

Chapter 13

3rd Order Analytics

Demand Planning: A Collaboration of BI and Predictive Analytics Tools

Keith McCormick
QueBIT Consulting, USA

Richard Creeth
QueBIT Consulting, USA

Scott Mutchler
QueBIT Consulting, USA

ABSTRACT

It is commonly proposed that a greater number of individuals should have access to enterprise-level data, and that they should be able to analyze it readily and individually with data mining tools. Although the authors support greater use of Predictive Analytics by the enterprise, they favor more ready access to predictions, not to raw data. Forecasting is among the more difficult analytical challenges. Despite the importance of accurate forecasts, organizations often resort to the subjective judgment of a business analyst. Forecasts are also among the most widely used analytics, broadly distributed to the organization. The authors propose an approach that centralizes the forecasting activity using Predictive Analytics but preserves the wide distribution of the resulting forecast using Business Intelligence technology.

INTRODUCTION

Some years ago McKnight (2002) suggested that Data Mining (DM) would benefit from the broadening of the pool of individuals that can use them. “Mining tools that are interactive, visual, un-

derstandable, well-performing and work directly on the data warehouse/mart of the organization could be used by front-line workers for immediate and lasting business benefit.” During the 10 years since he made his claim Data Mining tools have become easier to use and many business analysts without extensive training in statistics or machine

DOI: 10.4018/978-1-4666-6477-7.ch013

learning have access to them. Yet as Azevedo & Santos (2013) claim: “Powerful analytical tools, such as DM, remain too complex and sophisticated for the average consumer of BI systems.” One could argue that what is most needed is to further this trend and to further ‘democratize’ the access to sophisticated data mining tools, widening their daily use throughout the organization. Note, that we are using the term Predictive Analytics to include techniques like Data Mining, but are attempting to define it more broadly than most users of the term Data Mining.

In recent years, the opposite argument has been made – that organizations, even small ones, need access to highly trained ‘data scientists’, possessing in one individual high level skills in statistics, machine learning, programming, information management, and computer science. We argue that neither the wide expansion of end users engaged in modeling nor the increased specialization should be the highest priority. We argue that the next area for the integration of Business Analytics (BA) and Predictive Analytics (PA) is the implementation of deployed PA models directly into BA tools where knowledge workers can work with the resulting predictive scores without a large group of knowledge workers (the front line) engaging in the creation of predictive models. In short, that the wider application of PA techniques should grow through deployed models and in that way serving a wide population of business analysts. Deployed results are often most powerful when the predictions are inserted directly into business processes. Another theme of this discussion is the added benefit that can come from increasing the visibility of those predicted values by making them available to front line managers.

This chapter has four goals:

1. Offer a new approach to the integration of Business Intelligence (BI) and Predictive Analytics (PA) that focuses on the deployment of Data Mining models based upon retrieval of current data from BI and Business

Analytics (BA) tools which is then scored using PA Models built on historical data and then written out to the same BA tools which will typically perform additional prescriptive analytics or financial modeling.

2. Define our notion of 1st, 2nd, and 3rd Order Analytics.
3. To further expand on the analytics road map by defining Advanced Analytics as the combination of Predictive Analytics techniques like Data Mining with Prescriptive Analytics techniques like optimization and financial modeling..
4. Explore the application of these approaches using an extended case study focusing on Cognos TM1 as an example of a BA tool, and SPSS Modeler as an example of a PA tool. Although the case study focuses on Demand Planning in a retail environment the insights gained could be applied in a wide variety of forecasting situations.

BACKGROUND

A good forecast of demand, far enough into the future, allows an organization to invest in all and only the facilities, equipment, materials, and staffing that it needs to most profitably fulfill that demand. The value of a good demand forecast is readily apparent, and we valiantly load demand history into our software and statistical models to start the forecasting process. (Gilliland, 2010).

In traditional budgeting environments planning demand and thus revenues, has typically been a semi manual process. For example, an insurance company might model premium income by starting with policies currently in force, estimating attrition rates, forecasting new policies due to marketing efforts, and adding in the impact of increased or decreased premiums, in order to come up with projected policy volumes and premium income. This process relies upon the subjective

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