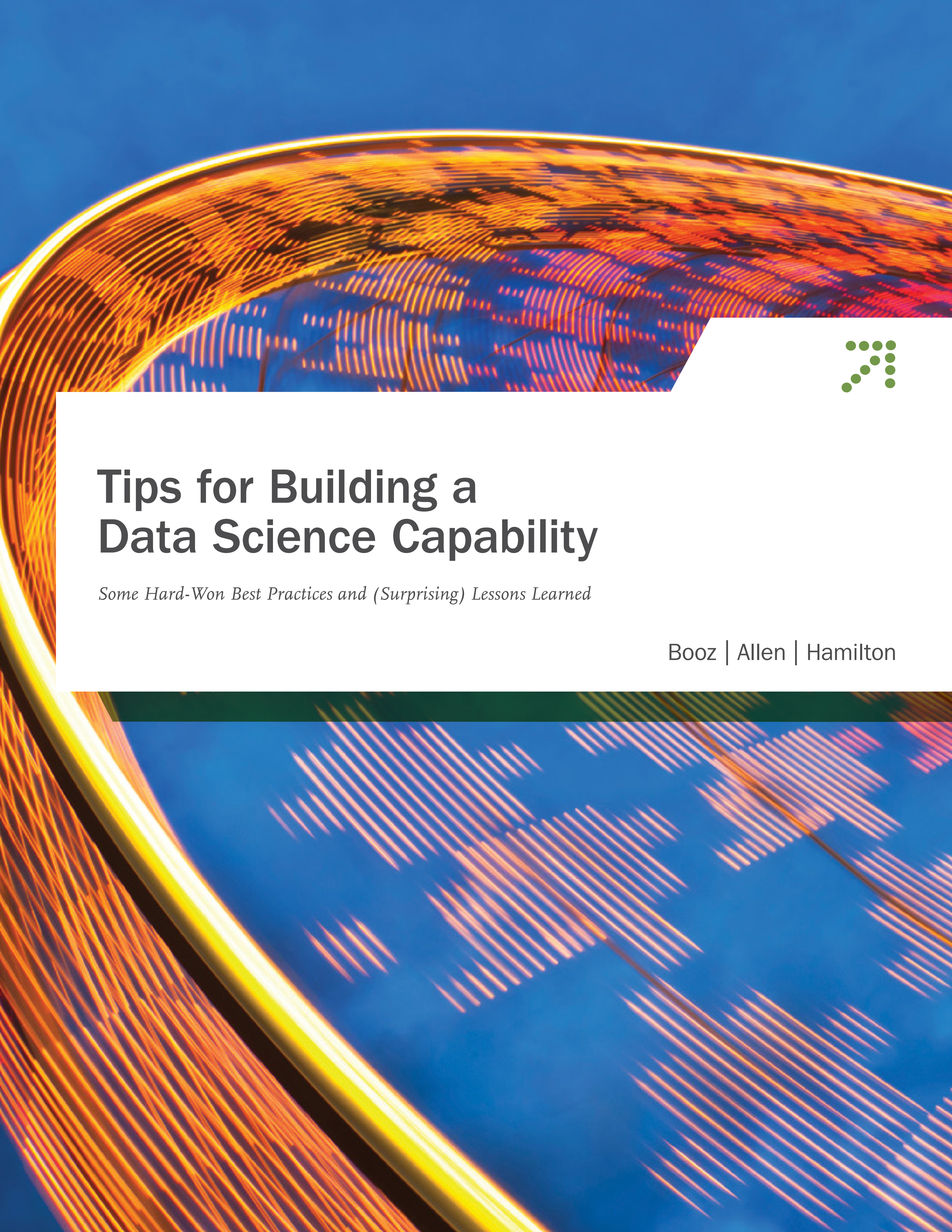


Tips for Building a Data Science Capability

Some Hard-Won Best Practices and (Surprising) Lessons Learned

Booz | Allen | Hamilton

CONTENTS

INTRODUCTION

Many organizations believe in the power and potential of data science but are challenged in establishing a sustainable data science capability. How do organizations embed data science across their enterprise so that it can deliver the next level of organizational performance and return on investment?

Building a data science capability in any organization isn't easy—there's a lot to learn, with roadblocks and pitfalls at every turn. But it can be done—and done right. This booklet will show you how. We've filled it with the most valuable best practices and lessons we've learned—both in our pioneering work with clients, and in building our own, 500-member data science team, one of the world's largest.

In these pages, you'll discover:

+ **Why your data science investment may not have delivered on its promise so far.** It could be that you haven't developed an analytics-driven culture.
+ **How to keep from getting bogged down.** Some organizations have difficulty prioritizing their data science projects. Others face skepticism from leadership. Here's how to overcome the most common roadblocks.
+ **How to get buy-in for data science throughout the entire organization.** We show you how to overcome resistance to everything from using analytics to sharing information.
+ **Where to place your data science teams in your organization.** Should they be centralized? Dispersed? Permanently embedded in individual business units? Each option has its advantages and risks.
+ **How to stand up the position of Chief Data Officer (CDO).** We tell you why a CDO needs to be one part "enforcer" and two parts "data evangelist."
+ **How you can leverage our Data Science Talent Management Model.** We'll help you answer three key questions: Who do you need? Where do you need them? How do you keep them?
+ **Why design thinking-when applied to data science-can unlock organizational value.** How the designer's mindset can ground and amplify analytic insights.

ANALYTICS CULTURE

Why Hasn’t Your Data Science Investment Delivered on its Promise?

The promise of game-changing results from data science has been touted for years, and the allure of that promise has driven organizations across all commercial markets and the public sectors to invest huge sums of money, time, and resources to make it happen. Encouraged by the outcomes of analytical pilots, organizations are now looking to scale data science across their enterprise. As they continue their pursuit, they have found the benefits are elusive and they are often humbled by organizational inertia. The hard truth is that a key enabler to delivering on the biggest promise of data science is transforming organizational culture. And, contrary to popular belief, it’s not about transforming to just any culture. Organizations must start to pursue an analytics-driven culture.

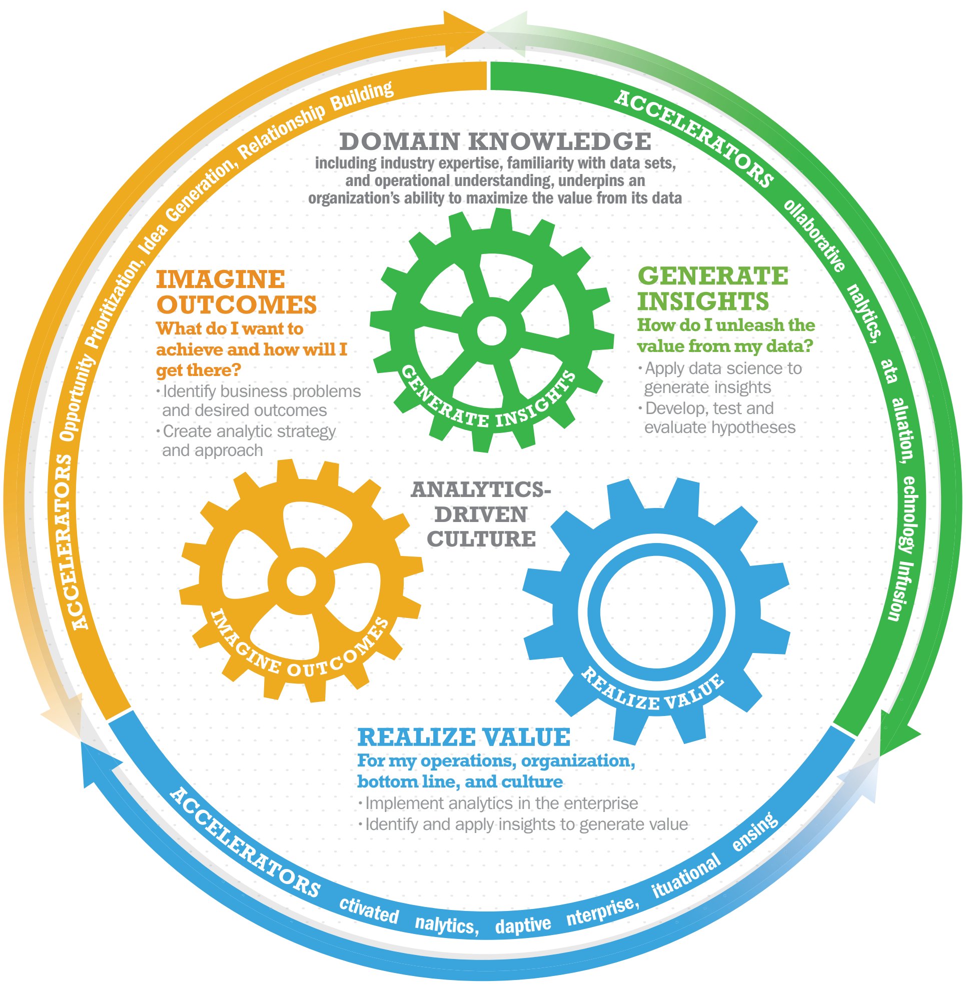
An analytics-driven culture uses analytics to generate insights that can be used by organizations to inform strategic decisions and propel the organization to the next level of performance. One of the key benefits of an analytics-driven culture is the difference in timescales in findings solutions. With an analytics-driven culture, the organization becomes particularly adept at asking the right questions and rapidly (within minutes sometimes) getting answers. That shifts the time available to thoughtful discussion on what analytical outputs mean and how they inform decisions to derive desired outcomes.

BOOZ ALLEN'S DATA SCIENCE DELIVERY MODEL

Booz Allen's Data Science Delivery Model describes the ongoing activities that collectively evolve an organization to an analytics-driven culture. We work with organizations to approach analytics in a holistic matter through three phases:

+ **Imagine Outcomes** focuses on deconstructing business problems to define objectives that will be met through analytics. We work with our clients to create analytics strategies, prioritize initiatives, and establish a collaborative environment around analytics.
+ **Generate Insights** is where our experts apply data science and advanced analytics methods, tools, and techniques to support our clients in unveiling analytic insights.
+ **Realize Value** turns the analytic insights into actionable results that enhance an organization's effectiveness, efficiency, and/or bottom line. We support our clients in putting analytics into production, developing feed-back ecosystems, establishing an environment of continuous learning, and building and managing their talent.

DATA SCIENCE DELIVERY MODEL



HOW TO INCUBATE AND SUSTAIN AN ANALYTICS-DRIVEN CULTURE

It is no surprise—building a culture is hard and there is just as much art to it as there is science. It is about deliberately creating the conditions for advanced analytics to flourish and then stepping back to empower collective ownership of an organic transformation. At Booz Allen Hamilton, we not only have experience in helping our clients navigate this challenge, but we also have experience from our own transformation. Led in part by our 500+ data science team, we began our own journey to an analytics-driven culture, and, through our experiences, we identified foundational building blocks that are universal to anyone who wants to deliver on the promise of analytics. While in the end each organization will have its own unique flavor of its final analytics-driven state, it is important to start any journey by pursuing these foundational elements. We've outlined the basics for how to incubate and sustain an analytics-driven culture.

RECALIBRATE YOUR TOLERANCE FOR FAILURE—FAILURE IS THE PRICE OF DISCOVERY:

To realize the full power of what data science can provide, it is important to foster curiosity and experimentation, and embrace failure for the unexpected insights and learning that it can provide. At Booz Allen, we created these conditions in a few ways. First, we empowered our data science team to investigate and discover; to design and run their own experiments that blend inductive pattern recognition with deductive hypothesis generation; and to explore "rabbit holes" of interest. Recognizing, like many others, that data scientists are rarely motivated by money and prefer the time and space to "geek out," we established a series of reward and recognition mechanisms focused on investing in passion projects. Discovery has an added organizational benefit.

HOW TO INCUBATE AND SUSTAIN AN ANALYTICS-DRIVEN CULTURE

We found that discovery is self-fulfilling and that once you start on the road to discovery, you gain momentum and energy that permeates throughout the organization, which provides powerful lift to your data science team. Finally, it is important to note that it is essential to fail fast in the discovery process. It does no good to toil on something for 6 months and then learn that it doesn't work. Experiment and fail quickly to discover more.

BE INCLUSIVE—DATA SCIENCE IS ABOUT MORE THAN DATA SCIENTISTS:

What we learned in our journey is that true curiosity and experimentation requires an enormous tent of skills, abilities, and perspectives to achieve meaningful outcomes for data science. It is important to take an inclusive approach to advanced analytics that extends beyond the traditional cadre of world-class data scientists. For example, our data science teams often include data scientists, technologists, domain experts, organizational design and strategy practitioners, design thinkers, and human capital specialists. Diversity of thought can help organizations unlock the particularly thorny problems and extract value from their data.

FLATTEN YOUR HIERARCHY—IT CAN BE THE ENEMY OF COLLABORATION:

Data scientists need the autonomy and the flexibility to explore analytical challenges without the added burden of unnecessary hierarchical structures. In practice, this means providing data science teams with access to resources, tools, and talent; the freedom to scope and run their own experiments; and the time and space to collaborate with a diverse team and the broader data science community. At Booz Allen, we have invested in tools, resources, and platforms to empower data scientists to share their work and build on each other's successes. This includes a sandbox to store algorithms and code so that good work can be replicated without permission. We also developed a tool that relies on collective community participation to source and share data sets that can be used for analysis.

PROVIDE A WAY INTO THE CLUB—STORYTELLERS LEARN BY DOING:

Data science and advanced analytics can be intimidating for some and exciting for others. What's important is to provide a variety of learning opportunities that can cater to the different skill sets and attitudes that exist within the organization. We tackled this challenge in a variety of ways: (1) We sponsored analytical challenges and "hackathons" both to test and satisfy the desire of advanced practitioners while at the same time providing a safe learning environment for those still developing their skills; (2) We created a self-paced online training course for data education, Explore Data Science, to teach both foundational and advanced data science concepts such as data visualization; (3) Additionally, we created a data science training program called TechTank to cultivate skills through apprenticeship and structured training. These are just a few examples. The bottom line is that we learned it is important to design opportunities and learning programs at all levels to help people get familiar with data science concepts and become more comfortable in practicing them. Don't cast data scientists as mythical rock stars and then

A KEY PITFALL TO AVOID

When building an analytics-driven culture, it is important to avoid creating high barriers to entry. Often organizations will showcase top data science talent as an example of the capability. While it is intended to provide context and vision, it can also be interpreted as an unrealistic comparison for some. Rather than illuminate a single data science rock star, it is important to highlight a diversity of talent at all levels to help others self-identify with the capability. It is also a more realistic version of the truth. Very rarely will you find "magical unicorns" that embody the full breadth of math and computer science skills along with the requisite domain knowledge. More often, you will build diverse teams that when combined provide you with the "triple-threat" (computer science, math/statistics, and domain expertise) model needed for the toughest data science problems.

"One of the difficult aspects of cultivating an analytics-driven culture is that there is a lot of noise on the topic."

not offer a way into the "club." Remember, all data scientists have a role in providing mentorship and learning opportunities. Data scientists need to attend hackathons, teach classes, and mentor junior staff whenever possible.

DEMOCRATIZE ANALYTICS—EVERYONE NEEDS TO FEEL CONVERSANT:

For something to be part of organizational culture, it must be part of the fabric of the employee behavior. That means to incubate and sustain an analytics-driven culture, employees must interact with and use analytics in their daily routines. In order for this to happen, analytics must be available and accessible to all employees in some form or fashion. For example, at Booz Allen, we developed a tool that allows users to drag and drop packages of coding to help solve analytical inquiries. The drag-and-drop feature lowers the barrier to entry and empowers "everyday employees" in performing data analysis. Additionally, all employees need a baseline of analytical knowledge, starting with a common lexicon, to facilitate productive collaboration and instill confidence. While not everyone will be data scientists, employees need to identify with analytics and be equipped with the knowledge, skills, and abilities to work with analytics to drive smarter decisions and deliver exponential organizational performance. One key way we democratized analytics at Booz Allen was through the development of the Field Guide to Data Science, which provides a baseline understanding about data science and a common lexicon so that employees can communicate with each other and engage in solving analytical problems.

MEASURE AND REWARD THE "MEANS" AS WELL AS THE "END" – IT REINFORCES BEHAVIOR THAT WILL DELIVER RESULTS:

When building an analytics-driven culture, it is important to reward the approach and thought process that people take as well as the results achieved. It is similar to when partial credit was awarded in school—some credit was given if you took the right approach even if you ended up at the wrong answer. The same applies here. In order to help shift mindsets and change behavior, people need to believe in the analytical process and thus be recognized for trying it until it is customary.

At Booz Allen, we believe analytics innovation starts at the staff level and have implemented systems and processes to reinforce that message. For example, when we evaluate project success, we look at more than just the expected results but also the approach and learning outcome. In one case, we were able to apply data science to devise an approach that significantly reduced the time it took to identify fraud. While the results were impressive, the innovative approach to the problem became the star. In the end, we have found that whether or not the results pan out, it's a win for us—either we've discovered a great new finding or we have inspired our teams to continue looking.

DEBUNKING COMMON MYTHS THAT MAY PREVENT YOU FROM EVOLVING TO AN ANALYTICS-DRIVEN CULTURE

One of the difficult aspects of cultivating an analytics-driven culture is that there is a lot of noise on the topic. In the above section, we have isolated six common cultural denominators that must exist for an analytics-driven culture to thrive. In reviewing various articles, press, and literature on the subject, and comparing to our own experiences, we also identified four common myths or misnomers to help organizations avoid potential hazards. The journey can be hard enough and it's important to focus resources on what counts.

MYTH #1: GOVERNANCE STRUCTURES ARE THE SOLUTION:

Governance helps—organizational bodies that represent multiple stakeholder groups and meet regularly certainly help facilitate collaboration and information sharing. As any good data scientist will tell you, however, correlation does not imply causation. That is, simply because we find that most successful analytics organizations have governance structures in place, it is not the structure alone that leads to the group's success. Participants in an analytics function (e.g., data scientists, business owners, operational experts) must work to establish relationships and trust. This is what creates an environment that is conducive to data transparency and development of shared challenges, goals, and priorities. Then, governance structures serve as an incredibly valuable mechanism for ensuring such topics are discussed with some regularity and formality.

MYTH #2: ANALYTIC SOLUTIONS AND OPERATIONAL REALITIES ARE MUTUALLY EXCLUSIVE:

A common characterization we hear from clients is, "operational owners are stuck in their ways with no vision, while data scientists don't understand the complexity required to turn analytical 'answers' into reality." As with most entirely divergent perspectives, the truth is found somewhere in the middle. Often, we observe data scientists pushing operational owners outside of their comfort zones when it comes to exploring the realm of what's possible. The responding hesitance is often the result of past, failed experiences, or knowledge that implementation will require overcoming a series of operational hurdles that can often take time. It is important that the analytics community continues to push the envelope, but also respect that change is a process, and the benefit of time and careful planning can prevent serious missteps and unintended consequences. Prototyping is typically an effective way to merge analytic solutions and operational realities. Prototyping analytic solutions can generate organizational buy-in while helping to anticipate expected implementation challenges to inform better planning.

MYTH #3: DATA SCIENTISTS PROVIDE A SERVICE TO THE BUSINESS:

In an analytics-driven culture, there is no customer or provider—only partners. The term "customer" implies that one party is a recipient of someone else's service, which here, are analytic outcomes. If this is the case, it is evidence that collaboration is failing. Throughout all analytics endeavors, data scientists and decision makers (or decision influencers) should work with shared goals, equally invested in both the process and the outcomes. This means partnering every step of the way—in developing hypotheses, determining appropriate/acceptable data inputs, validating analytic assumptions, and interpreting results. In this way, we eliminate the "us versus them" mentality and recognize that analytics is just part of doing business, rather than an add-on or an input. An added benefit is better business outcomes. As stated earlier, inclusive teams are a primary condition for any organization wanting to increase organizational performance through analytics.

MYTH #4: COMPLEX ANALYTICS AND TOOLS ARE BETTER THAN SIMPLE ANALYTICS AND TOOLS:

We are excited about the technical power introduced by tools like Hadoop and Spark, while techniques like machine learning carry a certain sort of mystique and excitement. Yes, modern tools and techniques provide a world of opportunity that was once nonexistent, but let's not forget there is also beauty in simplicity. The high-end, expensive tools are powerful, but most organizations are only prepared to use a fraction of their power. By “over-purchasing” on analytical tools, an organization can unnecessarily increase its analytical investment and make it harder to prove a return on that investment. Furthermore, the learning curve associated with the high-end tools may make it harder for organizations to realize the most value from their data. In the end, information consumers must understand the analytical insights from these tools with at least enough certainty that they are confident in its output. Embrace simplicity where simplicity will do, and save complexity for the hairy problems. If the information consumers understand the analytical results 95 percent of the time, perhaps they will “just trust us” the other 5 percent.

WHEN DONE RIGHT, THE PAYOFF IS WORTH IT

Like most things in life, if it is hard, it is worth it. Building an analytics-driven culture doesn’t happen overnight and it is not something that you can force. As many can attest, organizational inertia is powerful. However, by following these foundational steps and taking care to avoid common myths and pitfalls, organizations can begin a journey to set the cultural conditions needed to deliver on the promise of analytics. It is up to organizational leaders and employees alike to build upon these elements and design and grow their own version or interpretation of an analytics-driven culture. Only then can the promise of game-changing performance be truly realized.

ORGANIZATIONAL PROFILES

Getting Past the Bumps in the Road

With the explosion of data in virtually every aspect of society, a growing number of organizations are seeking to take full advantage of analytics to drive decision making. They are developing more sophisticated descriptive and diagnostic analytics to understand what has happened in the past, and why. They are poised to take analytics to an even higher level by using the new wealth of data to predict what will happen in the future, and to prescribe the best course of action.

No organization, however, instantly becomes adept at this next generation of analytics. It is a journey, and like any journey, there may be times when the way ahead is not clear, and it becomes difficult to move forward. Some organizations may be unsure of the best path to take. Others may hesitate because they are not convinced that continued investment in analytics will pay off. Still others may find themselves mired in data that is difficult to use.

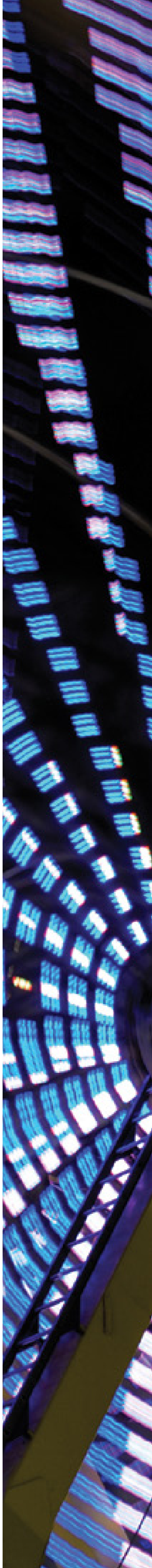
Even organizations that are further along in the journey can find their progress slowed. It may be that they have achieved success in pilot and proof-of-concept efforts, but have not figured out how to translate that to a wider capability. Or, perhaps they have all the elements in place—people, processes, and technology—but the larger organizational culture still has not embraced the potential of analytics to feed innovation.

These kinds of obstacles are natural and should be expected. But they do not have to slow down an organization for long. There are a number of ways that organizations can restart their progress. Booz Allen Hamilton's work with organizations across the commercial and government sectors found that organizations on the analytics journey generally fit one of five profiles, each with its own set of challenges. We have identified techniques that can help all organizations move forward.

THE WILLING ORGANIZATION—CHARTING A CLEAR PATH

This organization recognizes the potential of analytics to create opportunities and solve complex problems, but does not know exactly how to proceed. Typically, the willing organization is early in the journey, and may be using basic descriptive and diagnostic analytics to investigate specific problems. Now, however, it wants to broaden that capability with analytics that can guide decision making, and more fully support mission and business goals. But what is the best approach? Without a clear direction, any organization—no matter how willing and able—may find itself in a holding pattern.

Willing organizations often let their enthusiasm cloud the need to fully map out all of the many elements of an analytics capability. An analytics blueprint can



help organizations understand how those elements fit together, and what steps need to be taken in what order.

For example, the blueprint can guide one of the most effective steps: determining in advance where the value in the data might lie. What is the art of the possible? Instead of starting with a specific problem or goal, start with the data itself. Look for trends and issues that suggest how analytics can make a significant difference in your organization. This insight gives the organization a picture of what its full analytics capability might look like, and sets the context for creating the path to get there.

THE HESITANT ADOPTER—USING PROTOTYPES TO OVERCOME DOUBT

This organization may be exploring more sophisticated analytics, but is less sure of how to define its value and so finds it difficult to move forward. While the analytics visionaries want to increase investments in an analytics capability, they have not yet gained the organizational support for doing so. The organization's leadership, for example, may not be convinced that analytics will really help the bottom line. Or, individuals in the organization may not yet recognize the value of analytics, and still prefer to make decisions based on their own knowledge and experience—despite mounting evidence to the contrary.

These types of concerns can be overwhelming, stopping an organization in its tracks. One effective solution is to think big, but start small. Organizations sometimes believe that they must jump into the next generation of analytics all at once. But if they experiment with a limited number of prototypes, they have a chance to see what analytics can do. This approach does not require a major investment in technology or people, and positive results from prototypes will help build the business case for new types of analytics and demonstrate its potential value.

THE DATA-DISTRESSED ORGANIZATION—BRINGING THE STAKEHOLDERS TOGETHER

This organization is ready to develop more, increasingly sophisticated analytics, but finds it difficult to get its data all in one place in a form that is usable. Perhaps the data is of poor quality, filled with errors or incomplete. Or, there may be a reluctance to share data across the organization. The data may not be collected in a consistent way, or it might be

THE WILLING ORGANIZATION	THE HESITANT ADOPTER	THE DATA DISTRESSED ORGANIZATION
Characteristics + Beginning of the journey + Believes in the power of analytics, but overwhelmed with how to get started	**Characteristics** + Beginning/middle of the journey + Analytics visionaries want to invest more heavily in analytics, but lack organizational support	**Characteristics** + Beginning/middle of the journey + Organization wants to develop increasingly sophisticated analytics, but is stymied by an inability to get the underlying data in order
What To Do **Chart a Clear Path:** Explore data to help inform the organization's vision for analytics, and to chart a step-by-step path to achieve that vision	**What To Do** **Use Prototypes to Overcome Doubt:** Think big but start small, using prototypes to prove the value of analytics to end users and help overcome doubt	**What To Do** **Bring the Stakeholders Together:** Collaborate and build relationships between IT and analysts to develop data that can be used by both

locked in rigid data silos that are difficult to connect. The list goes on.

Organizations can help get their data in order by making sure that analysts are included in the data management framework and design. Although an organization's data usually belongs to IT, the analysts are the users—and data problems can arise when their point of view is not taken fully into account.

A second method is to encourage collaboration and relationship building through technical, organizational and physical structures, such as new governance policies, or activities in which teams from across the organization work together to achieve a common goal. Such structures help break down the barriers to information sharing, which is the largest obstacle to analytics at many organizations.

THE SCALING ORGANIZATION—ESTABLISHING A CENTER OF EXCELLENCE

This organization has achieved success using sophisticated analytics to drive decisions in a number of isolated efforts, but may have difficultly effectively growing an organization-wide capability. For instance, the organization may not yet have figured out how to achieve economies of scale. Or, it may have difficulty prioritizing—if several stakeholders are competing for limited resources, for example, how does the organization choose which analytics efforts will best advance the interests of the mission or business? These and other challenges often arise because organizations typically expand by simply doing more of what they are already doing, rather than leveraging their knowledge through collaboration, and the sharing of best practices and lessons learned. Establishing an analytics Center of Excellence is one of the most effective methods of achieving this task.

This Center of Excellence consists of a team that sets standards and promotes collaboration throughout the organization on a wide range of topics, such as training. The team also collects and disseminates best practices, such as analytical approaches, tools and techniques. It also shares lessons learned—typically, knowledge that is applicable from one effort to the next. With a Center of Excellence, an organization can steadily grow its analytics capability in an organic, efficient manner.

THE SCALING ORGANIZATION	THE EARLY ADOPTER
Characteristics + Middle/far along in the journey + Analytics have led to value in pockets of the organization, but leaders are uncertain about how to most effectively grow capabilities	**Characteristics** + Far along in the journey + Analytics generate insights, but not everyone has adopted analytics to drive decisions, nor do they look to analytics to answer new questions
What To Do **Establish a Center of Excellence:** Stand up a team dedicated to fostering collaboration, sharing best practices, and setting standards for analytics	**What To Do** **Initiate a Culture Change:** Begin by making the analytic models easier for the end user to ingest and use

THE EARLY ADOPTER—INITIATING A CULTURE CHANGE

This organization is well established in delivering predictive and prescriptive analytics, but it is still trying to reach its ultimate goal: creating a culture of analytics-driven decision making. The organization wants to use data and analytics to encourage curiosity among all its employees, not just in its analysts. It hopes to inspire its entire workforce to imagine how analytics might create exciting new opportunities for the enterprise, and solve its most difficult business and mission problems.

A particularly effective method of achieving this goal is to put data and analytics in the hands of end users from across the enterprise so they can see the possibilities for themselves. Some advanced technologies have visualization tools that enable this kind of direct interaction and give end users the flexibility to freely explore the data, following their ideas and hunches wherever they may lead.

Such direct interactions will encourage end users to think about how analytics might solve any number of problems. This approach also increases the transparency of the analytics, so that people understand and trust them more.

It gives end users throughout the organization a greater sense of ownership of the analytics and inspires them to use data and analytics to help drive their decisions.

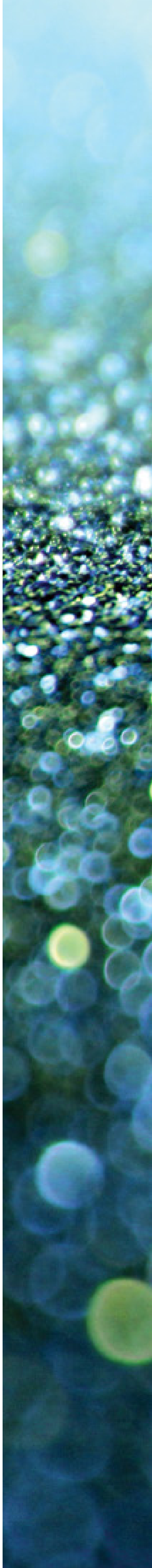
MOVING FORWARD ON THE JOURNEY

Data, like any resource, exists only as potential unless it can be tapped. Organizations that can best capture the value in their data—and use it in decision making—will be the ones that thrive.

Analytics is a rapidly expanding and dynamic field, and there is no single tried-and-true path to success. Every organization will encounter bumps in the road as it finds its own way. But no matter where an organization is on the analytics journey, it should think through where it is trying to go and why. What does the next step look like? What does the end state look like? By focusing on these kinds of questions, organizations can break free of their current constraints and continue on their path—from whatever point they may be along their journey.

ANALYTICS & CHANGE

Keys to Building Buy-In



Many organizations are poised to take full advantage of analytics to drive mission and business success—using analytics not just to understand past events, but to predict future trends and to prescribe optimal courses of action. This ambitious goal requires more than the right technology, people, and processes. Just as important is strong organizational buy-in from everyone involved in the analytics capability, including both the owners of the data and the analytics end users. This often requires overcoming resistance on a number of fronts, from a reluctance to share information to a hesitancy to use the analytics in driving business decisions.

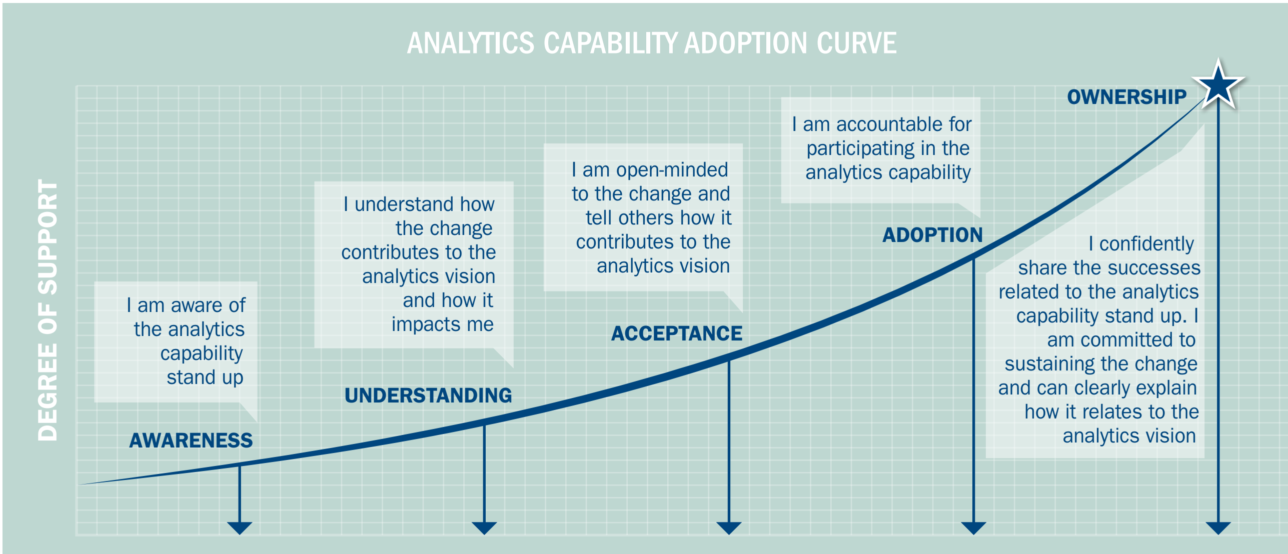
Booz Allen Hamilton, a leading strategy and technology consulting firm, helps clients create critical buy-in through a change management approach tailored to organizations that are standing up a capability to develop increasingly sophisticated analytics. Our experience with government and commercial enterprises has shown that three aspects of change management are particularly critical. Vision is needed to help stakeholders understand leadership's long-term goals for using analytics to drive decisions and actions. There must be stakeholder participation in the process to develop shared understanding of how analytics can create value. And prototypes are needed to demonstrate that the analytics vision can indeed become a reality. Together, these three elements build buy-in for the analytics capability and bring your organization together to work toward a common goal.

CREATING A VISION

To be successful, leaders must be able to clearly articulate why an analytics capability is important to the organization and what the organization will look like when the capability is in place. Some members of an organization may not be convinced that analytics will add value to the business, so it is up to leadership to make the case that it will be worth the effort.

Even if you already started down the path of adopting predictive and other sophisticated analytics, it is not too late to define a vision, one that is:

+ Aspirational
+ Based on an understanding of your organization's values
+ Reasonable to achieve
+ Mutually beneficial for everyone involved



A good place to begin when defining the vision is a stakeholder analysis. Whether you are planning to stand up an enterprise-wide analytics capability or provide analytics for a single business unit or division, you should understand the cross-organizational concerns such as improved access to data and data security.

A key to realizing the vision is communicating it to stakeholders. This is most often achieved through a strong leader at the top of an organization. But the vision can also be realized from the ground up. For example, Booz Allen's visioning process helped an intelligence agency—overwhelmed by the volume of data to be analyzed—create a vision for their analytics capability. That vision was communicated primarily through well-respected domain experts at the agency who led a grass-roots effort to build an analytics capability and successfully influenced leadership, staff, and peers. Whether the vision is top-down or bottom-up, it is essential to identify leaders and sponsors who can reinforce the ideas and keep the effort moving. Booz Allen gives you, as leaders and sponsors, the messaging and other change management tools to define your vision for analytics and present it to the organization.

Booz Allen's collaborative visioning process helps define a future state that reflects the unique realities of your organization and cultivates a willingness to participate. A key role of the vision is to help overcome the roadblocks to buy-in. Among the ways to accomplish this is by demonstrating leadership's commitment and sponsorship, and by helping analytics teams and end users establish shared values and goals for the analytics. As these efforts take shape through the vision, they must be reinforced through participation in the analytics capability and through prototypes.

PARTICIPATING IN THE ANALYTICS CAPABILITY

The next step to overcoming resistance and building buy-in is to encourage stakeholder participation in the analytics capability. One way to accomplish this is to have stakeholders from across multiple business units contribute to decisions on analytics tool development. Through this engagement, stakeholders become actively involved in making the vision a reality. Participation calls for true collaboration—leaders do not simply push their ideas down, but bring all the stakeholders into the effort. Through regular feedback and other methods, stakeholders can help shape and take ownership of the organization's analytics capability.

The Analytics Capability Adoption Curve shows the five basic stages of change adoption, from initial awareness to ownership. Organizations can move stakeholders along this path by establishing a network of change agents at different levels and domain areas. For example, change agents might include mid-level managers from each business unit or division, or representatives from analytics teams. They are essentially embedded advocates that facilitate communication among stakeholders. Booz Allen helps develop this network of change agents and gives them tools to target their communications and feedback collection.

By fostering collaboration among the stakeholders, the change agents—along with leadership—help break down the data silos and encourage information sharing so that the results of the analytics will be more complete and accurate. The stakeholders work out their differences, offer suggestions, and understand how they will all benefit. This same process can help all those involved in the analytics capability—from the owners of the data to the end users of the analytics—develop a set of shared goals. And it can help make the data more transparent so that users are more likely to trust the results.

GAINING BUY-IN THROUGH PROTOTYPES

As organizations develop greater analytics capabilities to drive decision making, prototypes are essential in solidifying the support that is built with the vision and participation. Prototypes should focus on areas where quick buy-in is needed most. For example, if there is strong resistance to sharing information, the prototype should be strategically designed to show how the various stakeholders will benefit. It is often helpful to start with smaller projects or less complex analytics where quick wins are more assured.

As illustrated in the chart below, prototypes that are most likely to generate buy-in have four qualities:

TO BUILD BUY-IN, AN ANALYTICS PROTOTYPE SHOULD:	
FEATURE A HARD PROBLEM TO SOLVE	If the problem is too easy to solve, people may not have confidence in the strength of the analytics capability. But make sure the problem is not insurmountable.
YIELD A HIGH RETURN	Demonstration of business value is the holy grail—the analytics outputs must be actionable, as people want to see results before they buy in.
PROVIDE AN ITERATIVE SOLUTION	Quick success, even if preliminary, is important—the solution does not have to be perfect to gain buy-in and inspire action. Be wary if the problem you are trying to solve requires extensive data collection or highly complex analytics to even begin to show results.
REACH ACROSS TARGETED GROUPS	If the analytics capability is intended to serve multiple business units/divisions, the problem you are trying to solve should resonate with all of them. Positive results for only a small portion of stakeholders will limit organizational buy-in.

OUR APPROACH

There are unique challenges to standing up a sophisticated analytics capability, and a one-size-fits-all change management approach will not be effective. Booz Allen can partner with your organization to implement a change solution tailored to your specific needs and goals. Here is the framework for our approach in the table below.

When standing up an analytics capability, organizational buy-in is just as important as the right data and analytics. Booz Allen can help you create the vision, participation, and prototypes needed for success.

VISION, PARTICIPATION, AND PROTOTYPE: A CASE STUDY

Vision: Booz Allen's work with the Department of Homeland Security's Immigration and Customs Enforcement (ICE) Enforcement and Removal Operations (ERO) began with development of analytics to support a new identification system. As value was realized within the organization, the engagement evolved to bring analytics to the forefront of the organization's operations, which established our clients as leaders in data-driven decision making for all of ERO. The vision: to enable ICE to align resources with demand, understand

CHANGE MANAGEMENT APPROACH FOR ESTABLISHMENT OF AN ANALYTICS CAPABILITY

PREPARING FOR CHANGE	MANAGING CHANGE	REINFORCING CHANGE
+ Understand the organization's analytics maturity and stakeholder needs/concerns + Define and communicate the analytics vision + Develop a change and communication strategy + Create a multi-disciplinary team (i.e., computer scientists, mathematicians, and domain experts) and cross-organization change agent network + Identify and select prototype(s) with the vision/end state in mind	+ Develop, test, and evaluate analytical hypotheses and integrate prototype lessons learned + Put algorithms into production; evaluate and refine + Determine tailored data visualization methods + Assess change impacts, update change and communication strategy, and provide training + Establish incentive structure and reward system, and implement operating model and process changes + Expand the team/change agent network + Establish mechanisms for measuring and communicating success	+ Continue operationalizing the analytics + Continue implementation of operating model and process changes + Establish mechanisms to enable supervised learning + Calibrate analytics success instrumentation and measurement + Establish pipeline of analytics priorities

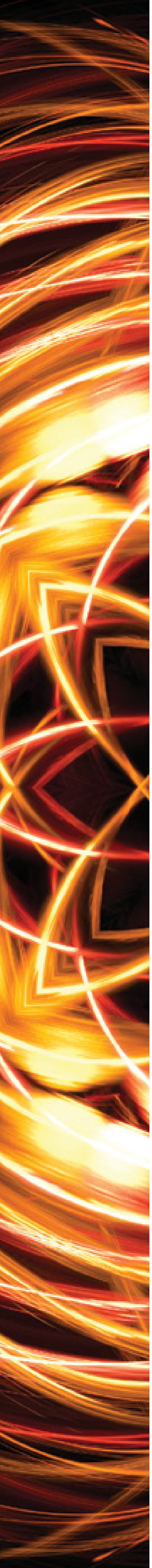
strategic and tactical gaps and potential mitigation strategies, and improve mission performance.

Participation: Booz Allen collaboratively established an Analytical Hierarchy Process (AHP), a system of voting to reveal the organization's preferences, to help executive leaders engage in analytics tool development and set overall direction for the models. We also worked with ERO to establish a Modeling Control Board (MCB) to serve as the internal governing body for the analytics tools developed in ERO. The board consisted of stakeholders from various units within ERO, which met regularly to discuss model assumptions, data issues (quality, availability, etc.), model updates and changes, and resource priorities. The board reviewed and validated all significant components of model development and usage and helped ERO determine how to effectively invest in and grow the analytics capability.

Prototype: Booz Allen assisted ICE ERO in using quick-turn tools to develop proofs, not masterpieces, in response to pressing concerns by leadership. The iterative approach provided a series of quick wins with senior stakeholders and enabled the organization to institutionalize analytics. At the heart of this effort was a commitment to data-driven decision making. Booz Allen's innovative spirit and strong partnership with our clients advanced ERO from a strictly reporting organization to an analytically driven organization that proactively manages its strategy, operations, budget, and performance with data. Recently, the Booz Allen team and client jointly received the award for Innovation in Analytics from the preeminent analytics organization in the US, the Institute for Operations Research and Management Science (INFORMS).

"Booz Allen embedded analytics at the core of ERO decision making and provided some of the best and brightest individuals to work on this ground-breaking project. The team worked closely with us to not only develop innovative tools, but also help us use these tools in our strategic and tactical decision making. As a result of Booz Allen's support, ICE understands how its data can help drive decisions and results."

— David Venturella, Former Director of ERO and Director of Secure Communities



ALIGNING DATA SCIENCE

Making Organizational Structure Work

As commercial and government entities develop data science capabilities, an inevitable issue they face is how their data science teams should align within the organization. Should the teams be centralized under a single data science leader? Should they be dispersed throughout the organization, permanently embedded in individual business units or divisions? Should there be some combination of those two models, or perhaps yet another alternative?

Organizations often adopt an approach without fully considering the implications. But that can be risky—unless the data science capability is closely aligned with the organization's size, diversity, culture, and other factors, it may have a limited ability to drive mission and business success.

While there are many possible organizational structures, we have found that three models typically work best for guiding where the data science capability should reside and how it will support the business. Each of the three—the Centralized Model, the Diffused Model, and the Deployed Model—has distinct advantages. Yet each also has potential pitfalls that organizations must guard against. What they all have in common is the need for data science leaders and teams to be proactive in ensuring that the selected model works as intended. They must take the lead in fostering the necessary collaboration and communication—both within the data science teams and across the rest of the organization.

Here is a guide to the three primary data science alignment models and how to choose which one is right for your organization.

THE CENTRALIZED MODEL

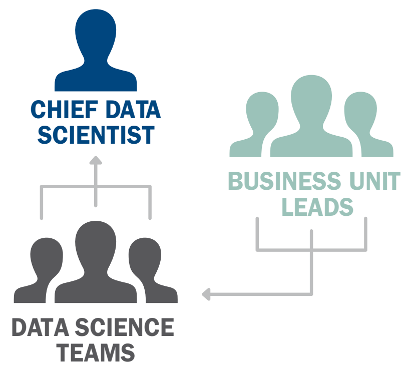
Centralized data science teams serve the entire organization but report to a chief data scientist, who decides which projects the teams will work on, and how to manage the projects. Business units work with the data science teams to solve specific challenges.

This model often works best for organizations that are operating with limited resources and have too few data science experts to embed any in business units for long-term assignments. With the centralized model, the chief data scientist can target projects—typically long-term—that offer the greatest benefit to the larger organization's immediate needs. In addition, because the data science teams are in close contact with one another (often co-located), they are likely to pool their knowledge so that lessons learned by one team can help others.

One primary challenge in the centralized model is that it can sometimes be difficult to establish trust and collaboration between the business units and the data science teams. Business unit members may view data science teams as outsiders who do not fully understand or feel invested in the business problems, and they may see their relationship with the data science team as "us versus them."

To avoid this pitfall, data science leaders and teams need to take the initiative to create a collaborative environment. They must develop a partnership mindset and demonstrate their commitment to helping the business units achieve their goals.

The chart below shows the advantages and challenges of the centralized model, and lists specific steps for making the model work.



Business units bring their problems to a centralized data science team, overseen by a chief data scientist.

THE DIFFUSED MODEL

Diffused, or decentralized, data science teams are fully embedded in business units such as marketing, research and development, operations, and logistics. The teams report to individual business unit leaders and perform work under their leadership.

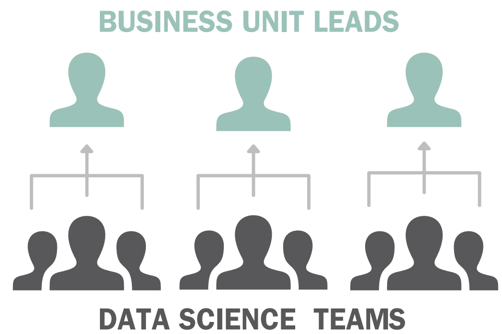
This model often works best in organizations that have large data science capabilities and the resources to embed teams in individual business units for long periods on open-ended projects. A benefit of this approach is that it allows data science teams to gain a deepened understanding of how analytics can benefit a particular domain or business

THE CENTRALIZED MODEL

ADVANTAGES	CHALLENGES	PLACES EXTRA FOCUS ON...
+ Greater efficiency with limited resources, including flexibility to modify team composition during the life of a project as needs change + Access to data science is organization-wide, rather than limited to individual business units + Central management streamlines business processes, professional development, and enabling tools, contributing to economies of scale + Organizational separation between the business units and data science teams promotes the perception that analytics are objective + Project diversity motivates data science teams and contributes to strong retention	+ It can be difficult to enlist business units that have not yet bought in to data science + Business units often feel that they compete for data science resources and projects + Teams re-form for every new problem, requiring time to establish relationships, trust, and collaboration + Business units must provide another organization (i.e., the data science unit) with access to their data, which they are often reluctant to do + As a separate unit with rotating staff, data science teams may not develop the intimate domain knowledge that can provide efficiency to future business unit projects	+ **Selling Analytics.** Demonstrate tangible impacts of analytics to business unit leaders—they are critical partners and need to buy in + **Portfolio Management.** Create transparency into how the organization will identify and select data science projects, including criteria to prioritize opportunities and align resources + **Teamwork.** Establish early partnerships between data science teams and business units, which will be integral to framing problems and translating analytics into business insights + **Education.** Train business unit leaders on the fundamentals of data science and the characteristics of a good data science problem, so people across the organization can recognize opportunities

unit. This is particularly valuable in diverse organizations where certain mission areas or product lines, for example, may require highly specialized knowledge.

The primary challenge in the diffused model is that it may be difficult for disparate data science teams to share the knowledge they gain in the individual business units. Data science needs to learn from itself; it is imperative that insights, best practices, and lessons learned are shared and incorporated into the data science capability. However, when data science teams are discrete, this can be hard to accomplish, especially in organizations that are already heavily siloed. To avoid this problem, data science teams must establish mechanisms that will make sharing an integral part of each team's work—for example, it might be established as a metric for success.



Data science teams are fully embedded in business units and report to individual business unit leaders.

The following chart shows the advantages and challenges of the diffused model, and lists specific steps for making the model work.

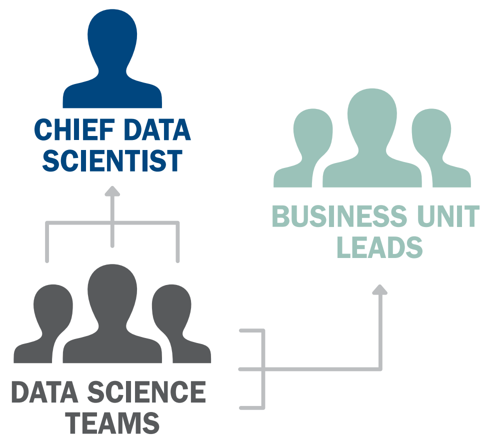
THE DIFFUSED MODEL

ADVANTAGES	CHALLENGES	PLACES EXTRA FOCUS ON...
+ Data science teams can quickly react to high-priority business unit needs + Business units are more likely to own the analytics—to be involved with the data science effort, accept the output, and adopt some change as a result + Data science teams learn the organization's data and its context, reducing project spin-up and helping them become equal partners in both solving problems and identifying the possibilities + A deepened understanding of the business inspires data science teams to ask new, hard questions of the data, and they understand the right questions to ask	+ Business units with the most money often have full access to analytics while others have none—this may not translate to the greatest organizational impact + Data science teams may face pressure to compromise their objectivity to avoid making a business unit "look bad" + Lack of central management may result in redundant software licenses and tools, which drives up total costs to the organization + The structure offers limited motivation for business units to integrate, inhibiting collaboration in already siloed organizations + Work may become stale to data scientists, driving them to seek new and diverse challenges	+ **Governance.** Establish cross-functional group(s) responsible for guiding organization-wide analytics standards, to include data, tool selection, and means of prioritizing analytics efforts + **Peer Collaboration.** Establish forums such as data science communities of practice and mentorship circles to share best practices and lessons learned (e.g., trends, algorithms, methods) + **Creative Outlets.** Fund analytics competitions, crowdsourcing, and conference attendance that allow data scientists to exercise their minds, solve new problems, and explore techniques

THE DEPLOYED MODEL

As with the diffused model, data science teams are embedded in the business units. The difference is that the embedded teams in the deployed model report to a single chief data scientist as opposed to business unit leaders. In this model, also called the matrixed approach, teams are generally assigned to individual business units, though they are sometimes also assigned to broader product lines, or to mission sets comprised of members from several business units.

This model often works best in organizations with medium-sized data science capabilities— ones that have a sufficient number of teams to handle multiple projects, but must still carefully target their resources. This model has many of the advantages of both the centralized and the deployed models; the data science capability is more of an organic whole, yet the embedded teams are close to the business units.



Data science teams are overseen by a chief data scientist and forward deploy to business units.

Because the deployed model is often seen as the best of both worlds, organizations may be quick to adopt this approach. But it is also the model with the

THE DEPLOYED MODEL

ADVANTAGES	CHALLENGES	PLACES EXTRA FOCUS ON...
+ Shared benefits of both the centralized and diffused model + Data science teams collectively develop knowledge across business units, with central leadership as a bridging mechanism for addressing organization-wide issues + Access to data science is organization-wide, and close integration with business units promotes analytics adoption + Project diversity both motivates data science teams and improves recruiting and retention + Central leadership streamlines career management approaches, tool selection, and business processes/approaches	+ Deployed teams are responsible to two bosses—staff may become uncertain about to whom they are ultimately accountable + Data science teams may face difficulty being accepted into business units, where long-time relationships have been established + Access to analytics-resources may still feel competitive between business units, and data science units risk alienating business units whose proposed projects are not selected	+ **Conflict Management.** The chief data scientist should proactively engage business unit leaders to prevent competing priorities from becoming the data science teams' responsibility to resolve + **Formal Performance Feedback.** Agree to performance goals at the onset of each project, and collect feedback during the life of project, including at its conclusion + **Rotation.** Allow data science teams to work on projects across different business units, rather than within a single business unit—take advantage of one of the main benefits this model affords + **Pipeline.** Regularly communicate the data science project pipeline, allowing business units to see how their priorities are positioned

most risk. Deployed data science teams essentially have two bosses, and conflicts inevitably arise. It is not unusual for business unit leaders and data science teams to disagree on how an analysis should be conducted—for example, the priority in which analytics efforts should be addressed. Typically, data science teams get caught in the middle of doing what is asked of them by the business unit leader and what they feel is right by their own technical merits. While they report to the chief data scientist, as a practical matter they may be reluctant to go against a business unit leader—particularly one with whom they work closely on a day-to-day basis.

The chart on the previous page shows the advantages and challenges of the deployed model, and lists specific steps for making the model work.

CONCLUSION

As organizations consider which model to choose, they should also establish the mechanisms needed to ensure communication and collaboration between the various data science teams, and between data science and business leaders. Regardless of the model, the data science teams must be proactive—they are responsible for initiating and sustaining that communication and collaboration.

Many factors go into choosing how to align data science teams, including the size of an organization, the diversity of its business or mission sets, its culture and strategic goals, and its ability to hire and retain data scientists. But it is important to note that data science alignment is not a one-time activity. As an organization and its data science teams change and grow, the organizational structure may need to change as well. Data science leaders should periodically re-evaluate their current structure and determine whether a different model would be more effective.

Data science is an emerging field that offers exciting new opportunities for commercial and government entities. But success will not happen on its own. Data science leaders and teams must chart their own path and continually search for new ways to improve.

THE LEADERSHIP ANGLE

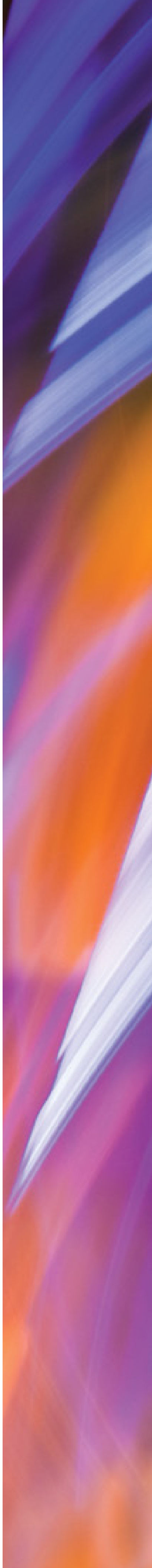
Harnessing the Power of Data Through The Stand-Up of a Chief Data Officer

Across government and industry, enterprises are realizing that they may be sitting on a pot of gold waiting to be discovered—their enterprise data and the insights it can provide. Many of these enterprises are responding by standing up Chief Data Officer (CDO) organizations to enable them to maximize the value from their data. This is an emerging and evolving role that varies depending on whether related roles already exist in the organization (e.g., Chief Data Scientist or Chief Analytics Officer) and how integrated data already is carrying out the organization's objectives (e.g., whether data is the primary business/mission, data is a driver, or data is a byproduct). Ultimately, a CDO must focus on the data assets, understanding and marshaling them in support of the overall enterprise strategy, and collaborating with other leaders (e.g., Chief Analytics Officer and business line leaders) who will facilitate achieving the potential of that data.

The best approach to fulfilling the CDO role is to be two parts "data evangelist" and one part "enforcer" by setting policy and developing technology frameworks/guidelines while still allowing the data owners and business lines to have the flexibility to implement them in their own way. Starting small and focused will enable the CDO to set the standard early and evolve as the data and collaboration mature. In doing so, a CDO faces a unique set of decisions with answers that are not black and white. Fortunately, there are five driving principles that can help a CDO answer these defining questions outlined in the table on page 28.

BE ROOTED IN THE ENTERPRISE STRATEGY

The CDO's objectives must be rooted in the value he or she seeks to generate. Enterprise-level priorities and constraints (e.g., resources and regulations) drive the need to identify the business and strategic imperatives that are best met through the CDO



Align Data Use and Policies With the Enterprise Strategy

A CDO must align data use and policies with the overall enterprise strategy to ensure that data sources are available to support the business lines' specific questions, objectives, and hypotheses.

versus other entities (e.g., business lines and IT). A CDO should develop a strategy that aligns with, and supports, the vision of relevant enterprise strategies and a clear intent for increasing the value data provides to the enterprise. Developing the strategy does not need to be a cumbersome or immovable process. It can be as straightforward as defining an articulate goal that serves as a guiding compass while being flexible enough to allow for course adjustments. That goal may focus on increasing data access, preserving equities, extracting more value from data, or enabling the business.

SUPPORT AND AUGMENT THE EXISTING ORGANIZATIONAL CONSTRUCT

The CDO must determine what functions to perform and where in the organization he or she will align. The CDO should keep in mind only a few of the most important functions should be focused on during the early start-up phase. Typical CDO functions can include enterprise data governance, data architecture, and data infrastructure—each of which has many subfunctions (e.g., data quality, metadata, document management, content management, data warehousing, reference data, and data security). These functions should support the enterprise architecture of the broader organization and align to the needs of its core partners including, business lines, IT, and data owners. Determining these functions will help delineate where the CDO should align and how the different parts of the organization will work together. Depending on the organization, alignment to the Chief Executive Officer may be necessary to have the authority to serve as a data access and governance enforcer or achieve the desired cultural shift. At the same time, alignment to the Chief Information Officer may facilitate acquisition of the technical infrastructure needed to achieve the CDO's

DEFINING QUESTIONS FOR A CDO	DRIVING PRINCIPLES
What value does the CDO bring, and how visionary versus tactical should the approach be?	**Be rooted in the enterprise strategy**
What functions should the CDO perform, and how should the team be aligned?	**Support and augment the existing organizational construct**
How does the CDO promote democratization of data and analytics and balance the need to ensure consistency and rigor?	**Ensure data access and governance as an enforcer**
How should the CDO engage with the enterprise to drive toward a data-driven culture?	**Be a data evangelist**
Once the CDO achieves quick wins and can focus on long-term goals, how can the CDO evolve the scope, role, and value?	**Scale it**

goals. No matter the alignment, the CDO must take the lead in fostering the necessary collaboration and communication to ensure alignment with the rest of the organization.

ENSURE DATA ACCESS AND GOVERNANCE AS AN "ENFORCER"

Well-defined governance processes and consistent ways to share, access, and manipulate data enable the enterprise to develop reusable, intraoperative, and legally compliant data capabilities in a short amount of time. A CDO's focus should be on setting a common definition of what constitutes shared data and how it should be moved across the enterprise. This includes the initial and practical governance or "the basic rules of the road" that will provide the necessary guidance to allow data to be tagged, shared, and accessed and a data architecture and infrastructure roadmap that is focused on enabling early, quick wins. Ultimately, the business and enterprise need to trust the data assets so they can rely on the accuracy of the derived analyses.

The policy set forth must also be implemented through technology in a manner that adheres to policy and is still lightweight and flexible for data owners and consumers. It should also take into account best practices and lessons learned from other partner organizations, as appropriate.

BE A "DATA EVANGELIST"

The CDO is a new and unfamiliar role for most organizations. As the data evangelist, it is the CDO's role to build a data-driven culture across the enterprise. While some of this comes from the CDO's inherent role as a facilitator of collaboration, equally important are proactive means of helping all layers of the organization, front-line employees through executives, develop an increased level of comfort with data—including collecting data, asking questions of the data, and continuing to use data/analytics to drive decisions. To do this, a CDO can identify and disseminate best practices and lessons learned while understanding shared, cross-organization areas of interest (e.g., most frequently used data, usage patterns, and techniques). A CDO can also proactively communicate new policies, guidance, and standards to all relevant parties and sponsor committees that work across the business lines to respond to gaps in data management processes and help resolve conflicts, particularly around data usage and sharing. In addition, a CDO can employ tools (e.g., drag and drop coding packages, reusable visualization interfaces) that democratize analytics by lowering the barriers to entry for those not as skilled in programming languages.

The Trusted Data Format (TDF)

Leveraging enterprise data headers, such as the Trusted Data Format (TDF), can reduce compliance and security complexity by creating self-describing or machine-learned data that prescribes how data systems must handle the multitude of organizational requirements placed on the data.

TDF remains flexible by providing the option for the CDO to define the basic schema and policies that form the enterprise standard while leaving the business lines and data owners to customize and provide further definition without being tied to a specific technology.

For CDOs, By CDOs

For CDOs, By CDOs: The Federal CDO Council connects senior data and analytics executives across government in a trusted, collaborative setting to share strategies on data and analytics. The Federal CDO Council is member led, following a grassroots agenda to amplify the most promising opportunities and address the most pressing challenges faced by CDOs today.

SCALE IT

Starting small and focused allows the CDO to build the required foundation and buy-in to scale and evolve his or her scope, role, and value over time. Long-term initiatives a CDO may focus on include the following:

+ **Partnering to Promote Advanced Analytics.** In many cases, the people closest to the mission do not understand the possibilities of advanced analytics, whereas the people with advanced analytics skills do not understand the mission well enough to spot opportunity. In the evangelist role, the CDO is in an ideal position to partner with the business lines and analytics teams to help them understand the "art of the possible" with advanced analytics while ensuring analytics efforts are connected to the "so what" or a business problem and ultimate solution.
+ **Implementing Portfolio Management.** As the data-driven enterprise culture continues to evolve and the organization begins to pursue more applications of data and analytics, portfolio management becomes increasingly important to identify existing capabilities, avoid duplicative work, and prioritize future endeavors. Portfolio management includes governance and maintenance of enterprise data capabilities and the tools for users to leverage existing data and analytics code for rapid development of ad hoc analytics. Portfolio management and the grassroots innovation associated with disruptive technology demand the CDO strike a thoughtful balance between structured process and the Wild West. Over-structuring the management of data and analytics capabilities will result in lost innovation, whereas a lack of structure can result in duplicative efforts and lost focus.
+ **Leveraging Innovation.** To continue evolving and promoting the enterprise's data-driven culture, a CDO can champion innovative activities such as internal hackathons and idea incubators to evolve the way an organization is tackling its most difficult data and analytical challenges. These events test and satisfy the desire of advanced practitioners while at the same time providing a safe learning environment for those still developing their skills.

A new CDO has the opportunity to set the standard. Starting small and focused on these five driving principles will help a CDO make the defining decisions for the organization and generate the momentum needed to garner support and further grow a data-driven enterprise. The focus, role, and value of the CDO will then evolve over time to fully achieve the insights or competitive advantage the organization's enterprise data can provide.

EVERYTHING YOU NEED TO KNOW ABOUT MANAGING YOUR DATA SCIENCE TALENT

The Booz Allen Data Science Talent Management Model

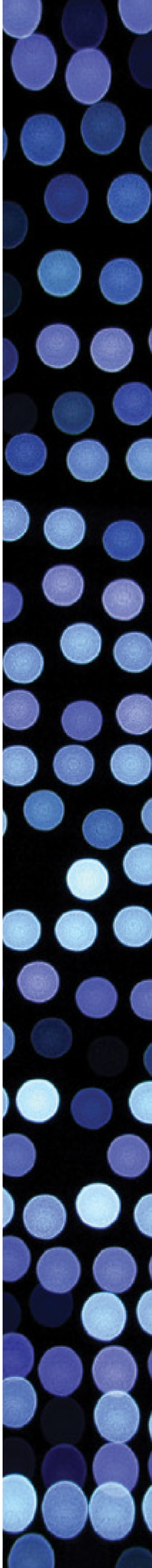
Recently, Harvard Business Review branded data science the “Sexiest Job in the 21st Century,” and the relatively new career field has been growing in popularity since. Organizations are clamoring to attract, hire, and build talent that can unlock the power of their data and deliver on its promising potential to increase organizational performance and drive complex business decisions. The hard truth, however, is that good data scientists are hard to find—current demand far outweighs supply. A recent survey by Gartner found that over half of business leaders felt their ability to carry out analytics was restricted by the difficulty in finding the right talent. Furthermore, not finding the right data science talent can have a cost. It is not as simple as renaming a business intelligence analyst, completing a day-long training, or hiring any candidate with “data science” in their resume. The National Business Research Institute estimates the cost of one bad hire can range from $25K to $300K depending on job complexity.

THE RANGE OF TALENT REALITIES

Given the current demand for data scientists, we often see organizations in a few different states when examining their data science talent reality:

+ *The Aspiring Star*: An organization that is just beginning its data science journey and needs to acquire and/or hire talent
+ *The Duckling:* An organization with potential data science talent that is struggling to develop and transform its staff
+ *The Enviable but Vulnerable:* An organization that has data science talent and must retain its much sought-after resources.

To complicate matters, organizations can transition organizational states at different points across their analytical journey, meaning that an organization’s talent challenges will also change over time. To succeed in this type of dynamic environment, a talent management model can be a difference maker.



Booz Allen identified key activities, tasks, and attributes required to successfully perform in a data science role to help clients understand the work to be performed.

WHY THE JOB ANALYSIS MATTERS:

+ Helps clients define and understand the most important work of their data science teams
+ Confirms the importance, frequency, and relevance of tasks and knowledge, skills, and abilities (KSAs)
+ Assists organizations to address expansion of mission, establishment of a new role, or an influx of new staff
+ Establishes the legal and scientific basis

Booz Allen developed a scientifically valid competency framework to help clients determine what KSAs their data science team needs.

WHY THE COMPETENCY FRAMEWORK MATTERS:

+ Provides clients with insights into what characteristics and KSAs are required for a data scientist's individual success
+ Establishes a legally defensible foundation for human capital practices
+ Useful when hiring/selecting talent, developing the workforce, assessing training needs, etc.

Data scientists have a unique blend of knowledge, skills, behavioral attributes, and personality traits that enable them to combine and analyze massive amounts of structured and unstructured data to solve some of an organization's most complex problems. Their inquisitive nature, as well as their ability to implement the scientific method and advanced tools and techniques, makes them exceptionally unique and vitally important in today's competitive environment. Yet few organizations have taken a proactive, rigorous approach to defining the unique characteristics of data science professionals, systematically documenting the type of work they perform; the competencies required for success; and the comprehensive approach to talent management required to identify, attract, grow, and retain these professionals.

Booz Allen Hamilton, a leading strategy and technology consulting firm, accepted the challenge. Recognizing the need to better understand the key elements that make up the data science role and data science talent requirements, Booz Allen took a rigorous, scientifically based approach to designing the foundation of a data science Talent Management Model. To meet the needs of business leaders, human resources professionals, and our own data science workforce, Booz Allen started from scratch, leveraging the expertise of our human capital team and the knowledge, capabilities, and experience of our 500+ data science team to describe core elements of data science work activities; define those characteristics that best represent successful execution of the work; and develop a Talent Management Model that will arm clients with the insights needed to best identify, attract, grow, and retain data science talent.

DEFINING THE CORE ELEMENTS OF THE JOB: JOB ANALYSIS

First, Booz Allen began by conducting a comprehensive job analysis on our own data science cadre. With the largest

BOOZ ALLEN'S DATA SCIENCE COMPETENCY FRAMEWORK

Clusters	Competencies
Technical: "Knows How and What to Do"	Statistical Modeling; Research Design; Data Mining and Integration; Data Visualization; Computer Science; Database Science; Machine Learning; Programming and Scripting; Information Assurance; Mathematics; Operations Research
Data Science Consulting: "Can Do in Client and Customer Environment"	Domain Expertise; Business Acumen; Program Management; Resource Allocation; Collaboration and Teamwork; Data Science Consulting; Ethics and Integrity; Communications
Cognitive: "Able to Do or Learn to Do"	Critical Thinking; Problem Solving; Inductive and Deductive Reasoning
Personality: "Willing or Motivated to Do"	Perseverance; Innovation and Creativity; Resilience and Hardiness; Inquisitiveness; Adaptability/Flexibility; Ambiguity Tolerance; Detail Orientation; Self-Confidence; Work Ethic

number of data scientists supporting government clients spanning every federal market sector in addition to numerous commercial clients, Booz Allen data scientists provide a rich and diverse cross-section of the data science career field. The job analysis identified both the criticality and frequency of specific job tasks mapped across consulting, cognitive, and personality areas, thereby solidifying their importance along with advanced technical skills. This kind of analysis not only deepened Booz Allen's understanding of the data science field but provided the basis for defining core client talent needs through developing a data science competency framework and, later, the Booz Allen data science Talent Management Model.

DEFINING CORE TALENT NEEDS: COMPETENCY FRAMEWORK

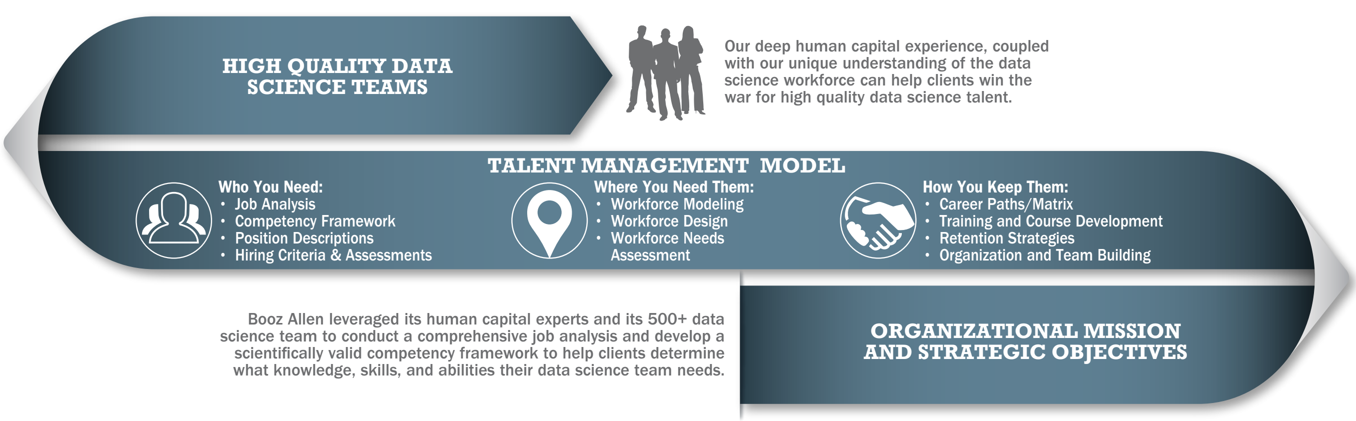
Next, Booz Allen used the findings from our job analysis to develop a data science competency framework that encapsulates the KSAs for successful job performance across data science roles. To develop the competencies, we surveyed our data science team and supplemented the findings, via convergent validity, using a secondary job analysis by Hogan Assessments—an industry leader in personality assessments. The findings indicated there are four unique and complementary data science competency clusters that, when considered together, convey the essence of what it means to be a successful data scientist.

The *technical competency cluster* depicts the foundational technical and specialty knowledge and skills needed for successful performance in each job or role. The characteristics in the *consulting competency cluster* can help data scientists easily integrate into various market or domain contexts and partner with business units to understand the environment and solve complex problems. The *cognitive competency cluster* represents the type of critical thinking and reasoning abilities (both inductive and deductive) a data scientist should have to perform their job. Lastly, the *personality competency cluster* describes the personality traits that drive behaviors that are beneficial to data scientists, such as inquisitiveness, creativity, and perseverance.

Though there have been numerous technological advances within this fast-growing field, to date, the job analysis and competency framework are believed to be the first, scientifically valid products to support the design and development of a data science Talent Management Model.

PUTTING IT TOGETHER: BOOZ ALLEN'S DATA SCIENCE TALENT MANAGEMENT MODEL

Using the results of the job analysis and competency framework, Booz Allen designed the remaining components needed for a comprehensive data science Talent Management Model. A Talent Management Model is a suite of integrated tools that help organizations strategically manage employees



BOOZ ALLEN TALENT MANAGEMENT MODEL

Who You Need

Key Benefits:

+ Identify the data science talent that will generate the most value
+ Rapidly define data science talent needs
+ Select talent based on legally defensible and scientifically valid data

Job Analysis identifies key content in terms of activities and tasks involved and attributes required to successfully perform in a given job, role, or position

Competency Framework encapsulates knowledge, skills and abilities for successful job performance

Targeted Position Descriptions define and differentiate the primary job responsibilities for a specific role within the organization

Hiring Criteria and Assessments identify candidates with the essential ability, technical skills, and personality traits necessary for successful job performance

Where You Need Them

Key Benefits:

+ Connect business goals to data science talent requirements
+ Shape the data science workforce of the future
+ Mitigate talent risks before there is a business impact

Workforce Modeling defines the type and amount of work within an organization with respect to the available talent supply and demand

Workforce Design describes the composition of the workforce and how work should be distributed across existing capabilities

Workforce Needs Assessment identifies and quantifies the need and/or prevalence of desired skills or competencies to be obtained

How You Keep Them

Key Benefits:

+ Reduce costly turnover in hard-to-find data science positions
+ Improve data scientists' job satisfaction and engagement
+ Motivate and grow data science talent

Career Paths/Matrix defines growth trajectories and transition points for personnel within the context of the organization's business objectives

Training and Course Development creates developmental learning opportunities to build new capabilities among junior talent and strengthen existing skill sets among senior talent

Retention Strategies provide organizations with the reward structure and environmental factors to keep employees engaged and motivated

Organization and Team Building helps clients further develop leadership skills and team dynamics to accelerate across the talent life cycle, including identifying, acquiring, developing, motivating, and retaining talent. The model is designed to be comprehensive to provide the insight and tools needed to help organizations strategically manage talent and flexible in allowing an organization to select and focus on immediate talent needs, where appropriate. In short, the model is designed to be customized depending on current organizational talent realities.

The Booz Allen data science Talent Management Model is not just a grab-and-go “toolkit.” Rather, it’s a set of comprehensive service offerings that allow clients to answer three key data science talent questions: *Who do you need? Where do you need them? How do you keep and develop them?* When Booz Allen created the Talent Management Model, we intentionally developed service offerings to help clients who are struggling to answer one or more of these key questions. Some of the foundational service offerings, such as the competency framework and position descriptions, are designed to be easily customized to an organization’s needs. Other offerings, such as workforce modeling, needs assessments, and team building, entail greater engagement and partnership with clients. Depending on where an organization falls within the data science talent spectrum, the Talent Management Model will help inform which offerings are most valuable for addressing its data science talent challenges.

Implementing a Talent Management Model not only helps data scientists understand their role and career path within the organization; it helps organizations establish, manage, and retain their data science workforce in a strategic and comprehensive manner.

TALENT MANAGEMENT AS AN ENABLER FOR SUCCESS

Recruiting and selecting the right talent is a critical component to building a robust data science workforce within an organization but it is only a piece of the talent strategy. To enable data scientists to flourish and deliver on their promise to enhance organizational performance, organizations must consider the full Talent Management Model, including the amount and type of work to be performed, the competencies and skills needed to perform the work, and the development and retention strategies the organization can employ to support this kind of unique workforce. By implementing a comprehensive Talent Management Model that addresses these critical components, organizations can achieve an engaged and successfully performing workforce, while gaining maximum returns on their analytical investment.

THE DATA SCIENCE CHALLENGE

How Design Thinking Can Help You Realize Organizational Value

Organizations are operating in an increasingly complex environment. They extend across traditional boundaries in both market reach and operational footprint. Operations often involve messy and complicated human interactions either through customers, partners, and/or employees. To further complicate matters, organizations are tapping into increasingly sophisticated technology capable of capturing oceans of data with varying degrees of structure and quality. Many organizations have turned to data science and advanced analytics to tackle today's complex organizational challenges. They still struggle, however, to capitalize on the power of analytics to address their most important business challenges. Therein lies the data science challenge. How does an organization focus the strength of its data and analytics to create impactful organizational value?

Two key dimensions make it hard for organizations to appropriately focus their data and analytics. First, they need to have a deep and innate understanding of their business. While this may seem obvious, the reality is that this type of understanding is often dispersed among organizational leaders, business units, data scientists, individual employees, and customers. It requires an insatiable curiosity and institutional collaboration to discover. Without this level of understanding, the organization will not be able to identify and articulate the most pressing business issues, and there is no way to ensure that the organization's analytical horsepower is cohesively focused on rich and relevant business questions. Second, the organizational value desired from data science is often found at the intersection of analytics and context. While data science can provide predictive and perspective analytics, insightful context can explain the answer of "why," including "why does this matter." Without the proper context, analytics will only go so far.

CASE IN POINT

Data scientists who are centralized in one government agency's organization are empowered to prioritize their own projects. Often the data scientists use financial return as the primary criterion to prioritize their efforts. This essentially means that projects focused on other strategic objectives, such as improving customer experiences or decreasing propensity for operational errors, are deprioritized. Those responsible for such outcomes must often design and plan solutions without the benefit of the analytical insight that data science can provide. The risk here is that data scientists may expend their tremendous talent on questions that only serve pockets of the enterprise, rather than delivering on the promise of data science that can drive the collective enterprise to the next level of performance.

DESIGN THINKING RISES TO THE DATA SCIENCE CHALLENGE: GROUNDING AND AMPLIFYING THE ANALYTIC METHOD

Solving the data science challenge is about an organization's ability to focus, embrace, and use analytics to generate meaning and impact that can result in the next level of organizational performance. One way to do this is to inject the art of design thinking into an organization's analytics approach. Design thinking is a problem-solving and innovation methodology—a tool box of techniques born from the designer's mindset. It emphasizes solving problems by starting with people (e.g., customers, employees, patients) rather than starting with technology or business positioning.

In particular, design thinking can be a powerful complement to data science, given its natural ability to support the seamless shift between deductive and inductive reasoning. Design thinking follows a

BOOZ ALLEN'S DESIGN THINKING METHODOLOGY

Immerse
Observe and document human experiences to gain qualitative knowledge

Synthesize
Use discovered knowledge to reframe the problem and shape understanding

Ideate
Combine and contrast dissimilar information to provoke unexpected ideas

Prototype
Build, test, and iterate light and lean examples to drive final selection

"Throughout Booz Allen Hamilton's methodology, there is an iterative flow of activities that deliberately sequences divergent and convergent steps."

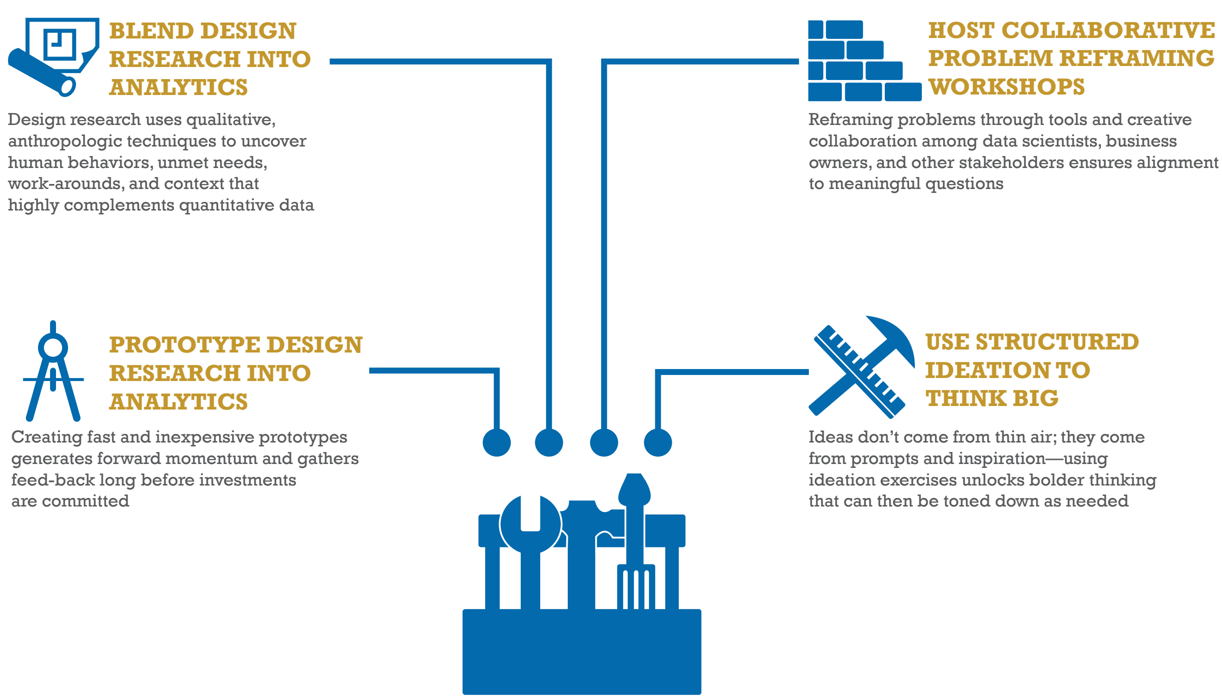
similar method in terms of diverging and converging in seamless succession to arrive at an increasingly finite focus. Design thinking pushes an organization to discover its most important business challenges, helps to frame the right set of questions to drive maximum value for the organization, provokes exploration to expose critical context to make sense of analytical findings, enables collaboration to create institutional knowledge, and drives testing of resulting conclusions. By pairing these like methodologies, organizations can not only generate analytically sound solutions but also provide a springboard for meaningful impact, whether as new growth opportunities or as areas for streamlining processes for efficiency gains.

BOOZ ALLEN'S APPROACH TO DESIGN THINKING KEY POINTS

+ Start from user needs, then factor in business and technology requirements
+ Bring multiple perspectives to the table
+ Sequence discussions to fully diverge before adding constraints
+ Make it real—don't just talk about solutions, draw them, build them, act them out

Booz Allen's design thinking methodology takes a collaborative, system-level perspective on a problem and incorporates tools that lead to better problem framing and reframing. Multiple perspectives and collaboration among stakeholders creates a more holistic understanding of the problem

BOOZ ALLEN'S DESIGN THINKING TOOL BOX FOR ANALYTICS



(i.e., context) and builds the institutional knowledge and critical buy-in necessary to ensure ongoing engagement and eventual scaling of capabilities and solutions. These techniques refocus data efforts into more meaningful and important questions that are both business focused and analytically meaty.

Throughout Booz Allen Hamilton's methodology, there is an iterative flow of activities that deliberately sequences divergent and convergent steps. For instance, instead of generating ideas in a linear fashion, where each idea is offered and then discounted for any number of reasons, in our approach to design thinking, ideas are generated in large batches, built on by others, and then prioritized based on any relevant criteria. The result is a much larger and more fertile sandbox of opportunity. These solution development activities help data scientists engage with business counterparts and work quickly and creatively toward identifying and executing the decisions and actions necessary to realize results with the buy-in of key business partners.

HOW BOOZ ALLEN EMBEDS DESIGN THINKING INTO ANALYTICS

Design thinking is both an end-to-end process and a toolbox from which to pull tools and techniques for modular application. As such, its integration with data science can take several forms and requires both experienced practitioners and sufficient training of data scientists and other stakeholders to achieve a shared mindset and language from which to collaborate. At Booz Allen, because we believe it is such a powerful complement, we train our own data scientists and our clients in these techniques so that they can get the most organizational value possible.

BLEND DESIGN RESEARCH INTO ANALYTICS

One of the key aspects of design thinking is looking for the hidden meaning or goals of the customer, employee, partner, or patient, etc. It's not enough to identify and understand a customer's need—organizations need to dig deeper. Establishing a design research capability and conducting research in sequence with quantitative methods of research (e.g., surveys, multivariate testing, and digital analytics) helps to generate a more complete picture of not just what's happening, but why. This can propel analytics organizations in new directions through new levels of insight into problems that have interactions among humans (customers, employees, partners, etc.). The result can be a more fulfilling analytical answer for all parties involved.

HOST COLLABORATIVE PROBLEM REFRAMING WORKSHOPS

Booz Allen's reframing workshops can bring together data scientists, business owners, and even customers (where appropriate) to explore and discover the hidden roots of business challenges and reframe problems into more meaningful questions. Reframing workshops are designed to challenge inherent assumptions made during the analytical process, allowing the potential for break-through thinking and solution development. Greater value from data can be unleashed by following a progressive cycle of analytical testing and reframing to arrive at more promising (and elegant for that matter) analytical solutions. Greater collective understanding helps to design more insightful research questions, and when paired with the right analytical technique, increases the potential for generating notable business impact.

USE STRUCTURED IDEATION TO THINK BIG

Design thinking includes many techniques for triggering ideas, drawing on existing patterns, solutions, and concepts and reapplying them in novel ways. With our design thinking techniques, ideation moves from a critical linear process of idea-constraint-idea-constraint to a sequenced divergent process of generating a wealth of ideas before converging on the most promising. These techniques allow teams to turn insights from analysis into "so what" actions necessary to move toward organizational value.

RAPIDLY PROTOTYPE IN LOW-FIDELITY WAYS

Design thinking generates low-fidelity prototypes to demonstrate applicability and test ideas quickly and cheaply before making significant investments. These prototypes span mock-ups, illustrations, paper-based interfaces, narratives, and other techniques that are quick and low cost to produce and easy to test with customers and stakeholders in near-real time. As feedback is gathered, teams can build smarter implementation roadmaps. For example, one technique we practice is a “cupcake road mapping” approach in which solutions are planned in delightful portions with increasing complexity added only when a solution proves worthwhile. This allows organizations to dedicate resources to only the most viable solutions that can make a difference.

FINAL THOUGHTS

The data science challenge is not going away, and it is often not as simple as creating an algorithm to generate organizational value. Rather, Booz Allen finds value by taking a holistic approach deriving meaningful insights by combining data science with innovative and creative methodologies such as design thinking. Booz Allen’s approach for realizing the real potential of analytics rests on this broader view of capabilities that moves beyond algorithms to creative and organizational approaches to institutionalize data science as more than a stove-piped function, but rather as part of organizational DNA.

CASE IN POINT

A major supply chain company was struggling with manufacturing data and determining the right questions to ask of the data. The Booz Allen team introduced design thinking as a technique to help reframe the questions and hypothesis. Using design thinking trained data scientists, the team conducted a co-generative workshop to unpack the problem and iterated until they determined a hypothesis and variable to test. The workshop and subsequent analysis were so successful that the client launched two international centers to apply the same techniques on a larger scale.

WE’RE HERE TO HELP

Booz Allen is one of the pioneers of data science. And now we’re the “go-to” firm for business and government agencies developing a data science capability. Let us know how we can help you.

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Leading our Data Science team shows me every day the incredible power of discovery and human curiosity. Don’t be afraid to blend art and science to advance your own view of data analytics. It can be a powerful mixture.

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We may not realize it yet, but we’ll all be data scientists in the future.

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Data Science is the most fascinating blend of art and math and code and sweat and tears. It can take you to the highest heights and the lowest depths in an instant, but it is the only way we will be able to understand and describe the why.

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The power of data science lies in the execution.

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You really can change the world through data science when you have the right capability in place.

Rick Whitford

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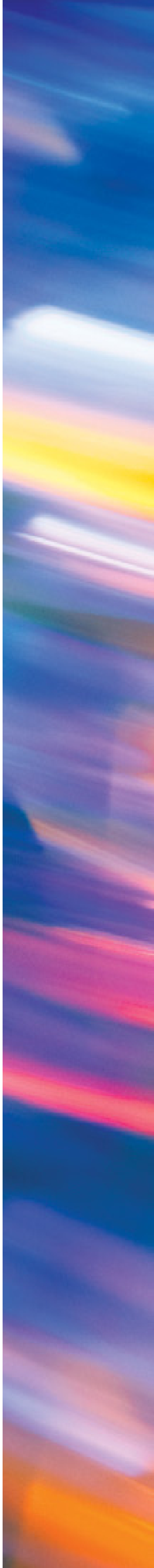
Save and analyze everything.



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CHIEF DATA SCIENTIST

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Data scientists should be truth-seekers, not fact-seekers.

Brian Keller, PhD

CHIEF TECHNOLOGIST

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I'll take passion over talent any day.

Jamie Lopez, PhD

SENIOR ASSOCIATE

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Fundamentally, people drive the analysis and make the interpretations, so it follows the more talented your people then the better your analysis and interpretations.

Patrick McCreesh

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Respect the data, bring on the science.

Kristen More, PhD

SENIOR ASSOCIATE

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All the data and tools in the world are meaningless unless you have the right data science talent to make sense of it.

Ari Hamalian

LEAD ASSOCIATE

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The cost of analysis will always be cheaper than the price of ignorance.

Katie Hanley

LEAD ASSOCIATE

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To make data science sing, hit the impact notes every day.

JD Hannick

LEAD ASSOCIATE

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Data doesn't solve problems, people armed with data solve problems.

Susan Michener

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Change agents are force multipliers – cultivating them to help drive your data science vision forward is time well spent.

Erin Senter

LEAD ASSOCIATE

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Building and managing data science talent is the difference maker in today's competitive data market.

Kelly Smith

LEAD ASSOCIATE

@kellemaries

If I asked what my customers wanted, they would have said faster horses. - Henry Ford

Katie Wilks

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Theory is great but let's make it real.

Kat Wood

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It's when the data influences an unprecedented decision, change, or impact that I'm inspired most.

Cutter Brenton

ASSOCIATE

@boozallen

Don't drive business decisions without a roadmap to a data science strategy.

Logan Gibson

ASSOCIATE

@Rivannarvr

Ignoring organizational culture will leave you data rich, information poor.

ABOUT BOOZ ALLEN HAMILTON

Booz Allen brings its pioneering work in advanced analytics—and the industry-leading expertise of its more than 500-member data science team—to transform our clients' data into actions that keep them competitive in today's data-driven economy. The first ever National Data Science Bowl, along with Booz Allen's recently launched Explore Data Science training program and Field Guide to Data Science is part of the firm's ongoing commitment to supporting data science education and awareness. Booz Allen Hamilton celebrated its 100th anniversary in 2014 and continues to be a leading provider of management consulting, technology, and engineering services to the US government and to major corporations.

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www.boozallen.com/datascience