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Stevan Dedijer
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A new model for identifying emerging technologies

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ABSTRACT Today, the complexity of so many emerging technologies requires an understanding of adjacent technologies often originating from multiple industries. Technology sequence analysis has been used by organizations, governments and industries to help make sense of the many variables impacting the evolution of technologies. This technique relies heavily on the input of experts who can offer perspectives on the status of current technologies while also highlighting the potential opportunities in the future. However, the volume and speed at which scientific research is accelerating is making it nearly impossible for even the most knowledgeable expert to stay current with research in their own industries. Today however, the use of big data search tools can help identify emerging trends around disruptive technologies well before many of the experts have fully grasped the impact of these technologies. Despite the fear of many in the intelligence community that these tools will make their jobs obsolete, we expect that the value of the intelligence expert will increase given their unique knowledge of relevant data sources and how to connect the data in meaningful ways to derive value for the firm. We propose a new forecasting model that incorporates a combination of technology sequencing analysis and big data tools within the organization while also leveraging experts from across the open innovation spectrum. This new model, informed by current client engagements, has the potential to create significant competitive advantages for organizations as they benefit from expanded search breadth, search depth and search speed all while leveraging a range of internal and external experts to make sense of the rapidly changing technological landscape confronting their environment.

KEYWORDS Big data analytics, competitive intelligence, emerging technology, open innovation, technology sequence analysis

1. INTRODUCTION

Recent technological innovations such as unmanned aerial vehicles (UAVs) or driverless cars are hugely disruptive forces that have already, or soon will, dramatically alter the competitive landscape of markets from aerospace and the automotive industry to communication and defense. These innovations often involve technologies from multiple technological domains that can make a challenging environment for the experts tasked with staying on top of all the innovative activity. Long established market leaders can be quickly undermined by start-ups who understand the potential value of a technology long before most of the rest of the market is even aware of its existence. Clayton Christenson (2000) in his landmark book, *The Innovator's Dilemma*, coined the term "disruptive technologies" to describe innovations that create new markets by discovering new categories of customers. Disruption, per Christenson, can be achieved by harnessing new technologies, developing new business models and/or exploiting old technologies in new ways.

To achieve the kind of disruptive innovation conceptualized by Christenson however, firms increasingly must look outside their own organizations and, often, outside their own industries to harness the innovative power of the crowd. These adjacent technologies are difficult for even the largest firms to uncover on their own. This innovation challenge is made even more difficult by the fact that so much innovative activity is taking place across the globe. Chesbrough (2003) coined the term "open innovation" to refer to firms that actively engage with outside organizations to enhance their own innovative capability. While firms have been doing this sort of thing for a long time, the focus on the positive impact of these activities on firm performance helped to jumpstart a broader acceptance across industries to utilize different types of external research partners such as universities, competitors, and government agencies, among others (Cohen and Levinthal, 1990; Parida, et. al., 2012). So, if firms want to take advantage of the wisdom of the crowd today, they must figure out how to become knowledgeable about all the activity occurring within their own industry, within adjacent industries and across the globe. They must also be able to identify and quantify the key researchers, associated organizations and the key technologies that would be most relevant to their own innovation processes. Finally, they must be able to accomplish this in an efficient, and relatively cost-effective manner.

Scenario analysis is one type of methodology that can help companies deal with the uncertainty of a future disruption. Bishop et al., (2007) suggested that "scenarios contain the stories of multiple futures" that are both creative and analytically feasible and help companies imagine a future world based on data and perspective grounded in the present. Scenario analysis techniques include a broad range of possible methodologies including expert judgment, event sequence analysis, backcasting, technology road-mapping, trend impact analysis, matrix analysis and technology emergent pathways among others (Bishop et al., 2007; Smith and Saritas, 2010). Smith and Saritas (2010) attempted to define the boundaries of these techniques a bit more specifically by suggesting that foresight analysis is a set of strategic tools that supports government and industry decisions by outlining multiple plausible futures over a 5 to 25 year horizon while highlighting emerging opportunities and threats along those various pathways. Each of these techniques is generally characterized in the following ways: provides a set of scenarios based primarily on expert judgment, sometimes, but not always, obtained through group engagement, mostly working from the present day set of events forward and rarely, involves the use of computers to assist the development process (Bishop et al., 2007). The utilization of external experts alone, or in a group, is rooted in the hope that they can provide a view of the future that is, ideally, not necessarily dependent on the company's present-day reality.

In the recent past, this type of analysis was mostly carried out by consulting organizations, working on behalf of big businesses, who accessed the expertise of Key Opinion Leaders (KOLs) to share their insight on where they believed the market was going and what was necessary to achieve this future state. There are three main problems with this approach. First, the focus of these efforts was often within single industries and lacked the perspective of an across-industry analysis which might uncover the adjacent technologies that are often so necessary to successful disruptive products coming to market today. For example, major camera manufacturers likely never thought about the possibility of a major technological change coming from *outside* their industry that smart phone-enabled photography would have on their market and thus, were unprepared for the seismic impact this technology had on their core business. Second, the use of consulting firms and KOLs to help make sense of the changing landscape of technology takes a long time to execute and produces a temporally-constrained view of what is happening with the technology. Finally, the length of time to recruit KOLs and execute an analysis of technologies from across industries can turn into an incredibly costly endeavor often outside the reach of most firms.

In this research, we propose the coupling of a big data analytics machine-learning capability with technology sequence analysis to offer an enhanced model for identifying emerging technologies. This approach can help firms deal with the huge challenge of initiating and managing disruptive innovation activities where success may depend on both the breadth and depth of the search as well as the convergence of varying maturation paths of different technologies. We also emphasize the importance of leveraging different kinds of experts in this model including internal intelligence experts, data analytic experts and industry content experts as each of these groups plays a vital role in identifying, linking and contextualizing data to understand the evolution of specific technologies and their impact on the industry.

2. OPEN INNOVATION

A recent headline in a July, 2016 edition of Fortune magazine declared "Data is the New Oil" and projected that with only 20% of the world's data open and available, data will soon become its own currency (Vanian, 2016). Even as more governments make commitments to open their data to the public, an estimated 2.5 billion GBs of new data is created every single day (Schneider, 2016). In the United States, there are over 193,000 databases available to the public (Data.gov, 2016) and within the European Union, there are over 9,000 and counting (EU Open Data Portal, 2016). The Economics & Statistics Administration of the U.S Department of Commerce estimated that anywhere from $24-$221 billion is generated annually from using the data the government provides (USEAS, 2016).

The open innovation model is premised on the idea that invention and innovation do not have to take place in the same place where they are turned into products and commercialized (Inauen & Schenker-Wicki, 2012). Largely, as a result, of the huge investments in research and development (R&D) efforts, government and academic institutions tend to generate a lot of the inventions and innovations that eventually do get commercialized. In 2016 alone, the federal government was responsible for approximately $138 billion in R&D efforts while academia invested another $18 billion (Bernstein, 2016). Researchers have touted the benefits of open innovation to include the lower cost of R&D activities (Chesbrough, 2006), lower risk for the R&D efforts that can be shared by external partners (Herzog, 2008) and, better innovation performance (Hwang & Lee, 2010; Un et al., 2010).

Researchers further distinguished the nature of the flow of open innovation activities by focusing on inbound open innovation, which describes the one-way flow of external knowledge into a firm (Sisodiya, 2013); outbound open innovation where the knowledge flows out of an organization to external research partners (Powell, et. al., 1996) and coupled open innovation where knowledge flows are bi-directional and result in active collaboration between internal and external researchers and partners (Cheng & Huizingh, 2014; Gassmann & Enkel, 2004). Research has also confirmed the positive impact on firm performance by assessing the type of collaborating firm (e.g. customer, supplier, competitor, academic institution) involved in a firm's open innovation strategy (Tether & Tajar, 2008; Un, et. al., 2010; Wang et. al., 2015).

While it is conceivable to imagine that opening a firm's internal R&D efforts to outside knowledge would benefit from exposure to the diversity of thought and ideas, there appears to be a limit to the actual benefit due to the complexity and cost of establishing, maintaining and monitoring these external collaborative relationships. To understand that limit, Greco et. al., (2016) looked at the effect of search breadth (how broad the search process is), search depth (how intensive the interaction is between external collaborative partners) activities and the volume of bi-directional collaborative relationships the firm is engaged in and their impact on firm performance and found diminishing marginal returns. The researchers found that the broader the firm's search breadth and the higher the number of collaborative relationships, the more returns were diminished. The authors suggest that "a firm may be harmed by interacting with an excessive number of innovation channels, consequently reducing its effectiveness in bringing innovation ideas into implementation" (Greco et al., 2016). These results did not hold on the search depth metric as relationships that experience repeated interactions between the partners tended to be more robust in general and did not appear to evidence diminishing returns. So, it appears that a firm's open innovation activity could benefit from a more systematic and targeted approach to identifying technologies that will align with the organization's research efforts if it wants to accelerate the innovative output arising from its open innovation efforts.

3. TECHNOLOGY SEQUENCE ANALYSIS

Firms use technology sequence analysis to help them understand the extent, interdependence and likelihood of a wide range of emerging and adjacent technologies that are necessary to achieve a desired future state in their industry. Sequence analysis breaks down broad patterns of overall processes into sequences of activities or events that produce specific outcomes constituting change (Isabella, 1990). So, the idea is to start with a future desired technology or product and work backwards by identifying the technologies or activities that must precede this future state. At each stage of the technology development process, there will be some assigned probability associated with their occurrence. Probabilities are assigned by accessing expert judgment, usually in the form of a panel of experts, who review the details of the required technologies to assess technological fit and estimated time to "market ready" status. Since we do not know exactly which event or events will occur, the probabilities assigned to later events will change as earlier events occur. This process produces a decision tree of nodes and branches with different outcomes listed along with assigned probabilities.

Van de Ven and Poole (1990) used sequence analysis to explain how and why innovations develop over time and which developmental paths lead to the success and failure of different kinds of innovations. Subsequent applications of sequence analysis looked at how organizational outcomes are influenced by changing the order of steps in a process (Pentland, 2003) or patterns of behavior (Adair & Brett, 2005) over some defined timeframe. Each of these efforts focused on process activities related to firm-level innovation.

Technology sequence analysis can also be used to assist in understanding how to accelerate product innovation. Abbott (1990) looked at whether and when certain events occur in the product development process as indicators of successful results. Salvato (2009) used sequence analysis to uncover the way capabilities are developed through everyday activities involved in the new product development processes and found organizations that track innovative activity occurring at all levels of the organization and, sometimes, outside its boundaries are generally more successful at renewing their core capabilities. Perks, et al., (2012) adopted sequence analysis to track the process of co-creation in the incremental development of a radical new service. Using sequence analysis on an experiential simulation dataset, Thatchenkery, et al., (2012) found that firms' R&D performance and performance in new markets increased significantly when firms engage in a consistent time-paced competitive sequence whose sequences follow regular (i.e. continuous or periodic) patterns and whose sequences do not conform to what their competitors perform well. Perks and Roberts (2013) utilized technology sequence analysis to investigate the series of micro activities, involved in product innovation, which are carried out by individuals within and outside the organization that create change over a longer time frame. Each of these applications of technology sequence analysis focuses on understanding the steps or processes involved in the innovation process, at a firm level, that can lead to more successful product outcomes.

There has been little publicized use of technology sequence analysis at the industry or country level, likely due to the inability of researchers to accurately access and categorize research being done outside the boundaries of individual firms. However, the ability to incorporate a big data research capability that leverages significant search depth and search breadth into this process makes technology sequencing at an industry or country level a more realistic possibility. Incorporating experts from outside the firm, across industries and from the furthest reaches of the globe is now possible due to the power of big data analytics, which can combine millions of records, aggregate search terms and, through the utilization of various machine-learning algorithms, identify the most relevant research and the companies and researchers most responsible for producing it.

4. EXPERT JUDGMENT

Expert judgment is one of the most common forms of scenario analysis and is used often to support many other forms of forecasting. Typically, expert judgment is accessed through panels convened for reviewing research or technology developed internally by organizations. The value of expert panels is that diverse ideas and alternatives can be examined especially by tapping into those outside the industry mainstream including "canaries", iconoclasts and idea provocateurs (Smith and Saritas, 2011). While not inexpensive, the cost of empaneling experts from academia and government entities is far cheaper than hiring these people on as employees of the organization and the perspective that is offered is often free from organizational bias.

Functionally, expert opinion supports a wide range of firm activities from strategy and competitive intelligence through to research and development. Competitive intelligence (CI) involves the collection of internal and external information to help companies predict the next moves of their competitors, customers, and government entities (Gilad, 1996). In the CI field, industry experts are a critical source of perspective and information used to inform a firm's tactical and strategic activities. Internal CI professionals are tasked with helping the company make sense of these activities and must be knowledgeable about where to find the most relevant data to answer the company's most urgent intelligence needs. In many ways, these individuals act as translational experts for the organization by helping to frame research requests from internal constituents and then identifying the appropriate external data sources and experts to address these requests. Most CI units will outsource their data collection efforts, including hiring or interviewing experts, to third-party research firms. These groups maintain lists of industry experts that they rely on for key insight into what is happening in the industry. A key limitation of this approach is that often the networks are not deep enough in their bench capacity, broad enough in their industry perspective or refreshed frequently enough with new perspectives to provide the kind of insight and foresight that can give an organization confidence about the magnitude of the changes that might lay ahead or how to respond to them.

5. PROPOSED NEW TECHNOLOGY SEQUENCE MODEL WITH BIG DATA CAPABILITY

The proposed new model follows closely the suggestions of several researchers to augment existing forecasting models to include utilizing big data analytic capabilities in the process (Kajikawa et al., 2010; Vaseashta, 2014; Park et al., 2016). In utilizing computer-assisted citation network analysis across a broad range of energy-related publications, Kajikawa and his colleagues were able to efficiently build a technology roadmap for energy research that was incredibly effective at highlighting emerging areas of technology such as fuel cell and solar cell technology, despite the huge proliferation of readily available science-related content. Vaseashta (2014) combined three different methodologies, including technology foresight analysis, trend analysis and automated data analytics to demonstrate the potential of a new model for surveillance of emerging trends in science, technology and intelligence environments. Park et al., (2016) used patent data as a source and, in employing various statistical measures, were able to map out where the market for 3D printing was in its technological evolution and where it might be heading into the future.

As previously highlighted, most forecasting techniques rely heavily on expert feedback. However, as the proliferation of data continues to grow and the speed at which this data is produced accelerates, constructing a future technology roadmap based strictly on expert feedback is quickly becoming an obsolete approach. The fact that so much of this data production is also occurring globally makes

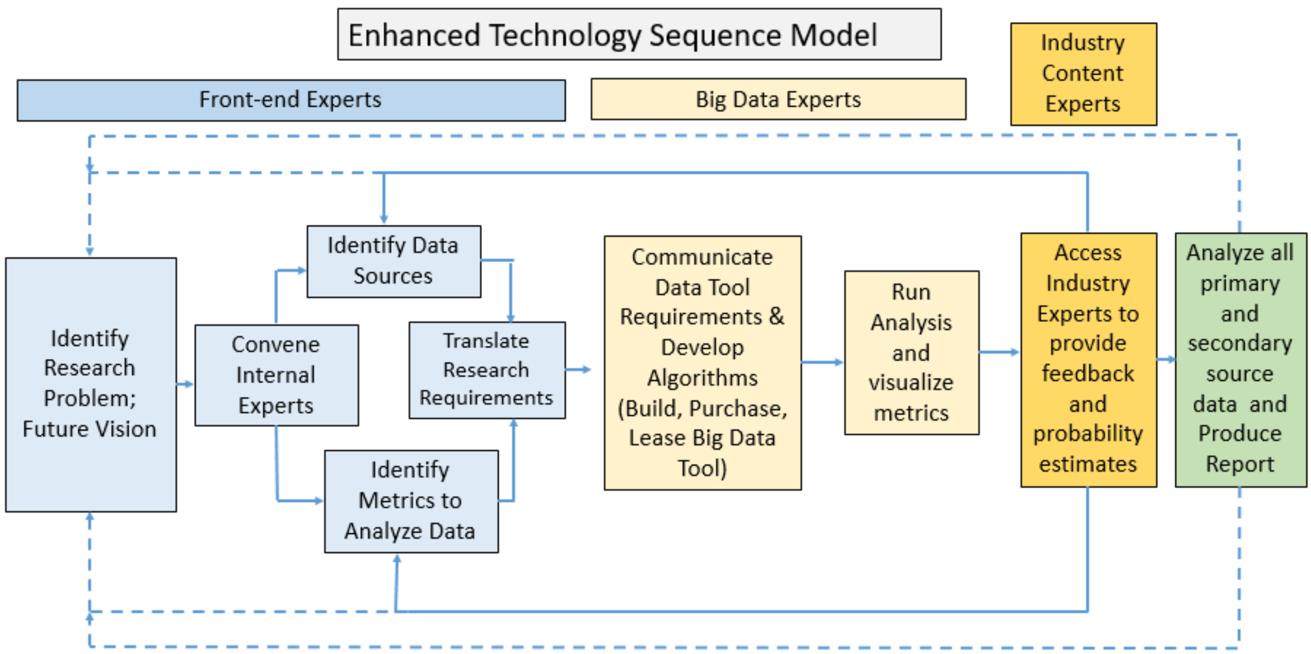

Figure 1 Enhanced technology sequence model.

expert-focused forecasting models even more of a concern as the ability to capture, process and analyze huge troves of global data becomes almost impossible to achieve without the assistance of some powerful data analytic platform. The very real possibility of missing a significant technological milestone can become an unfortunate reality if the company's network of experts does not stay up on the latest developments in their field of expertise.

The model in Figure 1 goes beyond merely augmenting existing foresight techniques with big data capability. Instead it places a heavy emphasis on the role and timing of when to include different kinds of experts along with big data capability to help firms achieve significant differentiation in technological forecasting. We separate the role of experts in the process into "front-end translation experts" who are primarily company insiders such as strategists or CI professionals, "data scientists" who attempt to address the needs of the internal client by automating data capture and analysis using machine learning capabilities and "industry content experts" who generally come from outside the company and who provide a view of the industry or technology that is free of organizational bias.

The role of the front-end expert is highlighted in this expanded forecasting model as someone who takes the requirements of internal departmental units and makes sense of them by identifying the appropriate data sources, metrics and internal experts to incorporate into the process to produce a relevant and targeted analysis. By leveraging the potential of the open innovation philosophy, the role of the data scientist expert is to enhance the search breadth, search depth and search speed by focusing on connecting relevant data sources (either open or proprietary) and utilizing machine learning to find underlying patterns between technologies, people and organizations. These tools help to quantify experts' contributions to their scientific and technical disciplines and makes uncovering industry experts a much more scientific process. In this way, the role of the industry content expert can then be leveraged in a much more meaningful way because we can identify and quantify the expertise of researchers within and across technological disciplines by their specific areas of expertise. This opens the potential for a much richer analysis of the technological landscape by broadening the firm's reach to those with very specific knowledge in technical domains and often from outside a single industry. These experts can provide insight and estimates of probabilities into the specific obstacles and opportunities around a broad range of core and adjacent technologies and help to develop a more sensitive and accurate technology sequence analysis.

Then recent emergence of many data analytic platforms provides organizations options for whether to "build", "buy" or "license" to get into the market. Obviously, the shortest path to implementation will be to license one of the many platform tools that are available today. The upside to licensing or leasing is the speed of implementation and lower upfront costs to participate. The downside is generally a lack of customization for both data sources and the algorithms that make sense of it all. The "buy" option provides some greater options for customization but with lower implementation speed than the license model and higher costs as well. Finally, the "build" option provides the greatest amount of flexibility around customization but costs significantly more than the other two options and takes far longer to implement.

6. CONCLUSIONS AND FUTURE RESEARCH

Traditional forecasting methods which rely heavily on expert guidance must begin to incorporate big data analytic capabilities in their process or risk soon becoming obsolete. This paper reinforces the important role of several different kinds of experts in technology forecasts but emphasizes the importance of adding big data tools to the process primarily because of the need in all industries to be "globally data aware" (Kostoff & Schaller, 2001), which is impossible to do today with the volume and speed of production of digital data.

The choice of whether to build, buy or lease a big data analytic platform will be heavily dependent on the long-term vision of the organization with respect to the choice of data sources. If an organization possesses data that they believe provides a true leading view of the market, they may want to exercise greater control over that data and opt for a custom-built platform tool. If they are unsure what data they want or need or are just getting started, they may want to consider leasing a tool early on. As they gain experience and better appreciation of the value of leveraging connected data, the buy or build approach becomes the more valuable option. One caveat to this choice is the fact that currently there is a dearth of data scientists and visualization professionals so if a firm lacks the resources to attract and retain these type of professionals, they may face limited options regardless of interest or need.

CI professionals who embrace the utilization of big data tools into their CI processes should find increased relevance and power within their organizations as they become crucial to the organization's ability to leverage the power of these new tools. The role of the "translational expert" who can take the research problems and, by leveraging data and speed, generate advantages for the organization over its competitors becomes exponentially more valuable to the organization. CI professionals should seek out training and seminars to learn as much as they can about big data tools and the various business models associated with the utilization of these tools so they can begin to identify opportunities inside their organization where these tools may provide value. Finally, CI professionals should begin to create a reference library for the automated data that the company currently produces, especially anything that highlights the behavior of its customers or market that can potentially be combined with external data to drive new and unique insights. The fact that CI professionals have responsibility for maintaining competitive and market intelligence oversight for entire product lines, divisions or for the firm makes them uniquely positioned to appreciate the research and data needs of their internal customers and able better translate these needs to the data analytic experts.

The new battlefield of the future for strategy and CI professionals will be to identify the appropriate mix of datasets and algorithms that create a truly predictive big data intelligence tool. As more and more data become available to mine, it is the company's knowledge of how to combine internal and external datasets utilizing proprietary algorithms and their access to industry experts that will become the new competitive advantage for the next generation of global market leaders.

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