Exploring Organizational Learning and Structuring

Matthew Koehler[1], Luciano Oviedo[2], Michael Taylor[3]

[1]The MITRE Corporation, McLean, VA
mkoehler@mitre.org
[2]The Intel Corporation, San Jose, CA
luciano.oviedo@gmail.com
[3]The Steelcase Corporation, Grand Rapids, MI
mtaylor5@steelcase.com
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Abstract. This paper discusses the creation of a general framework, expressed as a flexible agent-based model, to explore the impact of organizational learning and structure to the performance of firms or governmental intervention and regulation. The agent-based model is made up of firms, employees, products, and customers. The motivation is to characterize implications from different combinations of the framework itself and the results of an initial experiment to establish empirical relevance 0+ are discussed. While many aspects of the system under study have been dealt with in prior literature, we are unaware of any attempt to combine all elements of a functioning market in a tractable, parsimonious manner. The paper concludes with next steps[*].

Introduction

The 20th century gave birth to the modern notion of a corporation through companies such as Kodak and IBM; both of which evolved to reach a global presence. For example, by 1996, Kodak commanded over two-thirds market share in global photography, revenues reached nearly $16B, its stock exceeded $90, was worth over $31B and was the fifth most valuable brand in the world. On the other hand, IBM lost more than $8B in 1993, its third straight year of billion dollar losses, and since 1991 had lost $16B; leading them to shrink to 225K employees by 1995, a 45% decrease from 10 years earlier. Yet, by 2012, Kodak had filed for bankruptcy and IBM evolved to new heights.

How could this happen? Why do organizations, which can seemingly harness vast networks of resources, seem to struggle in coping and dealing with the complexity surrounding their value chain's evolution?

Although, these dynamics are not unique, the mechanisms that may lead to them are difficult to understand or anticipate. In order to pursue characterizing the major components of these dynamics, we designed and built a model and simulation for

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exploring how structuring and learning decisions in human-based systems impact organizations – i.e., how might we enable increased understanding for how structuring and learning (to anticipate) decisions impact organizations; as measured by (firm) performance or (governmental) economic policy.

To achieve this, we created an initial agent-based model to serve as a foundation for evaluating entry scenarios in preparation for the more detailed long-range goal of a detailed analytic capability.

Standing on the Shoulders of Giants

Agent-based modeling of exchange and firm dynamics has a comparatively rich history within the computational social science discipline. Some of the most notable previous works include: Epstein and Axtell's (1998) Sugarscape in which agents traded sugar and spice with each other. This work demonstrated, inter alia, that decentralized exchange can produce a clearing price despite the absence of a Walrasian auctioneer and perfectly rational actors (see also, Axtell 2007). More specialized market models have also been created from Lux's work in 1999 to the extremely rich "Santa Fe market model" (Darley and Outkin 2007) to the purposefully simple "zero intelligence trader" model (Farmer 2005). This work showed that the "traditional" stylized statistical signature of financial markets (Ghoulmie, et al. 2005) can be produced "naturally" by the interaction of multi-agent systems and does not require the strong assumptions necessary for canonical economic theory to produce non-Gaussian dynamics. There have also been larger programs examining economics as a complex system most notably the Economy as an Evolving Complex System series, and new work by Arthur (2015) and Kirman (2011).

Firm dynamics and group decision-making and influence have been a focus, also. Axtell (1999) examined the dynamics of firm formation, growth, instability, and eventual decline; as demonstrated by a very parsimonious model of firm growth driven by simple, utility maximizing worker agents. Perhaps the best known early work on models of social influence is Axelrod (1997) in which a population of agents show dynamics of local convergence while maintaining global heterogeneity. Additional mechanisms for the creation of this sort of dynamic have been articulated by Bednar and Page (2012). The importance of maintaining diversity for problem solving has been highlighted recently by Hong and Page (2009) and Page (2007 and 2011). Finally, the application of computational social science to the problems facing industry and government also has a rich history organizationally, e.g. The Santa Fe Institute Business Network, and within the literature (see, for example, Room (2011), Colander and Kupers (2014), Axelrod and Cohen (1999), North and Macal (2007), and Barry et al. (2008)).

The Simulation, Initialization & Instantiation

As discussed *supra* the purpose of the model is to create an analytic platform to allow us to explore the dynamics associated with organizational design and knowledge management. The current version of the model was created as part of a hypothesis development process to experiment on our initial views on what components would be necessary for such an exploration. Our intent was to create a minimal model that would have relational equivalence (Axtell, et al. 1996) to the dynamics seen in the “real” world via a Level of Empirical Relevance 0 (Axtell 2005) simulation. The model we created is an agent-based model (Epstein and Axtell 1998, Axtell 2000, Railsback and Grimm 2012, Wilensky and Rand 2015). We chose the NetLogo (Wilensky 1999) framework for this initial implementation given its relative development speed and ease of sharing across multiple platforms. There are four types of agents contained within the model: Firms, Employees, Customers, and Products.

At instantiation, the simulation initializes all global variables and data collection of data structures. A user specified number of Customers are then created and structured as a small world network (Watts and Strogatz 1998) via the Kleinberg model (Easley and Kleinberg 2010). Next, Customers are given their initial Product feature desires. This is a user specified, fixed length bit string that can contain one of three values in each string position: 0/1, or a wildcard. 0/1 represents two potential types of a feature and the presence of a wildcard means that that particular consumer does not care about that feature. To create the bit string customers first choose a random uniform number of features to care about from 1 to the length of their bit string. Next, they populate that number to 1s and 0s. Finally, the finish filling up their bit string with wildcards as needed. Therefore, for example, if the bit string is 50 positions long three will be 350, or ~7.2E23 possible feature set desires within the population. After Customers are created, the pool of Employees is created. Each Employee is given a skillset. It is created in a manner similar to that of the desires of the Customers. Namely, the Employee “chooses” a random number of skills which are randomly populated with a 1 or 0, the rest of the bit string is filled in with wildcards. Here wildcards represent the absence of knowledge about that particular feature or an inability to create said feature.

Upon completion of the initialization of Employees, a user specified number of Firms is created. Then, each Firm is given an Employee from the pool created previously (every Employee may be assigned to only one Firm and that assignment will not change over the course of a simulation run). The Firm also sets its tolerance for product performance (discussed below). Finally, the Firm creates a Product (discussed below).

Firm tolerance is used as a way for firms to react to the performance of a product. If a Product has drawups or drawdowns that exceed the firm’s tolerance then the firm may take action. If the Product is doing well (its drawups exceed the firm’s tolerance) and the Firm’s surplus (ie, revenue) is large enough, then the firm may add a feature to the Product or create a completely new Product. If the Product is doing poorly (its drawdowns exceed the firm’s tolerance) then the Firm has the option to either remove a feature (in the hopes that that will improve its sales) or discontinue the Product altogether. To remove a feature, the Firm replaces one non-wildcard value in the Product’s bit string with a wildcard. If the Product has only one feature in its bit string the firm discontinues the Product. Tolerance is used to impact a firm’s interest in “change.” Low tolerance (< 25) firms are thought of as innovators, high tolerance (> 75) firms are thought of as laggards, and firms in the middle are thought of as midlevels. Interestingly, drawups and drawdowns were much more effective signals for the firms. Initially, firms tracked a raw sales score (number of times purchased minus number of times offered). When firms tracked that signal every time the simulation was run eventually all firms went out of business or left the market. Essentially, the raw sales score had too much memory and would allow numerous past successes to overshadow changes in the preference of the Customers making firms blind to the need to adapt their products.

Firms create Products by building out a bit string of features that are assigned to a Product. Features may only be added to the Product if at least one of the Firm's Employees has a non-wildcard value in that bit string position. As wildcards in this case represent the absence of a feature, a Product's feature bit string may not include all wildcards.

Conformity and Consistency Dynamics

Both Customers and Employees may undergo conformity and consistency dynamics (Bednar et al. 2010). This process was used to account for potential homophily and contagion dynamics seen in social phenomena (Lazarsfeld and Merton 1954). After Bednar et al. (2010) consistency dynamics are accomplished by having agents take their bit string of desires (for Customers) or skills (for Employees) and with some probability copying the value from one location of their bit string into another location. The conformity dynamic is accomplished by allowing, with some probability, Customers to pick another Customer from their social network and then copying the value from one location within that agent's bit string into the same location within their own bit string. When these forces are turned on the customers are considered dynamic; otherwise customers are considered static. For Employees, the process is the same, however, rather than using a social network they choose another employee that is employed at the same firm as they themselves.

A fixed length bit string was chosen after Kollman (1998) and due to the relative ease to which it maps to real world product features, skills, and desires. Here the non-wildcard values correspond to one of two different options, 0 or 1, for a specific feature (for Products), desired feature (for Customers), or skills (for Employees). The wildcard is used to designate the lack of a feature (for Products), the idea that a Customer may not care if a Product contains a feature or not, or the lack of ability to create said feature (for Employees).

Runtime Dynamics

This simulation is time stepped, meaning at each round all existing agents are activated exactly once and perform some set of actions. At the start of each time step the simulation checks to see if all Firms have left the market or gone out of business. If that is the case, then the simulation ends. If there is at least on Firm in the market the run continues. For each type of agent, the order in which they are activated is randomized to emulate concurrency. However, an agent's state is not buffered; therefore, we are not emulating true concurrency such as is used in Conway's Game of Life. The potential impact of buffered versus unbuffered agent updating was not explored as part of this study. It should also be noted that we have not yet explored the impacts of scale on model dynamics (Anderson 1972).

If there is at least one Firm offering at least one Product, then Customers are activated and examine the available Products for the one they would "like to purchase." "Like to purchase" here means that the Customer has found a Product with a minimum feature set that matches their desires within a user specified error rate (which may range from 0, where the product must be a perfect match, to 1, where any product will do). The products are searched from the smallest number of features to the largest number. This introduces a bias towards choosing Products with a minimum number of features to satisfy the desires of the consumer. This was done to incorporate price elasticity to the system. If one assumes here, as we have, that the number of features is positively correlated with cost, then, ceteris paribus, Customers should be more willing to buy Products that just meet their desires and do not provide more features than necessary. If a Product is "purchased" then the firm that is offering a Product that is purchased by Customer, then it is given an abstract amount of utility equal to the number of features the Product contains (non-wildcard values in the products bit string). If conformity or consistency dynamics are turned on, then Customers undergo those processes.

Once the Customers are finished, the Firms are activated. The Firms first add a small amount of noise to their tolerance score (random normal distribution with a mean of 0 and a standard deviation of .05). This is used to create a bounded random walk (the values of tolerance are bounded at .1 and 99). Next, they check to see if they should leave the market/go out of business. If they have a great deal of debt or if they have no Products available, then they leave the market/go out of business. If barriers to entry are turned on then no new firm will take its place; otherwise, a new firm will take the place of an exiting firm. If they do not decide to leave the market or go out of business, then they decrement their surplus (i.e., revenue) by the carrying cost of their Product line and ask their Employees to undergo conformity and consistency dynamics. Finally, Firms examine the performance of their Products. If the Firm is performing poorly, e.g., the product has not been purchased in a number of consecutive time steps greater than the Firms tolerance value, then the Firm discontinues the product. Next, the Firm examines one, at random, "active" Product. Here "active" means a Product that is being purchased or not often but not consistently not being purchased. If a Product is being purchased frequently and the Firm has sufficient surplus, then the Firm will, with equal likelihood, add a feature to that Product or create a new Product. To add a feature, the Firm takes the Product's features bit string and moves across it until it finds a wildcard location that corresponds to a location in the skills bit string of at least one of its Employees and then replaces that wildcard with the value found at that locus within the skills bit string of its Employee. To create a new product, the Firm creates a new Product agent and then builds that Product's features bit string by randomly creating it from the skills bit strings of its Employees. If, on the other hand, the Product is not performing well (is not purchased regularly), then, with equal probability, the Firm may remove a feature or stop offering the Product altogether. To remove a feature, the Firm replaces a location within a Product's feature bit string with a wildcard. Once the firms are done, a new time step begins.

Analysis and Results to Date

As discussed supra, we created this model to evaluate entry scenarios that explore important components of a maturing market with dynamic customer preferences. This being the case, we attempted to create and analyze the model to demonstrate Level 0+, micro-level qualitative, Empirical Relevance (Axtell 2005) with Relational correspondence to the referent system (in our case the real world) (Axtell, et al. 1996). This overall framework is discussed in more detail in Koehler (2014). Practically speaking, what Empirical Relevance Level (ERL) 0+ means is that we should have agents that behave plausibly for the system being questioned and at a macro-scale, we have a system that displays aggregate dynamics that are qualitatively similar to that of the referent of interest (i.e., real world market dynamics). This being the case, our hypotheses, at a high level, are:

Hypothesis 1: Low barriers to entry lead to more variety available to Customers (in terms of Products and Features);

Hypothesis 2: Laggards (i.e., Firms that are slower to change) should be more likely to leave the market/go out of business;

Hypothesis 3: In the short-run, a static/mature market should produce more Firm surplus (revenue) than an emerging/fragmented market.

In order to perform an initial test of the aforementioned hypotheses, we completed a limited design of experiments (DOE) described in Table One.

Design of Experiment	Initial-Mix-Of-Firms (Innovators, Midlevels, Laggards)	Barrier-To-Entry	Customer-Dynamics
DOE1	25%, 50%, 25%	On	Dynamic
DOE2	25%, 50%, 25%	Off	Dynamic
DOE3	0%, 50%, 50%	On	Dynamic
DOE4	0%, 50%, 50%	Off	Dynamic
DOE6	25%, 50%, 25%	On	Static
DOE5	25%, 50%, 25%	Off	Static

Table One. The DOE that was run.

Results

All analyses were performed with Mathematica 10.2, All statistical comparisons were made via the nonparametric Kruskal-Wallis test (Montgomery 2005) due to the non-Gaussian distributions contained within our output data. Finally, as is the case with many simulation-based analyses, our simulation generated enough data and therefore, enough statistical degrees of freedom to make almost all numeric differences significant.

Hypothesis 1: Low barriers to entry lead to more variety available to Customers (in terms of Products and Features);

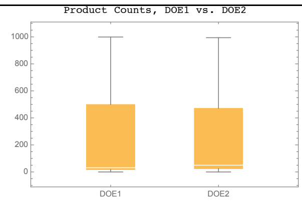
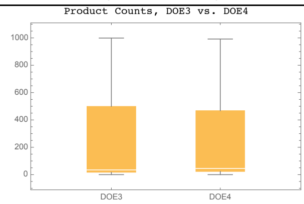
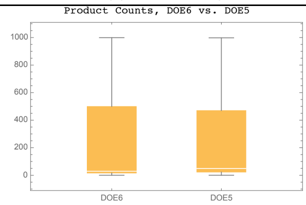
Comparison	Box and Whisker Charts	K-S test results
DOE1 vs. DOE2		P-value: 1.34×10^{-123}
DOE3 vs. DOE4		P-value: 1.77×10^{-83}
DOE6 vs. DOE5		P-value: 1.26×10^{-143}

Table Two. Results of Hypothesis 1.

Hypothesis 1 Support (summarized in Table Two): Fail to reject. In all cases, lower barriers to entry produced more products per time step than did high barriers to entry. This occurred despite the fact that there were no inherent limits to how many products a firm could make available to consumers.

Hypothesis 2: Laggards (i.e., Firms that are slower to change) should be more likely to leave the market/go out of business;

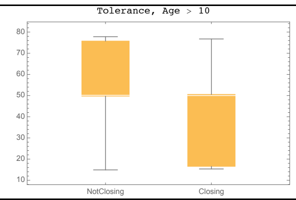
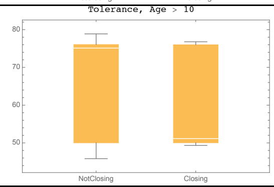
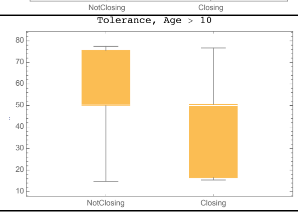
Design Point	Box and Whisker Chart of Results	Statistical Analysis
DOE1		P-value: $1.61x10^{-11}$
DOE2		P-value: $5.43x10^{-1433}$
DOE3		P-value: 0.203
DOE4		P-value: $4.69x10^{-3175}$
DOE5		P-value: $5.54x10^{-2597}$
DOE6		P-value: $1.03x10^{-31}$

Table Three. Results for Hypothesis 2.

Hypothesis 2 Support (summarized in Table Three): Rejected. The overall reactivity of closing firms is higher (lower tolerance values) for closing firms than for firms that stay open. This difference is not statistically significant. However, the reason the reactivity is increased for firms that close is due to the fact that most firms that leave the market are young and by definition more reactive. This dynamic washes out the other dynamics that may cause more mature, less reactive firms to leave.

Hypothesis 3: In the short-run, a static/mature market should produce more Firm surplus (revenue) than an emerging/fragmented market;

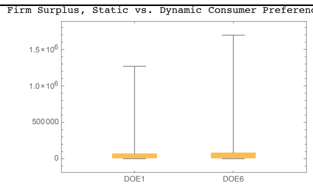
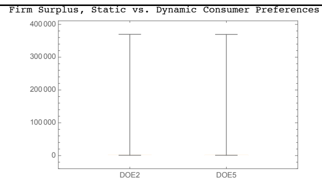
Comparison	Box and Whisker Chart	Statistical Results
DOE1 vs. DOE6		P-value: .0035
DOE2 vs. DOE5		P-value: 5.49×10^{-11}

Table Four. Results for Hypothesis 3.

Hypothesis 3 Support (summarized in Table Four): Mixed. In the case, with high barriers to entry the firm, surplus/revenue is statistically significantly higher when Customers preferences are static. However, in the cases with low barrier to entry, the Firm surplus/revenue is higher in the dynamic case. This is likely the case because new firms had little time to discover the preferences of consumers before they were driven back out of the market.

Conclusions

This model represents a first step towards building an analytic capability designed to provide a simulation-based laboratory to better understand the interplay between dynamic customers, adaptive firms with heterogeneous internal organization, and governmental economic policy. Our next step will be to represent the internal dynamics of the firm (employee organization, information flow, and movement) and build up the policy/regulatory layer. Although this is early in this work we felt it important to document the initial foundation rather than solely the finished product to aid in replication should a third party decide to do so. Finally, we also wished to elicit early review of the mechanisms chosen to drive the simulation dynamics. Our motivation was to find a small number of mechanisms to be used ubiquitously within the simulation. Humans are a collection of skills and desires that are influenced via social and employment networks. Firms are collections of humans. Products are collections of features driven by human skills and desires. From these relatively simple building blocks we hope to create a simulation tool that will let us explore the implications of organizational structure and governmental activities.

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