slaves. In swarm intelligence algorithms, the computation is decentralized and the global solution emerges from these distributed solver interaction.

The most famous swarm intelligence methods are Particle swarm optimization (PSO) [14] and ant systems [8]. In PSO, the distributed solvers are moving virtual particles. These virtual particles are collectively moving on a solution space. The collective displacement of the particles system is inspired from C. Reynolds Boids [19] system which aims to simulate the collective behavior of fish banks or bird flocks. The virtual particles of PSO interact by exchanging information in order to discover the best solution over the space solution.

In ant Systems the distributed solvers are ants moving in an environment. The emerging solutions are achieved through a concept called stigmergy. This concept is based on a system of indirect communication whose support is the environment. It is inspired by the behavior of natural ants depositing pheromone trails on the ground to communicate with their peers.

3. Ant Systems

3.1 Self-organization in natural ant systems

Natural ant behaviors have fascinated complex systems researchers since many years by their capacities to organize themselves on various aspects.

Computer Science researchers are using ant colonies behavior to design bio-inspired methods and algorithms. Their specific reactive individual behaviors are suitable to design efficient cooperation mechanisms in order to implement automatic processus leading to self-organization formation.

To achieve this objective, only the few essential aspects of the ant behavior which lead to the self-organization processes, have to be understood and then described with mathematical formulations.

Engineering applications of such artificial ant colonies systems start to be developed nowadays, specifically for problems which can be described in term of graph optimization, task allocation or clustering.

On figure 2, two examples of self-organization in natural ants are presented. On the left side, the well-known Deneubourg experiment consists to highlight with a very simple device the ant foraging problem. The ant objectives is to find the optimal way from nest to food source, using pheromone trail deposition. On the right side, cemetery clustering formation are shown at 4 successive times: ants form piles of corpses to clean their nests. Each of them has elementary actions, unknowing the whole situation, but dealing only with local information. There is no supervisor to lead the piles formation which emerges from ant interactions.
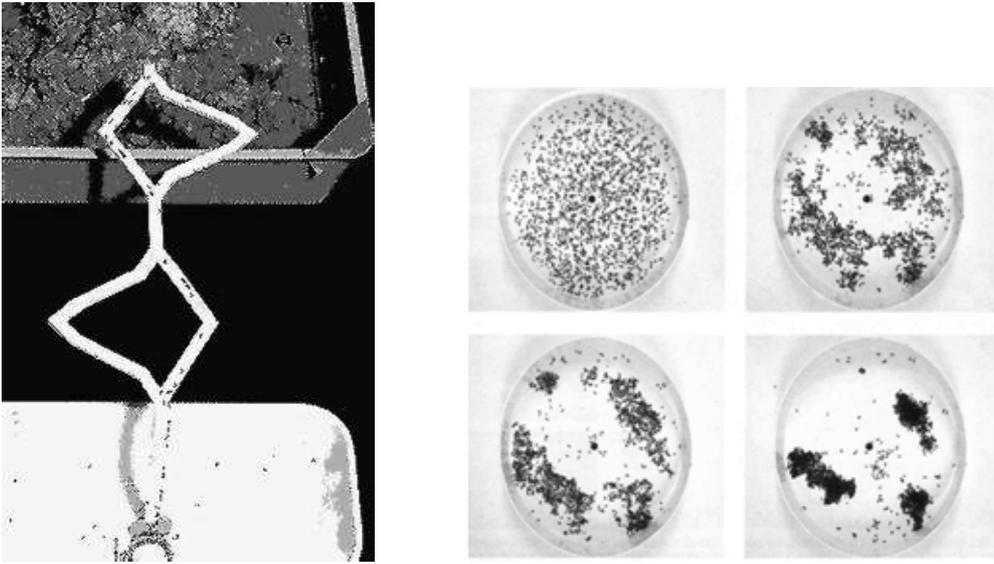
Figure 2: Optimization in natural ants collective behavior: foraging and clustering (from [8])

3.2 ANT COLONY OPTIMIZATION

Ant colony optimization [8] has been originally proposed to solve the famous Traveling Salesman Problem (TSP). This problem consists in finding the shortest cycle which links N interconnected towns within weighted graph with only one pass in each town. The problem is described by a graph where nodes C_i are towns and weighted edges D_{ij} are the distance between towns. $T_{ij}(t)$ are pheromone quantity deposited by ants on the edge (i, j).

When an ant is on the town i, it computes the probability to go to the non yet visited town j by the formula:

$$P_{ij}^k(t) = \begin{cases} \dfrac{(T_{ij}(t))^\alpha \left(\dfrac{1}{D_{ij}}\right)^\beta}{\displaystyle\sum_{l \in J_k(t)} (T_{il}(t))^\alpha \left(\dfrac{1}{D_{il}}\right)^\beta} & if \quad j \in J_k(t) \\ 0 & if \quad j \notin J_k(t) \end{cases}$$

where

- J_k is the set of towns not yet visited by the ant k;

- α and β allow to control the relative importance of the 2 quantities controlling the ant behavior: the pheromone trail quantity (T_{ij}) and the distance (D_{ij}).

When an ant has found a solution as a good cycle between towns, it deposits some pheromone on all of the edges of the cycle, inversely proportional to the length of the cycle (L_k):

$$\delta T_{ij}^k(t) = \begin{cases} \frac{Q}{L_k} & if \quad (i,j) \; is \; a \; edge \; of \; the \; cycle \\ 0 & elsewhere \end{cases}$$

Where Q is a constant parameter

On each edge (i,j), the pheromone quantity is updated from step t to step t+1, by adding all the contributions of each ant to previous pheromone quantity:

$$T_{ij}(t+1) = \rho T_{ij}(t) + \sum_{k=1}^m \delta T_{ij}^k(t)$$

Where ρ is an evaporation factor which allow that some first path/solution can be remplaced by better ones.

3.3 ANT CLUSTERING

Ants and other social insects deal with cooperative way in distributed clustering, like cimetery. From the beginning of aggregations of objects, small clusters formation appear and act themselves on social insects by stigmergy. This mechanism make the clusters formation increase with time.

The algorithm consists in making a great number of autonomous ants move in random direction inside an environment of objects to agregate them in clusters.

At each step, an ant is in one of the 3 situations:

1 The ant moves without carrying anything and meet no object. In this case, the ant continues to move randomly

2 The ant moves without carrying and meet an object. The ant can take this object to carry it. The probability of the ant take the object is:

$$P_p = \left(\frac{k_1}{k_1 + f} \right)^2 \tag{1}$$

  − f is a value corresponding of the number of objects perceived in the ant neighborhood
  − k_1 is a threshold, making this probability between 0 and 1, according to its relative position with k_1.

3 The ant moves and carries an object. The ant can leave this object on the ground. The probability of the ant to leave the carried object is:

$$P_d = \left(\frac{f}{k_2 + f} \right)^2 \tag{2}$$

  − f is a value corresponding of the number of objects perceived in the ant neighborhood
  − k_2 is another threshold, making this probability between 0 and 1, according to its relative position with k_2.

4. APPLICATIONS

4.1 METHODOLOGY FOR APPLICATIVE ISSUES DEVELOPMENT FROM BIO-INSPIRED ALGORITHMS

Original research works, from the research team RI2C (French acronym for swarm intelligence and interaction netwoks) of the laboratory LITIS, is

developed in this section. They belongs to a specific methodology of development to applicative issues about living and social complex systems, within distributed computing. Two major goals are defined and consist in (i) understanding and modelling the organization and self-organization of living systems using appropriate models and simulations, (2) taking inspiration from living systems to design new methodologies, new models and new algorithms suited to distributed computing. Our objectives is to integrate inside our simulations, some models of feed-back control of these emergent organizations over their own constituents. Swarm intelligence algorithms are the main basis of our implementation.

4.2 STRUCTURE DETECTIONS IN DISTRIBUTED SIMULATIONS

This research actions deal with dynamical agent-based simulation distribution over computer network based on ant system. The goal is to distribute the previous simulation interacting entities on a computer network: the communication has to be minimized, placing highly communicating entities on the same computer. Load balancing must be also considered in order to efficiently distribute entities to all the computers, respecting their power capabilities.

The proposed solution consits in developing an innovative algorithm called AntCO2, acronym for Ant Competing Colonies [12].

AntCO2 principle is an extension of the classical ant system with dynamical colored graph and colored pheromons. Each ant is associated to one color: it is attracted by the pheromone of its own color and repulsed by the pheromons of other colors.

AntCO2 results show the capability of this algorithm for cooperation and competition process leading to emergent clustering. On figure 3, graph clusterings are obtained by this algorithm. Its major characteristic is its decentralized process which confer flexibility and robutness properties.

4.3 URBAN DYNAMICS SIMULATION

Social and human developments are typical complex systems. Urban development and dynamics are the perfect illustration of systems where spatial emergence, self-organization and structural interaction between the system and its components occur [3, 4, 5, 6]. In figure 4, we concentrate on the emergence of organizational systems from geographical systems. The continuous
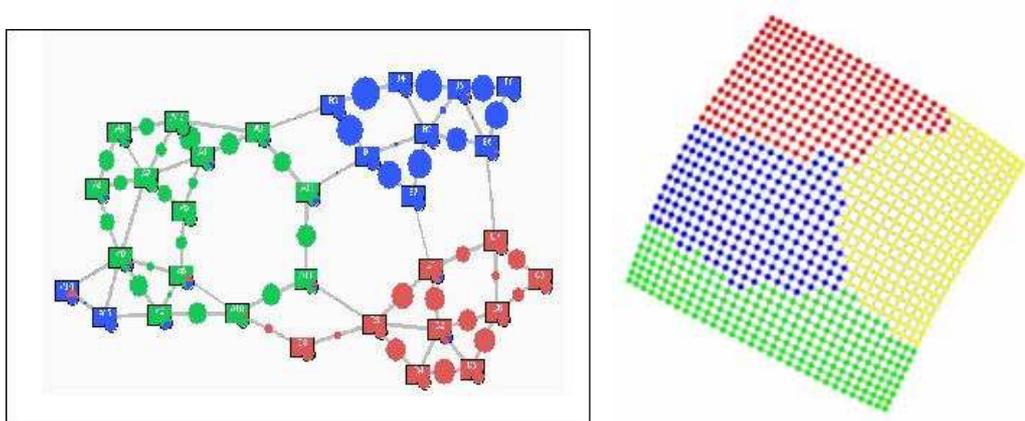
Figure 3: AntCo2 algorithm for graph clustering: on the left the output of the computation on a communication network; on the right the output on a regular grid
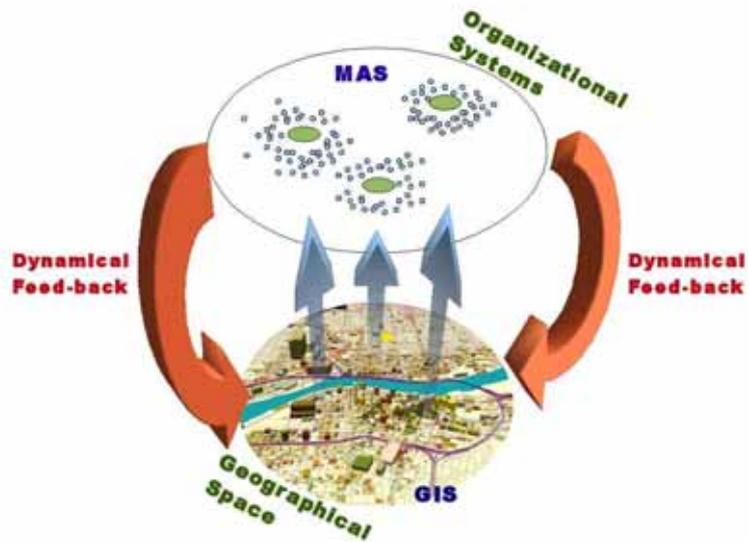
Figure 4: Complexity of geographical space with respect of emergent organizations

dynamic development of the organization feed-back on the geographical system which contains the organization components and their environment. To analyse or simulate urban dynamics, nowadays, we can use the great amount of geographical databases directly available for computational treatment within Geographical Information Systems [17, 20]. On the organizational level description, the new development of multiagent systems (MAS) allows nowadays to develop suitable models and efficient simulations [9].

The applications we focus on in the models that we will propose in the following, concerns specifically the multi-center (or multi-organizational) phenomona inside urban development. As an artificial ecosystem, the city development has to deal with many challenges, specifically for sustainable development, mixing economical, social and environmental aspects. The decentralized methodology proposed in the following allows to deal with multi-criteria problems, leading to propose a decision making assistance, based on simulation analysis.

The ant clustering shows some spatial self-organizations but has the specificity to generate clusters at random places. According to the first random moves that the ants start to do in the beginning of the algorithm, some material will initiate aggregation and the clustering processus will complete this aggregation from these initial random first aggregations. To simulate some urban dynamics, we need to introduce specific location with respect to city center, for example. The clustering here will represent the people usage of these centers or equipments and we need to introduce an attractive effect by using a pheromon template. This method follows the algorithm known as Ant Nest Building [10]. In ant colonies, the center corresponds to the position of the queen which needs to build the nest and the ant colony moves around it to protect the nest by various material taken on the ground. The queen emits a pheromon which allows to attract the ants during their building. The ant has to deposit the material carried only if the pheromon quantity perceived belongs to a specific range. We use an attractive fonction called P_t, corresponding to a pheromon template and represented by the top part of the figure 5.

Using this template function, we remplace in the clustering algorithm, the two previous probabilities defined previously in equation (1) and equation (2) by

$$P_p' = P_p(1 - P_t) \tag{3}$$

$$P'_d = P_d P_t \tag{4}$$

On figure 5, we can see a single queen simulation. It is possible also for each queen to emit many different kinds of pheromons : we called them colored pheromons [13]. Each colored pheromon will attract only the ants associated to its color. On figures (b) and (c), simulations on RePast [11, 16, 18] are provided at successive times. The last figure shows the adaptive mechanism of the queen which grows with time according to the material density around it, like in natural observations.

On the figure 6, we present a complete simulation with several centers and several queens [13]. On each center, a queen is emitting several colored pheromons and are able to attract some multi-colored material according to their initial location. Simulation outputs at different iteration times are presented, from RePast implementation and OpenMap GIS visualization.

The multi-template modelling can be used to model cultural equipment dynamics as described in figure 7. On this figure, we associate a queen to each cultural center (cinema, theatre, ...). Each queen will emit many pheromon templates, each template is associated to a specific criterium (according to age, sex, ...). Initially, we put the material in the residential place. Each material has some characteristics, corresponding to the people living in this residential area. The simulation shows the self-organization processus as the result of the set of the attractive effect of all the centers and all the templates.

5. Conclusion

In this tutorial, self-organization mechanisms are described in natural systems and are used to design algorithms for distributed computing. Applications on ecosytems or urban dynamics modeling are presented. A processus to distribute decentralized simulations from its communication graph is also presented. Standard algorithms extensions need to achieve these processes or simulations are developed. The decentralized approaches, inherent to these bio-inspired algorithms, allow to extend them, respecting the complexity of the phenomena to model.
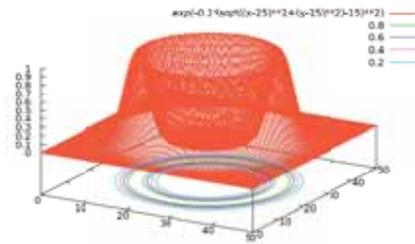
(a) template function
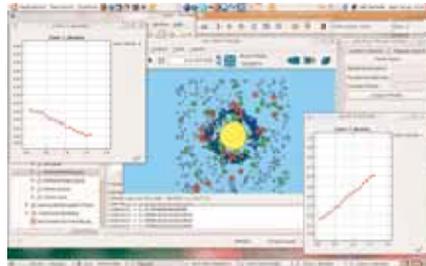
(b) simulation on Repast: after few step
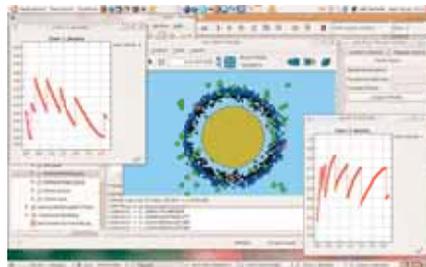
(c) simulation on Repast: after queen adaptive development

Figure 5: Adaptive queen behavior modelling: according to its surround material spatial perception, the queen evolves
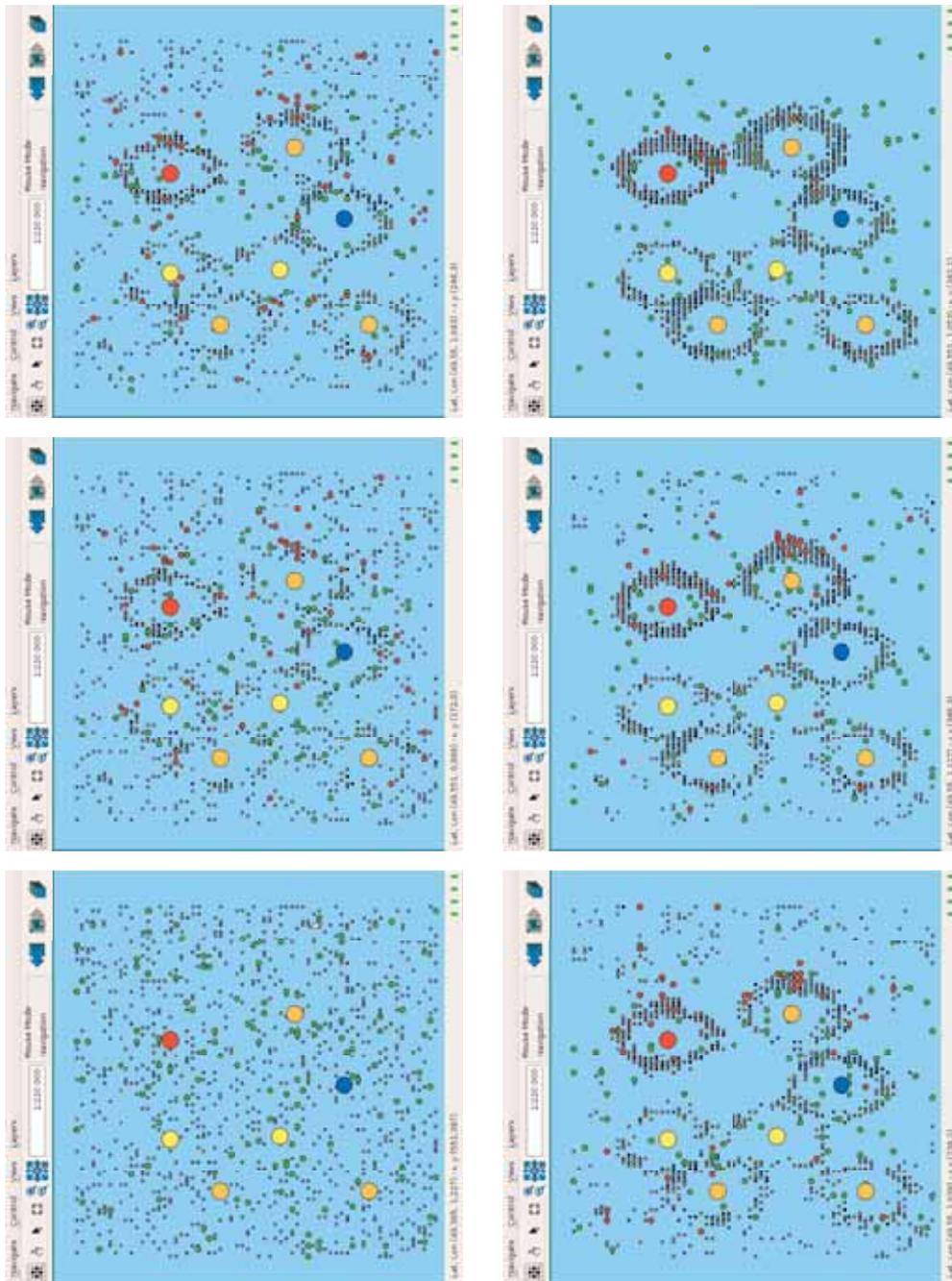
Figure 6: Simulation computation, at successive steps: iterations 0, 152, 250, 370, 601, 1601.
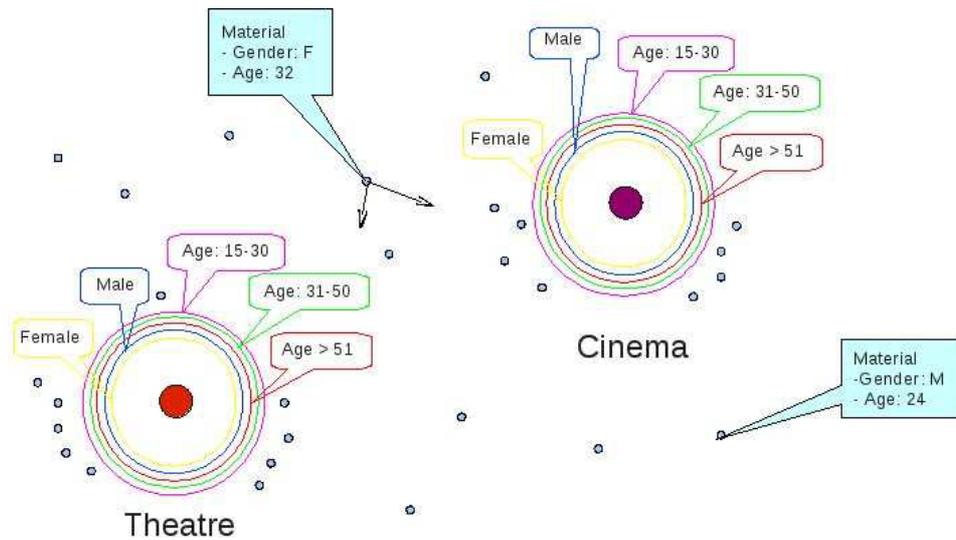
Figure 7: Cultural equipment dynamics modeling

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