3–Step Analytics Success with Parsimonious Models

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INTRODUCTION

'Business Analytics' (BA) and 'Big Data' have become household terms (McAfee and Brynjolfsson, 2012). Consultants like McKinsey & Company proclaim the arrival of a new business era, predicting across-the-board productivity gains of 6% (WSJ CEO Council, 2012). Yet little is understood as to what exactly these entail, much less how to create success stories. Many executives remember the struggle with previous data-centric decision support initiatives, such as the failure with CRM - customer relationship management. More than a decade and many hundreds of millions of dollars later, failure rates of far more than 50% indicate that the promise of better decision support remains unfulfilled (ZDNet/Gartner, 2009).

With BA being a conundrum, this paper responds to the need for clarity, guidance and pragmatism. The paper exhibits three elements: (1) an outside view – providing a framework to anchor BA, (2) a three-step view into BA, and (3) specific examples from the auto industry illustrating these views. Also, in order to help top executives with decisions on BA investments, a simple, yet powerful verification check is introduced – the so-called 'napkin test': Did you sketch a first causal, analytical model – before committing to any significant BA investments? The model should fit on a paper napkin. A pen and a paper napkin are all that are needed. Without this 'napkin', anything that follows is premature at best, or a terrible waste, as witnessed with many CRM initiatives.

BACKGROUND

Big Data and Business Analytics Framework

Miriam-Webster defines 'analytics' as "the method of logical analysis" (http://www.merriam-webster.com, 2013). 'Analysis' in turn is generally defined as "separation of a whole into its component parts" and more specifically as "an examination of a complex, its elements, and their relationships" (Miriam-Webster, 2013). Industry observers, such as Gartner, see BA as "comprised of solutions used to build analysis models and simulations to create scenarios, understand realities and predict future states"; furthermore, it "includes data mining, predictive analytics, applied analytics and statistics, and is delivered as an application suitable for a business user" (Gartner http://www.gartner.com/it-glossary/business-analytics/, 2013). In short, BA is seen as an assemblage of tools used to aid business decision-making. What are the most important decisions in business? According to Peter Drucker, "there is only one valid definition of business purpose: to create a customer" (1993, p. 37). Therefore, BA is framed here in terms of how it affects customers and the creation process.

Figure 1 presents a framework or 'map' that firstly ties 'analytics' with 'customers' and their product experience, as well as 'processes'. Secondly, it suggests that success with analytics requires a broader perspective, in which analytics is only one gear or element in a more complicated clockwork. Thirdly, the framework more specifi-

cally introduces analytics as one link in a 3-link chain of sensors-analytics-dashboards and how this chain can affect business in three ways: Better product, better process and transformation of an entire industry (as, for example, witnessed by Google's pay-per-click product in advertising). Fourthly, the 'map' recognizes that any business impact from BA will be moderated by environmental factors, such as privacy regulation, etc.

Emergence of New Sensors

Figure 1, the BA Framework, depicts 'sensors' as a key enabler of analytics; and not "data mining, predictive analytics, applied analytics and statistics" (Gartner http://www.gartner.com/it-glossary/business-analytics/, 2013). Of course, statistics is important, and in fact it is foundational for quantitative analysis. However, the t-test, to name one popular statistics tool, is not new. It is quite old. William Sealy Gosset discovered the t-distribution and invented the Student's t-test, and published it in Biometrika in 1908 (http://en.wikipedia.org/wiki/Student's_t-test). Therefore, it is obvious that BA owes its importance less to the tools and more to the data. And this data would not be available without new 'sensors', as "devices that respond

to a […] stimulus" (Miriam-Webster, 2013). Without sensors, there is no data; without data, no analysis can be performed. This data-sensor dependency presents one of the many challenges with BA. In order to find out if a BA investment is worthwhile, data is required first, which in turn necessitates investments in sensors even earlier. However, there is no guarantee that the analysis of the data will in the end be able to help make a better decision. One managerial default, therefore, is understandable: use data that does already exist and mine it.

However, there are three key caveats with this approach. Firstly, the data may simply not be representative. Intuitively, using data on what one group A does (e.g., French consumers) to infer what another group B does (e.g., Chinese consumers) may seem questionable from the outset. Secondly, there are methodical issues. Data-mining is an inductive exercise (using reasoning of events and making generalizations), as opposed to the hypothesis-deductive approach ('if A then B') (American Statistical Association, 2006). The latter is often seen as the paradigm for how modern science progresses. This explains why the term data-mining is often used synonymously with 'data dredging' or 'data fishing'. Thirdly, and

Figure 1. Big Data and Business Analytics Framework (Schlueter Langdon, 2013)
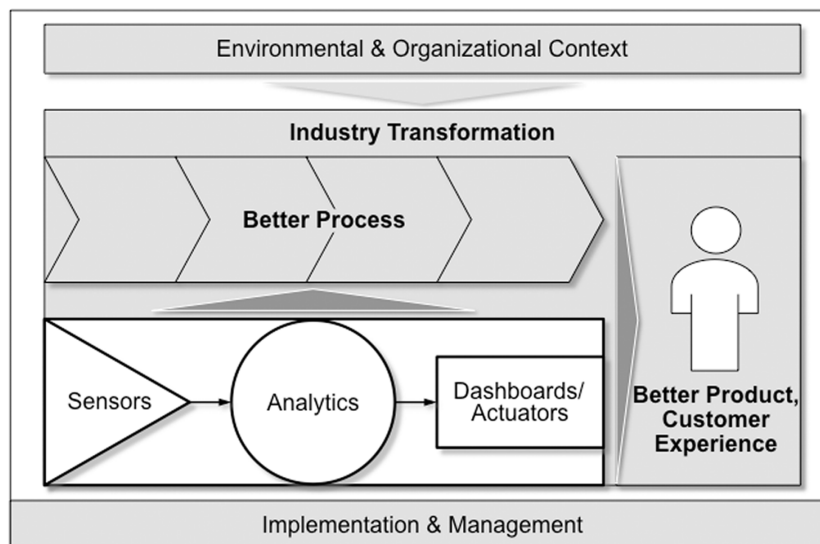
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