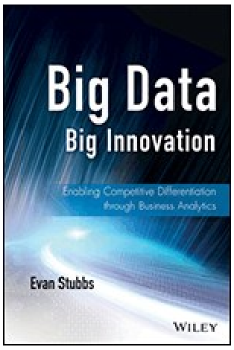

Big Data, Big Innovation: Enabling Competitive Differentiation through Business Analytics

by Evan Stubbs

Chapter 7: Human Capital

Overview

Change is inevitable and business analytics is a profession of change. The domain has and will continue to change—as our data grows exponentially, the real game is moving away from sheer brainpower to being able to harness and reduce complexity. Having the right answer is only the first step. Without the right supporting systems to act on that answer, it's all wasted effort.

That doesn't necessarily preclude sophistication or highly advanced analytics. What it does instead is encourage focus on developing the right competencies, tasking people with the right objectives, and structuring the organization in a way that allows it to foster, retain, and develop talent. By focusing in the right areas, the leadership team can hire the right people, establish the right incentives, drive efficiencies, and nurture the right behaviors.

One of the reasons it's so hard to find the right people is because of the breadth of the field. Business analytics is a spectrum that ranges from relatively simple information management to highly specialized fields such as operations research or machine learning. Assuming people with different skills are substitutable just because they work in "analytics" is a recipe for disaster. Much like building a house requires more than just a carpenter, most of these skills are not interchangeable.

That in itself is a challenge—without the right domain knowledge, hiring someone with highly specialized experience can be a shot in the dark. Complicating things further is that while analytics tends to focus on hard skills, business analytics requires both hard *and* soft skills. As a profession, business analytics is primarily about blending change management skills with technical domain knowledge. To help with building human capital, the rest of this chapter focuses on three things:

1. What capabilities do I need?
2. How do I get the right people?
3. How do I keep them?

Reducing uncertainty during the hiring process is difficult. Luckily, though, there are a few things to be aware of that can help improve the odds of getting the right person. Getting off on the right foot starts with knowing what you're looking for. The rest of this chapter will answer these questions and lay the foundation for skills acquisition and development.

What Capabilities Do I Need?

Data scientists have been getting a lot of interest. There are many reasons for this, not the least of which is the amount of chatter about big data. However, it's more than just a title. There's a very real need to describe in a concise way the difference between a statistician or analyst and someone who practices business analytics. In markets characterized by imperfect information, buyers and sellers often develop signals that help communicate relevant information in a concise (and often difficult to replicate) way. Being aware of this and taking advantage of it can make the difference between hiring the right or wrong person for the job.

Numerical analysts have been described by a variety of titles. Depending on the context, industry, and organization, they've been called applied statisticians, data miners, predictive modelers, risk analysts, or just simply quantitative analysts. The field is broad, but these roles consistently exhibited some common patterns:

- A focus on numerical analysis in some form
- Specialized in technical skills
- Strong background and focus on theoretical knowledge
- Ability to generate and communicate insight

These are critical in generating insight. Business analytics, however, goes beyond this—it also requires the ability to:

- Emphasize recommendations over insight and outcomes over analysis.
- Define processes based on an organization's ability to execute, not on what's possible.

- Create repeatable processes rather than doing independent, discrete, and one-off activities.
- Understand and apply organizational psychology and influence.

For an organization hiring someone to drive business analytics, these differences can make or break a project. To see why, consider Figure 7.1.

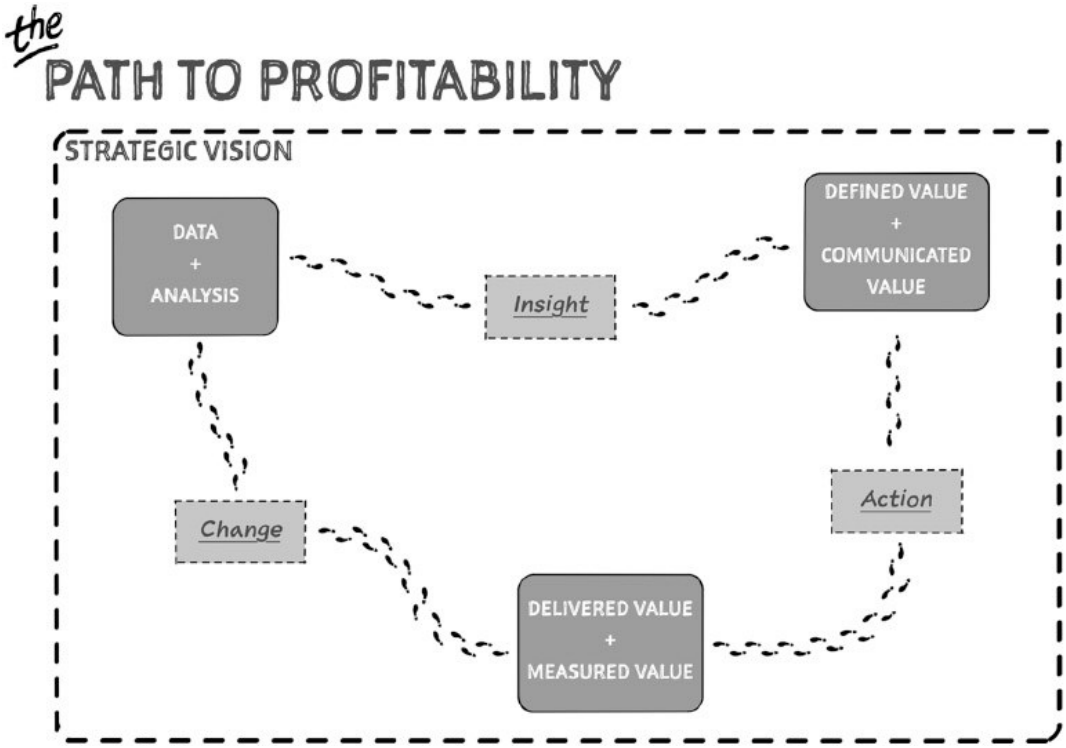

Figure 7.1: The Path to Profitability

As covered in the previous chapter, value comes from using information to generate insight and take action. This value needs to be aligned against strategic priorities and the organization's unique business model. However, action is impossible without change. And, change requires a reason to act. The value needs to be understood *and* communicated. And once delivered, the only way to fuel more change is to build trust through measuring that value and demonstrating that everything promised was delivered.

These are very different skills. Getting insight out of big data is impossible without access to high-powered analytical capabilities. However, getting an organization to change is impossible without the ability to communicate, sell, and build trust. This, at its most basic, is the difference between a *data scientist* and a *value architect*. And, organizations interested in maximizing their return from big data need *both*.

For those hiring, advertising a role for a "data scientist" rather than an "applied statistician" can help communicate the different focus and intent. However, if they're unaware of the importance of change in the overall process, they can quickly find that what they got wasn't what they were looking for. These differences also need to cascade down to the job description and be made obvious—while it won't stop the wrong people from applying, it will help improve the odds of getting the right person.

Data Science

Generating insights from data isn't a new profession. Historically called *quants*, *statisticians, analysts*, or even the now-quaint term *computers*, organizations have been using data-crunchers to create competitive advantage for centuries. In fact, it sometimes comes as a surprise how *long* the profession has been around. It's arguable that Bletchley Park managed to shorten World War II by years through their cryptographic analysis.[1] Even Guinness, the well-known brewer, was using analytics at the turn of the twentieth century to create competitive advantage.[2]

Still, there are some differences. First, data science is more than just analytics; it blends communication skills with information management and experimental testing knowledge. While the difference may seem small, a key part is the scientific mindset data scientists bring. They emphasize testing and validating a hypothesis using big data rather than simple exploration or statistical reporting. Good data scientists excel in simplifying the complex, always striving to get to the core of the problem.

While they demonstrate an academic or scientific mindset, their goal is to solve the problem, not necessarily expand the boundaries of knowledge. In that sense, their focus is very much applied rather than theoretical. Characterized by curiosity, they get excitement out of answering the *why* and working out the *how*. Faced with impossible challenges, they'll look for a way to overcome them rather than accept them.

Second, they have the ability to work with big data. At a minimum, they're completely at home with "large data." More typically, they're comfortable with big data in its purest sense. Unstructured, high-velocity sensor data presents an exciting challenge to them. For experienced data scientists, experience working with petabytes of data simply justifies membership to the club, not recognition.

Finally, they are highly multifunctional. They draw their knowledge and experience from multiple disciplines and often, multiple domains. Many have experience in domains as diverse as linguistics, graph theory, and unsupervised machine learning. Programming is a given, as is knowledge of statistical methods. This forms the heart of one of their greatest strengths—their ability to draw from multiple schools of thought. They have an almost-supernatural ability to see the patterns among industries, cross-referencing and using their experience to solve diverse problems using common skills.

Competent data scientists are hard to find. As in every growth industry, many claim the titles that seem to carry the greatest remuneration. Unfortunately, just because someone has the title Data Scientist on his resume doesn't necessarily mean he is one.

Value Architecture

Data scientists are a key part of the picture. However, they're not the answer on their own. Insight without the ability to get the organization to act on it is wasted potential. The biggest mistake organizations often make is to assume that their data scientist can do *everything*. In some rare cases, she can. Usually though, getting value out of big data and business also requires someone to focus on selling the value of change.

Like the opposing forces of *yin* and *yang*, data scientists need their counterpart if they're to create value. Too much insight can be detrimental; faced with a data deluge, the worst thing one can do is to use that data to generate even more data! Left alone, many data scientists will fly beyond their organization's ability to comprehend the value of what they're doing.

The answer isn't to stop them from being smart or innovative. Instead, it's to make sure that they're complemented by someone focused on helping the organization transition and change. This is a different skill set, one characterized by *value architects*. These *theotors*, literally the "gods of twist," are experts in change. Almost *actipreneurs*, they are experts in making sure insights are acted on to drive real benefits.

Unlike data scientists, they care a bit less about the insight. Instead, they care about the organization's ability to realize *value* from that insight. They're often more passionate about innovation and getting the business to change for the better than they are about the specifics of the "how."[3]

Communication is obviously a key part of this. However, their skills go beyond those of a data scientist. Their role is that of a true change agent, one who understands how to define, persuade, and drive organizational transformation. While they may not have the analytical capability to mirror the best data scientists, they're unparalleled in getting the organization to change the way it operates.

Change starts with a sense of urgency. Value architects help the organization understand what the change is worth. They help the organization navigate the path to get there. Finally, they use those successes to fuel the next round of change. Value architects are the link that enables the organization to get value out of the analytical capabilities. While some data scientists are *also* value architects, most aren't. The goal of a value architect is to move the insight through to action and, eventually, change. They're also the key to unlocking longer-term differentiation. They ensure a focus on linking tactical gains into strategic benefits.

The Power of Both

Left alone, few analytics teams are good at change management. That's not a criticism—if their primary objective is to generate insight, there's little need for skills that don't support that goal. Business analytics, however, is about driving change. And so, part of establishing an effective business analytics team involves augmenting the analytics team with business analytics skills.

Given most data scientists are focused on data, detail, and mathematical creativity, it's rare to find one person who has all the right skills. Unfortunately, without someone to evangelize and drive real change, the investment most organizations make in data scientists goes to waste. Establishing a strong capability means having a plan to acquire *both* types of skills, not one or the other.

Good value architects are an even-rarer breed than data scientists. They draw heavily from knowledge of operational analytics, change management, and strategic planning. As Figure 7.2 shows, they complement the skills of the data scientists and together, they are the lynchpin to unlocking value and enabling innovation from big data.

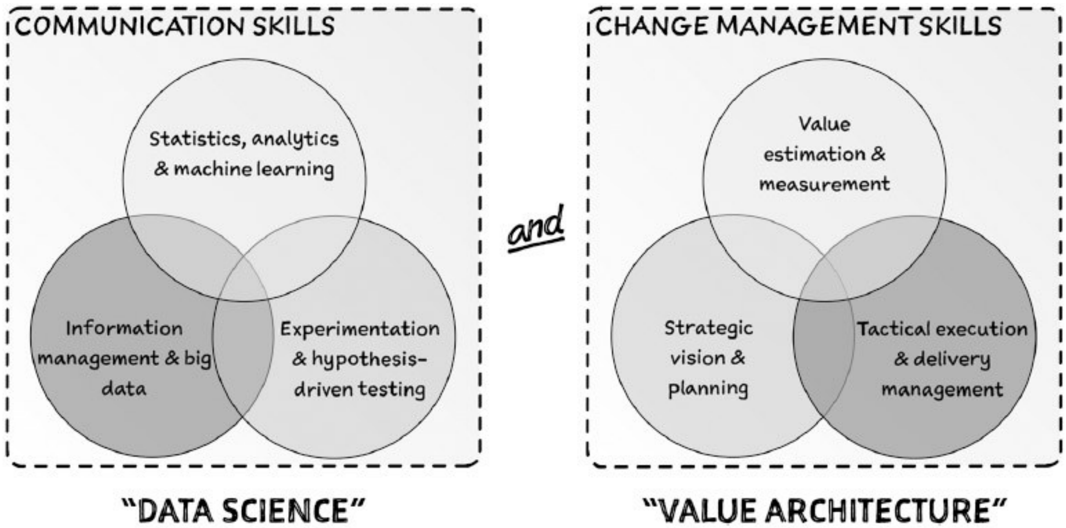

Figure 7.2: Data Science vs. Value Architecture

The most effective business analytics teams structure themselves to support two somewhat different objectives. On one hand, they provide enough role coverage to span the entire analytical lifecycle from information management to operationalization and value measurement. On the other, they also understand that delivery, while essential, is only part of the picture. Delivery also requires a defined opportunity, broad stakeholder support, and the right frameworks in place to ensure every initiative represents a connected steppingstone to true competitive differentiation.

In many ways, these represent two sides of the same coin: one is focused on value creation while the other is focused on value identification. These are tightly interdependent—without its counterpart, each is largely ineffective. Delivery without an opportunity usually regresses to exploration and research. An opportunity without the capability to deliver is simply a good idea. The best teams have a blend of resources and responsibilities that support both.[4]

Rather than simply accepting the team's environment as a given, the most effective teams play an active role in transforming the organization, focusing on:

- Proactively identifying opportunities to drive value through business analytics
- Driving and managing change
- Ensuring consistency in execution and measurement across the organization

This reflects a very real move toward playing a proactive role in driving transformation. Instead of being fearful of change, the team embraces it and, by developing skills in change management, helps the organization move toward best practice. They each focus on different things, as shown in Figure 7.3. The heart of business analytics is change. This requires both an answer as well as a reason to change.

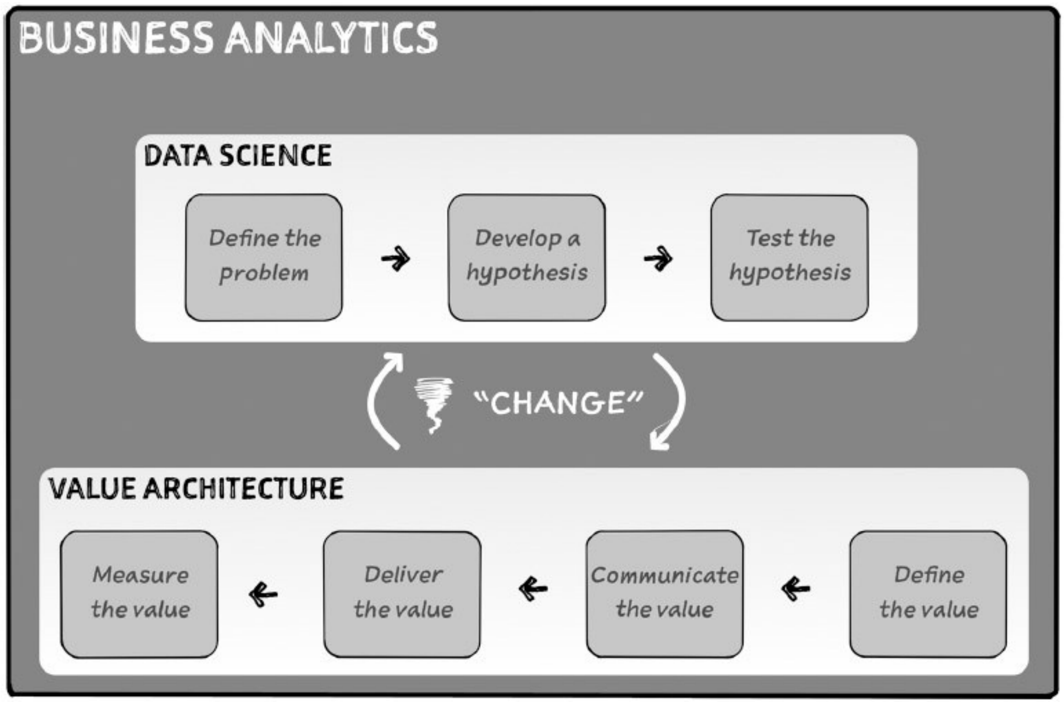

Figure 7.3: Data Science Combined with Value Architecture

Data scientists concern themselves with the answer, value architects with the reason to change.

Together, they link insight to value. Often, they form a partnership to lead a broader team. These roles do not necessarily map one-to-one with individuals. People in smaller teams may play more than one role. Critically, though, an effective team has coverage across both these activities to some degree. When there's insufficient coverage, the odds of success drop substantially.

[1]T. M. A. Lomas and Computer Security Group, "The Influence of ULTRA in the Second World War" (interview by Harry Hinsley), Computer Laboratory, University of Cambridge, Nov. 26, 1996, www.cl.cam.ac.uk/research/security/Historical/hinsley.html (accessed Apr. 21, 2013).

[2]Joan Fisher Box, "Guinness, Gosset, Fisher, and Small Samples," *Statistical Science* 2, no. 1 (1987): 45–52.

[3]Evan Stubbs, *The Value of Business Analytics: Identifying the Path to Profitability* (Hoboken, NJ: John Wiley & Sons, 2011).

[4]For a full list of the roles that normally fall within a business analytics team along with typical hiring patterns, see Chapter 3, Evan Stubbs, *The Value of Business Analytics*.

How Do I Get The Right People?

It shouldn't be surprising that some teams are just better than others. While it's true that technology, data, and process can all influence success, it's also true that these pale in comparison to having the right people.

This isn't unique to business analytics; it's a well-documented phenomenon that shows up across every industry sector and discipline. Fred Brooks found that their most highly performing programmers were 10 times more productive compared to their average peers.[5] Robert Glass set this even higher, suggesting that the most productive programmers were *up to 28 times more productive* than their peers.[6]

Great results require great talent; Steve Jobs often spoke of his need to hire "A" performers.[7] This is equally true in business analytics. While performance obviously varies, the most capable firms are able to achieve a level of productivity (as measured by outputs or financial impact) often over an order-of-magnitude higher than the second. This is despite often having an order-of-magnitude fewer data scientists employed.

The SMART Model

There's clearly a difference. And, it's not surprising that given a choice, it everyone wants more of the first type of people and fewer of the second. The obvious question is, how do you identify them?

High-performing people display three different types of capability. At a minimum, they need to know how to do their job. Hard skills allow entry; applicants need to understand their tools, apply the scientific method to data analytics, and be competent in interpreting their results. Validating these skills is fairly straightforward; because they're precise, it's a case of testing knowledge. To this end, many interviews focus on case studies, artificial problems, or experiential validation. Unfortunately, it's here where most interviews stop. And, these skills are the *least* important when it comes to success.

The trick to developing an effective team is in recognizing that not everyone needs to be expert in everything. Some people will naturally develop into analytical experts. Some will become change agents. Others will become experts in driving business value. Having the right framework makes it easier to hire better people as well as develop internal talent. Luckily, there's a simple way of identifying the right people. Figure 7.4 shows a technique to ensure high-quality human capital.

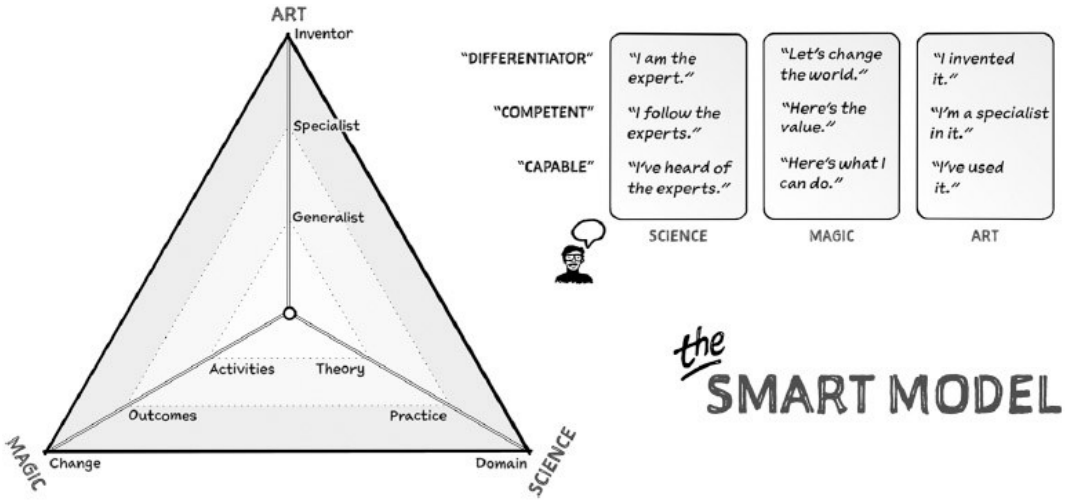

Figure 7.4: The SMART Model

Art

The ideal data scientist knows everything. She can make magic happen. And, she has that "art," the knowledge of how not just to do the job but to excel in it. We'd all love to hire that person. Realistically, though, finding the perfect person is impossible. Instead, it's easier to make sure that in aggregate, the team has access to all the capabilities it needs. While no one person might be perfect, the whole may yet be greater than the sum of its parts.

On the scale of effort, the *art* is the easiest to develop. It simply requires the right training and exposure combined with the right attitude. Gaps can be filled by on-the-job training, courses, or higher education.

The starting point is having access to generalist experience. While the person may have held many functional roles or responsibilities, at this level he has rarely encountered the same problem multiple times. Regardless of whether one is considering analytics, big data, or even managing innovation, challenges are solved from first principles and efficiency is relatively low. The bare minimum of competence is having the hard skills necessary to "do the job."

Given enough time, individuals face the same challenges repeatedly. Exposure causes their functional knowledge in specialist areas to increase, thereby increasing their efficiency through sheer experience. They understand best practice and hold to it.

A small set of people go beyond this. Drawing on their deep functional knowledge, they transition from being a specialist into an inventor. Rather than following best practice, they define it, often relying heavily on emerging technologies, knowledge, or networks. They ride on the crest of the wave, leading the industry as a whole.

Hiring an inventor is intuitively attractive. Unfortunately, in isolation these skills rarely correlate well with long-term success. Competency always has a role to play in the problems people can solve. However, just because someone *can* solve a problem with the skills he has does not necessarily mean that he *will* solve the problem.

This is often one of the reasons "B" performers end up hiring "C" resources. Without intuitively knowing how high performers are different from average performers, those doing the hiring need to rely on quantitative and objective methods to shortlist candidates. And, there's nothing more explicit than stating and evaluating technical and nontechnical requirements for a role. Knowing how to do the job plays an important role in eliminating bad candidates but it helps little in differentiating the good from the great.

Skills are important, but without the maturity and science to go along with them, they don't guarantee success.

Magic

If having the right degree and the right experience says little about a candidate's ability to succeed, what else is there to go on? Beyond being able to know how to do their job, high performers also demonstrate different behaviors. They approach their work from a perspective of "getting things done," and more often than not, understand the importance of quality. Their motivation is aligned with the organization's higher intent, their focus is on making a difference, and they deeply understand the organization's high- and low-culture characteristics.[8] This is the *magic* that turns someone from an expert into an enabler for change.

Needless to say, these skills are far harder to identify and evaluate without prolonged exposure. They're also the hardest to develop in a structured way. Unfortunately, they're also the most important factor in determining success. It's for good reason these are often referred to as "soft" skills. They come with *maturity*, something that's hard to train. To be effective, much of the effort focused on organizational change and human capital development *needs* to be focused on reinforcing and developing these skills. Coaching and mentoring are the main ways of developing these skills.

In practice, these differences span a broad spectrum of cognitive, behavioral, communication, and motivational factors. More than anything else, it's these characteristics that distinguish "A" performers from their counterparts. And, whether it be intuitive or deliberate, "A" performers often have an innate ability to identify people with similar behaviors. As managers or leaders, they either shape and enforce their culture around them or they leave; nothing frustrates a high performer more than being around incompetent or unmotivated people.

Getting people with the right soft skills is essential. Of course, the core challenge is that those same soft skills, by their very nature, are exceedingly hard to pin down. Consistently, though, high performers in business analytics tend to exhibit one or more of the following behaviors. They:

- Are effective and often passionate communicators and evangelists Have a deep and often diverse platform of hard skills to draw on
- Maintain a focus on value and outcomes rather than insight and answers
- Demonstrate a balance of creativity in problem solving with pragmatism in practicality of execution
- Understand the importance and role of culture and change management in driving outcomes

It's useful to view this "*behavioral*" *spectrum* across three levels, each of which builds on the previous. The starting point is understanding the importance of delivery. Without activity, nothing happens. The bare minimum of competence is ensuring that the job "gets done." Usually, they benchmark their professional success on whether they've met their performance metrics.

At some stage, most individuals start to question the impact their activities have on the broader business. When this happens, some make the intuitive leap to understanding the importance of outcomes rather than effort. Their attention often moves to demonstrating return, measuring outcomes, and building a culture focused on value creation. They benchmark their professional success on the value they have created.

Again, a small set of people go beyond this. Rather than being content with their organization as it is, they see the potential of what it could be. Their focus shifts toward change and evangelism and their effort moves toward organizational transformation. They benchmark their professional success on the degree to which they've changed the world around them.

Science

The need for experience and soft skills is not unique to business analytics. Whether they're employed in consumer goods, the public sector, or any other industry, high performers everywhere demonstrate these characteristics. Where business analytics differs from many other disciplines is the need for cross-functional knowledge. Without *science*, the best skills in the world are just theoretical.

Analytics is a technical discipline based on rich theory. However, it can't happen in a vacuum; to create value, it needs to be applied to a business problem. And, solving this problem most effectively requires domain knowledge. This spectrum of *science* is the final dimension that differentiates high performers from average performers.

At the lowest level is theory. This often spans a wide range of disciplines, including mathematics, computer science, machine learning, and the scientific method. The bare minimum of competence within this dimension is having a sufficiently deep prerequisite level of knowledge to start experimentation. While individuals may have solved problems in academic or theoretical contexts, they lack the "battle experience" of solving the same problems in environments clouded by politics, poor data, and constantly shifting organizational priorities.

Over time, this theory transitions into practice. They apply their skills to real-world problems and, by doing so, build an understanding of how abstract mathematical or computational processes can be applied to business problems. These individuals have the knowledge *and* ability to solve business problems using analytics.

Yet again, a small set of people go beyond this. Building on their raw analytical knowledge, they gain an understanding of their organization's business model. They make the leap from practice to domain expertise, bridging the gap between deduction and intuition. Rather than having generic analytics skills, they straddle the gap between mathematics and business, having the ability to play the role of both the analyst *as well as* the business representative. They understand the constraints the business is operating under, the outcomes it is trying to drive, and all of the low-level intricacies that might prevent it from realizing the opportunity.

[5]Frederick P. Brooks, *The Mythical Man-Month: Essays of Software Engineering* (Reading, MA: Addison-Wesley, 1975).

[6]Robert L. Glass, *Facts and Fallacies of Software Engineering* (Boston, MA: Addison-Wesley, 2003).

[7]Walter Isaacson, *Steve Jobs* (New York: Simon & Schuster, 2011).

[8]For more detail on organizational culture and how it often affects value architects, see Chapter 5 in Evan Stubbs, *The Value of Business Analytics*.

How Do I Keep Them?

The difference between a team that retains its high performers and one that lets them churn is like night and day—there's nothing that undermines an organization's ability to capitalize on business analytics like losing the team.

There's good reason for this. As covered in Chapter 2, the labor market will continue to tighten. Still, it's important to remain pragmatic. The fact that skills are scarce shouldn't be a reason to live in fear. The mantra for the future is, achieving excellence requires *developing* excellence.

Retention is critical because it takes time to understand an organization's processes, information sources, and business models. On one hand, new starters face a variety of technical challenges. They need to understand what information is captured and available, how trustworthy that information is, as well as how best to take advantage of their technology landscape. However, this is only a small part of their overall learning curve. Because business analytics is fundamentally about driving change, they also need to understand the organization's political landscape, business model, and culture. This doesn't come easily— it takes time to absorb.

Because of this, employee turnover is the bane of every team. Losing the wrong people can set a team back by months. These pains are particularly acute in a business analytics team. It's not uncommon to see new hires be almost totally unproductive for anywhere up to a year while they come to terms with an organization's unique characteristics. An analyst is only as good as her ability to understand the data she is working with.

Given that a team should ideally be creating value in under a 12-month horizon, delays caused by employee turnover can totally undermine a team's success. Retention is always difficult. However, there are some useful guidelines to keep in mind. Effective leaders:

- Understand their team's worth
- Keep things interesting

- Develop first, and hire second

First, keep on top of what you're paying. Wage inflation is likely to continue over the next decade. However, the equally harsh truth is that not everyone is worth what the market is willing to pay for their skills. Shortages have a tendency to raise prices equally across the board, not just for those who deserve them.

On one hand, being price competitive is mandatory. On the other, so is balancing the opportunity cost of replacing existing skills with new. Long-term success requires developing a very real and frank understanding of how effective every resource is when benchmarked against market averages and paying rates to suit.

Second, match interests to activities. For some people, stability and repeatability is attractive. They value developing deep skills in a specific area. Others value innovation and breadth of experience. They value constantly facing new challenges and exploring the unknown. Retaining a good team often comes down to understanding what people enjoy and ensuring that the roadmap aligns with their interests.

This isn't to say that the tail should wag the dog. The roadmap should always be defined to drive value and competitive differentiation. However, the breadth of what's possible is enormous, and wherever it makes sense, this roadmap should capitalize on the team's interests.

Finally, don't assume that extending capabilities requires going external. Many believe that good analysts can't be trained; the subject matter is sufficiently complex that practitioners require higher education simply to create the right foundations. However, this misses a key difference between advanced analytics and business analytics. Within business analytics, it's possible to create significant value using anything from relatively simple techniques to the most sophisticated. This *can* be developed, especially through coaching or mentoring. Developing maturity is something that's best done under the guidance of a leader with vision and understanding.

Of course, there's always the attraction of bringing in "new blood." Sometimes, this is a good thing. However, because business analytics is so heavily aligned against an organization's business model, a cornerstone of this is a strong understanding of the business. Relying on employee turnover to build skills is limiting; the best teams fully understand their business. And, the best way to do this is to develop first and hire externally second. The obvious exception is when the team moves toward more and more sophisticated techniques. Often, these require heavily specialized experience that can only be found in the market. However, this should be the exception rather than the norm.

Notes

1. T. M. A. Lomas and Computer Security Group, "The Influence of ULTRA in the Second World War" (interview by Harry Hinsley), Computer Laboratory, University of Cambridge, Nov. 26, 1996, www.cl.cam.ac.uk/research/security/Historical/hinsley.html (accessed Apr. 21, 2013).

2. Joan Fisher Box, "Guinness, Gosset, Fisher, and Small Samples," *Statistical Science* 2, no. 1 (1987): 45–52.

3. Evan Stubbs, *The Value of Business Analytics: Identifying the Path to Profitability* (Hoboken, NJ: John Wiley & Sons, 2011).

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6. Robert L. Glass, *Facts and Fallacies of Software Engineering* (Boston, MA: Addison-Wesley, 2003).

7. Walter Isaacson, *Steve Jobs* (New York: Simon & Schuster, 2011).

8. For more detail on organizational culture and how it often affects value architects, see Chapter 5 in Evan Stubbs, *The Value of Business Analytics*.