Simulate the knowledge co-creation process for social emergence studies

Shu-Yuan WU

Faculty of Business and Law, Auckland University of Technology

Auckland, New Zealand

ABSTRACT

At the centre of entrepreneurship research we need to find out how cross-boundary sensemaking and knowledge creation may occur. This paper builds upon the literature of organizational learning and knowledge management to simulate the process. Experiments with the simulator help to further our understandings on how knowledge co-creation may happen and lead to social changes such as successful innovations and the emergence of new industries.

Keywords: cross-boundary sensemaking, Knowledge creation, Innovation, Simulation

1. INTRODUCTION

There is only one body of human knowledge and each organization or individual knows only a few dimensions of this knowledge—mostly the specialized area and related matters. Yet, with cross-boundary communications and knowledge sharing, human knowledge as complex adaptive systems evolve [1]. Along this evolution, innovations lead to social changes in the ways of human working and living. In the words of Adam Smith, innovations involve "combining the powers of the most distant and dissimilar" knowledge elements across disciplinary areas [as cited by 2] .

Taking a social cognition view, we see entrepreneurs and potential customers co-create, through interactive learning, the success of an innovation—i.e., the emergence of a market [3]. The success of innovation takes a knowledge co-creation process, because a market can be seen as a body of shared local knowledge on what is needed and how this need should be fulfilled.

This paper reports, for interdisciplinary exchanges, how the author uses Agent-based modelling (ABM) method to simulate the knowledge co-creation processes for entrepreneurship research and, possibly, teaching.

Following this introduction I report in details the construction of ABM simulators. Some results from simulation experiments are presented and the paper ends with a discussion on the ABM methodology.

THE CONSTRUCTION OF THE SIMULATORS

The author sees the process of simultaneous knowledge generation and communication through cross-boundary sensemaking as the core of entrepreneurship & innovation. According to Mckelvey [4: 314], the ABM approach helps to investigate the creation of order through such processes, "without assuming away the complex causality invariably driving the most entrepreneurial decisions."

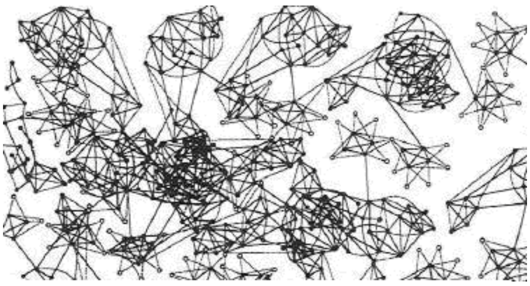
Variation-Selection-Retention

The evolution of human knowledge, similar to any other complex adaptive systems arguably [1] takes the VSR (Variation-Selection-Retention) pattern [5, 6].

Variations are trials of different combinations of knowledge elements. Generally speaking, all types of knowledge—expertise, opinions, concerns, needs and values are more homogeneous within than between discipline areas, industries, or, any type of socially constructed communities. The shared knowledge components build cognitive ties [7], through which communities of practice [8], technological communities [9], or effectuation networks [10] form and dissolve, giving the system of knowledge temporary structures.

FIGURE1. VARIATION: KNOWLEDEG COMMUNITIES CLUSTER AND

DISSOLVE



Source: Adapted from Burt (2004): *Structural holes and good ideas*, p. 352

The formation of communities follows the "selection by and of" potential stakeholders. For example, if a need is fulfilled and all the parties are satisfied with this solution, the community emerges as a new market/industry. Such a means-end framework stays in equilibrium until the next new elements (a need, a new issue of the need, a new technology) come into the system to disrupt the current order[11, 12].

The simulators are built as a multiple dimensional (20D or 50D for example) space of knowledge within which learning agents are moving particles whose coordinates vectors denote their knowledge profile. The heterogeneity of agents is distributed randomly through the populations. These agents move around, learning about and from each other following simple rules. Researchers can observe how some agents commit to combining their knowledge components and hence form clusters and, their commitments to knowledge communities may lead to social changes.

Initial conditions of some of the learning agents

The "particles" are the *problem representations* [13] of entrepreneurs and customers. Some start the learning journeys with technology components while the others start with their senses of latent needs. Please see figure 2 for the initial knowledge of the divergent learning particles.

FIGURE2. INITIAL POSITIONS OF SOME

AGENTS

[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
K1	1	0	0	2	2	2	0	0	0	0	0	0	1	0	0	0	0	1	0	0
K2	0	0	0	1	2	2	1	0	0	0	0	0	0	0	0	1	0	0	1	0
K3	1	0	0	2	2	2	1	0	0	1	0	1	0	0	1	0	0	0	0	0
K4	0	0	1	2	2	2	0	1	0	0	0	1	0	1	0	0	0	0	1	0
K5	0	0	0	2	2	2	1	0	0	1	0	0	0	0	0	1	0	0	0	1
Y8	0	1	0	0	0	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0
Y9	1	0	0	0	1	0	1	1	2	1	0	0	0	1	0	0	0	0	0	1
Y10	0	0	0	0	0	0	2	2	2	0	1	0	0	0	0	0	0	0	0	1
Y11	0	0	0	1	0	0	1	1	1	0	0	1	0	0	0	0	0	1	0	0
Y12	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	1
Y13	0	0	0	0	0	0	1	1	1	0	0	0	0	0	1	0	1	0	0	0
P10	1	0	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	2	1	2
P11	0	0	0	0	1	0	0	2	0	0	2	0	1	0	0	0	0	0	0	1
P12	1	0	0	0	0	1	0	0	0	0	1	0	0	1	2	0	0	0	2	1
P13	0	1	1	2	0	0	0	1	1	1	0	0	0	1	0	1	2	1	0	0
P14	0	0	0	0	1	0	0	0	1	2	1	2	0	1	1	1	1	0	1	0
P15	1	0	1	0	2	0	0	1	0	1	0	1	1	1	2	1	0	0	1	1
B1	2	2	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0
B2	2	1	2	0	0	0	1	0	0	0	0	0	1	0	0	0	1	0	0	1
B3	1	2	2	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
B4	1	2	1	0	0	0	0	0	1	0	0	0	1	0	0	0	0	1	0	1
B5	1	1	2	0	0	1	0	0	1	0	0	0	0	0	0	0	0	1	0	0

On each dimension of the knowledge space, a particle's level of knowledge can be 0—sheer ignorance [14], or 1—the recognition heuristic [15], or 2—expertise level.

At the starting point, all the particles carry partial and dispersed knowledge components of some potential product (entrepreneur's ideas) or customer needs. Each particle's knowledge is limited to a few dimensions, and so that the system lies in the realm of true uncertainty of unknown unknowns[16, 17]. Using Sarasvathy and Dew's [10] "curry in a hurry" example here we illustrate what the knowledge profiles mean. For example, an entrepreneur has a knowledge profile as (2 2 0 0 0 0 1 0 0 0 1 0 0 0 0 1 0 0 0 0) , this means she has expertise on dimensions1 and 2, (e.g., cooking expertise she possesses as a good cook); prior knowledge about some potential market domains on dimensions 7, 11, and 16 (e.g., knowledge about a grocery store owned by a friend with whom she may start a deli business; or, about a popular media for whom she might produce cooking videos). In the meantime, other dimensions are unknown to her; in other words, s/he stands at a point in a little corner of the 20D space. At another corner, one of the 200 customers, initially locates itself at a point (0 0 0 0 0 1 0 0 0 0 0 0 1 0 0 0 0 0 0 1 2 1) sharing little knowledge with the entrepreneur (so this may be, say, a ship taking tourists for world-cruises).

New market(s) will emerge endogenously as a combination of knowledge components such as entrepreneurial ambition, new technologies, and customer needs. Therefore, at the system level, we expect to observe different populations of agents converging together on building their shared knowledge.

System level emergence

In the multiple dimensional space of knowledge, a particle's current position, its coordinate vector represents its knowledge at that moment. Agents initially have blind-sights on most of the dimensions and may possibly build up later their knowledge about some other dimensions during their learning journey. In this sense, each of the agents is in an open and evolving world (which reflects the impact of information asymmetries, or bounded rationality).

Agents carrying knowledge-components move around in the knowledge space, and can potentially sense others' existences, decide whether others' knowledge is relevant to her wellbeing and, learn from/about each other. Empirical studies have shown that such learning requires structural connections, unlearning previous constraints, and trust building[18].

Knowledge about a new dimension, once acquired, is taken into an agent's updated knowledge-profile and hence the particle moves to a new position in the knowledge space. Originally dispersed knowledge components from various agents can therefore be integrated and knowledge sharing leads to a new cluster of particles.

Among the dimensions, some are interconnected with each other. So knowledge on one dimension may leads to the recognition of other dimensions. For example, once a mobile-phone provides a camera function, customers start to concern its storage capacity. The interconnections among the dimensions actually make the knowledge space a twisted torus, somewhat like an N-K landscape [19-21].

Programing the behaviors of the agents.

At each time-step (tick) of the algorithm, learning agents are displaced from their current positions by applying a velocity vector to them [22-24].

$$X_i(t+1) = X_i(t) + V_i(t) \quad \text{Eq.(1)}$$

The magnitude and direction of an agent's velocity at each step are determined by simple rules: whom a learner decides to learn from, and how large this movement can be.

The likelihood of a learner to sense distant knowledge elements is similar to that of a predator sensing a prey from a distance [25], which we believe is a decreasing exponential function of the distance [24]:

$$C = Ae^{-bD} \qquad \text{Eq. (2)}$$

D is the Euclidean distance in the knowledge space between the locations of this learning agent and the source of the knowledge element to be recognized. Alertness coefficient, ***b***, represents the extent to which such a distance obstructs the learning activity- in other words, the extent to which an agent can take advantage of information asymmetry [26]. For an *alert* learner, ***b*** is smaller than 1, whereas for someone who has ***b*** as large as 2, the distance seems doubled in their eyes. ***A*** is Entrepreneurial Orientation (EO), the level of motivation, or the 'will' of committing to new learning under uncertainty[10]. For the implementation of EO concept, the simulation models adopt a 5 point Likert scale, with 1 being the lowest in EO and 5 the highest.

Combining Equations (1) and (2), the learning activities of entrepreneurial entities are expressed by the following equations.

Entrepreneurs, Eq. (3)

$$V_i(t+1) = A_i e^{-b_i D_i}(leaduser\ \ (t) - X_i(t))$$

Customers: (Eq.4)

$$V_i(t+1) = \alpha(lbest\ (t) - X_i(t)) + A_i e^{-b_i D_i}(heard\ (t) - X_i t))$$

Where α is random number U (0, 1); ***lbest*** is a neighbor customer who is recognized as happier (having more dimensions of need served); and *heard* is the entrepreneur whose solution elements has been recognized by this customer.

If an agent has '0' level of knowledge on a dimension before making a step of movement, it may have a chance, after learning from others, to flip to a '1'.

$$Sgmd(V) = \frac{1}{1+e^{-|V|}}$$

Eq.(6)

When the sigmoid function of the velocity on a dimension is larger than a random number U (0, 1), knowledge on that dimension flips from '0' to '1' [27]. After recognizing a dimension as relevant, the knowledge-gain along the dimension is cumulative from '1' to '2'. An agent can unlearn about a dimension by unloading its knowledge from '2' continuously down to '1', but not from '1' back to '0'. After recognising the existence of a dimension, one cannot be ignorant of its existence any more. Taking into account the interconnectedness of dimensions, if a learner's knowledge level on one dimension is higher than 1, there is a chance for this learner to recognize the existence of some other dimensions randomly.

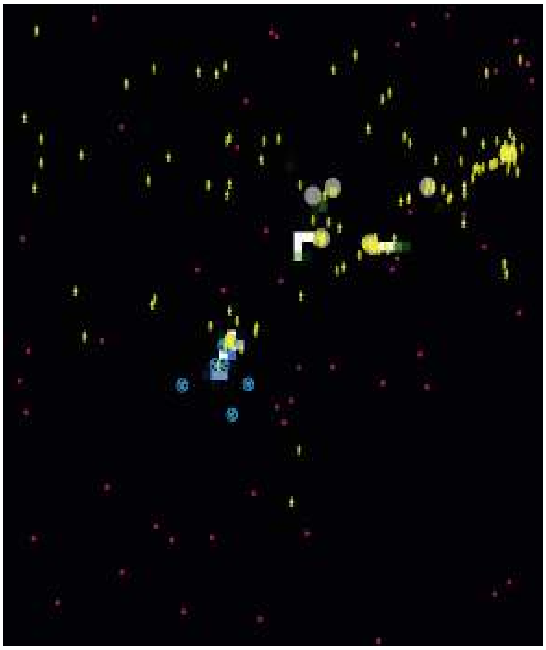
For selection and retention: Financial Constraints and Rewards

Movements in the knowledge space consume energy, the same as learning behaviours of organisations costs financial resources. Before each run of the simulator, all the agents are automatically financed with a "start level energy". During the running for each tick, an agent checks whether it has enough energy to afford the identified movement. If not, it has a chance (random number) to borrow energy from the system or otherwise it stays "dead" at the current position during this tick. The entrepreneurial particles gain financial rewards from involving each customer to commit to its solution-building venture.

RESULTS

Figure 3 shows a simulator snapshot on the emergence of two competing technological communities, the green and blue patches within the system. The snapshot was captured after 265 ticks of one running of the simulator. Yellow human figures represent customers, blue happy faces are technology entrepreneurs, and grey pillars are the old technology practitioners. The picture shows an overall result of the new market emergence through interactive learning.

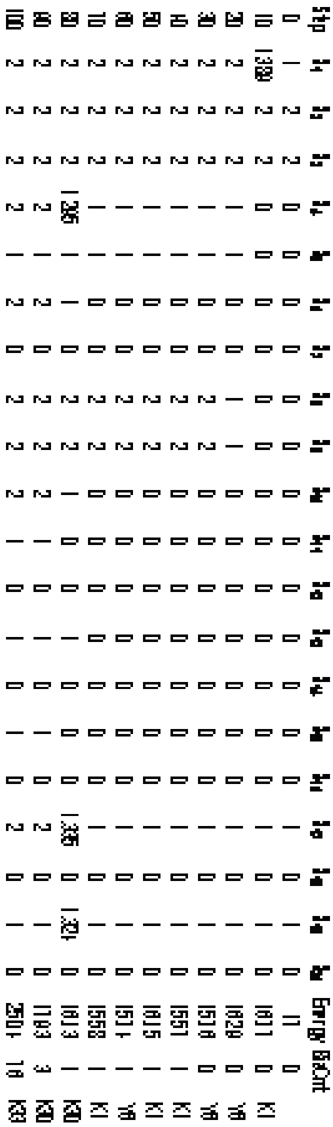
FIGURE3. EMERGENCE OF COMMUNITIES



The simulator can generate spreadsheets of the demographics of the agents: level of EO, alertness, number of initial ties with others, etc. Some linear regression analysis on these data can find whether there is relationship between these factors and the performances in forming communities, i.e., the count of how many "customers" an entrepreneur has made, or the energy gain.

Also, the learning journey of each individual agent can be traced. For example, figure 4 is the learning journey of an entrepreneurial agent in making her markets.

FIGURE4. AN ENTREPRENEUR'S JOURNEY



The learning journey is presented every 10 ticks: the updates of knowledge profile, the energy it possesses, number of customers it has attracted (BizCount), and the lead-customers from which it learned new knowledge elements.

Figure 5 and 6 are results of experiments on the effect of the innovativeness at the potential customers' side and the effect of boundary spanners [28].

FIGURE5. DEMAND-SIDE INNOVATIVENESS

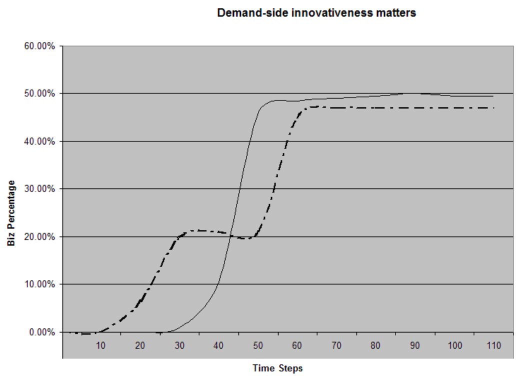
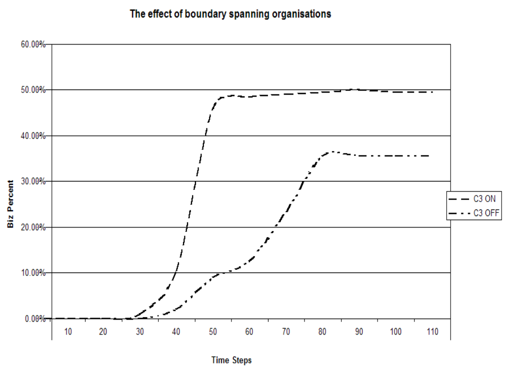


FIGURE6.BOUNDARY SPANNERS MAKE LIFE EASIER



DISCUSSION

For interdisciplinary communication, this paper summarized the ABM simulators the author had built for entrepreneurship studies. The underlying assumption of this kind of simulator is the social cognition view of entrepreneurship and a complex adaptive system perspective on human knowledge evolution. ABM can serve as a data generator and experimentation tool for processual research since it is normally very difficult to collect data for processes such as radical innovation and technology entrepreneurship. The issue in question for this methodology lies in the empirical validation. For future development of simulators to facilitate teaching and communication, better visualization and user-friendly interfaces are also necessary.

REFERENCES

[1] B. J. Loasby, "The Evolution of Knowledge: beyond the Biological Model," *Research Policy,* vol. 31, pp. 1227-1239, 2002.

[2] R. N. Langlois, "Transaction-cost Economics in Real Time," *Industrial and Corporate Change,* vol. 1, pp. 99-127, 1992.

[3] S.-Y. Wu and A. Brabazon, "The Emergence of a Market: What Efforts Can Entrepreneurs Make?," in *Natural Computing in Computational Finance*. vol. Vol. 2, SCI 185, A. Brabazon and M. O'Neill, Eds. Verlag Berlin Heidelberg: Springer, 2009, pp. 225–243.

[4] B. McKelvey, "Toward a Complexity Science of Entrepreneurship," *Journal of Business Venturing,* vol. 19, pp. 313-341, 2004.

[5] D. T. Campbell, "Blind Variation and Selective Retention in Creative Thought as in other Knowledge Processes," *Psychological Review,* vol. 67, pp. 380-400, 1960.

[6] D. T. Campbell, "Evolutionary Epistemology," in *The Philosophy of Karl Popper*. vol. 14, P. A. Schilpp, Ed. Lasalle, IL: Open Court Publishing, 1974, pp. 14I, 413-463.

[7] J. S. Brown and P. Duguid, "Knowledge and Organization: A Social-Practice Perspective," *Organization Science,* vol. 12, pp. 198-213, 2001.

[8] J. S. Brown and P. Duguid, "ORGANIZATIONAL LEARNING AND COMMUNITIES-OF-PRACTICE: TOWARD A UNIFIED VIEW OF WORKING, LEARNING, AND INNOVATING," *Organization Science,* vol. 2, pp. 40-57, 1991.

[9] L. Rosenkopf and M. L. Tushman, "The Coevolution of Community Networks and Technology: Lessons from the Flight Simulation Industry," *Industrial and Corporate Change,* vol. 7, pp. 311-346, June 1, 1998

[10] S. D. Sarasvathy and N. Dew, "New market creation through transformation," *Journal of Evolutionary Economics,* vol. 15, pp. 533-565, 2005.

[11] T. H. Chiles, A. C. Bluedorn, and V. K. Gupta, "Beyond Creative Destruction and Entrepreneurial Discovery: A Radical Austrian Approach to Entrepreneurship," *Organization Studies,* vol. 28, pp. 467-493, April 1, 2007 2007.

[12] I. M. Kirzner, "Entrepreneurial discovery and the competitive market process: An Austrian approach," *Journal of Economic Literature* vol. 35, pp. 60-85, 1997.

[13] H. A. Simon, "Bounded Rationality and Organizational Learning," *Organizational Science,* vol. 2, pp. 125-134, 1991.

[14] I. M. KIRZNER, *Perception, opportunity and profit: Studies in the theory of Entrepreneurship*. Chicago: University of Chicago Press, 1979.

[15] D. G. Goldstein and G. Gigerenzer, "Models of Ecological Rationality: The Recognition Heuristic," *Psychological Review,* vol. 109, pp. 75-90, 2002.

[16] F. H. Knight, *Risk, Uncertainty, and Profit*. Boston MA: Hart, Schaffner & Marx; Houghton Mifflin Company, 1921.

[17] D. N. Sull, "Disciplined Entrepreneurship," *Sloan Management Review,* vol. 46, pp. 71-77, Fall 2004 2004.

[18] K. Pavlovich and P. D. Corner, "Knowledge creation through co-entrepreneurship," *International Journal of Knowledge Management Studies,* vol. 1, pp. 178-197, 2006.

[19] [20] S. Kauffman and S. Levin, "Towards a General Theory of Adaptive Walks on Rugged Landscapes," *Journal of Theoretical Biology,* vol. 128, pp. 11-45, 1987.

[21] D. A. Levinthal and M. Warglien, "Landscape design: Designing for local action in complex worlds," *Organization Science,* vol. 10, p. 342, 1999.

[22] J. Kennedy and R. Eberhart, "Particle Swarm Optimization," in *The IEEE International Conference on NeuralNetworks*, 1995, pp. 1942-1948.

[23] J. Kennedy, R. C. Eberhart, and Y. Shi, *Swarm Intelligence*. San Mateo, California: Morgan Kaufman Academic Press,01

[24] S. Wu and A. K. Brabazon, "A Garbage Can Model for Schumpeterian Process: the Network Effects," *International Journal of Foresight and Innovation Policy,* vol. 4, pp. 287-306, 2008.

[25] A. Silva, A. Neves, and E. Costa, "An Empirical Comparison of Particle Swarm and Predator Prey Optimisation," in *Lecture Notes on Artificial Intelligence (2464)*: Springer,02.

[26] M. Minniti, "Entrepreneurial Alertness and Asymmetric Information in a Spin-glass Model," *Journal of Business Venturing,* vol. 19, pp. 637-658, 2004.

[28] M. L. Tushman and T. J. Scanlan, "Boundary Spanning Individuals: their Role in Information Transfer and their Antecedents," *Academy of Management Journal,* vol. 24, pp. 289-305, 1981.