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# Carving A Wheel or Assembling A Widget? Insights Into the Management Of Advanced Analytics

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# Carving A Wheel or Assembling A Widget? Insights Into the Management Of Advanced Analytics

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**ABSTRACT**

Medieval guilds and assembly plants are unlikely metaphors in an information-based economy. My experience with advanced analytics suggests that such descriptions are nevertheless apt. This paper explores two distinct situations within a single firm. In one department, predictive models were generated through adopting a craft style approach. In another department, a production type of approach was deployed. The reasons for their adoption are explored, followed by their consequences for job satisfaction, performance, staffing, change-management, and more. Craft and production approaches have implications not just for modeling analysts and their managers but also for senior leaders, business partners, and human resources staff. Finally, I describe the pressure to adopt a production approach, and attempt to unravel the extent to which this reflects broader cultural and technological influences or firm-specific traits. This reflection ends with a call for professionals to share their encounters with advanced analytics.

## INTRODUCTION

In today's information-based economy, analysts mine data, information technology professionals predict that "big data" will transform business, and dot coms are touted as corporations of the future. In this context, medieval guilds and assembly plants are unlikely business metaphors. Such descriptions, however, are nevertheless apt based on our recent experiences, and were doubly striking because they occurred within a single firm. This paper explores them in the context of advanced analytics, defined as the use of predictive statistical models, forecasting, and complex analyses to solve customer targeting, segmentation, and trending problems. Advanced analytics are vital for marketing as well as business functions that range from logistics to pricing, risk, underwriting, and human resources. These are areas where managers make decisions about which customers to target and when, how much product to stock and how much to sell it for, to whom to extend credit and for how much, and how many employees are needed with which types of skills.

 

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This paper shares and interprets two distinct experiences. In one, a "craft" style approach was used to generate advanced analytics. This brings to mind classic artisans who carved wheels as members of guilds during the medieval or renaissance periods. In contrast, another department within the same firm relied upon a "production" style method that typified the assembly of widgets in a 19th century manufacturing line. This paper explores the reasons for the adoption of craft and production approaches. These appeared to be related to department differences in terms of the nature of customer contacts, management's perceptions with regard to predictive models, staffing levels, and more. Lastly, the unique solutions had implications for analysts, managers, senior leaders, business partners and human resources staff. There were consequences for job satisfaction, performance, staffing, change-management, project timelines, and costs.

In the remainder of this paper, I describe the setting in which these observations took place. Next, is an outline of craft and production solutions, with insight into why they were adopted, and the implications for those affected. This is followed by a discussion of pressures to adopt one of the approaches over the other and the larger questions it raised. Finally, this paper closes with an invitation for other professionals to share their experiences.

## SETTING

This experience was situated across two departments within the same firm. One department supported analytics for brick-and-mortar stores, in which management used predictive analytics to increase customer shopping at retail stores. The second department supported advanced analytics for the direct channel. Here, statistical modeling was used to increase customer shopping from a website and call center, with catalogues and email as the marketing vehicles. Both departments had similar overarching business goals: To optimize marketing spend and revenue.

### Industry

The corporation was ranked within the top 25 specialty retailers in terms of market capitalization, and was an established enterprise with more than 40 years in business across multiple brands. It sold a range of products that has included women's and men's clothing, intimate apparel, swimwear, shoes, accessories, beauty care, fragrances, and other home-based items. The retailer sold its products through various channels: brick and mortar stores, the internet, and telephone call centers. The firm targeted its customers through direct mail, catalogues, and email.

These insights and reflections represent more than four years of our experience working in both the direct and store-supported departments of the firm where marketing analytics were used. Each department deployed and tested statistical models and other advanced analytic tools. The need for advanced analytics was especially important because costs for direct marketing were increasing (e.g., paper, printing, postage) when customer response was declining. Customers receive a deluge of postal mail and email which has resulted in decreased response rates, along with a deep economic recession that has affected consumers' wallets. Thus, senior managers used customer targeting models as a key tool to select the best customers for the most relevant products matched to their shopping behavior.

### Occupation

Occupations have distinct job duties as well as unique, shared attitudes and views of the workplace (Goodrick and Reay, 2009; Kwantes and Boglarsky, 2004; Trice, 1993). Fortunately, our observations allowed us to compare a similar occupation across departments (i.e., statistical modelers and their functional managers) to control for any differences that would otherwise affect the experiences reported here. Core job duties included building statistical models, evaluating model performance, and scoring models for deployment in marketing campaigns. Managers supervised their work, and in most cases performed similar duties themselves. In the store-focused department, managers met with brand leaders to plan modeling needs. Managers in both the store- and direct-focused departments met with operational staff to plan timelines for model deployment when campaigns were created. Senior managers sought to achieve targeted financial goals, forecast sales through the quarter and sought to fill shortfalls with additional campaigns and other sales-building opportunities.

### Firm culture

This firm had a pragmatic corporate culture that emphasized personal accountability and hard work. From the perspective of an analyst, there was much work to be done in a limited amount of time. For management, there was constant pressure to exceed sales targets despite reduced budgets, low staff levels, and increased costs. As a result of a flattened organizational hierarchy, many marketing roles supported the operational aspects of direct mail, catalogue, and email execution. Thus, overall there was an emphasis on a "task-focused" rather than a "people-focused" orientation (see Kwantes and Boglarsky, 2004), particularly within the marketing department that supported the direct business. Although no official metrics were published, employee attrition was relatively high, which increased pressure for managers, leaders, and human resources staff alike.

## CRAFT AND PRODUCTION ANALYTIC SOLUTIONS: CONCEPTS DEFINED

In this firm, the two departments had similar overarching goals. Both built, scored, and monitored predictive statistical models to rank customers based on their probability to respond to marketing communications or to purchase category-specific products. Each, however, developed distinct ways to meet their advanced analytics needs. The store-based department adopted a "craft" approach, and the direct-based department developed a "production" solution. The primary source of this craft-production paradigm was derived inductively from our experiences at this firm. A secondary source is supported by organizational theory, particularly the idea that knowledge is acquired through either "exploration" or "exploitation" (March, 1991). Applying this concept to the context of advanced analytics, for example, a marketing department that exploits data via a production approach may use internal transactional data to predict future behavior and mail the identical customer base repeatedly. In contrast, businesses that rely on data exploration often use external data and alternative analytic approaches in search of novel customer insight. Each approach can shape the nature and pace of change within the business (e.g., maintenance on data warehouses, changes to the customer selection process), challenges that have not gone unnoticed in business research (Sutherland and Smith, 2011).

### Carving a Wheel: A "Craft" Solution

The craft solution was customized, flexible, creative, iterative, time-intensive, thoroughly documented, and more complex to deploy. The craft approach involved predictive models that were highly tailored to business needs. Indeed, each model met distinct objectives. For example, some statistical models targeted consumers to grow the prospect base, to expand product purchases among existing customers (cross-sell) or to stem attrition by identifying customers at risk of no longer shopping with the retailer. Within these broad categories, the analytic models were often developed with a specific product or customer segment in mind. Among other components, each model within the craft approach required analysts to define the concepts of customer universe, response, and the types of predictor variables to be considered.

Iteration and engagement characterized the craft approach from beginning to end, meaning from model planning to deployment and subsequent monitoring. Initially, the statistical staff met weekly with the business sponsors because the statistical model was built especially to meet detailed business needs and objectives. Discussions involved model objectives, timelines, definitions of independent and dependent variables, and more. These meetings sought to ensure understanding of the scope of the model. Changes to these elements resulted in a substantial delay of model delivery for a particular campaign, or its lack of delivery altogether. Such mid-course model corrections were at best expensive and at worst impossible to make.

In the craft environment, the model development process offered an opportunity for statisticians to be creative. Analysts had flexibility. They were expected to test competing modeling algorithms, to consider separate customer scorecards when building models, and to decide what types of candidate variables should be constructed when predicting behavior. In the craft approach, analysts decided which model predictors to generate and offer to the model based on the nature of the behaviour being predicted. Analysts also solved advanced statistical problems using several statistical techniques, including regression models, artificial neural networks, decision trees, machine learning tools, and other techniques.

Once the analyst selected several qualifying models, the advanced analytics team debated the merits of the competing models. It recommended a best model, but ultimate approval rested with their business partners. The algorithm would then be deployed. In a craft approach, the uniqueness of each model translated into a complex process for model implementation. Not only did one model vary from another in terms of objectives and customer definitions, but the model builder and list personnel had to synchronize their work in model deployment. Building models for those who shopped in the last 12 months, but inadvertently scoring the model on a list of shoppers from the last 24-36 months was certain to introduce an "apples and oranges" problem in applying the model. These needs required multiple quality controls and accuracy checks, which further increased model timelines in a craft environment.

In a craft environment, models were often reused. That is, the values of the independent variables were refreshed and the model parameter coefficients were unchanged so that a new prediction was obtained. In contrast to complete redevelopment, which often occurred within the production environment, re-scoring insured that the store-supported business maximized the substantial time and effort invested in initial model development allowing model shelf-life to span from one year to several years. Although this reduced the investment required for new model planning, re-scoring still required analysts to regularly track changes in model inputs, to decide when deterioration occurred and when new model development was necessary.

Craft based models required extensive documentation covering all decisions in the life cycle of the algorithm, including initial model objective, planning, development, scoring, deployment, testing, and suggestions for model retirement or future enhancements. Within the craft approach, for example, analysts documented which segments of customers were selected to build the model, the sampling rates and methodology, the definition of customer response and its associated response period, the product and time frame used to define response, due dates for model implementation, and more. When the store-business was ready to deploy a craft model, the process of preparing scores for later use in a campaign took a week or more. Analysts had to write efficient programming code to score the model, and to load scores into the data mart for operational use. In sum, a craft solution to advanced analytics involved a four to six week timeframe for each analyst to build a model, with more time for particularly complex projects. This translated into annual productivity in the craft environment of three to twelve new models and about six to twelve rescored models.

### Assembling a Widget: A "Production" Solution

In contrast to the craft solution, there was a production solution in place for the modeling team that supported the direct channel. The production approach was standardized, rigid, self-contained, rapidly built, linear in development, constrained to a reduced set of predictors and statistical algorithms, minimally documented, quickly deployed, and developed in relative isolation of business partners. Each model met a business objective that did not change from one communication to another. Rather than a customized purpose, each model supported the same business goal. In a production solution, most models typically targeted responsive customers for each marketing contact.

 

As a consequence, a production environment simplified and standardized issues related to the definition of the customer universe, sampling methodology, and the types of competing predictive algorithms fit to the data. Analysts in a production environment had little to no choice in these matters.

In a production solution, the development and deployment of advanced analytics involved limited interaction with business partners. After analysts learned how to build their first model, future models were built in the same fashion because the general business objectives did not change. There were a constrained set of predictors and one statistical methodology. The need for business partners to understand the inner-workings of a model was less important in the production solution, and after modelers educated their business partners about one model, business partners could easily generalize their knowledge across models.

From a production approach, model stability (i.e., its ability to effectively predict behavior over a long period of time) was less important because new models were constructed for each customer marketing communication. The analytic modeling product had a short shelf-life. Because models were so similar in a production environment, written model documentation was not required; instead, the programming code, which was used to score the model, served as documentation.

When each model was ready to use, operational teams in the direct-department had access to model scores through a point and click interface that provided near read-time availability of model scores. Unlike the craft solution, the similarity of each model reduced the risk of a disconnection between the methodology used to build versus deploy a model. In summary, because models were similar in this factory-like environment, delivering advanced analytics simply involved computational calculations to score and load models, which stands in sharp contrast to the six month or longer timeframe often required in non-production environments (Taylor, 2010). This standardization led to high productivity. In one to two weeks, each analyst could build a single model; annually, each production analyst could build and score 50 models.

So far the focus has been on how two departments solved advanced analytic challenges. One developed a craft approach, and another evolved a production solution. Although unique, the description of two radically different approaches to solving advanced analytic problems within the firm should not overshadow their similarities. Both departments shared business objectives. They sought to optimize marketing contacts and target the best customers. Both management teams relied upon analysts to build predictive, multivariate statistical models as a means to solve their customer targeting problems, and they shared the high pressure corporate culture of a retail enterprise in which senior leaders expected models to be available rapidly, yielding nothing in quality or effectiveness. Thus, despite the effort to craft a model over four to six weeks, this was still a relatively short timeline for model development relative to other industries and firms (Taylor, 2010). In comparison, analysts in insurance or banking industries may toil for a year or more to develop a single predictive model. Figure 1 summarizes these approaches to solving advanced analytics problems by listing the characteristics of each.

 

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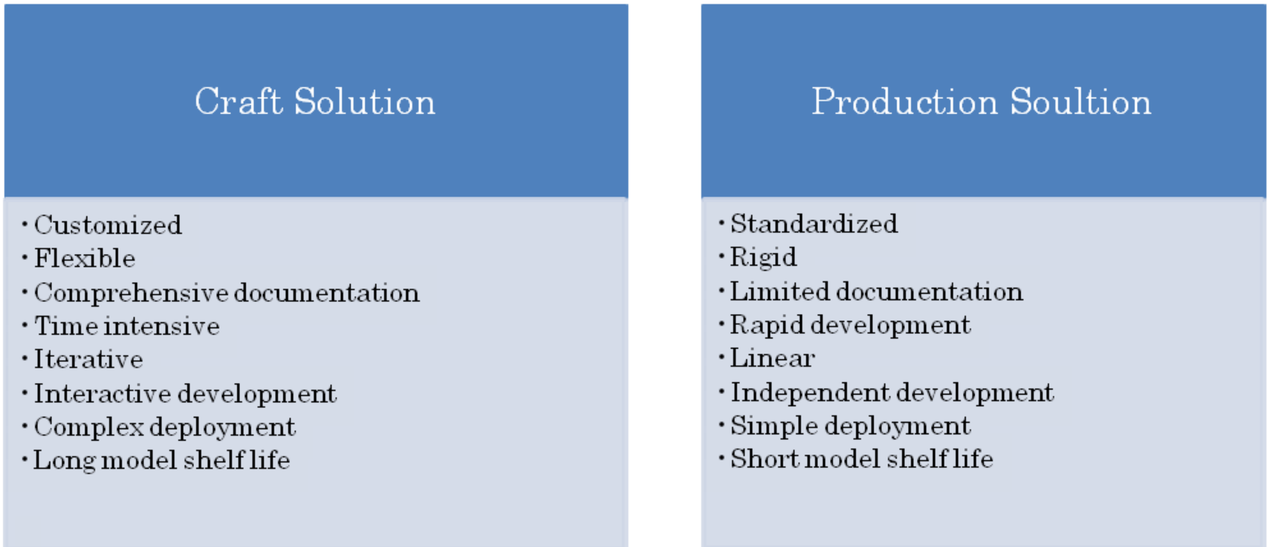
**FIGURE 1.** Terms that describe Craft and Production solutions to advanced analytics.




## WHY DID MANAGEMENT ADOPT A CRAFT OR A PRODUCTION SOLUTION?

Why did management develop such distinct ways of addressing their advanced analytic challenges? Causation is difficult to establish even under the most stringent experimental conditions. These reflections are certainly no exception. However, our experiences at this firm over a four year time frame suggest several factors that are likely to have contributed to differences in the adoption of a craft versus a production environment. They include the history of the two departments, the nature of the customer contacts, differences in business objectives, staffing and other resources, and management philosophy. Each is discussed in turn.

First, the direct and store businesses had unique histories within the corporation. The direct department was the first to have an internally staffed analytics team. The brick-and-mortar business, in contrast, was initially supported by an out-sourced analytics vendor. This vendor had a consultative, hands-on relationship with the management team and its projects. A decade later, the store leaders eliminated the vendor arrangement, forming an internal analytics team to support the store-based department. The store and direct departments therefore evolved in relative isolation, which included their business and staffing models. With such relationships previously, leaders in the store business continued to expect the analytics staff to provide consultative and communication-rich interactions just as the third-party vendor did.

Second, the nature of the business objectives fluctuated in subtle ways across the two departments. The store-supported department was a changing environment. In any particular quarter, leaders sought to increase store visits among holiday or single-visit customers. Such changing objectives required analytics to be crafted to meet business needs. In contrast, the objectives of the direct channel did not change: Drive customers with the highest potential sales to buy from the firm. When business objectives rarely change, a routine or production analytic solution was possible. This described the factory approach used by the direct department.

Third, the direct business evolved from a simple to a more complex marketing plan. It initially sent its customers a handful of marketing communications within any year. However, it evolved to send customers a multitude of communications. For example, a typical direct customer might receive 12-18 catalogues a year and three to six emails per week. Store customers received about one-third as much direct mail and one to two emails per week. With such frequent customer communications, each of which used distinct models, and a consistent definition of the customer universe, a

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production solution best met the business needs in a direct business. This was a high-volume, steady-state marketing environment. It translated into a routine approach to advanced analytics for the direct department.

Fourth, staffing resources had a role in determining whether a craft or production approach to advanced analytics was adopted. The previous vendor support of the store department prided itself on intensive communication and unique marketing solutions. This required more modeling personnel than the production environment to solve advanced analytic business problems. Communication alone was a large part of the craft based modeling role. The direct department, in contrast, was launched with few staff and resources in an effort to test the impact of modeling. Years later the direct department still relied upon a small staff. In a cost-competitive industry, the adoption of a production based analytic approach to modeling was attractive on the basis of staffing efficiency alone.

Fifth, the store and direct departments of the firm were led by different management teams. Each had its own philosophical approach to advanced analytic work, consistent with the comments of Blattenberg and Hoch (1990) who discussed different management opinions pertaining to modeling. During the period under observation, leadership in the store department sought to build the best possible statistical models, often defined as one in which the top five or ten percent of customers had the highest response rate. To do so, analysts used a craft approach to fit multiple models using different algorithms until they could identify the best performing model. Confidence in the model, prior to its deployment in a campaign, was also necessary because a model was used repeatedly. Thus, model performance was compared across several prior samples or previous campaigns, an effort that could substantially increase the model timeline depending on the number and nature of these model validations. Under such conditions, a craft approach was more consistent with these business needs. In contrast, leaders in the direct department supported the use of the same modeling technique for nearly every analytic problem. It was used to target all customer communications in the belief that statistical approaches had similar expected modeling benefits.

## IMPLICATIONS AND APPLICATIONS FOR MARKETING PRACTITIONERS

Adopting a craft or production approach to solve advanced analytic problems was more than a novel observation. The decision to use a craft or production approach shaped the day-to-day work of analysts and managers, with far reaching consequences for topics such as employee sourcing, satisfaction, business flexibility, and timelines. Because implications were dependent upon one's role in the organization, the following section provides separate reflections for analysts, managers, and senior leaders / business partners, each of whom serve key functions in analytics departments (SAS, 2003; 2005).

### Modeling Analysts

When building advanced analytics, analysts faced different job conditions based on whether they worked in a craft or production environment. In the craft approach, analysts had significant interaction with business and modeling peers throughout the life cycle of the model. In contrast, analysts who worked in the production environment spent most of their time working independently. The job was highly structured and routine. There was little need to discuss modeling details, even among statistical peers. Moreover, a production environment offered analysts a limited exposure to modeling algorithms and methodologies because one technique was used to build all predictive models. For those analysts with a breadth of experience using modeling techniques, or a career goal of obtaining broader exposure to various modeling algorithms, the narrowly focused production solution limited professional growth. This was a sharp contrast to the craft solution where analysts regularly used multiple statistical techniques.

 

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For analysts, both craft and production roles posed a distinct possibility of a disconnection between day-to-day job duties and future career goals. This can be seen as part of a larger issue of how an individual fits within departmental culture. When the fit is suboptimal, it has the potential to result in employee dissatisfaction and staff attrition (for a review, see Adkins and Caldwell, 2004; for research on satisfaction and attrition more generally, see Haines et al., 2010). In the experiences described here, certain staff members in the production environment were unable to utilize their breadth of statistical training, business knowledge, or communication skills. For example, the production solution deemphasized consultative skills. In contrast, working effectively with business partners was a key component of the craft approach given the distinct business needs, demands, and brand idiosyncrasies of internal business partners. As a result of their dissatisfaction, production analysts occasionally sought new roles in a craft approach and the reverse was also true – craft analysts who struggled with meeting the communication and business needs of a varied and demanding clientele occasionally sought refuge in production approaches. Such job movement had implications for human resources staff as well. For example, in such situations, human resource partners can act as strategic resources to optimize the alignment of staff according to their aptitudes and career aspirations rather than serve exclusively in a traditional capacity where they assist managers in simply filling open positions (Buller, 1988; Ulrich, 1987).

Initially, one modeler who worked in a production solution was satisfied with completing a large number of models in a short timeframe. However, after she mastered the production process, the rigid methodological approach did not offer as much intellectual stimulation as a craft environment. Neither did the production environment offer her enough interaction with business partners as she would have preferred. In contrast, an analyst who worked in both areas reported that the craft role provided him with an opportunity to develop and enhance communications skills by explaining technical issues in a non-technical language to business partners. Preparing documentation and explaining the unique features of craft-based models provided a sense of accomplishment because it was an opportunity to hone his communication skills. In the end, he found that delivering a craft product was most satisfying.

Nonetheless analysts found a craft environment to be challenging. Chief among the challenges was interaction with business partners, who planned and approved the model. Often, this seemed to take as long as actual model development itself. Furthermore, when planning or building a model, analysis were often frustrated that their strategic and technical recommendations were not held in equal regard to those of their business partners. Finally, some analysts preferred to focus their effort on the statistical aspects of the role, finding it burdensome to invest time in intensive communication with business partners and assemble detailed model documentation.

Clearly, craft and production approaches to advanced analytics required distinct job skills, which had the potential to be misaligned with the analyst's preferences. Because the approaches met established business needs, neither approach seemed likely to change in the long-term. As a result, with inaction on their part, unhappy analysts and their managers could look forward to some combination of dissatisfaction, performance issues, or attrition, which have been a major concern of research on job satisfaction (Anderson, 2009; Dijk and Brown, 2006; Jordan, et al., 2006; Morrison, 2008; but see Judge, et al., 2001 who found a weak correlation between job satisfaction and employee productivity for less complex jobs).

### Managers

Organizing advanced analytics around a craft or production approach had implications for managers as well. Although the managerial role has many purposes (Hales, 1986), two key duties are employee performance and staffing. Regarding staff performance, managers were affected by the way this firm solved its advanced analytics objectives because craft and production approaches required unique skills. Each approach had a different flavor when it came to the day to day modeling role. Managers therefore had an interest to ensure that their staff was working within the environment that was

 

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optimal for them. When this was not the case, there was the possibility that dissatisfaction and performance problems could follow, which characterized one modeler in particular. Vacated positions also raised issues that required staffing managers and human resource personnel to consider the work environment within a craft or production solution. Candidates had to be evaluated for more than just their traditional skills and technical abilities. For example, candidates who sought to rely on strong oral and written communication skills were best suited for a craft rather than a production approach because this skill was an integral requirement for the role. Analysts who craved variety were also good candidates for the craft approach because each model was built to meet unique business needs.

Craft and production approaches to advanced analytics also had distinct sources for prospective candidates, a responsibility of both managers and human resources partners to fill. For example, junior candidates were more easily recruited from graduate school or from the ranks of those with only a year or two of professional experience. With less experience in regard to business knowledge and advanced analytics communication skills, junior modelers were ideal for more structured production roles. Furthermore, junior modelers with less experience often had lower starting salaries relative to senior modelers, which was an attractive consideration for managers in the low-cost production environment. For all these reasons, traditional job advertisements could often suffice to identify a pool of candidates. The craft approach was much different. Few junior analysts had the depth of experience needed to be successful in these roles. They needed strong communication skills. A craft environment also required experience with a wider variety of statistical algorithms than offered by many graduate programs, and it often helped to have broader experience than simply the retail industry, both of which came at a higher cost. To identify such candidates, it was often necessary to use the services of recruiters or recommendations from existing craft modelers to identify potential candidates. Ultimately, the need for managers and human resource staff to solve these distinct challenges may be just one such way to offer strategic resources to the organization and positively shape staff investment (Turpin, et al., 2005; Walker, 1988; for a competing view, see Labedz and Lee, 2011).

**Senior Leaders and Business Partners**

The decision to use either craft or production analytics had consequences for senior leaders and business partners (e.g., brand managers and managers of functional areas). This was because one solution was typically better suited to meet business goals. For example, a production environment could run smoothly when business objectives were clear and stable over time such as seeking to target core customers who had the highest response to a mail campaign. Using the same set of analytic and business requirements, the automated infrastructure of the factory solution produced many models within a short time. However, when business objectives changed, the production approach offered little flexibility to meet that need. It did not allow leaders opportunities to quickly adjust parameters surrounding the modeling universe, to shorten or lengthen the campaign response window, to change the preferred sampling method or adjust its rates, or test optimal statistical techniques when fitting models. To achieve a high-volume modeling factory, the production approach relied upon complex programming code. All of these elements left business leaders with less ability to adjust their modeling approach when business needs changed. Such was the case during a recession. Response rates among customers declined, so existing response models were not wholly adequate to meet business needs. Profitable customers were the new targeting objective, but the highly-structured automated programming code required a year or more to fully modify.

As was the case for a production approach, a decision to use a craft approach was not without its own challenges for senior leaders and business partners. Management sought to reduce model delivery timelines for craft-based models to two weeks, similar to the timelines for production-based analytics, but with the same demands for customization, communication, and model documentation. The pressure to decrease the delivery timeline in a craft environment was particularly acute during

 

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an economic downturn. Budget limitations did not allow for additional staff within the store-based department, which could have otherwise increased model output.

Finally, the ways in which advanced analytics was organized also had consequences for business partners such as project managers and operational personnel. Project managers responsible for direct mail execution were especially sensitive to model timelines because delays in model delivery could impact list selection, campaign launch date, and ultimately the very success of the campaign itself. Because customized craft models required a six week lead time prior to a direct mail campaign, it was not easy to recover from changes in mid-stride. Moreover, details relevant to model building process were often nebulous in the planning phase months before the campaign launch (e.g., target customer definition, product focus), but analysts nevertheless needed to understand these to begin model development. This too led business partners to be frustrated with the longer timeline involved in building a craft model, although they were unwilling to sacrifice their demands for model objectives, specifications, documentation, transparency, and comparison of various models when selecting the best model.

In sum, both methods of solving advanced analytic needs – craft and production – had implications for positions across the organization. I hope that by sharing these experiences, marketing practitioners will gain insight into the issues to be considered when they decide to adopt a craft or production solution. In cases where a particular solution is already in use, I wish to raise awareness of the challenges that are faced. Ultimately, if the concerns and challenges can be addressed, organizations can more efficiently solve their marketing goals.

## IMPLICATIONS FOR THE FUTURE OF MARKETING AND ADVANCED ANALYTICS: TOWARD A "WORLD OF WIDGETS?"

Although each department addressed its analytic needs uniquely, senior leaders did not value the craft and production solutions equally. In particular, there was pressure exerted upon analysts and their managers in the store-supported department to adopt a production approach. With such strains at one firm, it is reasonable to ask if managers and analysts in other organizations are similarly pressured to solve analytic challenges through a production approach. Will the future of marketing analytics be a world of widgets?

In reflecting on this question, both firm specific and more general trends seemed to be at play. First was the business environment particular to this company and its industry – an ever evolving, fast-paced retail marketing business. In this light, a production approach was appealing for its potential for rapid model delivery. Specifically, senior leaders suggested that craft-based analysts could increase the efficiency of their modeling process by borrowing the coding, algorithms, and other aspects of the production approach. To develop a final model more quickly, senior leaders recommended analysts reduce the number of competing models, among other suggestions. In return, analysts and their managers reiterated the business benefits of a craft approach, stressed the effectiveness of the craft approach, and emphasized the challenges of adopting a production methodology. Nevertheless, leaders and partners continued to value a production solution.

More generally, the tendency to value a production over a craft approach likely reflects the technological and cultural changes taking place in society. For over a century, Western culture has valued the ability of technology to solve problems (Gendron, 1977). Even in times of economic downturn, such as the latest global recession, businesses around the globe continue to invest heavily in information technology infrastructure (European Commission, 2011). There is also the astronomical pace of technological change. Computing power has increased at an annual growth rate of 50 percent (Nordhaus, 2002). It is faster, more powerful, less expensive, and more widely available than ever before. And there are massive amounts of data. A recent estimate was more than 295 exabytes of telecommunication, broadcasting, and digital information in the world (Hilbert and Lopez, 2011). Data mining and statistical software packages have also attempted to keep pace with growth in data and computing power. Over the past several years, software developers have made statistical packages easier to use particularly for general business analysts (see Azvine, et al., 2003). With the deployment of point-and-click graphical user interfaces, analysts need little to no programming experience and fewer keystrokes to build predictive models rapidly. Among many that are commercially available are IBM's SPSS Model Builder™, SAS' Enterprise Miner™ and Tibco's S-Plus®.

On the surface, increased access and sophistication of such software for the average business user would appear to encourage the adoption of a production approach. However, other interpretations should be considered before declaring the demise of craft analytics. For example, although data mining software is often marketed as a way to reduce model development costs through more rapid delivery, data mining tools can also support goals consistent with a craft approach. By simplifying the need for what was previously complex programming syntax, data mining packages now easily and quickly compare the performance of statistical algorithms in a search for the optimal mathematical solution. Analysts can spend less time writing, testing, and debugging programming code and more time on other important aspects of algorithm development such as the model planning and evaluation processes. Likewise, more time spent on understanding the underlying data and the business objectives are invaluable investments in the process of developing better advanced analytics, both of which are key elements of the craft approach. For these reasons, the craft approach will likely continue to exist, if not thrive, because a production approach does not meet every business objective across all organizations. When it comes to solving the advanced analytic needs of businesses, "one size does not fit all." Despite the pressures within this firm, our experiences with advanced analytics suggest that there is tension in adopting a production-oriented advanced analytics future that is "all about widgets."

## FUTURE QUESTIONS AND OTHER EXPERIENCES

These experiences as a modeling analyst and manager conjured up images of craft guilds and assembly plants. Such stark metaphors described unique ways to solve the advanced predictive analytics needs of a particular firm. This paper sought to describe these approaches in greater detail, outline their possible origins, and show how each had far-reaching implications for a marketing department. With such experiences described, it would be beneficial to learn how and to what extent these reflections resonate with professionals in other situations. For example, do management teams in smaller firms adopt one solution compared to their larger counterparts? Do new teams and younger firms have a different approach relative to mature ones? What about other macro-level factors such as industrial sector and country of operation? Shifting to the micro-level, how might management resources, personalities, team dynamics, and skills play a role in shaping the kinds of analytic solutions that were developed? And how might the experiences of senior leaders differ from the experience of modelers and manager described here? These are more than questions of isolated interest for any specific function or business unit. They are relevant wherever analytics are required to operate an efficient business: marketing, logistics, inventory, pricing, risk, fraud, and human resources. Analysts, managers, senior leaders, business partners, and human resources staff alike need predictive analytics to run their businesses in the 21st century, particularly as firms face pressures to mine "big data" and take action on it faster than ever before.

## REFERENCES

Adkins, Bryan and David Caldwell (2004), **"**Firm or Subgroup Culture: When Does Fitting in Matter Most?" *Journal of Organizational Behavior,* 25 (8) December, 969-78.

Anderson, Marc H (2009), **"**The Role of Group Personality Composition in the Emergence of Task and Relationship Conflict Within Groups.**"** *Journal of Management & Organization*, 15 (1) March, 82-96.

 

Azvine, Ben, Detlef Nauck and Colin Ho (2003), **"**Intelligent Business Analytics – a Tool to Build Decision-Support Systems for eBusinesses." *BT Technology Journal*, 21 (4) October, 65-71.

Blattenberg, Robert C. and Stephen J. Hoch (1990), **"**Database Models and Managerial Intuition: 50% Model + 50% Manager." *Management Science,* 36 (8) August, 887-99.

Buller, Paul F (1988), "Successful Partnerships: HR and Strategic Planning at Eight Top Firms." *Organizational Dynamics,* 17 (2) Autumn, 27-43.

Dijk, Pieter A. and Andrea Kirk Brown (2006), "Emotional Labour and Negative Job Outcomes: An Evaluation of the Mediating Role of Emotional Dissonance." *Journal of Management & Organization,* 12 (2) September, 101-15.

European Commission (2011). *Innovation Union Competitiveness*, *Report 2011.* (Accessed January 3, 2013), available at http://ec.europa.eu/research/innovation-union/index_en.cfm?pg=home&section=competitiveness-report&year=2011

Gendron, Bernard (1977), *Technology and the Human Condition.* New York: St. Martin's Press.

Goodrick, Elizabeth and Trish Reay (2009), "Florence Nightingale Endures: Legitimizing a New Professional Role Identity." *Journal of Management Studies,* 47 (1) September, 55-84.

Haines, Victor Y, Patrice Jalette, and Karine Larose (2010), "The Influence of Human Resource Management Practices on Employee Voluntary Turnover Rates in the Canadian Non Governmental Sector." *Industrial and Labor Relations Review,* 63 (2), 228-46.

Hales, Colin P (1986), "What Do Managers Do? A Critical Review of the Evidence." *Journal of Management Studies,* 23 (1) January, 88-115.

Hilbert, Martin and Priscila Lopez. (2011), "The World's Capacity to Store, Communicate, and Compute Information." *Science,* 332 (60), 60-65.

Jordan, Peter J., Sandra A. Lawrence, and Ashlea.C. Troth (2006),"The Impact of Negative Mood on Team Performance." *Journal of Management & Organization,* (12) 2 (September), 131-45.

Judge, Timothy A., Carl J. Thoresen, Joyce E. Bono, and Gregory K. Patton (2001), 'The Job Satisfaction-Job Performance Relationship: A Qualitative and Quantitative Review." *Psychological Bulletin,* 127 (3) May, 376-407.

Kwantes, Catherine T. and Cheryl A. Boglarsky (2004), "Do Occupational Groups Vary in Expressed Organizational Culture Preferences? A Study of Six Occupations in the United States." *International Journal of Cross Cultural Management*, 4 (3) December, 335-54.

Labedz, Chester S. and Jegoo Lee (2011), "The Mental Models of HR Professionals as Strategic Partners." *Journal of Management & Organization,* 17 (1) January, 56-76.

March, James G (1991), "Exploration and Exploitation in Organizational Learning." *Organization Science,* 2 (1) February, 71-87.

Morrison, Rachel L (2008), "Negative Relationships in the Workplace: Associations with Organisational Commitment, Cohesion, Job Satisfaction, and Intention to Turnover." *Journal of Management & Organization,* 14 (4) September, 330-44.

Nordhaus, William D. (2002), "The Progress of Computing." (Accessed January 2, 2013), available at http://nordhaus.econ.yale.edu/prog_030402_all.pdf

 

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SAS. (2003), *Advanced Marketing Automation for Retail*. Cary, NC: SAS Institute.

---. (2005), *Analytic Intelligence in Retail.* Cary, NC: SAS Institute.

Sutherland, Fiona and Aaron C.T. Smith (2011), "Duality Theory and the Management of the Stability-Change Paradox." *Journal of Management & Organization* 17 (4) July, 534-47.

Taylor, James (2010), "Critical Issues in Applying Analytics at Production Scale." *International Institute for Analytics,* research brief, October.

Trice, Harrison (1993), *Occupational Subcultures in the Workplace.* Ithica, NY: ILR Press.

Turpin, Tim, Samuel Garrett-Jones. and Kieren Diment (2005), "Scientists, Career Choices, and Organizational Change: Managing Human Resources in Cross Sector R&D Organizations." *Journal of the Australian and New Zealand Academy of Management*, 11 (2) January, 13-26.

Ulrich, Dave (1987), "Organizational Capability as a Competitive Advantage: Human Resource Professionals as Strategic Partners." *HR: Human Resources Planning,* 10 (4) December, 169-84.

Walker, James W (1988), "Managing Human Resources in Flat, Lean, and Flexible Organizations: Trends for the 1990's." *HR: Human Resources Planning,* 11 (2) June, 125-32.

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