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Statisticians as innovation leaders

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ABSTRACT
Innovation leading to business growth is increasingly important in many industries. We discuss the unique roles that statistics and statisticians can play in facilitating and leading innovation efforts. Many of the statistical tools to improve quality can also be used to generate more business value through innovation. We also believe that many applied statisticians are especially well positioned to drive and even lead innovation efforts. For statisticians to be successful in leading innovation, they will need to strengthen their skills beyond what they have traditionally needed in the past, but we believe this will be worth the effort.

KEYWORDS
design of experiments; leadership; new product development; quality tools; six sigma; statistical engineering

Introduction

In today's competitive environment, companies are looking to remain financially strong by increasing their profitability. In recent years, this has often come from more efficient processes and driving waste out of systems, as popularized by the Six Sigma and Lean movements. However, there is a limit to the gains that can be secured through continuous process improvement. When those sources to improve profitability are exhausted, new sources are needed. We believe that a primary future source will come from the processes of innovation. In other words, companies will have to develop new processes, products and business models to satisfy their evolving customer base. Continuous process improvement is still critical as new products, processes, and business models are developed and reach maturity, but companies need an increased focus on innovation in order to compete successfully.

Recent statistics literature has discussed the role of statistics in innovation. For examples, see Jensen et al. (2012) and Box and Woodall (2012) and the presentations of Gardner (2013), Hockman (2013, 2014), and Janis (2013). Within the American Society for Quality (ASQ), there has been an increasing focus on innovation with the recent creation of the ASQ Innovation Division. This increasing focus has taken place within a broader interest in innovation by many governments and companies throughout the world. Indeed, there is a wealth of articles and books on the topic such as those of Merrill (2008), Berkun (2010), and Christensen (2011).

Though many authors have described ways in which companies and individuals can be more innovative, there is less discussion of the role of statistics and statisticians. Our firm belief is that statisticians are uniquely positioned to facilitate and lead innovation. We expand on the earlier literature by describing some specific roles that statisticians can have in innovation efforts and give examples from our own experiences. The examples given here generally focus on our experiences as statisticians in new product development and manufacturing, but the roles described here are applicable to other environments where innovation is needed. We also include as statisticians those who have gained considerable practical experience in statistical concepts and tools without a formal statistics degree.

Innovation

So what do we mean by "innovation?" Simply stated, In-nova-tion means doing a new thing. The website businessdictionary.com defines innovation as "The process of translating an idea or invention into a good or service that creates value for which customers will pay." Jensen et al. (2012, p. 2) defined innovation as "the process of moving an initial invention or idea through

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research and development to the eventual market introduction." Bisgaard (2012, p. 31) defined innovation as "the complete process of development and eventual commercialization of new products and services, new methods of production or provision, new methods of transportation or service delivery, new business models, new markets and and new forms of organization." These definitions deal with the ability to make money from a new product or service by creating value for the customer. This ability to make money is called the "value proposition" (Hockman 2014). The value proposition involves the work of marketing to identify true customer needs, the technical group delivering something that meets that need, and the business model defining how to maximize the value, all in the most efficient way possible.

It is worth noting that "innovation in statistics" is not the same as "statistics in innovation." Both are important. The former shows creativity in developing new statistical methods and training for solving different types of problems. The statistical literature is full of innovations that continue to be produced at a high rate. Box and Woodall (2012) list examples of innovations in statistics over history and point out some new opportunities that are enabled by increased computing power. We believe that innovations in statistics outpace the ability of the practitioners to adopt them and that a greater focus on statistics in innovation is essential to the success of statistics as a discipline.

One of the many myths concerning innovation, as discussed in Berkun (2010), is that innovation is the result of an idea that pops into one's head; that is, an epiphany or eureka moment. Rather, most innovations require a lot of work to refine and perfect the initial idea and to make it reality. Berkun (2010, p. 14), in discussing major innovations of the last century, noted that all of these innovations "involved long sequences of innovation, experimentation, and discovery." Though there are well-known stories of innovations that occur as a sudden idea that leads to a breakthrough, we believe these to be less common than breakthroughs that come from a series of smaller incremental changes. Duggan (2010) described how even a product as revolutionary as the Google search engine was the result of a series of smaller insights building on existing ideas.

A fundamental aspect of the use of statistics is the sequential knowledge gain that comes from use of the scientific method. This sequential learning process is prevalent in the design of experiments literature, such as the books of Box, Hunter, and Hunter (2005), Myers, Montgomery, and Anderson-Cook (2009), and Montgomery (2012). The building of this series of experiments should be adapted based on knowledge gained from earlier experiments and further refined over time as the learning increases. This iterative process of learning results in incremental changes that result in more innovation. We agree with Schrage (2014), who noted that the key is to decrease the time that it takes to gain knowledge from a well-planned experiment. Statistics can play a key role in this sequential learning process and make it more efficient, which increases the speed at which innovation occurs.

From quality to innovation

Historically, statistics and statisticians have played a driving role in improving quality in the context of operations. This is illustrated in the left-hand pillar of Figure 1. In the past two decades, Six Sigma programs have been used to improve and streamline existing processes to make them as cost efficient as possible, driving out waste. Statistical methods useful for quality improvement include data collection strategies, measurement systems analysis, graphical tools, hypothesis testing, design of experiments, statistical process control, and others. The DMAIC (Define, Measure, Analyze, Improve, Control) methodology described in Pyzdek (2003) and Lean Six Sigma methodologies described in George (2002) are effective approaches

Figure 1. Quality and innovation.

to improvement, as are the seven basic quality tools (Tague 2005). Six Sigma and Lean Six Sigma can result in systemic or sustainable improvements that make a company more profitable through yield improvement, discovery and elimination of root causes, and variance reduction. Statisticians have played leading roles in the Six Sigma movement and will likely continue to do so.

The right-hand pillar of Figure 1 shows the relationship between innovation and statistics within the marketing and development arenas. Innovation is synonymous with designing quality into new products and services. The statistical tools needed to develop candidate concept designs and then to assess them based on data include hypothesis testing, rating and ranking processes, measurement system assessment, quality function deployment (Ficalora and Cohen 2009), TRIZ (Gardner 2013; Oxford Creativity 2015), conjoint analysis (Li et al. 2013), design of experiments (Box, Hunter, and Hunter 2005; Montomgery 2012), and risk management (For Dummies 2015). These tools are typically contained within innovation methods such as Design for Six Sigma, described in Yang and El-Haik (2008), which often utilizes the DMADV (Define, Measure, Analyze, Design, Verify) approach.

Both pillars are needed for business excellence, and we encourage the strengthening of the innovation pillar to be equal to that of the quality pillar. Reflecting on this shift of emphasis, Bisgaard (2012) encouraged expanding or even rebranding quality engineering as innovation engineering. Statisticians working as quality leaders bring tools relevant for making production and release decisions based on data. Statisticians working as innovation leaders bring tools relevant for making marketing and development decisions based on data. Underlying both areas is solid systems or statistical thinking, the view of work as a process, integration of disciplines, combination of several tools into a solution, and the mastery of what have traditionally been considered quality tools.

Statisticians and innovation

So what does a statistician have to offer to innovation? It is more than what is generally recognized. In fact, we believe that statisticians are well positioned to facilitate and lead innovation. Some of the necessary skills include driving decisions based on data, good communication skills, and diverse experiences in many areas. Many of these are already foundational skills for all statisticians. Beyond these foundational skills, we describe five specific roles that statisticians can play in innovation, which are (1) provide a holistic view and systems thinking, (2) bring an independent perspective, (3) promote statistical tools in R&D and marketing efforts, (4) facilitate problem definition, and (5) teach relevant statistical methods. After discussing each of these roles, we address the necessary skills for statisticians to fill these roles before providing some general conclusions.

Provide a holistic view and systems thinking

Because statisticians work across a variety of projects, we are positioned to have a more holistic view of systems involving products and processes. As stated in Leonhardt (2000), John Tukey famously mentioned that the cool thing about being a statistician is "being able to play in everyone's backyard." Extending Tukey's analogy, because statisticians play in many backyards, statisticians can see how they all fit together to form a neighborhood or city, while others who never leave their own backyard would never see that bigger picture.

In addition, statisticians can be experts in statistical thinking, which starts with the fundamental tenet that "all work occurs in a system of interconnected processes" (ASQ Statistics Division 2005, pp. 105–106). Understanding that everything can be thought of as a process that is related to other processes allows one to see how those processes work together to form a holistic system. Looking at the system more holistically allows one to see how the different elements of the system interact and see solutions that would not be apparent to one who only sees a portion of the system.

For example, one of the authors was able to stop a plan for adding redundant testing by seeing a broader scope of work than any of the other persons involved. He was helping a team set up a lot acceptance sampling plan for a particular product component. The team was developing a plan for testing of the component prior to final assembly, because the assembly would not change the fundamental nature of the component. While trying to understand the problem context, he learned that a similar test of this component was already being done when initially received by the warehouse prior to assembly as part of an incoming inspection. With a relatively minor adjustment to the test method being used by the warehouse, the single test was found to be adequate for both needed purposes. The thought had never really occurred to the other members of the team, who were focused on their part of the process and not aware of the full process. Having a holistic view was essential to be able to see the redundant testing and provide solution that resulted in a process improvement.

With a holistic view, a statistician can play a valuable role as a cross-pollinator of ideas and an integrator of disciplines. Because of our broad networks spanning many individuals and areas, we can refer people to someone else who has tackled similar problems and reduce their time in searching for a solution. In this role, statisticians facilitate best practice sharing across a large organization.

One of the authors is in an organization with many specialized engineers and scientists with a great variety and depth of expertise and experiences. When she leads a team or works on a problem to create a concept for a new product, she brings to the problem many diverse ideas of different approaches to consider. If any ideas seem particularly relevant, she connects the team with the right expert(s) to develop the ideas for further evaluation. In this way, product candidates are rapidly developed and concepts more likely to succeed are found earlier in the product commercialization process. The original ideas are not those of the statistician, but the statistician can act as a pollination agent for rapidly developing successful concepts. This ability to innovate by considering intersections of different subject areas is described in greater detail in Johannson (2006) and is a way for a statistician to be a catalyst for new innovation and greater efficiency in existing processes.

Bring an independent perspective

Because the statistician is not typically the principal investigator on a process or product design, he or she can bring an independent and objective perspective to problems. Being outside the day-to-day work allows the statistician to ask fundamental questions and challenge basic assumptions. This new perspective can lead to new ideas valuable in innovation.

When someone says, "We've always done it this way," there is likely an opportunity to improve the current process because of the hidden waste that has always been tolerated. Bringing an independent perspective allows one to question why things are done in certain ways and identify better ways of doing things.

When involved as a member or leader of a project, a statistician can focus on the unbiased reasons for continuing or ending a project. With a data-based mindset, we can help project teams make better decisions. Sometimes the best decision is to stop a potential innovation that will waste time and resources that would be better used elsewhere. This is of huge value when making such critical decisions with sometimes large amounts of product development dollars.

For example, one of the authors was working on a development project as a team member. The team was working with a partner to develop a new technology for making product that would then use specialty (higher priced) materials. Statistically designed experiments were used liberally and the team learned that there was indeed a set of process conditions that would work well with the specialty material to make high quality product. The project team wanted to move forward. However, the data also showed that there was another set of operating conditions that would work equally well with a commodity (inexpensive) product available from many suppliers. The team could have moved forward and developed the process to use the specialty material, but it would not be long until someone discovered that with some rather minor process adjustments, cheaper material would work, and there would no longer be a market for the product made using the specialty material. The decision was made to stop the project. An objective view of the experimental data and honest assessment of the market were key to making the correct decision in this situation.

Promote statistical tools in R&D efforts

Beyond improving existing products, statistical methods play a large role in development of new products. There are almost as many processes for new product development as there are companies in the world, but there are basic similarities among them. There is a funneling of ideas associated with the product development pipeline. Many ideas are needed at the beginning of the funnel to sift, evaluate, develop, and further assess to ensure that at the end, a few result in a successful commercial offering. A framework often used for product commercialization is one that involves stages, stage gates, and decision boards, as illustrated in Figure 2.

Throughout these stages, there are many tools the statistician should promote to make this commercialization process more effective. Early in the process, the stage gate objective is typically to understand the market needs. Is the idea coming in to the development

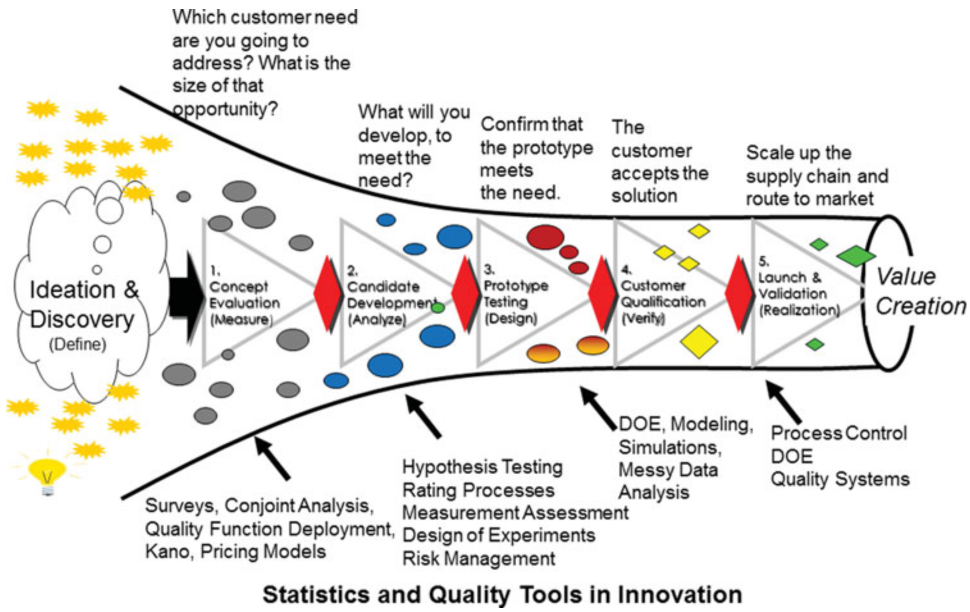

Figure 2. Product commercialization framework developed inside DuPont for commercializing new products. This is an example of a stage-gate methodology described in Cooper (2011).

process one that will meet a critical need in the market? Is there a compelling value proposition for the new offering being proposed?

Tools a statistician may bring at this point include those mentioned in the right pillar of Figure 1. Some additional useful tools for market research studies include survey methods for collecting voice of the customer data (Iacobucci 2014; Rossi, Allenby, and McCulloch 2005), Kano analysis (Coleman 2015), the analytic hierarchy process, and pricing models (Sodhi and Sodhi 2007). As in any good scientific investigation, marketing studies only produce results that reflect the design and thought going into the planning of data collection. Statisticians can listen to the team's information needs, design the right study, employ the right statistical tools, and then help analyze and interpret the data that are collected to extract meaning and direction for the development.

Later in the commercialization process, design of experiments has proven to be successful in R&D environments for generating new products that are optimal in meeting different customer needs. Rather than have a team/individual tinker endlessly by tweaking design features, they can be studied comprehensively in a designed experiment that covers a broad range of product design characteristics. The use of an experiment allows for building knowledge of the interplay between the features in terms of the product characteristics that customers really care about. Throughout the development, a statistical approach provides power and confidence in the decisions that result.

Because there is always the pressure to move forward without all of the answers, managing risk is crucial. This is best approached in an analytical way, complete with scenario planning techniques. One of the authors was asked to take the leadership for a project that was early in Stage 3, yet its value proposition in the market was debatable. Several small (and one not so small) snags had been encountered along the development path, and compromises began to stack up. As a statistical thinker, she used a criteria-based decision matrix (Tague 2005) approach to evaluate the value proposition. It is not a rigorous statistical technique complete with confidence levels, but it is a quantitative analysis approach that considers the recently accumulated voice of the customer data. It was concluded that enough had changed that the value proposition was no longer compelling enough to pursue the idea. A recommendation was made to stop development in favor of pursuing something more promising. The information was there, but the statistician organized and viewed it using a quality tool in a way that facilitated decision making.

Facilitate problem definition

Perhaps the hardest part of an innovation may be defining the problems that need to be solved. Once a problem is clearly articulated, the solution often becomes straightforward, but it can be a lot of work to define the real questions that must be answered. A statistician can play a role as a listener and facilitator in helping to define the relevant problems. As an objective, independent individual, the statistician can ask probing questions, challenge fundamental assumptions, and help others determine the true issue at hand. To play this role requires good listening skills and a willingness to ask difficult, challenging questions. This can involve the asking "Why" five times, which helps drive to the true root causes for a problem. It requires a resistance to jumping to a solution too soon while restating and repeating what we think we have heard. The result is clarification and alignment on the issues at hand.

Often when someone seeks statistical help, they dive right into the questions that they have on a particular tool or analysis. In order to make sure that the analysis is appropriate, we find ourselves asking, "What is the question you are trying to answer with this tool?" It is not unusual for someone to struggle in providing a coherent answer. Thus begins a discussion around the problem context and gaining clarity around the data and analysis that are really needed. Once that has been clarified, it is not unusual for the original questions to be moot, because a whole different analysis is needed.

There are a variety of questions that can be used to help facilitate problem definition. For example, Heilmeier (1992) describes a catechism or series of questions that have become know as Heilmeier's catechism or critical questions. They are given in Heilmeier (1992) as follows:

1. What are you trying to do?
2. How is it done today?
3. What are the limitations of the current practice?
4. What is new in your approach and why do you think it can succeed?
5. Assuming you are successful, what difference does it make?
6. How long will it take?
7. How much will it cost?
8. What are the midterm and final exams?

These probing questions help others articulate more precisely what they are trying to do and why they are trying to do it. The increased precision in problem definition can result in better solutions. Facilitating problem definition means challenging individuals and teams on their true objectives. It requires suspending judgment on an issue as long as possible until the issue is truly understood, then moving forward, managing a few potential solutions in parallel. O'Neill, as cited in Jensen et al. (2012, p. 5) referred to this as the ability of innovators to "clear their minds from distracting questions to make space for entertaining a variety of solutions to the central issue."

Teach relevant statistical methods

In being able to generate innovation, one does not necessarily need the most sophisticated statistical tools. We believe that more innovation results when a large number of individuals have access to basic statistical tools than when a small number of individuals know more sophisticated tools. This explains some of the success of the Six Sigma movement, which has put basic statistical methods in the hands of the masses as discussed in Montgomery and Woodall (2008). Though there is certainly some misuse of these statistical methods by some users, the overall effect has been positive with many new process and product innovations as a result.

We agree with the sentiment of Box (1990, pp. 367–368) who stated, "There are hundreds of thousands of engineers in this country, and even if the 2^3 [factorial design] was the only kind of [experimental] design they ever used, and even if the only method of analysis that was employed was to eyeball the data, this alone could have an enormous impact on the experimental efficiency, the rate of innovation and the competitive position of this country."

As statisticians, we have to put basic tools in the hands of more users. The most critical of these basic statistical tools are graphical tools. Modern computer software such as JMP now provides dynamic graphing capabilities that allow the user to view data in many different ways. This dynamic capability facilitates innovation because it allows the user to visualize what is happening with the data. With a graph they can see patterns and information in the data and then ask why the patterns exist. They can ask questions such as "Why are the data that way?" "Why is that point different than the others?" "Why is there a difference between those groups of data?" and others. Once they are able to frame the questions, they can then investigate and find explanations, which then lead to solutions and innovations. Bisgaard (1996) gave a nice example of how graphical methods led to additional questions and innovations.

This ability of graphical methods to generate additional questions means that statistical training must focus less on fitting sophisticated models to data, confirmatory analyses, and its calculation-heavy, theoretical roots. Statistical training should align more with the exploratory data philosophy of Tukey (1962, p. 13), who famously stated, "Far better an approximate answer to the right question, which is often vague, than an exact answer to the wrong question." A graph is an extremely valuable tool for obtaining approximate answers.

Feder (1974) used an analogy of the detective vs. the judge in comparing graphical methods to numerical analysis. Like a detective, graphical methods are exploratory in nature, trying to find clues in the data. In contrast, a judge uses the data to determine the level of evidence for a particular hypothesis. To innovate, one needs to know when to play the role of detective and when to be the judge. Statisticians can play both roles effectively. The exploratory use of statistical methods rather than a confirmatory use of statistical methods was described in more detail in de Mast and Trip (2007) and de Mast and Kemper (2009) and its discussion. This ability of graphical methods to encourage inductive reasoning was noted by Snee and Hoerl in Jensen et al. (2012). As a result, statistical training must include more critical thinking skills.

Students should be taught statistical methods for identifying data anomalies. There is a large literature on ways to robustify statistical methods by making them less susceptible to unusual data points or non-standard distributions. Though these methods can be valuable for some situations, it is important from an innovation perspective to highlight unusual points, not obscure them. Outliers can be rich sources of information, and it is crucial to study them to gain insight as to why they are different than the rest of the data. Thus, though robust methods are appropriate for certain data sets, they may also cause one to miss opportunities for innovation. Many innovations throughout history have come as a result of an outlier, where something unexpected happened. See Berkun (2010) and Box and Woodall (2012) for examples.

Finally, in this focus on teaching appropriate statistical analysis methods, there must also be a focus on good data collection methods. As all statisticians know, the value of the analysis depends strongly on the quality of the collected data. Data collection principles such as those discussed in Doganaksoy and Hahn (2012) and Anderson-Cook and Borror (2013) are absolutely crucial.

Necessary skills for statisticians in innovation

In addition to technical competence, statisticians wishing to lead innovation must possess a variety of skills. In considering these necessary skills, we note the recent discussion around the concept of statistical engineering as described in Hoerl and Snee (2010). In particular, Hoerl and Snee (2012) and Anderson-Cook et al. (2012) discussed the necessary skills to be successful in statistical engineering projects. We believe that the skills needed to facilitate and lead innovation are similar to those needed by statistical engineers; thus, the skills that we describe here are also relevant for statistical engineering projects. The skills we discuss are good people skills, business acumen, integration and self-positioning skills, and an understanding of organizational readiness.

People skills

In order to lead innovation, statisticians must move beyond being calculators and analysts and move more into roles such as coach, mentor, facilitator, cross-pollinator, etc. The skills necessary to facilitate and lead innovation are not often found in statistics textbooks. Rather, these skills are people skills as described in Hahn (2002) and in more detail in Hahn and Doganaksoy (2012). So what does this mean for a statistician? It means that we have a role to play in training, teaching, and coaching to broader groups of people. This role is closer to the idea of a proactive statistician described by Hahn (2002). Doganaksoy, as cited in Jensen et al. (2012, p. 4), referred to this concept in describing "end-to-end involvement and providing guidance throughout the process rather than on-demand engagement to answer specific technical questions." This would result in a statistician moving away from a passive analyst role and playing an active role as a team member or team leader, as was noted in Anderson-Cook et al. (2012).

Business acumen

In addition to people skills, the statistician would need a broader understanding of other areas such as business, marketing, finance, information technology, sales, and human resources. The statistician must be able to speak the language of these other areas and move beyond statistical jargon. It requires an ability to explain difficult concepts in a simple way. It requires a focus on tools that really will be used by these individuals, regardless of their lack of statistical sophistication. It requires expanding horizons and learning about other areas.

Business acumen also means that the statistician has a good idea of relevant metrics. Though statisticians are strong promoters of collecting data to track progress, it is important that the metrics be related to what the business leadership really values. The choice of metrics must balance cost of resources and time with the efficient use of resources and the risk associated with business decisions. The problem-solving skills that statisticians have can be valuable in determining the appropriate metrics for business priorities.

Expanded technical expertise

Technical expertise is a must, but that knowledge of statistical methods must expand to include tools shown on the right-hand side of Figure 1, as discussed previously. In addition, future statisticians could be more useful in innovation areas if they could be trained to facilitate the use of creativity tools (de Bono 1970, 1985).

Success depends on our abilities to expand our horizons beyond the traditional areas where statistics has been applied to improve quality. Jensen et al. (2012, p. 4) stated that "statistics at its heart is about facilitating decision-making based on quantitative objective information." If we take that as a mission statement for statisticians, we will see that there are many opportunities throughout an organization to help make better decisions based on data.

Integration and self-positioning

Statisticians need great ability to interact with other team members. Because statistics is such an integral part of the road to commercialization, it is clear why a statistician should be a full member of the development team and should be part of all team meetings and processes. The statistician's tools are those that enable other team members to better apply and interpret their own sciences, so it is critical that the statistician on a development team can work with a variety of different disciplines and be flexible enough to partner with others in investigative studies of all kinds. Again, a good applied consulting statistician often finds him or herself in such roles.

Beyond simply being a member of a team, some statisticians can be very effective in actually leading innovation projects. The team leader is tasked with being able to listen well to discern what expertise may be relevant when and to engage and empower the right set of people. Leaders are responsible for interpreting the data being generated, extracting meaning, and making decisions based on that data. They are integrators and work across technology and disciplines on a routine basis. Candidates for project leadership generally need to develop knowledge of project management and develop stronger leadership skills. Snee and Hoerl (2004, 2012) encouraged the transition from statistical consultant to leader, and this concept, though applied to the context of statistical engineering, has always been in play for those maturing in their fields. Statisticians who can effectively lead people as well as projects can and should be leading innovation.

We note that in these leadership roles, we are not advocating that statisticians be gate-keepers, as cautioned by Jones in Anderson-Cook et al. (2012). Rather, these roles are more collaborative in nature with the goal of helping projects be more successful. A collaborative role helps ensure that the entire team is supportive of major project decisions, including decisions to end a project. Statisticians are well equipped to make decisions because they are trained to do so and are skilled at being unbiased.

Organizational readiness

An organization for which innovation is a key focus area might want to consider how prepared they are to meet the statistical competency needs for innovation. They should ask questions such as how to assess the performance of junior statisticians in a way that encourages the right sorts of behaviors. How do we promote development of the essential skills? How can we enable some to excel in innovation leadership, while others can excel in more highly technical statistical application development? How can we recruit statisticians with a more well-rounded set of skills and who are excellent at interacting with a wide variety of people?

And from the reverse perspective, a statistician seeking to work in innovation should consider a broader look at statistics as a competency. The statistician should ask questions such as, How can I encourage better data-based decision making across a broader slice of the organization? How can I be trained to work in marketing statistics or to use creativity tools and lead teams? How can I develop good team interaction skills?

Conclusion

Innovation is an exciting space in which to work. Statisticians should embrace the unique opportunity they have to play a role in facilitating and leading innovation. The good applied consulting statistician already brings several advantages to innovation work, and the stronger he is in these roles, the more naturally he will fit within innovation team processes. As statisticians seek to expand their current roles to include some of the roles discussed here, they would do well to develop additional skill sets to increase the likelihood of success. In doing so, they will be recognized for their contributions and can enjoy a deep sense of satisfaction in knowing that they helped in creating some of the new innovations of the future.

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