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Forecasting technological progress potential based on the complexity of product knowledge

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ABSTRACT

Investing in R&D for a product employing new technologies is a challenging issue for companies and governments alike, especially at the critical juncture of deciding the degree of resource allocation, if any. Decision-makers generally rely either on historical data or intuitive prediction to gauge the rate of improvement and level of R&D spending to achieve the desired improvement. This paper introduces a systematic way of forecasting the endogenous progress potential of a product based on the complexity of its knowledge structure. The knowledge structure represents knowledge associated with the product's core technology and the configuration of the components and sub-systems supporting the core technology. Topological properties of complex networks are applied to assess the knowledge complexity of a product relative to its class. Analyses of the complexity of knowledge structures for a set of energy harvesting devices confirm that node degree and clustering coefficient provide distinguishing topological properties whereas community size and membership number do not clearly differentiate the knowledge structure complexity. We discuss the implications of these findings on forecasting progress potential.

1. Introduction

A central concern in R&D investment in product innovations employing new or untested technology is the necessary level of resource allocation to grow the stock of knowledge [1,2]. A model of the intrinsic improvability of a product would allow decision makers to forecast a product's endogenous rate of improvement, or progress potential, which would inform their decisions on the appropriate level of research budget and the time span for the stock of knowledge to accumulate [3]. Similarly, companies or governments aiming to allocate investments across a number of potential product innovations, all of which appear attractive, may prefer to invest in those that have a higher likelihood of faster progress. We contrast this problem of forecasting the endogenous progress potential of a product based on its intrinsic improvability with forecasting the diffusion of product innovation [4,5], which generally focuses on exogenous, market-driven factors, or forecasting the general growth of knowledge about technologies through environmental scanning, for which bibliometrics and Delphi have played a key role [6,7].

The extent to which a product and its core technology respond to investment and improve has been quantified by progress functions [8] and ‘learning curves’ or ‘experience curves’. Progress functions measure the result of companies gaining experience and making improvements to production, which is assessed by data on cumulative volume of production and unit cost. Despite subtle differences in the definition of progress functions and learning curves or experience curves [8], they all rest on the same principle: the cost of production decreases as individuals, companies, or industries ‘learn by doing’. The precise nature of the relation between the inherent

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difficulty in 'learning by doing' posed by a specific technology and cumulative volume of production is not yet fully understood, though. In the energy sector, for example, experience curves only weakly explain the change in cumulative volume of production, with the endogenous factor of technical barriers being more significant [9]. Two other causal factors downplayed in progress functions are the intrinsic degree of difficulty in 'learning' about a technology at a component level and the degree of architectural complexity in configuring parts and sub-systems around the technology into a commercial product. Understanding how the intrinsic complexities in the design and underlying technology of a product affect growing the stock of knowledge, and hence the progress potential of a product, would be a powerful tool for investors and policy-makers to forecast the progress potential of new products at the early stages of technological development.

To address this question, we bring engineering design to the problem of forecasting technological improvement by exploring a seldom-cited link, which is the knowledge that is embodied in the design of a product. When we mean design, we refer to both the componentry of the core technologies and the configuration of the parts and sub-systems of a product, that is, the product architecture. Significant knowledge is embodied in the components of the product and in the way that they fit together. One way in which a number of academic studies have connected technological improvement and design is through the modularity of product architecture. A highly modular product architecture has been shown to decrease the time to design the product [10], support end-user innovation [11], and facilitate the establishment of product platforms and families [12,13] among other benefits that increase the rate of innovation [14]. Architectural modularity turns out to be an important way to link the design of a product to its progress potential. McNerney et al. [15] developed an intriguing model showing that the progress potential of a product is driven by a power law with exponent $b = 1 / (\gamma d^*)$, where γ is the intrinsic difficulty of finding a better component and d^* is the maximum design complexity of the product. The maximum design complexity of the product is determined by the component that has the most influence on other components, such that it is not possible to alter that component without simultaneously altering the other dependent components. Through simulation on synthetic data, they showed a correspondence between their model and reported rates of progress.

A notable caveat to this perspective is the work by Henderson and Clark [16], who studied the relationships between architectural knowledge as embodied in the product architecture and the capability of companies to implement architectural innovation. They showed that simply modularizing the physical architecture of a product does not then mean that knowledge underlying the product has also been modularized. Brusoni and Prencipe [17] emphasize the point "that product modularization does not derive from, nor bring about, knowledge modularization". When there is a correspondence between architectural and knowledge modularity, Ethiraj et al. [18] showed that an increase in physical product modularity decreased the cognitive complexity of the product, leading to easier and quicker imitation by competitors. In essence, they point toward the main thrust of this article: the complexity of the knowledge structure underlying a product influences the dynamics of progress. The questions are, how complex and complex relative to what?

Modeling progress according to architectural modularity alone downplays the inherent difficulty in producing new knowledge relevant to the product and the knowledge dependencies between interacting components and systems. When it comes to product innovation, knowledge is both a requisite of innovation and a barrier to innovation. It is a barrier to innovation because the process of acquiring and transforming knowledge input into innovation output is costly and requires coordination. Previously, scholars have examined the problem of the complexity of the coordination in relation to the complexity of the task structure [19,20] or product architecture [21]. Much less is known, though, how the complexity of the knowledge structure may affect the cost of transforming the knowledge into an innovation, with the exception of the study by Dollinger [22], who demonstrated that increasing complexity of information requires more boundary spanning across knowledge domains by individuals so as to produce cohesive strategic plans.

We thus make one important correction and contribution to studies aiming to forecast the progress potential of products: the fundamental factor in the progress potential of a product is not the complexity of the product architecture, but rather the complexity of the underlying knowledge structure for the product. Our main hypothesis is that progress potential is bounded by the degree of complexity (or simplicity) of the underlying knowledge structure of a product, which represents both knowledge associated with the product's core technology and the configuration of the parts and sub-systems around the core technology to produce a commercially viable product. The challenge lays in understanding the differentials in underlying knowledge structures for products. Which characteristics of knowledge structures distinguish the complexity of products and how can the complexity of product knowledge structures be assessed to ascertain progress potential?

This paper explores the hypothesis that a relationship exists between product knowledge structure and the product's progress potential. We describe an approach based on complex network theory and tensor analysis. The complexity of the knowledge structure for a product is compared to products within its class in a form of outside-view reference class forecasting [23]. We present three hypotheses to test which topological properties distinguish the complexity of products and examine these topological properties for a set of products. Our first hypothesis tests the degree of connectivity between knowledge elements associated with a product. The second hypothesis tests the relative sizes of modules of knowledge elements. The third hypothesis tests the links between knowledge elements to elements outside of its knowledge module. Each of the hypotheses is based on a set of arguments relating to challenges associated with producing new stock of knowledge as the knowledge structure complexity increases. We illustrate our approach on a set of energy conversion devices employing various core technologies including piezoelectric, wind, wave, and solar to find evidence to support our principle hypothesis that a relationship exists between the complexity of product knowledge structures and the rate of progress.