Next Generation Analytics and Dynamic Decision Support: AutoMarketSIM and Vehicle Sales Decay Navigation

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INTRODUCTION

In 1991 "Terminator 2" revolutionized the use of computers for digital effects or computer-generated imagery (CGI) in movies (Wikipedia.org, 2006). Costs were high and few saw digital effects to grow beyond a niche of few scenes in a few movies (Marr & Kelly, 2006). Fifteen years later, digital effects are widely considered a key success factor. For example, in 2005 all top five grossing movies, including Harry Potter and Star Wars sequels, relied extensively on digital effects (Box Office Mojo, 2006).

Many industry observers foresee a similar success of computational methods in business intelligence analytics (BIA) and decision support (Davenport, 2006; Heingartner, 2006; March, 2005; Kimbrough, 2003). Just as CGI has not diminished the value of story telling, so will computational BIA not reduce the value of an experienced decision-maker but it will enhance it. After all, very few decision-makers make the right decision based on gut instinct all the time.

Computational BIA and decision support is seen as yet another example of how a rapid increase in processing power and advances in software design have enabled embedding of more and more business activities in software routines. This process has been referred to as "softwarization" (Schlueter Langdon, 2003). Softwarization has expanded far beyond enterprise resource planning, billing, and customer relationship management. Today, few passengers and pilots seem to mind that computers land their jet liners.

This article presents two examples of how advanced BIA can improve precision of managerial and executive-level decision-making. Both examples follow a multi-step approach derived from research science that explicitly addresses instrument validation. Both examples are taken from the auto industry, a global, complex, and important industry in developed countries. The first example uses traditional methods but combines them creatively to increase analytical precision. It is focused on lifecycle aging and baseline sales estimation to improve the return on marketing investments (RoMI) using gap analysis and ordinary least squares estimation. While the first example is essentially a backwards-looking analysis, the second one is forward-looking. The second application simulates the impact of a disruptive event, a recession on profitability of automakers and their suppliers. It takes advantage of complex adaptive system modeling techniques and agent-based software implementation methods.

BACKGROUND

Connectedness and Causal Networks

Ever more intense competition is reducing the margin of error in decision-making, which, in turn, increases the need for higher precision. At the same time decision problems have become more complex across domains, such as in marketing and channel management (e.g., Schlueter Langdon & Shaw, 2002). IT and Internet-enabled interconnectedness has enabled productivity increases but at the same time increased business complexity (e.g., Brynjolfsson & Hitt, 1996). Due to interconnectedness an outcome that used to be affected by a single, primary cause is now often the result of a multitude of causes or causal networks.

Disruptive Events, Business Dynamics, and Feedback Loops

Furthermore, time has emerged as an important variable in its own right. Temporal change may make decision models obsolete: A model that worked fine yesterday, is failing today. In the past, CFOs would advance projections linearly using compound annual growth rates (CAGRs). Today, business interaction is such that business decision makers incur ever-bigger risks of failure relying on such primitive, static models. Business is certainly dynamic, changing over time, and planning tools or decision support systems (DSS) would have to be able to capture these dynamics. But time is a complicated variable. The future or next time step, such as the next quarter, may be significantly different from the past. The future could be the result of adaptive processes between market participants or disruptive. These conditions present a challenge to traditional statistical and econometric tools, which assume that the future is essentially an extrapolation of the past. If the future were disruptive, such in the case of a competitive product launch, an interest rate hike or a jump in the oil price, then new tools would inevitably be required. While the "mechanics" of the new tools may differ from traditional methods, they would have to offer similar levels of reliability, making instrument and measurement validation a *conditio sine qua none* for any new tool and approach.

MAIN FOCUS: BUSINESS INTELLIGENCE ANALYTICS FRAMEWORK

An analytical approach is introduced that has been applied to ensure relevance and rigor of results (see Figure 1). It has been instrumental for success with the two examples presented later. The approach distinguishes a sequence of three distinct phases of analysis, is rooted in scientific methods and has been refined in research practice as well as applied research involving different analytical techniques (Schlueter Langdon, 2005c, 2007).

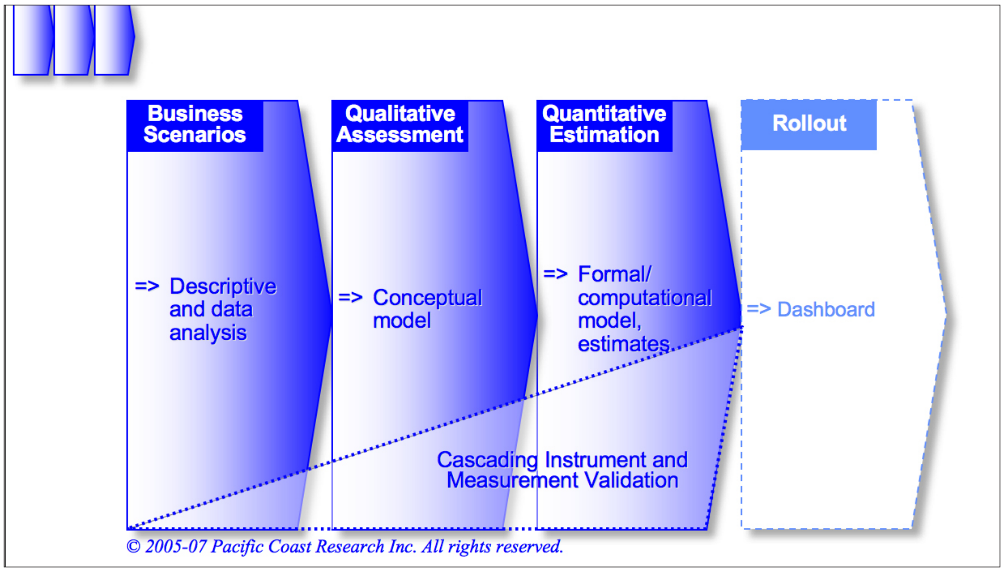
Phase 1: Problem Description and Research Question

In order to focus any investigation, a research question is required. This question can emerge from a descriptive review of the business problem or a scenario, understood as the synopsis of a possible course of action or events (Webster.com, 2007). Furthermore, data is being examined to aid understanding of the business problem. Data analysis will also reveal first modeling constraints, as it is not helpful to propose a model for which data cannot be obtained.

Phase 2: Conceptual Model

The conceptual model is an intermediate step. It captures observations of the phenomenon of study and structures them into categories of variables useful for formal and computational modeling (dependent/independent variables, mediating/moderating effects). A model and external validity of results can only be as good as a conceptual understanding of the true phenomenon.

Figure 1. 3-phase business intelligence analytics approach



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