Computational Modeling of Business Ecosystem Dynamics

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Abstract

This paper presents a multi-method approach for computational modeling of complex business ecosystem dynamics that enables strategic decision support. Our computational model is informed by theories of business strategy, organizational ecology, and interfirm networks, and uses real-world data mined from public and proprietary sources. Using a complex system and network analytic lens, our model provides insights into how the interconnected nature of actors, capabilities, and interfirm behaviors (mergers, acquisitions, and collaborations) can lead to different ecosystem characteristics. We discuss results and extensions of this work.

1. Introduction

Today's business environment is characterized by rapid change, significant technological advances, emerging actors, global competition, and a continuous need to innovate. To cope with these challenges and ensure sustained competitiveness, companies increasingly seek interfirm collaboration and acquire new capabilities through mergers or acquisitions. Indeed, there is an increased recognition that value is co-created through a complex ecosystem of actors. Existing business frameworks, however, appear to fall short in fully capturing the intricate complexities that shape this new dominant form of economic organizing; consequently new theories of ecosystems are emerging [1]. Yet, there still remains a paucity of empirical studies and practical tools that can aid decision makers in quantifying, characterizing, and understanding complex ecosystem dynamics and using those insights to drive strategies. This paper fills this gap by presenting and illustrating a multi-method approach for computational modeling of complex business ecosystem dynamics.

2. Related Work

The study of business ecosystems has been growing steadily over the past two decades [2, 3, 4, 5]. The key tenet is that business ecosystems are characterized by a heterogeneous and continuously evolving set of firms that are interconnected through a complex, global network of various types of relationships, including alliances, partnerships, investments, or subsidiaries. The primary focus of studies to-date has either been on describing the nature of ecosystems, goals of members, and relationship between members.

The lack of work on understanding the dynamic, evolutionary aspects of business ecosystems as a whole, which may determine an individual company's success within the ecosystem, may in part be attributed to challenges in identifying comprehensive temporal ecosystem data that could help inform our understanding of the dynamic complexities inherent in these systems [6]. To overcome this, scholars have often reverted to studying the evolution of ecosystems using a snapshot approach, interpolating structural changes over time.

More recently, there has been a call to adopt a complex adaptive systems lens to the study of ecosystems [7]. It has been argued that phenomena like dynamism, emergence, or adaptability are often missed in studies with a predominantly static snapshot investigations of ecosystems. With advances in computational methodologies and tools, such as visual analytics and agent-based modeling, it is now possible to model ecosystems as a system of heterogeneous agents that evolve and interact with one another, leading to emergent system behavior that would be difficult to understand by studying individual parts alone [8].

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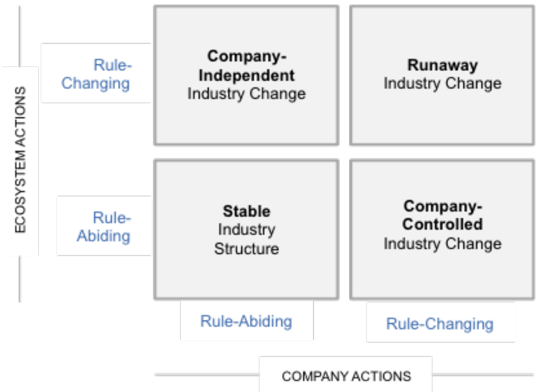

Figure 1. Ecosystem Strategy Dynamics.

A valuable guidance for developing a computational model of ecosystem dynamics is the framework on strategy dynamics for corporate longevity [9]. The framework juxtaposes actions taken by a focal company and members of the ecosystem (see Figure 1). A *stable* industry structure is characterized by the fact that the focal company as well as all members in the ecosystem are rule-abiding, i.e., predictable. A *company-controlled* industry change reflects an ecosystem where the focal company drives changes in the ecosystem while the *company-independent* industry change reflects a changing ecosystem driven by various players in the ecosystem that does not include the focal company. The most dynamic ecosystem is labelled *runaway* industry change; it reflects the fact that both the focal company along with ecosystem players are rule-changing, i.e., unpredictable. Our computational model operationalizes these definitions.

3. Methodology

To model and understand business ecosystem dynamics, we utilize a multi-step research approach (see Figure 2), broadly grouped into two parts: an empirical analysis and a simulation analysis. The approach extends key steps proposed in prior data-driven studies of ecosystems [10, 11] with best practices from complex systems modeling and simulation [12].

Our approach begins with the identification and curation of relevant ecosystem data (STEP 1). Sources can include existing public and proprietary databases or mining highly unstructured data, such as press releases or analyst reports. The primary focus of this step is to identify actors (companies), capabilities (i.e., knowledge, skills, technologies) , and relationships (explicit or inferred) between them. STEP 2 converts the data into a network model, with nodes representing companies and capabilities and links between nodes representing relationships. Pending on the type of data, links can also be weighted (e.g, relationship length, intensity, value). STEP 3 involves selection and computation of relevant graph theoretic metrics (e.g., centrality, modularity, etc. [13]). In STEP 4, we visualize the resulting ecosystem graph using a force-directed network layout, with key attributes and/or graph theoretic measures visually encoded. STEP 5 then involves ecosystem sensemaking, which involves an analysis of structure, dynamics, and rules/behaviors.

Results from the empirical analysis informs the simulation analyses. We construct synthetic networks that either resemble the structural characteristics of our real-world ecosystem or variations thereof (STEP 6). We define rules and behaviors that companies in the ecosystem pursue (STEP 7). These rules can be drawn from empirical evidence as well as operationalization of theoretical ideas. Finally, we conduct various what-if scenario experimentation and make sense of the resulting ecosystem structure (STEP 8).

4. Illustrative Example

4.1. Empirical Analysis

We mined unstructured data (news, press releases, blogs, and webpages) provided by Netbase Quid to extract events and entities associated with two focal industries: the Hardware Accelerator (HWA) and the Edge Computing (EDGE) industry. The HWA dataset contained 490 relationship events associated with 502 unique companies. The EDGE dataset contained 792 events with 330 companies. Next, we constructed bi-partite graphs of companies and capabilities, projected these onto the company graph, and computed graph theoretic metrics. Since an event has a timestamp the resulting graphs may be time dependent. For instance, the event: ”Company A collaborates with company B at time t_1 on using capability $C_1 ... C_n$” creates a bi-partite graph between capability nodes and company nodes, whose projection onto the company network creates a link between company node A and B at time t_1.

Figure 3 shows a visualization of the bipartite graph of the HWA ecosystem for the data collection time period. We observe that core companies have many capabilities while companies in the periphery have just one. Further analysis reveals structural characteristics, using e.g., eigenvector centrality of a node in a network as a proxy for market dominance. For instance, collecting label nodes that are important in particular domains into subsets we can determine the eigenvector centrality in the projections of the different subsets and

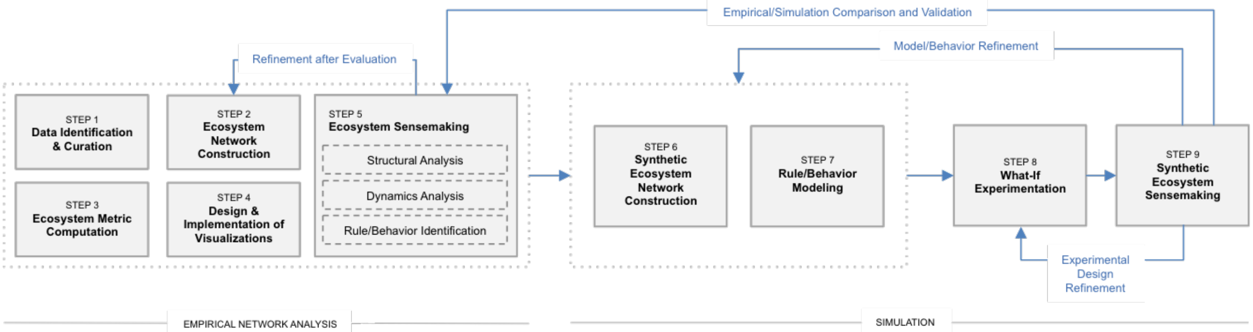

Figure 2. Multi-Phase Research Approach to Computational Modeling of Business Ecosystem Dynamics.

thus create power rankings in different sub-markets. Similarly, betweenness centrality is a proxy for flow control in a network.

The study of observed (i.e., Nvidia and Mellanox) and proposed mergers (i.e., Nvidia and ARM) illustrates the potential of network analysis. Specifically, we are interested in measuring the structural impact of these two events on the whole business ecosystem beyond the merging companies. A key result is the different impact of these mergers on the betweenness centrality ranking: the ARM merger creates winners (Nvidia, Microsoft) and losers (IBM, Intel) whereas the Mellanox merger is irrelevant, i.e., does not change the betweenness centrality. This suggests that Mellanox was not a gatekeeper in the HWA network; it had no or little control over the flow of information or supplies in this network.

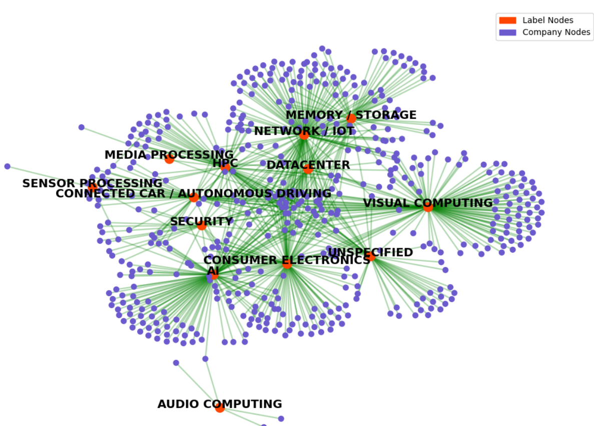

Figure 3. Visualization of the HWA Ecosystem.

4.2. Computational Model

While empirical data can be used to study the evolution of an ecosystem, the task of collecting sufficiently comprehensive data to enable more fine-grained time and sub-segment analysis is resource intensive. In addition, the rule/behavioral modeling is often noisy and would require large datasets to extract any statistically significant statements. A computational model allows us to generate a large number of relevant events at a high granularity in time. Moreover, a computational model of a business ecosystem enables us to investigate and analyze a wide-range of potential scenarios by varying the characteristics of the network structure and behaviors of companies.

To do so, we reduce an ecosystem to a minimal model that allows us to create an agent-based simulation that may act as a digital twin of a real-world context. We retain the structure of a bi-partite graph with label nodes (which are passive) representing capabilities and company nodes (the active agents of the simulation). Our initial networks are similar to the EDGE/HWA network in terms of the degree distributions of the nodes, the degree distribution of the capabilities, and the clustering coefficient of the company networks [14, 15]. The only action that we allow agents to perform are (1) collaborations and (2) mergers and acquisitions. Our experimental setup assumes an innovative market that is characterized by a set of capabilities which have to be acquired by companies that want to be successful. Initially all companies have a subset of the necessary capabilities and their goal is to win the race to the top, i.e., to be the first company to have direct/indirect access to all necessary capabilities.

Drawing on fundamental ideas from econophysics (see [16]), we consider two sets of rules which we associate with low and high entropy decisions. *Low entropy decisions* will be predictable, lead to rule-affirming actions, have narrow distributions for random choices and a low rate of activities. *High entropy decisions* will be surprising, lead to rule-breaking, have near uniform distributions for random choices, and a high rate of activities. A priori, high and low entropy decisions have no value

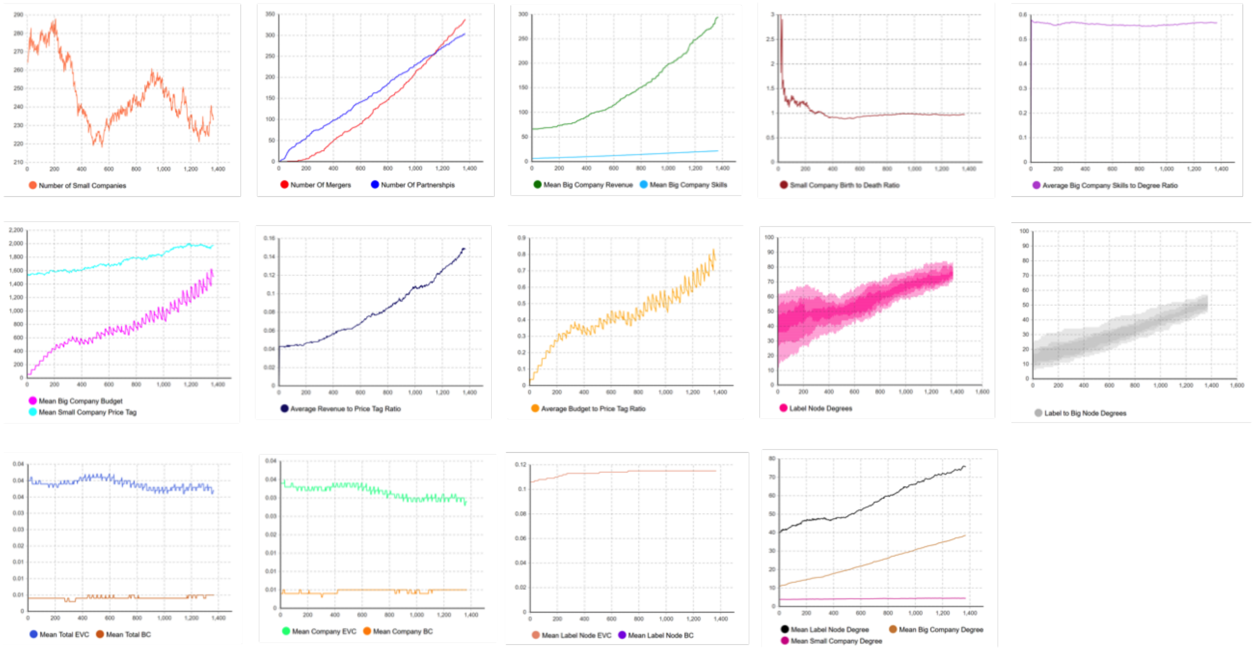

Figure 4. Temporal Structural Characteristics and Performance Metrics for an Illustrative Scenario.

statement associated with it, i.e., it does not necessarily mean that a low entropy decision is the most prudent, most risk averse or most profitable decision. However, computational experiments can be set up such that low/high entropy decisions are correlated to low/high risk-taking. We then study how much this and other correlations (e.g., between the entropy of the decision options and revenue increase and speed of market development) depend on the network structure and the state of the ecosystems.

Operationally these dichotomies are coded as (i) rules that constrain M&A e.g., through network or financial constraints (low entropy) or allow completely arbitrary mergers (high entropy); (ii) rules that assign capabilities to startup companies based on some preference scheme or distributed uniformly randomly; and (iii) lower or higher rates of events. The four quadrants in Figure 1 are thus associated with low and high entropy ecosystems and the relative position that a focus company finds itself. We implement our computational model using Python and AnyLogic, conduct a wide-range of practical scenarios, and compute corresponding key metrics. An example of the outputs generated by our computational model is shown in Figure 4. Our initial experiments provide several important observations into ecosystem dynamics.

- High entropy rules typically lead to faster success.
- Constrained decisions on M&A slow down the acquisition of capabilities. Companies prefer to acquire capabilities through collaboration. It does not matter whether the constraint is network-based (e.g., merge only with neighbors) or financially directed (e.g., insufficient budget to acquire a company).
- Ecosystems that start out unpredictable become more predictable over time. This happens for two reasons: certain capabilities become more valuable making M&A harder, and a company's action to acquire the last few missing capabilities are more predictable since its choices are limited.

The last observation points to a resolution of the obvious conundrum associated with unstable ecosystems: a steady state for an unstable ecosystem is a contradiction. How do ecosystems then evolve to something stable? Obviously this stabilization is likely driven by the goal of racing to the top. However, one can argue that many highly innovative economic phases are characterized in that way, followed by less innovative phases that may be driven primarily by financial objectives.

5. Concluding Remarks

Our computational modeling approach provides a foundation and important initial insights for exciting future research directions, including exploration of the target(s) and timing of collaboration and M&A, strategies to use in highly dynamic and/or stable ecosystems, evaluation of different competitive rules and behaviors, or the impact of new capabilities. As complexity grows in ecosystems, such insights will be critical to understanding the nature of the industry dynamics and a company's strategic advantage relative to its position in the network structure. At the same time, there are many opportunities to refine the underlying mechanism of our computational model, including the notion of managing product and capability portfolios, competing for market share, or maximizing revenue given budget constraints. Similarly, there are opportunities to extend our model to explore the impact of "black swan" events (e.g., introduction of disruptive capabilities, technologies, or innovations) or geo-political changes (e.g., supply chain sourcing, collaboration policies, etc.).

The practical implications of our work are immense. Exponential competitive dynamics, rapid innovation cycles, and blurring industry boundaries makes a comprehensive and ideally anticipatory understanding of business ecosystems a critical strategic capability. Tools that allow decision makers to computationally explore existing and potentially unknown scenarios are critical to successfully navigate uncertain times, eliminating bad strategies early and enabling the identification of promising ones. The approach and computational model presented in this paper represents an important step in this direction.

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