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Modeling the evolution of generativity and the emergence of digital ecosystems

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Abstract

Recent literature on sociotechnical systems has employed the concept of generativity to explain the remarkable capacity for digital artifacts to support decentralized innovation and the emergence of rich business ecosystems. In this paper, we propose agent-based computational modeling as a tool for studying the evolution of generativity, and offer a set of building blocks for constructing agent-based models in which generativity evolves. We describe a series of models that we have created using these building blocks, and summarize the results of our computational experiments to date. We find in several different settings that key features of generative systems can themselves evolve endogenously, including "core" components and reusable parts. Moreover, we find that boundedly rational designers without coordination or foresight can evolve business ecosystems that satisfy a diverse range of consumer preferences and exhibit robustness to changes in these preferences over time.

Keywords: Simulation and modeling IS, digital business ecosystems, complexity theory, platform design, innovation

Introduction

The capacity to generate novelty is critical to a wide variety of systems, from biological organisms to firms and industries to the global economy. Recent literature on sociotechnical systems has focused on the concept of *generativity*, "a system's capacity to produce unanticipated change through unfiltered contributions from broad and varied audiences" (Zittrain 2008, p. 70). Digital artifacts have proven to be remarkable enablers of generativity due to their distinctive characteristics (Yoo et al. 2010). Information systems (IS) scholars have thus taken a keen interest in understanding the structure of generative systems and the generative mechanisms that give rise to them (Yoo 2013; Henfridsson and Bygstad 2014), especially in the context of digital infrastructures such as the Internet (Tilson et al. 2010) and platform-based software ecosystems (Tiwana et al. 2010).

In this paper, we respond in three ways to recent calls for theorizing about generativity:

1. First, we propose agent-based computational modeling as a tool for studying the evolution of generativity, and explain how this tool can complement both verbal theorizing and empirical

analysis. This allows us to connect these calls to broader currents in the social sciences and the sciences of complexity, where scholars have been asking similar questions in different domains.

2. Second, we offer a set of building blocks for constructing agent-based models in which generativity evolves. These discrete clusters of modeling assumptions can be combined in many different ways to investigate the forces that give rise to digital business ecosystems.
3. Third, we describe a series of models that we have created using these building blocks, and summarize the results of our experiments with them, with a focus on the implications for generativity and its evolution.

Despite the challenges of studying a phenomenon as complex and subtle as generativity, our initial results are promising. We find in several different settings that key features of generative systems can evolve endogenously, including "core" components and reusable parts. Moreover, we find that boundedly rational designers without coordination or foresight can evolve rich ecosystems of products that satisfy a diverse range of consumer preferences and exhibit robustness to changes in these preferences over time. These findings present exciting opportunities for IS researchers to develop models that can account more directly for the emergence of familiar features of digital ecosystems such as interfaces, standards, and layered architectures.

The remainder of the paper is structured as follows. In the next section we briefly review the literature on generativity and the modeling of generative processes. We then describe the building blocks of our models, which include assumptions about material entities (components and products), social entities (consumers and producers), institutions (organizations and markets), and dynamics (population selection and environmental change). After that we present our models and results, followed by a concluding discussion of the research opportunities for adventurous scholars.

Approaches to Generativity Within and Beyond IS

Although the term generativity can be traced to Erikson's (1950) model of psychosocial development and Chomsky's (1965) concept of a generative grammar, it came into use as a property of sociotechnical systems primarily through Jonathan Zittrain's law review article (2006) and book (2008) on the topic. Yoo et al. (2010) and Tilson et al. (2010) brought the term into the information systems literature in their research commentaries on digital innovation and digital infrastructures for the 20th anniversary special issue of *Information Systems Research*. Yoo et al. (2010) noted that layered modular architectures promote generativity by enabling "loose couplings across layers whereby innovations can spring up independently at any layer, leading to cascading effects on other layers" (p. 728), while Tilson et al. (2010) posed the question, "how can we understand the dynamics of generative change associated with digital infrastructures?" (p. 753). Yoo (2013) subsequently called for the IS community to "provide a leadership role in shaping the theoretical and practical discourse around digitally-enabled generativity" (p. 231).

This burst of attention to generativity has coincided with a broader surge of interest among IS scholars in theories that embrace the complexity of technologies, organizations, and markets. For example, El Sawy et al. (2010) recently introduced the concept of digital ecodynamics to highlight the "dynamic mutual interdependence" (p. 837) between environmental turbulence, dynamic capabilities, and IT systems. In a similar spirit, Tiwana et al. (2010) proposed a framework for studying the coevolution between platform architecture and governance in dynamic environments characterized by technological convergence, multihoming costs, and influential complementors. Tanriverdi et al. (2010) observed more generally that businesses are increasingly faced with "wicked" problems in which "the parts of the problem interact with each other in nonlinear ways, self-organize, and produce emergent macrolevel behaviors that differ in scale and kind from the microlevel behaviors of the parts" (pp. 823–824). To address these problems, they called for the application of ideas from complexity science, such as the use of fitness landscape models (Kauffman 1993, Beinhocker 1999), to reframe the dominant "quests" of IS strategy research.

In the remainder of this section, we look beyond the IS discipline to identify a specific set of theories and methods that bear directly on generativity and provide a foundation for studying its evolution in the context of sociotechnical systems.

From Generative Social Science to Design Evolution

Zittrain's (2008) concept of generativity is an instance of a more general phenomenon that has long held the attention of scholars who study complex systems: emergent outcomes ("unanticipated change") arising from decentralized behavior ("unfiltered contributions from broad and varied audiences"). Over the past two decades, the complexity community has produced a large and growing body of research that seeks to explain this phenomenon in a wide range of settings and provide conceptual tools for reasoning about the causal mechanisms involved (Holland 1995; Kauffman 1995; Sawyer 2005; Mitchell 2009).

Epstein (1999) coined the label "generative social science" for efforts to explain the emergence of societal regularities as different as behavioral norms or price equilibria by asking what he called the generativist's question: "How could the decentralized local interactions of heterogeneous autonomous agents generate the given regularity?" (p. 41). Cederman (2005) developed the related concept of generative process theory to connect these efforts with the long tradition of process theories in sociology. Others have forged connections with economics by seeking to explain what the neoclassical tradition cannot, namely the explosion of variety and complexity in the goods and services produced by an increasingly interconnected global economy (Beinhocker 2006; Arthur 2009).

Taken together, these developments point to a simple explanation of how generativity arises: it evolves endogenously, without prior planning or central control. Systems that do not initially possess the capacity to produce unanticipated change gain this capacity through the same fundamental processes of variation and selection that operate in both biology (Mayr 2001) and socio-cultural systems (Campbell 1965), including organizations (McKelvey 1982), economies (Hodgson 1993), and design processes (Baldwin and Clark 2000).

Recognizing that generativity evolves is a powerful source of insight, but it leaves many questions unanswered. Why do some societies appear to be more generative than others? What kinds of policies promote or inhibit generativity? How can the generativity of a system be managed for competitive advantage, and under what conditions does this benefit or harm consumers? To answer these kinds of questions, we need tools that can be used to study the evolution of generativity in specific settings.

Agent-Based Modeling as a Theory Building Tool

Although agent-based computational modeling is not a tool solely of complexity science, it achieved prominence and a certain degree of respectability through the efforts of the complexity community to secure its epistemological and methodological foundations (Axelrod 1997; Epstein 1999; Carley 2001; Henrickson and McKelvey 2002; Miller and Page 2007). A broad consensus now exists that agent-based modeling and computational simulation constitute "a third way of doing science, in contrast to both induction and deduction" (Axelrod 1997, p. 35), and a useful tool for building theories of complex adaptive systems. It has also been observed that there is a natural alignment between agent-based modeling and critical realism (Miller 2014), which emphasizes the concept of "generative mechanisms" and has attracted recent interest in the IS community (Mingers et al. 2013), in particular as a philosophical basis for theorizing about digital infrastructure (Henfridsson and Bygstad 2013).

Our own agent-based models are related to the NK family of fitness landscape models (Kauffman and Levin 1987; Kauffman and Weinberger, 1989), which we adapted to study populations of product designs in which different products have different architectures. This distinctive feature of our approach allows us to study product architecture as the endogenous outcome of an evolutionary process. Other scholars who have used the NK framework to study design choices include Marengo et al. (2000), Ethiraj and Levinthal (2004), Rivkin and Siggelkow (2007), and Frenken and Mendritzki (2012). Our models are also indebted to the generalized NK model of Altenberg (1994), which was adapted to the domain of complex technological systems by Frenken (2006).

Building Blocks for Generative Models of Product Design

Having established, we hope, that complexity science and agent-based modeling provide appropriate foundations to study the evolution of generativity, we now ask: What building blocks are needed to develop models that exhibit generativity and shed light on issues of interest to IS scholars?

The most satisfying kind of answer to this question would establish necessary and sufficient conditions for generativity across a well-defined class of models. We are a long way from this kind of answer, but that is probably true of the vast majority of formal modeling efforts in the social sciences. (Consider neoclassical microeconomics as an exception that proves the rule: it took nearly three quarters of a century to get from Alfred Marshall's *Principles of Economics* to the Arrow–Debreu model of general equilibrium.)

Instead, in the remainder of this section we describe in a schematic way the family of models we have created over the past five years to study a range of phenomena related to generativity, including the emergence of modularity and platform architectures. These models share a broad set of features, but differ substantially in their detailed assumptions. We thus adopt the term "building block" to denote a discrete cluster of modeling assumptions can be combined with others in a variety of ways.

While we cannot prove that any particular combination of building blocks is either necessary or sufficient for the evolution of generativity, our hunch is that collectively they provide a useful starting point for modelers interested in exploring the forces that give rise to generativity. Thus, in the spirit of maximizing the generativity of our own work, we believe it is worthwhile to describe them before turning to the specific models and their results.

Material Entities: Components and Products

Two types of entities are present in all of our models to date: *designs* and *designers*. From a sociomaterial perspective (Orlikowski and Scott 2008; Yoo 2013), the former belong to the domain of material artifacts while the latter belong to the social domain. We further distinguish two types of designs: *components* are primitive units of design structure, which can be combined into *products* (which, in turn, may possibly be combined with other products in a nested hierarchy).

Components are the most basic design elements in our models. They play a role analogous to that of genes in biological models or decisions in models of organizational choice. In some models, a component can either be present or absent, while in other models all components are present but designers can choose between two more *variants* (alternative designs or configurations, analogous to the alleles of a gene).

A complete design consists of a set of components, which we call a product. Following convention in the NK modeling literature, a product can be represented as a string of digits (usually binary), each of which represents the state of a given component (its presence or absence, or the variant chosen). In some models we also allow products to be further combined in a nested hierarchy (Murmann and Frenken 2006). This setup allows us to investigate open-ended architectures, where products can be combined in ways that are unanticipated by their designers (Adomavicius et al. 2008, Yoo et al. 2010).

Social Entities: Consumers and Producers

The social entities in our models are the agents. All of our agents are designers in the sense that they engage in design by combining components or products together, either for their own use or the use of others. Agents who design for their own use are called *consumers*, while those who design for others are called *producers*.

Following Baldwin and Clark (2000), both types of designers "see and seek value." They are boundedly rational in the sense that they cannot instantaneously evaluate all possible combinations of components or fully anticipate the consequences of their design choices. But they are "smart" enough to form expectations based on limited information (e.g., if nothing else changes, will adding this component raise or lower the value of my existing product?). And given a limited set of possible choices (e.g., adding one of 10 components to a product), they choose the action with the highest expected value.

Value is created by consumers, who derive benefits from the *functions* enabled by a design. Each component enables (or affords) one or more functions, each of which contributes value to a product as a whole. An *interaction* occurs when multiple components jointly enable the same function. For a particular design, the amount of value contributed by each function is determined by the states of the components that enable it. Again following the NK modeling literature, we typically assume that these function values are drawn independently at random, and that the total value of a product is simply the sum (or mean) of its function values.

Producers earn a living by capturing a share of the value created by their designs (see Lepak et al. 2007 on the distinction between value creation and value capture). The rules that determine how producers and consumers interact with each other and how value is appropriated are discussed below.

Institutions: Organizations and Markets

The designers in our models, as in real-world sociotechnical systems, are embedded in an institutional context that enables and constrains their actions (Orlikowski and Barley 2001).

While we have not yet devoted significant effort to modeling many features of the environment that institutional theory regards as first-order concerns, such as culture, norms, and beliefs, we embrace the institutionalists' call to make explicit the "rules of the game" (North 1990) that govern the interactions among the agents. Following Simon (1991), we focus on rules relating to *organizations* and *markets*.

In the simplest case, a fixed number of agents engage in repeated episodes of product design by selecting among freely available components. In this case, there is no need to introduce organizational boundaries; we can simply assume that the agents represent individual consumers who obtain direct use value from their products. There is also no need for a market, since no transactions occur, and every consumer captures all of the value he or she creates.

In a model with both producers and consumers, however, we need to specify how producers are paid for making products that consumers combine in a nested way. If a consumer combines three products into a system with a value of 0.87, for example, how much should each producer receive? To answer questions like this requires making assumptions about market structure. This is a daunting proposition, as the entire field of industrial organization economics is devoted to such questions (see, e.g., Tirole 1988).

While we cannot possibly create models that are robust to all reasonable institutional assumptions, we believe it is both feasible and useful to explore a limited set of alternatives, and to study their impact on the evolution of generativity. For example, we have experimented with two different value capture rules (equal division and division according to the Shapley value) as well as a variety of explicit pricing mechanisms. We have also experimented with supply chains of various lengths, restrictions on which consumers can transact with which producers (as a proxy for geography or specialization), and varying degrees to which producers can copy each other's designs (as a proxy for intellectual property rights).

Dynamics: Population Selection and Environmental Change

Two additional building blocks could be considered institutional features of the agents' environment, but we call them out separately to highlight their role in the evolutionary dynamics of our models.

Population selection among producers can complement the selection of designs by individual agents as a source of evolutionary pressure. In some models we follow Levinthal (1997) in assuming that the probability that a producer survives is proportional to the ratio of its fitness to that of the most fit producer in the population. Non-survivors are replaced by new entrants in order to maintain a constant population size; a new producer may either replicate the design(s) of an existing one or start fresh with a new design.

An alternative approach to Levinthal's survival mechanism is to endow new producers with an initial stock of capital which depreciates at a constant rate in each period. Producers' revenues (value captured from consumers) are offset by production costs (fixed and/or variable), resulting in net increases or decreases to the capital stock. If costs and depreciation exceed value creation, producers can eventually go bankrupt; in this case, bankruptcy rather than relative fitness removes producers from the population.

Environmental change can take a variety of forms, including the introduction of new components that afford different capabilities (technological change), changes in consumers' preferences (market change), and changes in the ability of producers to interact with consumers (institutional change). Environmental change can be exogenous (determined by simulation parameters) or endogenous (determined by the state of the model as it unfolds in time). The need for adaptability in the face of exogenous environmental shocks turns out to be an important driver of generativity.

Models and Results on the Evolution of Generativity

This section describes a series of models we created using the building blocks described above, and summarizes the results of our experiments with them. Space constraints prevent us from including formal specifications of each model, so our intent in this paper is simply to provide a guided tour, highlighting the implications of our research for the study of generativity and its evolution.

We have been exploring what we called *endogenous adaptability* for more than five years. We were initially intrigued by the differences between biological ecosystems and human market-based ecosystems. The Cambrian Explosion was an almost preemptive event; virtually every body plan for multicellular animal life that has ever emerged on earth emerged during this brief geological period. Major extinction events have pruned some body types out and killed off enough existing species to create ecological niches that encouraged the emergence of new species, but these new species always evolved from existing species and no new body plans have been introduced since the Cambrian. In contrast, major market shifts lead to a process of Schumpeterian creative destruction, in which entire "body types" like horse-drawn carriages are replaced with steam engines and trains, or internal combustion engines and automobiles.

In preliminary modeling and simulation efforts, we were able to replicate both the Cambrian Explosion and Schumpeterian creative destruction by varying only a limited set of assumptions on the behavior and rationality of the agents in our model. This led to thinking about how much we could achieve in terms of explanatory models without any reliance upon explicit coordination among agents, and without assuming any planning or prediction at the individual level. That is, we sought to understand how much of current best practice in product development and engineering design could emerge endogenously from the simultaneous but uncoordinated behavior of boundedly rational agents.

Model 1: From Primordial Soup to Component Platforms

Our first full-fledged model of product design (Woodard and Clemons 2011) envisioned a population of products assembled from a "primordial soup" of primitive components. In this model, the value (or fitness) of a product depends solely on the particular combination of components it contains. Boundedly rational product designers modify these combinations in search of higher fitness. In some parameter settings, a population-level selection process weeds out designers with inferior products and replaces them with new entrants. Our model thus includes both blind (or myopic) variation and selective retention, the key elements of evolution in both natural and artificial systems (Campbell 1965).

To explore the structures and dynamics that are generated by different kinds of evolutionary processes, we studied three types of boundedly rational behavior (blind local search, myopic hill climbing, and greedy hill climbing) in the presence or absence of population selection. For the hill-climbing agents, we also varied the search radius of each step (1 or 2 component-level changes). We thus simulated 10 distinct processes, including the trivial case of blind search without population selection.

In 2010 we conducted a set of experiments using this model. Each of our three main experiments focused respectively on a different observable outcome: product size, superadditivity in component values, and a measure of platform emergence. The results are summarized below.

Experiment 1: Emergence of Complex Products

Our first experiment was designed to ensure that we understood the conditions needed for complexity to emerge in the products of our simulated ecosystem.

If we could not create conditions in which designers combined components to create products with greater functionality and value than the individual components available to them, we would be unable to demonstrate anything else of interest. We sought a minimum set of conditions that would be sufficient to ensure the emergence of complexity in that all of the assumptions were necessary and collectively they were sufficient; we made no attempt to guarantee that this was a unique set of necessary and sufficient conditions, or that it was the smallest such set.

We expected to find that complex products emerge under all of our simulated evolutionary processes (except the trivial case), since they all include the basic elements of variation and selection that characterize evolution in biological, organizational, and technological settings. As expected, these processes proved sufficient to produce the emergence of complex product designs, as measured by the average number of components per product. This finding is illustrated in Figure 1. The similarity in average product sizes (especially in the presence of population selection) provides evidence of the model's robustness to a wide range of assumptions about designers' environment and behavior.

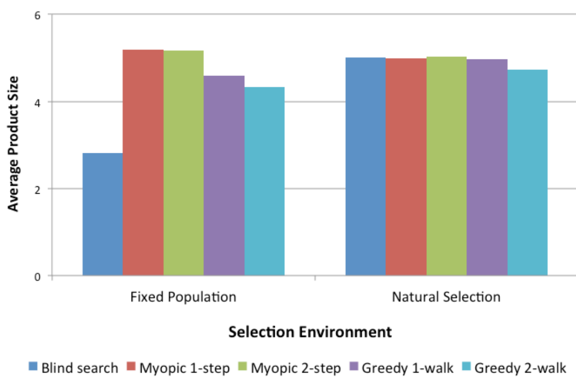

Figure 1. Average Product Size by Number of Components, Search Mode and Selection Environment

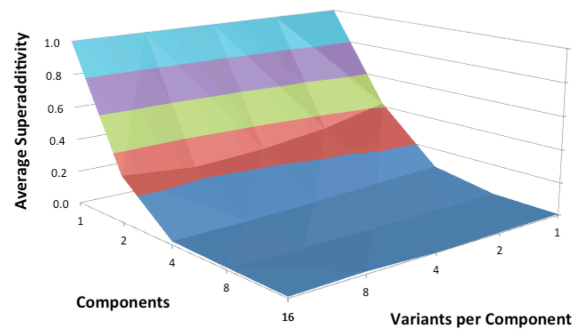

Figure 2. Average Superadditivity by Number of Components and Variants per Component

Experiment 2: (Non-)Emergence of Value-Added Systems

Our next experiment was designed to examine the emergence of products that are worth more than their components, which we called systems.

For the purposes of this model, we defined a *system* to be a product whose components exhibit superadditive value. That is, a system is a collection of components with greater value than the sum of the values of the individual components, much as a Swiss watch is worth more than the value of its case and gears, and an Apple iPhone is worth more than the sum of its case, chips, and operating system. We hoped to observe the emergence of behavior in which agents did not add any component to a product when its addition created incremental value less than the stand-alone value of the component itself.

However, we did not observe this behavior, as shown in Figure 2, which plots the fraction of products that exhibit even weak superadditivity (i.e., product value that equals or exceeds the sum of component values) under differing number of components and variants per component. Instead, we observed what we whimsically called asparagus-hats: despite the fact that the incremental value of adding an asparagus stalk to a Tyrolean hat is surely less than the value of the asparagus alone, there was no force in the model that prevented these kinds of subadditive combinations.

Despite our initial disappointment at this result, we concluded that a high degree of superadditivity may have been too much to expect under assumptions of limited intelligence among designers. Conversely, we did not want to simply impose superadditivity as an assumption (e.g., artificially constraining designers to only create superadditive combinations). In our combinatorial fitness landscapes, adding one or two products to an existing one might appear unproductive (i.e., yield subadditive value), but superadditivity might emerge with the addition of a third or fourth product. In other words, limiting the addition of components to those that create value-added systems might place excessive restrictions on evolution.

Experiment 3: Emergence of Component Platforms

Our final experiment with this model was designed to test for the emergence of platforms.

In the context of this model, we defined platforms as collections of "core" components (i.e., those that interact with a large number of other components) that were reused across a wide range of products. To measure the degree of platform emergence in a population of products at a given point in time, we constructed a "platform index" that accounts for the extent to which a particular variant of a given component achieves high reuse within the population, as well as the extent to which the component is core to the products that contain it and the diversity of other variants with which it is combined.

Our platform index captures the intuitive idea that a platform is not just a component or product that achieves 100% market penetration (i.e., a dominant design). Imagine if all "Wintel" personal computers were identical, regardless of their manufacturer; they used Intel chips, Microsoft Windows, Seagate hard drives, and the same flat-screen displays. In contrast, real Wintel PCs exhibit great diversity in their internal components and the software available to run on them, but commonality in their Intel-based processors and Microsoft-supplied operating systems. The real Wintel ecosystem would thus earn a higher platform index than a hypothetical monolithic one.

To investigate the forces that might drive the emergence of platforms, we added economies of scale and positive network externalities (participation benefits) to the model, as well as a form of innovation (the arrival of new variants over time). Without these forces, we found that the emergence of platforms is much less common than the emergence of dominant designs (i.e., convergence to a population of identical products). With them, we found that platforms emerged and persisted over time, as shown in Figure 3.

Additional findings include the following:

- The simple set of assumptions that were sufficient to generate complexity in the basic model are not sufficient to generate platforms.
- Increasing the strength of economies of scale and participation externalities further strengthens the emergence of platforms.
- In dynamic environments (when new component variants arrive over time), there is a cost to platform emergence in the form of technological lock-in.

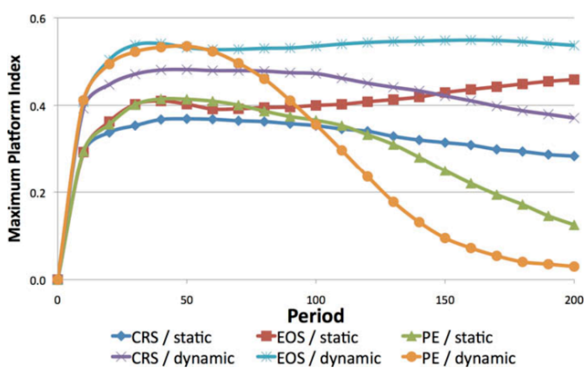

Figure 3. Maximum Platform Index by Returns to Scale and Participation

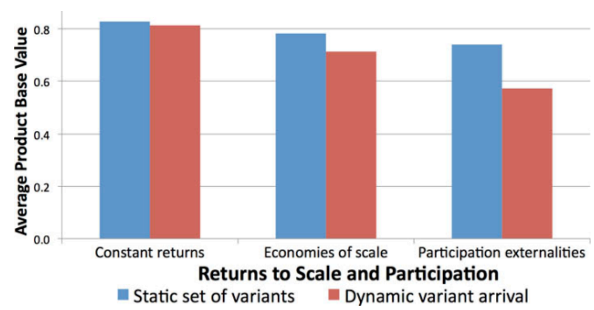

Figure 4. Costs of Lock-In: Differences in Product Base Value Under Static vs. Dynamic Variants

The cost of lock-in can be observed as a decrease in the average product base value, as shown in Figure 4. What this shows is that, on average, economies of scale and participation externalities tend to cause early-arriving variants to gain market share rapidly, making it more difficult to dislodge them later. In contrast, when all variants are present at the beginning of each simulation run, there is a greater chance that designers will select the ones that contribute the most use value to their products rather than the ones that simply have the lowest costs or strongest network effects.

This finding is intuitive, and echoes familiar results in the network economics literature. We found after further analysis, however, that even in the most extreme cases—under the highest value of the parameters driving the ecosystem towards platforms—the benefit from extensive periods enjoying the benefits associated with platforms more than compensated from the future loss associated with premature lock-in on an imperfect de facto standard.

Model 2: Modular Product Architectures and Platform Ecosystems

Our second model (described in Woodard and Clemons 2012) was designed to overcome some of the limitations of the first and allow us to explore a wider range of phenomena related to the evolution of complex products and systems.

The main change was to introduce an additional level of aggregation by allowing consumers to assemble products into multi-product systems. (We dropped the definitional requirement that a system be worth more than the sum of its parts; in the context of this model, any collection of products assembled by a consumer is referred to as a system.)

In this setup, the same functionality can be delivered in different ways. For example, a system containing five components could be assembled from one product containing all five components, or five products containing a single component each. This gives us a natural way to explore the emergence of modularity, which can be operationalized as the extent to which a system's functionality is delivered by multiple products rather than a single one.

The price for this additional richness is that we now need to specify how producers and consumers interact—in particular, how they divide the value created by the products that are combined into systems. To reward producers for contributing to high-value systems, we simply award each producer the full value of the system in which its product is used in a given period. This assumption creates favorable conditions for the emergence of modularity, since it avoids creating pressure for producers to inflate the size of their products to capture a larger share of their customers' system value. (On the other hand, it prevents us from treating value as a transferable quantity like money, which would otherwise be desirable.)

The main goal of our experiments with this model, which were conducted in 2011 and 2012, was to pick up where the first model left off, exploring the emergence of modularity and platform architectures in response to different set of economic forces—namely environmental change (in the form of changing consumer preferences) and consumer heterogeneity (the presence of multiple market niches). Our focus on these forces was driven by the recognition that modularity arises, at least in part, from the need to accommodate diverse and possibly changing consumer needs (Langlois and Robertson 1992).

In a static environment, there is little need to accommodate diverse or changing requirements. If consumers' preferences were the same and did not change over time, producers would be driven to maximum vertical integration. They would capture as much of the final value for themselves as possible, by producing products that consumers could use, "out of the box," with no need for combination or final assembly by the consumer. We modeled this by running experiments in which all consumers were endowed with the same set of fixed preferences (i.e., a single static fitness landscape).

In contrast, varying preferences over time would limit the possibility of full vertical integration, because consumers' requirements could change more rapidly than a fully vertically integrated producer could accommodate. These changes would create opportunities for producers of flexible modules, which could be combined in different ways in response to changes in consumers' preferences. Producers whose products can be easily recombined in new ways (e.g., because they contain fewer components that interact negatively with components in other products) should have an advantage in the marketplace. We modeled this by introducing periodic shocks that partly or fully randomized the mapping between component combinations and function values. In different simulation runs, we allowed these shocks to occur with different frequencies and different degrees of severity.

Likewise, having different sets of consumers with different preferences would reward creators of products that can easily be combined by different users to meet their own needs. For example, Seagate produces disk drives, assembled from many components, that are used in market segments as different as personal computers (desktop and portable), external storage devices, and enterprise data centers. We modeled this by having creating several sets of preferences (i.e., multiple fitness landscapes), each for a different market segment. In different simulation runs, we allowed variation in the number of segments and the degree of statistical correlation among them.

The main dependent variable in our experiments was a measure called average product centrality, which is based on the concept of group betweenness centrality from the social network literature (Everett and Borgatti 1999). This measure was motivated by our desire to identify not just fully formed and easily recognizable platforms (or fully modular architectures), but also proto-platforms: configurations of products and systems with platform-like characteristics.

Figures 5 and 6 summarize the main results of these experiments. The vertical axis in both graphs is the average product centrality measure defined above, and both graphs are shaded using the same color scheme.

Reasoning by analogy from biological evolution, we expected a complex and non-linear relationship between frequency and severity of change and the emergence of platforms. Environments that are very stable lead to stable, optimized systems that are often produced by a single integrated firm. As environmental change increases, it becomes advantageous to produce modules that can be reassembled in a variety of ways by a variety of producers (Baldwin and Clark 2000). In the technologically more stable markets of the 1960s, IBM was a vertically integrated computer company, GM was a vertically integrated car company, and AT&T was a vertically integrated telecommunications company. In the more turbulent environment of the early 21st century, it is more profitable to produce disk drives, or processor chips, or office software, that can be "mixed and matched" to satisfy changing market demand. When environmental change becomes too rapid or too severe, however, evolution can no longer select for products that work well together, and even well-adapted products fall victim to random shocks.

Figure 5 exhibits a striking visual pattern that supports this prediction: a diagonal "ridge line" that peaks in the region of frequent but moderate change. This figure shows that platform architectures are most strongly favored under precisely the conditions in which it is most valuable to have a stable set of core components that work well with a variety of peripheral ones. Most importantly for our research, we were able to induce the emergence of platforms without explicitly modeling participation externalities favoring widespread adoption or economies of scale favoring reuse, and without memory, learning, or anticipation on the part of product designers.

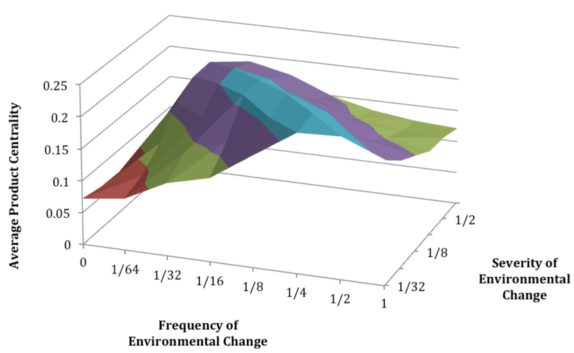

Figure 5. Average Product Centrality by Frequency and Severity of Environmental Change

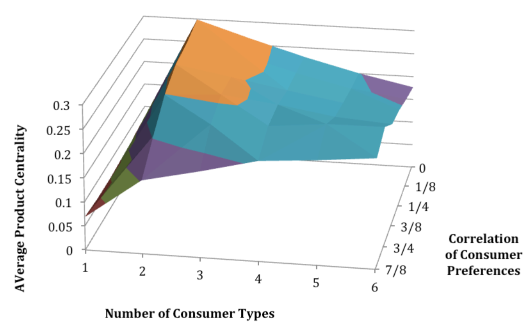

Figure 6. Average Product Centrality by Number of Consumer Types and Correlation of Consumer Preferences

Introducing consumer heterogeneity in the form of multiple market niches yielded results that were qualitatively similar to environmental change, as shown in Figure 6. As the number of market niches increases, so does the advantage of having a product that can be combined into systems with high fitness in multiple niches. Each niche represents a sub-population of consumers whose ideal products differ in one or more functional attributes (e.g., business or home computer users). As niches diverge, they begin to resemble separate, unrelated markets, and it is difficult to develop products that can succeed in all of them. Not surprisingly, the maximum average product centrality appeared under consumer heterogeneity rather than under environmental change, because in a stable environment evolution has more time to converge to a population of well-adapted products.

Model 3: Toward Generativity in Digital Ecosystems

Our modeling work in 2013 and 2014 has pursued two major goals: (1) to consolidate the results of the previous models into a single coherent framework, and (2) to account more directly for the emergence of familiar features of digital ecosystems such as interfaces, standards, and layered architectures.

To achieve the first goal, we have converted many of the "hard-coded" assumptions of the previous models into parameterized modules that can be configured independently. This process has enabled a variety of generalizations. For example, the current model supports an arbitrary number of nested layers of product assembly, and the ability to add new layers endogenously. We have also continued to explore ways to make the model more realistic without sacrificing parsimony and transparency, including implementing several different "budget-balanced" value capture rules and product pricing mechanisms. These efforts have yielded a nice meta-result: a model of platforms that itself has a platform architecture.

Our interest in the second goal has been spurred by our engagement with the IS literature on generativity and digital ecosystems, which emphasizes the distinctive features of digital artifacts and suggests that they can play a uniquely powerful role in the evolution of generativity. For example, the self-referential nature of technology means that "the diffusion of digital innovation creates positive network externalities that further accelerate the creation and availability of digital devices, networks, services, and contents" (Yoo et al. 2010, p. 726). In contrast to physical technologies like internal combustion engines and emission control systems, which operate on different physical principles and draw upon knowledge from different fields, digital artifacts seem to catalyze their own complexification, which Arthur (2009) calls structural deepening. While some of these differences can be captured by existing parameters in the model (e.g., digital artifacts tend to have stronger network effects and greater economies of scale than physical ones), we see the potential to obtain new insights by focusing on distinctively digital phenomena.

Conclusion

In this paper, we responded in three ways to recent calls for theorizing about generativity. First, we proposed agent-based modeling as a tool for studying the evolution of generativity, and explained how this tool can complement both verbal theorizing and empirical analysis. Second, we offered a set of building blocks (i.e., discrete clusters of modeling assumptions) for constructing agent-based models in which generativity evolves. These building blocks can be combined in many different ways to investigate the forces that give rise to digital business ecosystems. Third, we described a series of models that we have created using these building blocks, and summarized the results of our experiments with them.

We believe the findings from this research present exciting opportunities for like-minded IS researchers. For example, we see opportunities to bridge the sociomaterial and economic perspectives on platforms and generativity through models that incorporate boundedly rational value-seeking behavior without "black-boxing" the structural and dynamic complexity of evolving digital artifacts, as game-theoretic models of platform competition are often forced to do by the imperative of obtaining closed-form mathematical results. We also see opportunities to connect these models with the empirical analysis of network data from large software systems (e.g., Um et al. 2013). Empirical data can be used to calibrate the models once they reach a certain level of maturity, and the models may be able to help shed light on the causal mechanisms behind the data. Finally, it only takes a casual glance at the news to appreciate the practical relevance of these ideas to the world of high-technology strategy and innovation. Despite the fact that formal models can seem forbiddingly abstract, we believe that an important indicator of their success is the extent to which they can be applied to problems that matter in the real world.

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