DataInformed
Big Data and Analytics in the Enterprise

How to Build and Lead a Winning Data Team

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Why Soft Skills Matter in Data Science

by John W. Foreman

In this excerpt from his book "Data Smart," John W. Foreman, chief data scientist at MailChimp.com, discusses what it means to practice data science in the business world.

John W. Foreman

I'd like to offer up some thoughts about what it means to practice data science in the real world, because merely knowing the math isn't enough.

Anyone who knows me well knows that I'm not the sharpest knife in the drawer. My quantitative skills are middling, but I've seen folks much smarter than me fail mightily at working as analytics professionals. The problem is that while they're brilliant, they don't know the little things that can cause technical endeavors to fail within the business environment. So let's cover these softer items that can mean the success or failure of your analytics project or career.

Get to Know the Problem

My favorite movie of all time is the 1992 film Sneakers. The movie centers on a band of penetration testers led by Robert Redford that steals a "black box" capable of cracking RSA encryption. Hijinks ensue. (If you haven't watched it, I envy you, because you have an opportunity to see it for the first time!)

There's a scene where Robert Redford encounters an electronic keypad on a locked office door at a think tank, and he needs to break through.

He reaches out to his team via his headset. They're waiting in a van outside the building. "Anybody ever had to defeat an electronic keypad?" he asks.

"Those things are impossible," Sydney Poitier exclaims. But Dan Aykroyd, also waiting in the van, comes up with an idea. They explain its complexities to Redford over the comms.

Robert Redford nods his head and says, "Okay, I'll give it a shot."

He ignores the keypad and kicks in the door.

You see, the problem wasn't "defeating an electronic keypad" at all. The problem was getting inside the room. Dan Aykroyd understood this.

This is the fundamental challenge of analytics: understanding what actually must be solved. You must learn the situation, the processes, the data, and the circumstances. You need to characterize everything around the problem as best you can in order to understand exactly what an ideal solution is.

In data science, you'll often encounter the "poorly posed problem":

1. Someone else in the business encounters a problem.

2. They use their past experience and (lack of?) analytics knowledge to frame the problem.

3. They hand their conception of the problem to the analyst as if it were set in stone and well posed.

4. The analytics person accepts and solves the problem as-is.

This can work. But it's not ideal, because the problem you're asked to solve is often not the problem that needs solving. If *this problem* is really about *that problem* then analytics professionals cannot be passive.

You cannot accept problems as handed to you in the business environment. Never allow yourself to be the analyst to whom problems are "thrown over the fence." Engage with the people whose challenges you're tackling to make sure you're solving the right problem. Learn the business's processes and the data that's generated and saved. Learn how folks are handling the problem now, and what metrics they use (or ignore) to gauge success.

Solve the correct, yet often misrepresented, problem. This is something no mathematical model will ever say to you. No mathematical model can ever say, "Hey, good job formulating this optimization model, but I think you should take a step back and change your business a little instead." And that leads me to my next point: Learn how to communicate.

We Need More Translators

I'm assuming you know a thing or two about analytics. You're familiar with the tools that are available to you. You've prototyped in them. And that allows you to identify analytics opportunities better than most, because you know what's possible. You needn't wait for someone to bring an opportunity to you. You can potentially go out into the business and find them.

But without the ability to communicate, it becomes difficult to understand others' challenges, articulate what's possible, and explain the work you're doing.

In today's business environment, it is often unacceptable to be skilled at only one thing. Data scientists are expected to be polyglots who understand math, code, and the plain-speak (or sports analogy-ridden speak . . . ugh) of business. And the only way to get good at speaking to other folks, just like the only way to get good at math, is through practice.

Take any opportunity you can to speak with others about analytics, formally and informally. Find ways to discuss with others in your workplace what they do, what you do, and ways you might collaborate. Speak with others at local meet-ups about what you do. Find ways to articulate analytics concepts within your particular business context.

Push your management to involve you in planning and business development discussions. Too often the analytics professional is approached with a project only after that project has been scoped, but your knowledge of the techniques and data available makes you indispensable in early planning.

Push to be viewed as a person worth talking to and not as an extension of some number- crunching machine that problems are thrown at from a distance. The more embedded and communicative an analyst is within an organization, the more effective he or she is.

For too long analysts have been treated like Victorian women — separated from the finer points of business, because they couldn't possibly understand it all. Oh, please. Let people feel the weight of your well-rounded skill set — just because they can't crunch numbers doesn't mean you can't discuss a PowerPoint slide. Get in there, get your hands dirty, and talk to folks.

Beware the Three-Headed Geek-Monster: Tools, Performance, and Mathematical Perfection

Many things can sabotage the use of analytics within the workplace. Politics and infighting perhaps; a bad experience from a previous "enterprise, business intelligence, cloud dashboard" project; or peers who don't want their "dark art" optimized or automated for fear that their jobs will become redundant.

Not all hurdles are within your control as an analytics professional. But some are. There are three primary ways I see analytics folks sabotage their own work: overly complex modeling, tool obsession, and fixation on performance.

Complexity

Many moons ago, I worked on a supply chain optimization model for a Fortune 500 company. This model was pretty badass if I do say so myself. We gathered all kinds of business rules from the client and modeled their entire shipping process as a mixedinteger program. We even modeled normally distributed future demand into the model in a novel way that ended up getting published.

But the model was a failure. It was dead out of the gate. By dead, I don't mean that it was wrong, but rather that it wasn't used. Frankly, once the academics left, there was no one left in that part of the company who could keep the cumulative forecast error means and standard deviations up to date. The boots on the ground just didn't understand it, regardless of the amount of training we gave.

This is a difference between academia and industry. In academia, success is not gauged by usefulness. A novel optimization model is valuable in its own right, even if it is too complex for a supply chain analyst to keep running.

But in the industry, analytics is a results-driven pursuit, and models are judged by their practical value as much as by their novelty.

In this case, I spent too much time using complex math to optimize the company's supply chain but never realistically addressed the fact that no one would be able to keep the model up to date.

"The mark of a true analytics professional, much like the mark of a true artist, is in knowing when to edit."

The mark of a true analytics professional, much like the mark of a true artist, is in knowing when to edit. When do you leave some of the complexity of a solution on the cutting room floor? To get all cliché on you, remember that in analytics great is the enemy of good. The best model is one that strikes the right balance between functionality and maintainability. If an analytics model is never used, it's worthless.

Tools

Right now in the world of analytics (whether you want to call that "data science," "big data," "business intelligence," "blah blah blah cloud," and so on), people have become focused on tools and architecture.

Tools are important. They enable you to deploy your analytics and data-driven products. But when people talk about "the best tool for the job," they're too often focused on the tool and not on the job.

Software and services companies are in the business of selling you solutions to problems you may not even have yet. And to make matters worse, many of us have bosses who read stuff like the Harvard Business Review and then look at us and say, "We need to be doing this big data thing. Go buy something, and let's get Hadoop-ing."

This all leads to a dangerous climate in business today where management looks to tools as proof that analytics are being done, and providers just want to sell us the tools that enable the analytics, but there's little accountability that actual analytics is getting done.

So here's a simple rule: *Identify the analytics opportunities you want to tackle in as much detail as possible before acquiring tools*.

Do you need Hadoop? Well, does your problem require a divide-and-conquer aggregation of a lot of unstructured data? No? Then the answer may be no. Don't put the cart before the horse and buy the tools (or the consultants who are needed to use the open source tools) only to then say, "Okay, now what do we do with this?"

Performance

If I had a nickel every time someone raised their eyebrows when I tell them MailChimp uses R in production for our abuse-prevention models, I could buy a Mountain Dew. People think the language isn't appropriate for production settings. If I were doing high-performance stock trading, it probably wouldn't be. I'd likely code everything up in C. But I'm not, and I won't.

For MailChimp, most of our time isn't spent in R. It's spent moving data to send through the AI model. It's not spent running the AI model, and it's certainly not spent training the AI model.

I've met folks who are very concerned with the speed at which their software can train their artificial intelligence model. Can the model be trained in parallel, in a low-level language, in a live environment?

They never stop to ask themselves if any of this is necessary and instead end up spending a lot of time gold-plating the wrong part of their analytics project.

At MailChimp, we retrain our models offline once a quarter, test them, and then promote them into production. In R, it takes me a few hours to train the model. And even though we as a company have terabytes of data, the model's training set, once prepped, is only 10 gigabytes, so I can even train the model on my laptop. Crazy.

Given that that's the case, I don't waste my time on R's training speed. I focus on more important things, like model accuracy.

I'm not saying that you shouldn't care about performance. But keep your head on straight, and in situations where it doesn't matter, feel free to let it go.

You Are Not the Most Important Function of Your Organization

Okay, so there are three things to watch out for. But more generally, keep in mind that most companies are not in the business of doing analytics. They make their money through other means, and analytics is meant to serve those processes.

You may have heard elsewhere that data scientist is the "sexiest job of the century!"

That's because of how data science serves an industry. Serves being the key word.

Consider the airline industry. They've been doing big data analytics for decades to squeeze that last nickel out of you for that seat you can barely fit in. That's all done through revenue optimization models. It's a huge win for mathematics.

But you know what? The most important part of their business is flying. The products and services an organization sells matter more than the models that tack on pennies to those dollars. Your goals should be things like using data to facilitate better targeting, forecasting, pricing, decision-making, reporting, compliance, and so on. In other words, work with the rest of your organization to do *better business*, not to do data science for its own sake.

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Data Expert Explains What Makes the Best Data Analysts

by Ellis Booker

Big data author, speaker, and instructor Kaiser Fung says that without the development among analysts of an instinct he calls "numbersense," more data, more sources, and more analysis can lead to more uncertainty.

***Kaiser Fung**, Vice President, Business Intelligence and Analytics, Vimeo*

In an age of ever-increasing data volumes and data sets, analysts and business people alike must become much more careful how they approach questions and use statistics.

That was the message in Kaiser Fung's riveting keynote address at Predictive Analytics World in Chicago. The VP of Business Intelligence at Internet video-sharing company Vimeo, Fung is also the author of "Numbers Rule Your World: The Hidden Influence of Probabilities and Statistics on Everything You Do." In addition, he teaches business analytics and data visualization at New York University.

Quoting from his book, Fung said, "When more people are performing more analyses more quickly, there are more theories, more points of view, more complexity, more conflicts, and more confusion."

In the coming five to 10 years, there will be "less clarity, less consensus, and less confidence," he predicted.

For Fung, the solution to this worrisome situation is the development of what he calls "numbersense," a problem-solving instinct that, he contends, is necessary *before* analysis begins.

Analysts with numbersense tend to have a plan, avoid distractions, and "recognize wrong turns early," Fung said, and they are able to adapt their analytical strategy when new information arrives.

Fung said numbersense can help avoid common analytical problems. For instance, many such problems involve observational data, such as a Web server's logs, that were collected for other purposes and are only used incidentally and after the fact by others, such as marketers, to try to uncover correlations and trends. But these observations are generally taken at face value and aren't subjected to rigorous experimental design.

"When you are running an experiment, the type of questions you can actually address are, 'What if we color the buttons red or green, or send the email an hour later, or insert a video?' " Fung said. "Instead, what generally happens is someone asks the data analyst to account for some unexpected observation, such as a decrease in traffic to the Web site.

"You know what happened, and now need to figure out why, which is the exact opposite of an experiment," he added.

A second issue is the lack of legitimately random control groups, which makes attribution ("Our consumers bought this product because they saw the ESPN ad") suspect. Marketers, Fung said, tend to attribute things like conversions to the "channels they can actually observe" but they don't consider the influence of unobserved channels.

In a world of observational data sets without control groups, "it is really important to be thinking about what would be the right control," he said.

Likewise, problem solvers need to consider what data may be missing. Fung said analytical errors in big data are caused by what he calls OCCAM. This refers to information that is:

- Observational
- Controls (lack of)
- Complete (seemingly)
- Adapted (data collected for one purpose and repurposed for another)
- Merged (joined datasets that make attribution even more difficult and introduce anomalies).

"Most of the big challenges today are not really about the amount of data," he said. "The amount of data can always be solved by more storage and faster processors, and so on. But a lot of these problems I am pointing out are endemic across all big data analysis."

College and university programs that are now pumping out data professionals in record numbers may not be helping either, Fung said, because these programs focus on teaching statistical techniques, such as computing standard deviations, rather than training students how to spot and address the right problems.

The right problems, Fung said, often don't have a single correct answer. They also involve lots of uncertainty, require assumptions (or figuring out what the assumptions were), lack complete information, or have problems with the data itself, he said.

For instance, Fung said some of his own New York University students give accurate answers but miss seeing fundamental problems with the dataset itself. Other students notice the problem but don't feel "uneasy" about it. A third group spots the abnormality and tries to explain it. A fourth group, he said, notices the problem, feels uneasy about it, and tries to explain it. But, crucially, that group goes on to develop approaches to the data that can be used to solve it.

This last group, he said, has numbersense.

"Numbersense differentiates a good data analyst from a bad one," Fung said. "Additionally, in the age of big data, this is also going to be an important skill for any citizen to develop."

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Rethink Your Org Chart for Big Data Analytics Teams

by Elana Varon

The success of a data analytics team set up to exploit big data depends on the skills and knowledge of the team members and their experience working together.

***Sandra Woodley**'s analytics team at U. of Texas involves many experts in its research.*

Here's a way to understand the difference between a traditional analytics team and one that's set up to exploit big data: compare bank tellers to orchestra musicians.

Traditional analytics teams, often centered in IT departments, are the bank tellers. Like bank patrons waiting in line to conduct standard transactions, business users line up to hand business intelligence and data warehouse experts their requests for reports on questions that have been well-defined in advance. Then they wait for their results.

Orchestras, on the other hand, employ a core group of musicians, but the conductor has to assemble different teams to play a variety of pieces. The resulting performance, and its value to the audience, depends on the skills, knowledge and experience that the musicians, working together, bring to the stage.

"Big data is pretty complex music," says Bill Hostmann, vice president and distinguished analyst at Gartner. And the expertise companies need to use it effectively depends on the questions they are trying to answer. "A one-size-fits-all approach doesn't work."

Having a central analytics team may be a sign that your organization is mature in its analytical ways, says Jack Levis, a vice president with the Institute for Operations and Management Science (INFORMS), a professional society, and director of process management with UPS. But when it comes to embedding analytics into daily business decisions (the goal of many current analytics initiatives, even when they don't involve massive or unstructured data sets) "you can't separate the brains"—the statisticians and developers—"from the operations."

In other words, hiring data scientists and training technologists on Hadoop isn't the only step business leaders need to take in order to build their capacity to use big data. They also need a structure that makes it easy to coordinate expertise across the enterprise and facilitate collaboration.

The Organizational Focal Point

Many business and IT leaders are familiar with the concept of a center for excellence (CoE). Typically, such groups provide a focal point for a particular type of business expertise, allowing an organization to share skills, develop standards and disseminate best practices.

In IT, such groups can help to break down functional silos, says Michael Kopp, technology strategist with Compuware's application performance management CoE. For example, application performance improves—and customer demands can be managed more easily—when developers, testers, quality assurance and production experts share knowledge and cooperate, as well as communicate with business leaders who know how the application will be used.

Similarly, having an interdisciplinary team focused on analytics—whether you call it a CoE or something else—provides a way to organize people so they can collaborate on identifying relevant questions, collecting and preparing data, building statistical models and delivering results in a way business leaders can use them. IBM, which last month announced a service to help customers build analytics centers of excellence, says such groups often manage analytics strategy, "including centralization of the data and implementation of technology."

Analytics Central

An interdisciplinary analytics office, with both data science and subject matter expertise, offers several organizational benefits, including:

- Provides a focal point to coordinate analytics expertise across the enterprise.
- Facilitates collaboration among experts to identify relevant questions and create results in formats that decision-makers find useful.

When Sandra Woodley joined the University of Texas System two years ago as vice chancellor for strategic initiatives, the analytics group that reported to her focused mainly on producing descriptive data and statistics. "Your traditional fact book," Woodley says. Part of her charge: to develop the capacity for predictive analytics, in order to help the 15 institutions within the UT system use data become more cost effective, improve faculty productivity and serve its 200,000 students better.

Woodley invested in a new business intelligence and data warehouse system from SAS. She hired additional people to organize and provision the data—which they aggregate from many terabytes across the UT system and other sources—as well as manage data quality. And she hired researchers "to do deep dive analytical studies. We've set up a research agenda a year out," Woodley says, to support the system-wide strategic plan. Among their projects, the researchers are studying what makes students successful, including how factors influencing graduation rates differ from school to school within the Texas system.

One tenet of the team is to involve experts across the UT system in developing new research. Dashboards allow users to access data for their own analyses. Meanwhile, the team partners with key constituents to craft its studies. For example, for its research on student success, the team consulted with subject-matter experts throughout the system, including administrators and institution-based research directors. "We rely heavily on existing relationships," Woodley says. Who gets involved in a particular project happens organically, depending on the topic. "We know who the experts are. We do the heavy lifting, they provide ideas and they can react to the drafts."

No Analyst Is an Island

The ability to involve experts in business areas, is critical, says Hostmann. Whoever leads big data initiatives needs to be able to "reach across the white space in the org charts" to tap employees with relevant skills and get "the commitment and the buy in" from managers.

Levis observes that mathematicians can develop great algorithms to optimize business processes, but the results might be impossible to implement. If you want analytics to be used for front-line decision-making, "you need data—often the analysts don't think about where they're going to get the data—you need the mathematics, you need the interface. And when you get a bad answer, you have no idea which one of the three caused the problem, so you need people who can research it." His analytics teams at UPS include "PhDs who are mathematicians, software engineers who can do data cleanup and displays and can iterate with IT systems [and] business people who understand enough of the math" to know how to make a new data-driven process work."

Using analytics to improve operations has become critical in healthcare, says Randall Gaboriault, CIO at Christiana Care Health System, which is among the largest healthcare providers in the United States (it ranks 17th in hospital admissions). Regulations issued as a result of the Affordable Care Act penalize hospitals with high readmission rates and reward providers that deliver quality care. The rules aim to cut costs by changing how healthcare providers get paid; instead of revenue from each procedure, they'll be held accountable for managing each patient's health. Predictive analytics can help providers uncover factors that put patients at risk and take preventive measures.

So Gaboriault is revamping Christiana Care's analytics team. Now, within the organization's business intelligence/data warehouse group, one team is responsible for technology, training and delivering projects. But another team, enterprise analytics, is charged with mining data across functions and business processes. Domain experts on this team, who come from the business, collaborate with clinicians and administrators to ask "radical" questions, such as what can be learned about treating cardiac patients by analyzing all the data about them, including information from their primary care doctors.

All the technology and data expertise is a shared resource. Although the analytics capabilities live within IT, the point of it is to empower business users with access to data and support. Says Gaboriault: "We're taking the IT organization out of the middle."

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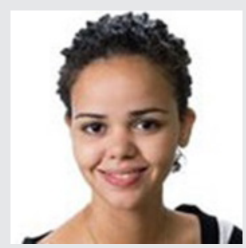
Analytics Leaders Discuss Care and Feeding of a Successful Data Team

by Scott Etkin

BOSTON – Analytics team leaders from a variety of industries gathered at the INFORMS Conference on Business Analytics and Operations Research for a panel discussion on how to build a well-rounded data-analytics team and manage data professionals: where to position them; how to keep them challenged, engaged and motivated; and what it takes to lead them.

The panel was moderated by Julia Kirby, editor at large at the Harvard Business Review, and included team leaders from major corporations, including Brian Eck, quantitative analyst at Google; Kerem Tomak, vice president of marketing analytics at Macy's; Erica Klampfl, global future mobility manager at the Ford Motor Company; Dayana Cope, manager of operations research engineering at Disney; and Jeanne Harris, managing director of IT research at Accenture.

***Erica Klampfl**, Global Future Mobility Manager, Ford Motor Company*



***Dayana Cope**, Manager, Operations Research Engineering, Disney*

Kirby led off the discussion by asking what she referred to as "the perennial question": Where do data scientists sit in an organization? Do you keep them together in their own group so they can keep their skills sharp with constant interaction with each other, or do you distribute them throughout the company's business units because that is where they must have an impact?

"I think where the analytics professionals sit in an organization depends on the size of the organization," said Klampfl. "It's not one extreme or the other. I think it needs to be a combination of that. I do think that analytics professionals working together provides them the ability to learn from each other and have their own community, but it's nice to have rotational opportunities to bring in lessons learned and work closer to the business. So I think the sweet spot is really a combination of those."

"I think there's advantages and disadvantages [to keeping them in a group]," said Cope. "The advantages are that you have the opportunity to share learnings, a centralized approach and you have more resources the ability to hire specialized knowledge. The disadvantages of a centralized approach come with when you put the word 'business' in front of analytics because that requires a concerted effort to connect it to the business and that is harder to do when you are centralized. At Disney, we have more of a hybrid approach. We have centralized analytics functions that have smaller subgroups that are connected to the business, that have business alignment. We find that is very useful and works well for us. One thing to keep in mind is that, when you have a centralized approach, relationships become very important, and at Disney we are very proud of our analytics culture because we spend so much time and effort developing those relationships and maintaining those relationships."

"About four years ago we did a survey of how companies are organizing their analytics talent," said Harris. "And back then there was more of this debate of, 'Should we centralize them or should we decentrailize?' And what we found was the right organizational model is largely dictated by the level of maturity of the organization itself. And if you think about it, that makes a lot of sense. An organization that's just getting started needs to keep those analysts very close to the decision makers. But today I think the thing that's really changed, and I think we are hearing it reflected by the companies on this panel, is that there's much more of a movement toward going back to first principles, trying to define, 'What's the right operating model for us?' with regard to analytics and defining certain principles which then dictate whether an individual or a group is going to remain local in the business unit or in a business function, or get centralized."

Kirby raised the question of how companies keep data professionals, with their in-demand, specialized skills, happy and engaged in their work.

"I think it has a lot to do with what you are working on and whom you are working with," said Eck. "The ability to network with peers with a similar level of expertise that may be in different areas is very enriching. And also the amount of autonomy you have in your work plays a big role."

"To keep these types of people happy," said Cope, "I think we have to, first and foremost, acknowledge that they are different in the organization. I think the analytic professional should be led by analytic professionals because they understand those differences and those analytics leaders should communicate those differences throughout the organization constantly. They should acknowledge different processes for them, they should have different technical ladders, different job expectations. They should also acknowledge that they have different motivations. I think you keep them challenged, that's what motivates them. And if you can't keep them challenged all the time, you can provide that framework to share learnings. The last thing I want to point out is that it's important to communicate and always celebrate wins."

"[I am asked] what's keeping them with you, especially in Silicon Valley, where they can walk across the street and go somewhere else," said Tomak. "And I was thinking about it and I came up with several ideas. One of them is I basically get out of their way. I empower them, I give them the tools. I give them the exposure because we are deeply embedded in the C-suite. The senior executives at Macy's want to make decisions based on data and they trust us tremendously because we have proven ourselves to them. So I essentially get them in front of the C-suite and give them the platform to talk to them directly as to what they are doing. I think that's what's keeping them there, because they see they are driving the bus."

Kirby then asked the panel what it takes to be a great leader of this kind of function.

"I think it's important to get people with complementary skill sets," said Klampfl. "You don't want to have all people who do stats or all people who do optimizations, so you really have to build a team recognizing individual strengths. Analytics is a broad space and there are a lot of specialties, so it's really understanding that difference and I think that's why if you are an analytics professional it makes it easier to be an analytics leader because you understand the space, you understand specialties. … So to be a good leader of a team you really have to focus on the individuals on your team and help them succeed."

"How well the leader can identify opportunities for the team and position the team to solve those opportunities is a key issue," said Eck. "Reaching out to the organization, the person needs good leadership skills, not just strong technical skills. But they do need the technical literacy to be able to position the problems correctly."

"You cannot be too disconnected from the people you are managing. You have to keep yourself up to speed as well," said Tomak. "You have to understand what they are talking to you about and you have to talk back to them in a language they understand."

"Someone who leads an analytics group, whether it's a single analytics group in a single department or a Chief Analytics Officer for an entire company, they really need to be a tireless advocate for analytics and an agent of change," said Harris. "The truth of the matter is, being able to communicate, being able to persuade people, helping them understand the potential of analytics to transform their business and being able to work with them to take those ideas, put them into practice and actually get the results at the other end, that's maybe the most important thing a leader can do."

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Island of Misfit Toys: Building an Analytics Team from Within

When Rob Fosnaugh, manager of BI at Brotherhood Mutual Insurance, was building his team with candidates from inside his company, he valued personal attributes and business knowledge above analytics training.

by Allen Bernard

For organizations just starting down the path of business intelligence, figuring out the right mix of people to take the company from reports-driven, spreadsheet-focused decision-making to one that embraces analytics can be particularly challenging.

For Brotherhood Mutual Insurance in Fort Wayne, Indiana, this journey began in 2007, when the company realized it was time to replace its Excel spreadsheets with an analytics package from Information Builders that would allow it to gain a deeper understanding of its customers and its business.

It took two years, but by 2009 the company had put Rob Fosnaugh in charge of selecting the team members who would ultimately be responsible for this transition. Because of his consulting background and deep understanding of analytics, Fosnaugh knew that you just can't take a stack of resumes and turn them into a high-functioning group of people who would understand Brotherhood's business well enough to do more than take orders and put out reports.

"To me, a BI developer should have visibility and input into every business process to be flexible and innovative," Fosnaugh, the manager of BI at Brotherhood Mutual, said in an interview at the Information Builder's Summit 2014. "I tell my team all the time, 'When a request comes in, that is usually not the answer [they are looking for]. What they are asking for is what they think they need. But we, because of who we are and the experience we have … we have the tools and resources to advise them to create the tool they need.'"

To find the people for his team, Fosnaugh likes to walk around his company's offices and take the time to identify those individuals who would make great analysts. These folks may not have any formal BI training, but what they lack in technical knowledge, they more than make up for in organizational and cultural knowledge. In short, they know the business.

Fosnaugh likes to call these individuals "misfits" because, like Hermey, the elf in the children's classic Rudolph the Red Nosed Reindeer, they are often the people who struggle to fit into the roles they've been assigned. It's not that they are bad employees — far from it. But stuck inside a business process role, these individuals chafe and often give their managers fits because they want more out of their careers and life.

"Look for the ones that are not cookie-cutter," said Fosnaugh. "Because the ones who are not cookie-cutter are trouble employees a lot of times for managers. So a lot of times it's a negative on both ends. The person is frustrated in their job and the manager doesn't know what to do."

Fosnaugh said these employees are usually looking to do more. They are creative, intuitive, questioning, adaptive, and independent. They think for themselves and they often ask why.

Specifically, when building a data team, Fosnaugh looks for individuals with the following attributes:

Independent. They don't always expect to be spoon-fed the work that needs to be done. They build on past experience, take ideas and run with them. They are very self-sufficient.

Questioning. They are not afraid to ask the "dumb questions" that often lead to greater insight and changes to processes that have become ingrained in the corporate culture.

Innovative. They are always looking for better ways to see the world. They use tools and resources to extend beyond what is merely expected.

Adaptive. They are flexible and embrace new technologies and ways of thinking in order to solve complex problems in novel ways.

Intuitive. They know the end result and how to get there before the discussion begins. This is where deep organizational knowledge comes in particularly handy.

Mentoring. They enjoy working with managers to develop their strengths and work through their weaknesses in a collaborative fashion.

"These are skills that I value very much when I bring people on my team," he said. "It's hard to tell from a resume and a couple of interviews. It's a cultural thing. If we keep our eyes open as the directors of BI, we should be able to identify the soon-to-become-possible BI candidates to move into our area."

Now a freelance writer, in a former, not-too-distant life, **Allen Bernard** was the managing editor of CIOUpdate.com and numerous other technology websites. Since 2000, Allen has written, assigned and edited thousands of articles that focus on intersection of technology and business. As well as content marketing and PR, he now writes for Data Informed.com, Ziff Davis B2B, CIO.com, the Economist Intelligence Unit and other high-quality publications. Originally from the Boston area, Allen now calls Columbus, Ohio, home. He can be reached at 614-937-2316 or abernie182@gmail.com. Please follow him on Twitter at @allen_bernard1, on Google+ or on Linked In.

How to Get Sales Reps to Adopt and Crave Predictive Analytics

The success of predictive analytics hinges on getting sales reps to use the data. Here are some tips to encourage adoption by sales teams.

by Javier Aldrete

***Javier Aldrete**, Senior Director of Product Management, Zilliant*

Business intelligence alone is no longer good enough to boost company performance. As such, many companies are moving to analytics, particularly when it comes to trying to help their sales teams sell more. But despite managers' best efforts, it is unlikely that sales reps will ever really adopt analytics — at least the way analytics is most commonly deployed within organizations.

For the majority of companies, their first step into the world of analytics is with descriptive analytics, or hindsight analytics. By definition, descriptive analytics is inherently backward-looking and provides little to no value other than reporting on what happened in the past. It gives no indication of how to improve performance in the future.

Predictive analytics, on the other hand, promises many benefits to B2B sales organizations.

As the market shifts to a more progressive form of intelligent guidance, the success of predictive analytics will hinge on the approach companies take to encourage adoption by sales reps. Like any new technology roll-out, if sales reps don't buy in to the change, the deployment is likely to fall flat. Yet, providing sales reps with tools and reports actually hinders adoption rather than encouraging it. What most companies don't realize is that sales reps don't need access to the analytics, they simply need the guidance generated by it.

Why Sales Reps Abandon Analytics

B2B sales organizations are faced with massive decision complexity. Tens of thousands of customers, hundreds of thousands of products, and mercurial factors such as new products, new markets, and competitive pressures result in hundreds of decisions for one sales rep to make each day about which customers to call on, what products to sell, and what price to quote.

Company leaders are well aware of this decision complexity. In an attempt to help, they provide reps with extensive reports that contain customer-spend analysis, customer churn trends, and high-level price guidance about margin targets. While this effort is well-intentioned, adoption rates are still abysmal and initiatives typically fail, primarily for these three reasons:

Salespeople aren't analysts. They don't like or read reports. Sure, your top reps may use the reports, but most salespeople simply ignore them.

Reports are backward-looking. The reports can tell reps what their customers purchased in the past, but they don't provide explicit guidance as to where reps should spend their time in the future. It's certainly helpful to understand historical customer data, but a backward-looking report won't help employees make better decisions in the future.

Manual approaches can't scale. To manage the complexity and perform thorough analysis on each customer and product in the entire book of business on a weekly or even monthly basis, you would need an army of analysts. As a result, most companies are able to address only the top 20 percent of customers and products, leaving the remaining long tail to guesswork.

Sales reps don't want to spend their time sifting through reports. They want to spend their time doing what they do best: selling. They crave the answers to their questions, not just the data and analytics behind the answers. Reps need sales guidance that's immediately actionable and tells them explicitly where to find the opportunities most likely to result in a win.

How to Give Reps the Guidance They Crave

It's possible to deliver analytics-based guidance to sales reps that they will actually use. The data to generate that guidance already exists. By applying predictive science and algorithms to transaction data and delivering the output as actionable guidance to sales reps, you can halt customer defection, grow organic revenue, hit or exceed margin targets and gain share. In essence, it's all about the leads and the quality of pricing guidance delivered to the reps.

For example, to keep and expand wallet share with existing customers, predictive models can find the purchase patterns in the data and uncover the retention and cross-sell opportunities for each account. These actionable opportunities can be delivered to sales reps to help them understand what each customer should be buying from them.

A predictive model also can help set specific, market-aligned prices that account for every selling circumstance. The model allows you to understand how those pricing strategies will impact future P&L performance before prices are put in-market. You can then deliver market-aligned price guidance directly to your sales reps in the quoting systems they use today.

If predictive analytics are leveraged this way, it removes the need to ask sales reps to decipher reports and gives them specific answers about where to spend their time and how to quote a price that won't lose the deal while achieving the company's P&L objectives.

How to Tackle Adoption Challenges

Generally speaking, this type of approach to deploying predictive analytics helps to minimize adoption challenges. However, sales reps still have to trust and use the guidance. The first step to aid in adoption is to ensure the guidance is easily accessible to sales reps in the systems and tools they already use today: e-mail, mobile devices, CRM, etc.

Sales reps might believe their "gut feeling" is more reliable than the sales guidance, so expect them to be resistant at first. Here are a few tips to help with adoption:

- Clearly articulate the benefit to them as individuals as well as to the organization. Address the "what's in it for me?" question
- Consider using rewards and recognition programs to drive adoption of the guidance.
- Ensure that sales managers are engaged and incorporate the guidance into the overall sales process.
- Communicate early and often about quick wins and successes.

The sales reps' experience is still highly valuable, and they should view the predictive guidance as a "personal analyst" that simply helps them be more effective, ultimately helping them and the company make more money. Analytics can boost company performance, but only when deployed in a manner that is actionable for employees making decisions on the front line.

Javier Aldrete has more than 16 years of experience applying advanced business intelligence and predictive analytics to solve business problems in multiple industries. As senior director of product management at Zilliant, Aldrete is responsible for the company's sales optimization product offerings' vision and road map.

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