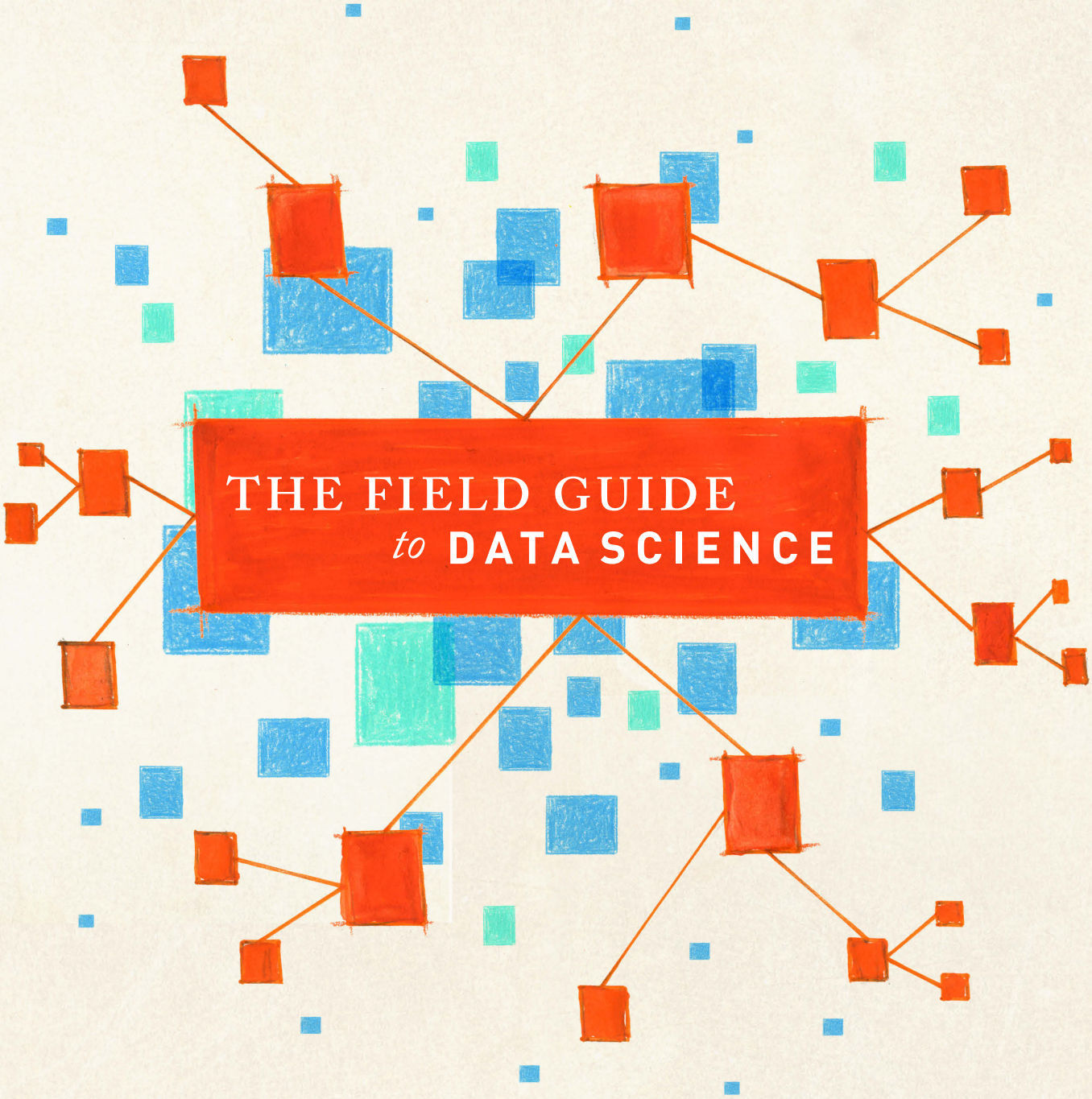


THE FIELD GUIDE *to* DATA SCIENCE

Booz | Allen | Hamilton

THE FIELD GUIDE *to* DATA SCIENCE

Booz | Allen | Hamilton

FOREWORD

Every aspect of our lives, from life-saving disease treatments, to national security, to economic stability and even the convenience of selecting a restaurant, can be improved by creating better data analytics through Data Science.

We live in a world of incredible beauty and complexity. A world increasingly measured, mapped, and recorded into digital bits for eternity. Our human existence is pouring into the digital realm faster than ever. From global business operations to simple expressions of love – an essential part of humanity now exists in the digital world.

***Data* is the byproduct of our new digital existence.** Recorded bits of data from mundane traffic cameras to telescopes peering into the depths of space are propelling us into the greatest age of discovery our species has ever known.

As we move from isolation into our ever-connected and recorded future, data is becoming the new currency and a vital natural resource. The power, importance, and responsibility such incredible data stewardship will demand of us in the coming decades is hard to imagine – but we often fail to fully appreciate the insights data can provide us today. Businesses that do not rise to the occasion and garner insights from this new resource are destined for failure.

An essential part of human nature is our insatiable curiosity and the need to find answers to our hardest problems. Today, the emerging field of *Data Science* is an auspicious and profound new way of applying our curiosity and technical tradecraft to create value from data that solves our hardest problems. Leaps in human imagination, vast amounts of data on hundreds of topics, and humble algorithms can be combined to create a radical new way of thinking about *data*. Our future is inextricably tied to data.

We want to share our passion for *Data Science* and start a conversation with you. This is a journey worth taking.

Everyone you will ever meet knows something you don't. [1]

»THE STORY *of* THE FIELD GUIDE

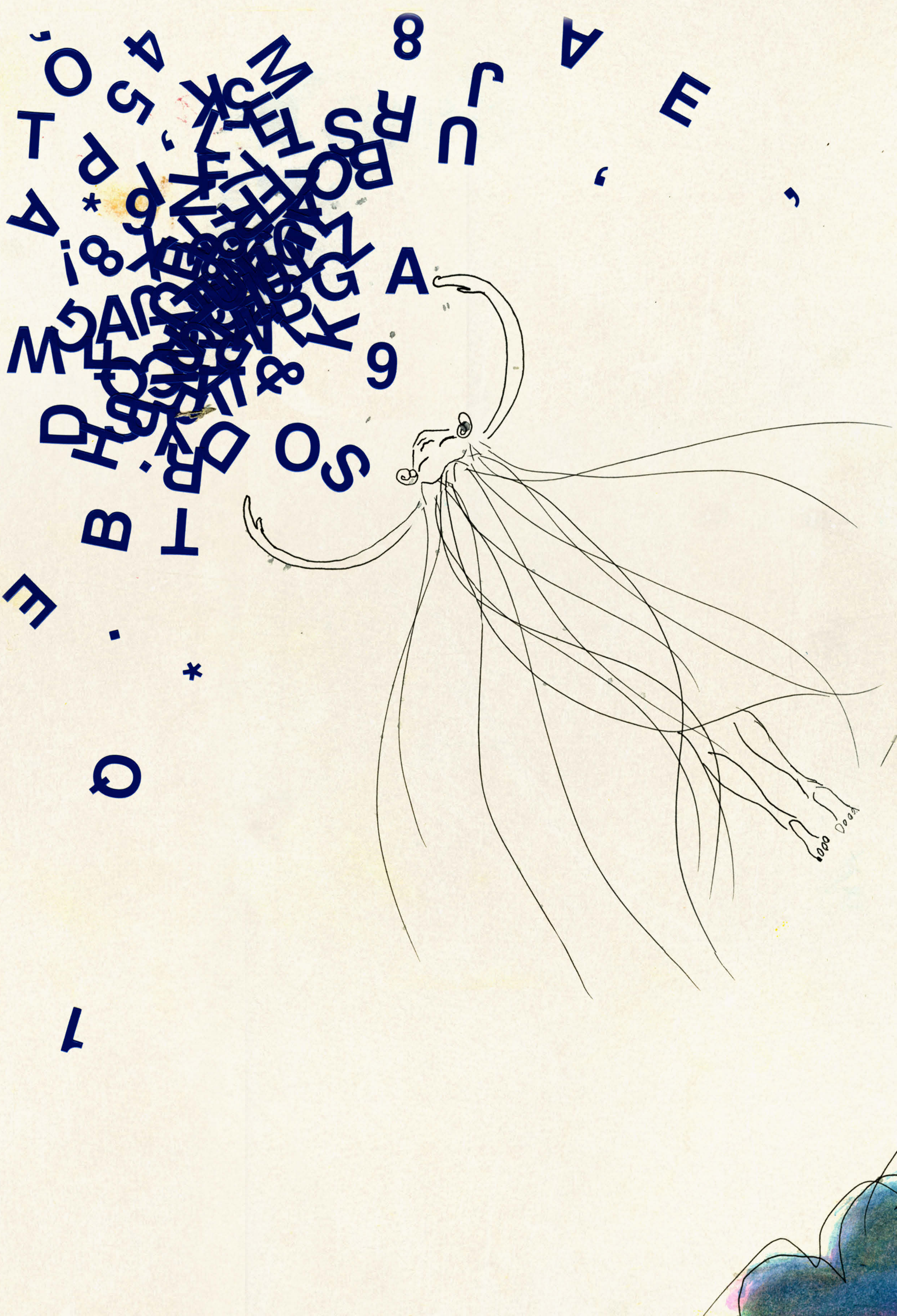
While there are countless industry and academic publications describing *what* Data Science is and *why* we should care, little information is available to explain how to make use of data as a resource. At Booz Allen, we built an industry-leading team of Data Scientists. Over the course of hundreds of analytic challenges for dozens of clients, we've unraveled the DNA of Data Science. We mapped the Data Science DNA to unravel the *what*, the *why*, the *who* and the *how*.

Many people have put forth their thoughts on single aspects of Data Science. We believe we can offer a broad perspective on the conceptual models, tradecraft, processes and culture of Data Science. Companies with strong Data Science teams often focus on a single class of problems – graph algorithms for social network analysis and recommender models for online shopping are two notable examples. Booz Allen is different. In our role as consultants, we support a diverse set of clients across a variety of domains. This allows us to uniquely understand the DNA of Data Science. Our goal in creating *The Field Guide to Data Science* is to capture what we have learned and to share it broadly. We want this effort to help drive forward the science and art of Data Science.

This field guide came from the passion our team feels for its work. It is not a textbook nor is it a superficial treatment. Senior leaders will walk away with a deeper understanding of the concepts at the heart of Data Science. Practitioners will add to their toolbox. We hope everyone will enjoy the journey.

»Why Data Science DNA?

We view Data Science as having DNA-like characteristics. Much like DNA, Data Science is composed of basic building blocks that are woven into a thing of great beauty and complexity. The building blocks create the blueprint, but successful replication also requires carefully balanced processes and the right set of environmental conditions. In the end, every instance may look superficially different, but the raw materials remain the same.



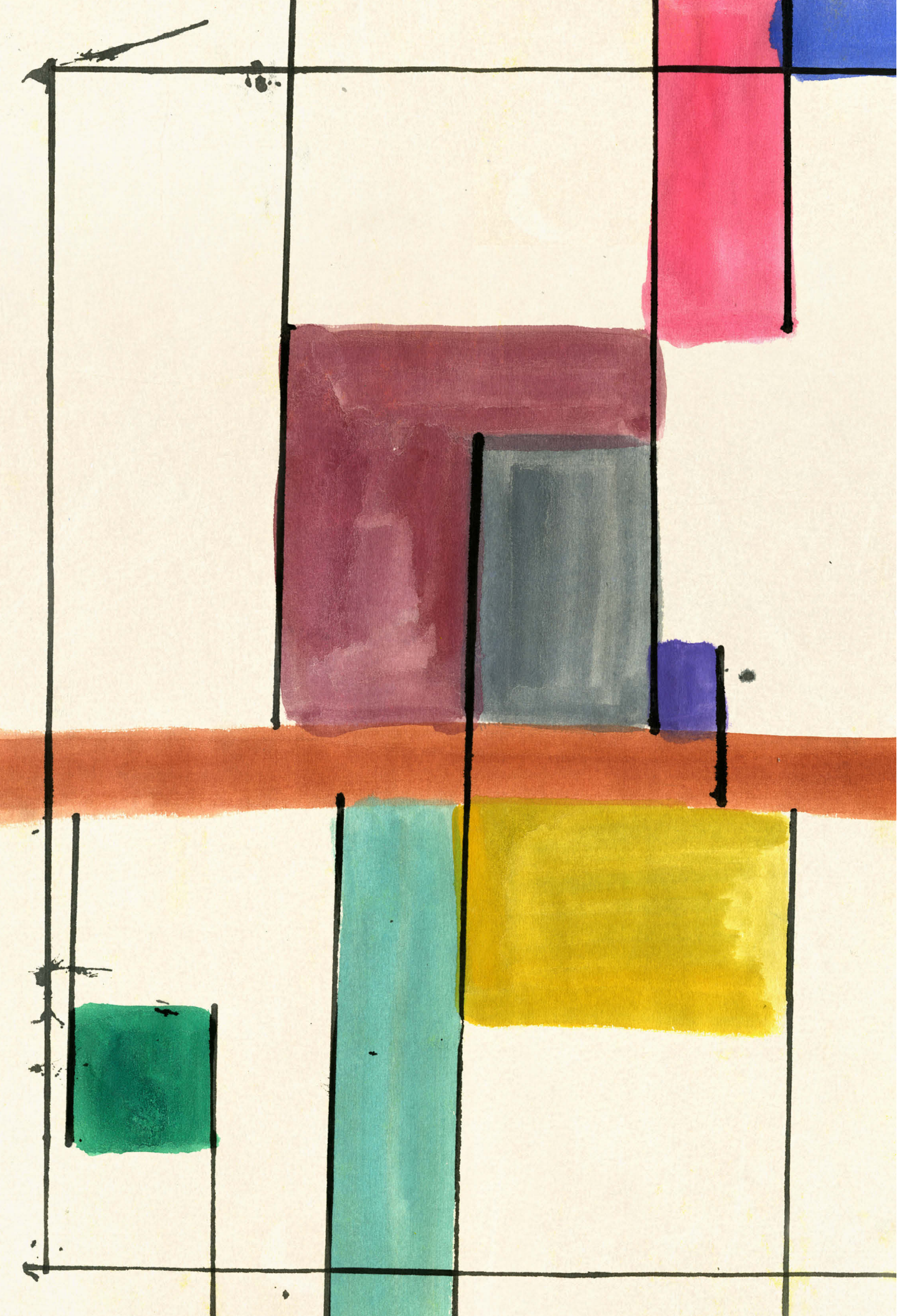
›› WE ARE ALL AUTHORS *of* THIS STORY

We recognize that Data Science is a team sport. *The Field Guide to Data Science* provides Booz Allen's perspective on the complex and sometimes mysterious field of Data Science. We cannot capture all that is Data Science. Nor can we keep up - the pace at which this field progresses outdates work as fast as it is produced. As a result, we have opened this field guide to the world as a living document to bend and grow with technology, expertise, and evolving techniques. If you find the guide to be useful, neat, or even lacking, then we encourage you to add your expertise, including:

- Case studies from which you have learned
- Citations for journal articles or papers that inspire you
- Algorithms and techniques that you love
- Your thoughts and comments on other people's additions

Email us your ideas and perspectives at **data_science@bah.com** or submit them via a pull request on the **Github repository**.

Join our conversation and take the journey with us. Tell us and the world what you know. Become an author of this story.



THE OUTLINE *of* OUR STORY

›› MEET *your* GUIDES

Mark Herman
(@cloudEBITDA)

End every analysis with …
'and therefore'

Stephanie Rivera
(@boozallen)

I treat Data Science like I do rock climbing: awesome dedication leads to incremental improvement. Persistence leads to the top.

Steven Mills
(@stevndmills)

Data Science, like life, is not linear. It's complex, intertwined, and can be beautiful. Success requires the support of your friends and colleagues.

Josh Sullivan
(@joshdsullivan)

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.

Peter Guerra
(@petrguerra)

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.

Alex Cosmas
(@boozallen)

Data miners produce bottle cap facts (e.g., animals that lay eggs don't have belly buttons). Data Scientists produce insights - they require the intellectual curiosity to ask "why" or "so what"?

Drew Farris
(@drewfarris)

Don't forget to play. Play with tools, play with data, and play with algorithms. You just might discover something that will help you solve that next nagging problem.

Ed Kohlwey
(@ekohlwey)

Data Science is about formally analyzing everything around you and becoming data driven.

Paul Yacci
(@paulyacci)

In the jungle of data, don't miss the forest for the trees, or the trees for the forest.

Brian Keller
(@boozallen)

Grit will get you farther than talent.

Armen Kherlopian
(@akherlopian)

A Data Scientist must continuously seek truth in spite of ambiguity; therein rests the basis of rigor and insight.

Michael Kim
(@boozallen)

Data science is both an art and science.

We would like to thank the following people for their contributions and edits:

Tim Andrews, Mike Delurey, Greg Dupier, Jason Escaravage, Christine Fantaskey, Juergen Klenk, and Mark Rockley.

The SHORT VERSION

- ***Data Science is the art of turning data into actions.***
  It's all about the tradecraft. Tradecraft is the process, tools and technologies for humans and computers to work together to transform data into insights.

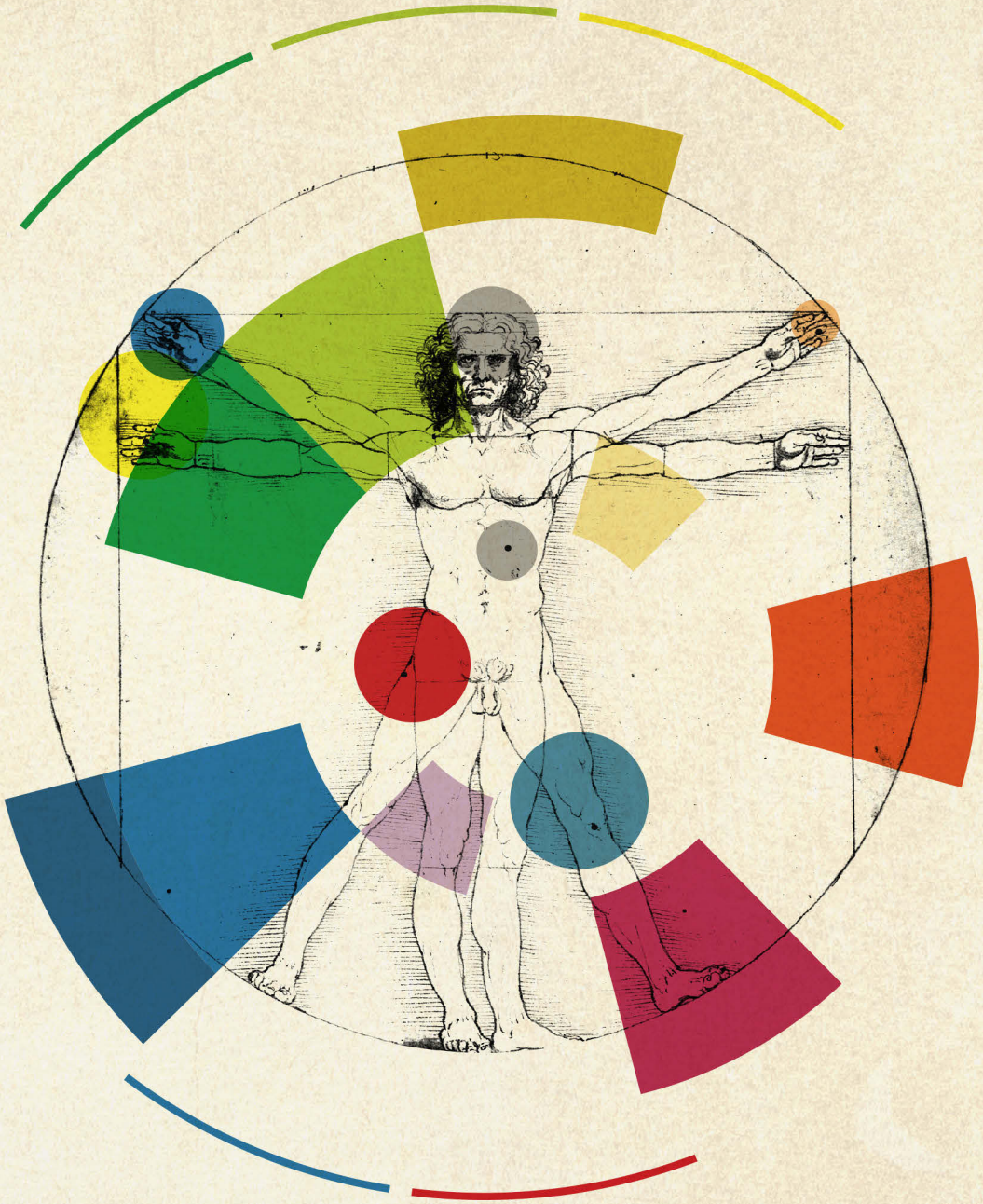
- ***Data Science tradecraft creates data products.***
  Data products provide actionable information without exposing decision makers to the underlying data or analytics (e.g., buy/sell strategies for financial instruments, a set of actions to improve product yield, or steps to improve product marketing).

- ***Data Science supports and encourages shifting between deductive (hypothesis-based) and inductive (pattern-based) reasoning.***
  This is a fundamental change from traditional analysis approaches. Inductive reasoning and exploratory data analysis provide a means to form or refine hypotheses and discover new analytic paths. Models of reality no longer need to be static. They are constantly tested, updated and improved until better models are found.

- ***Data Science is necessary for companies to stay with the pack and compete in the future.***
  Organizations are constantly making decisions based on gut instinct, loudest voice and best argument – sometimes they are even informed by real information. The winners and the losers in the emerging data economy are going to be determined by their Data Science teams.

- ***Data Science capabilities can be built over time.***
  Organizations mature through a series of stages – Collect, Describe, Discover, Predict, Advise – as they move from data deluge to full Data Science maturity. At each stage, they can tackle increasingly complex analytic goals with a wider breadth of analytic capabilities. However, organizations need not reach maximum Data Science maturity to achieve success. Significant gains can be found in every stage.

- ***Data Science is a different kind of team sport.***
  Data Science teams need a broad view of the organization. Leaders must be key advocates who meet with stakeholders to ferret out the hardest challenges, locate the data, connect disparate parts of the business, and gain widespread buy-in.



START HERE *for* **THE BASICS**

AN INTRODUCTION TO DATA SCIENCE

If you haven't heard of Data Science, you're behind the times. Just renaming your Business Intelligence group the Data Science group is not the solution.

What do We Mean by Data Science?

Describing Data Science is like trying to describe a sunset – it should be easy, but somehow capturing the words is impossible.

Data Science Defined

Data Science is the art of turning data into actions. This is accomplished through the creation of data products, which provide actionable information without exposing decision makers to the underlying data or analytics (e.g., buy/sell strategies for financial instruments, a set of actions to improve product yield, or steps to improve product marketing).

Performing Data Science requires the extraction of timely, actionable information from diverse data sources to drive data products. Examples of data products include answers to questions such as: "Which of my products should I advertise more heavily to increase profit? How can I improve my compliance program, while reducing costs? What manufacturing process change will allow me to build a better product?" The key to answering these questions is: understand the data you have and what the data inductively tells you.

» Data Product

A data product provides actionable information without exposing decision makers to the underlying data or analytics. Examples include:

- Movie Recommendations
- Weather Forecasts
- Stock Market Predictions
- Production Process Improvements
- Health Diagnosis
- Flu Trend Predictions
- Targeted Advertising

Read this for additional background:

The term Data Science appeared in the computer science literature throughout the 1960s-1980s. It was not until the late 1990s however, that the field as we describe it here, began to emerge from the statistics and data mining communities (e.g., [2] and [3]). Data Science was first introduced as an independent discipline in 2001.[4] Since that time, there have been countless articles advancing the discipline, culminating with Data Scientist being declared the sexiest job of the 21st century.[5]

We established our first Data Science team at Booz Allen in 2010. It began as a natural extension of our Business Intelligence and cloud infrastructure development work. We saw the need for a new approach to distill value from our clients' data. We approached the problem with a multidisciplinary team of computer scientists, mathematicians and domain experts. They immediately produced new insights and analysis paths, solidifying the validity of the approach. Since that time, our Data Science team has grown to 250 staff supporting dozens of clients across a variety of domains. This breadth of experience provides a unique perspective on the conceptual models, tradecraft, processes and culture of Data Science.

What makes Data Science Different?

Data Science supports and encourages shifting between deductive (hypothesis-based) and inductive (pattern-based) reasoning. This is a fundamental change from traditional analytic approaches. Inductive reasoning and exploratory data analysis provide a means to form or refine hypotheses and discover new analytic paths. In fact, to do the discovery of significant insights that are the hallmark of Data Science, you must have the tradecraft and the interplay between inductive and deductive reasoning. By actively combining the ability to reason deductively and inductively, Data Science creates an environment where models of reality no longer need to be static and empirically based. Instead, they are constantly tested, updated and improved until better models are found. These concepts are summarized in the figure, *The Types of Reason and Their Role in Data Science Tradecraft*.

THE TYPES OF REASON...

DEDUCTIVE REASONING:

- Commonly associated with ***"formal logic."***
- Involves reasoning from known premises, or premises presumed to be true, to a certain conclusion.
- The conclusions reached are certain, inevitable, inescapable.

INDUCTIVE REASONING

- Commonly known as ***"informal logic,"*** or "everyday argument."
- Involves drawing uncertain inferences, based on probabilistic reasoning.
- The conclusions reached are probable, reasonable, plausible, believable.

...AND THEIR ROLE IN DATA SCIENCE TRADECRAFT.

DEDUCTIVE REASONING:

- Formulate hypotheses about relationships and underlying models.
- Carry out experiments with the data to test hypotheses and models.

INDUCTIVE REASONING

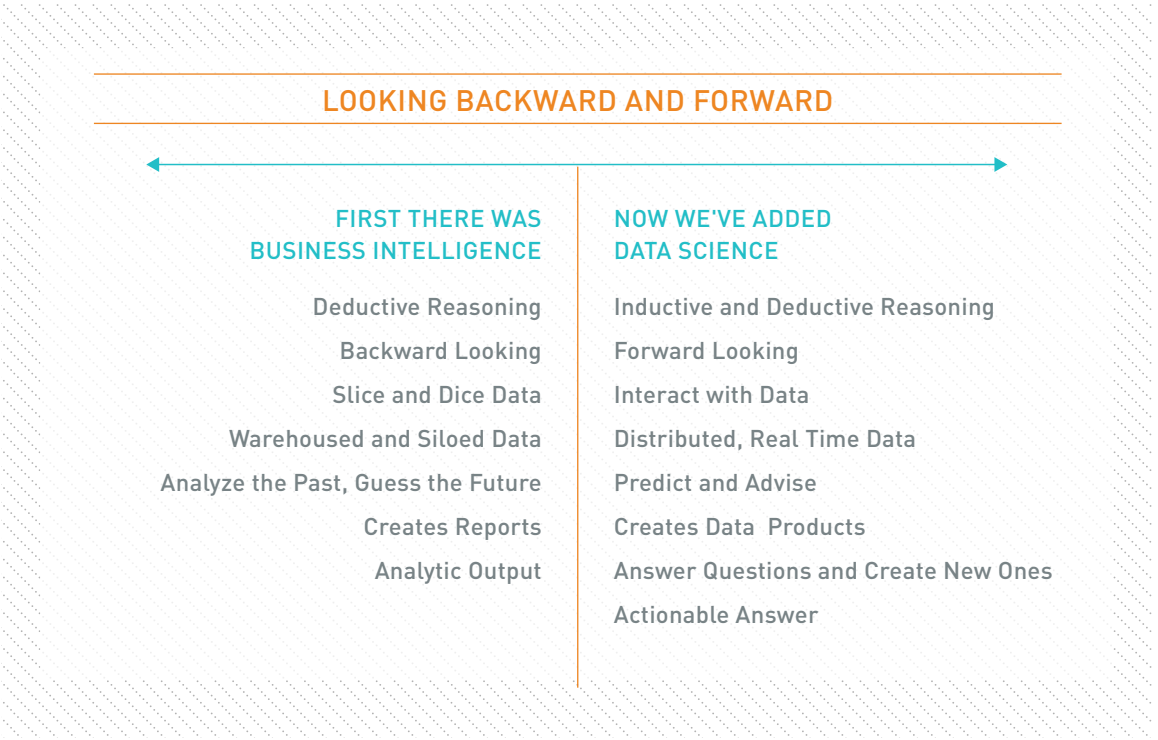
- Exploratory data analysis to discover or refine hypotheses.
- Discover new relationships, insights and analytic paths from the data.

Source: Booz Allen Hamilton

The Types of Reason and Their Role in Data Science Tradecraft

The differences between Data Science and traditional analytic approaches do not end at seamless shifting between deductive and inductive reasoning. Data Science offers a distinctly different perspective than capabilities such as Business Intelligence. Data Science should not replace Business Intelligence functions within an organization, however. The two capabilities are additive and complementary, each offering a necessary view of business operations and the operating environment. The figure, *Business Intelligence and Data Science – A Comparison,* highlights the differences between the two capabilities. Key contrasts include:

- ***Discovery vs. Pre-canned Questions:*** Data Science actually works on discovering the question to ask as opposed to just asking it.
- ***Power of Many vs. Ability of One:*** An entire team provides a common forum for pulling together computer science, mathematics and domain expertise.
- ***Prospective vs. Retrospective:*** Data Science is focused on obtaining actionable information from data as opposed to reporting historical facts.



Source: Booz Allen Hamilton

Business Intelligence and Data Science - A Comparison (adapted in part from [6])

What is the Impact of Data Science?

As we move into the data economy, Data Science is the competitive advantage for organizations interested in winning – in whatever way winning is defined. The manner in which the advantage is defined is through improved decision-making. A former colleague liked to describe data-informed decision making like this: *If you have perfect information or zero information then your task is easy – it is in between those two extremes that the trouble begins.* What he was highlighting is the stark reality that whether or not information is available, decisions must be made.

The way organizations make decisions has been evolving for half a century. Before the introduction of Business Intelligence, the only options were gut instinct, loudest voice, and best argument. Sadly, this method still exists today, and in some pockets it is the predominant means by which the organization acts. Take our advice and never, ever work for such a company!

Fortunately for our economy, most organizations began to inform their decisions with real information through the application of simple statistics. Those that did it well were rewarded; those that did not failed. We are outgrowing the ability of simple stats to keep pace with market demands, however. The rapid expansion of available data, and the tools to access and make use of the data at scale, are enabling fundamental changes to the way organizations make decisions.

Data Science is required to maintain competitiveness in the increasingly data-rich environment. Much like the application of simple statistics, organizations that embrace Data Science will be rewarded while those that do not will be challenged to keep pace. As more complex, disparate data sets become available, the chasm between these groups will only continue to widen. The figure, *The Business Impacts of Data Science,* highlights the value awaiting organizations that embrace Data Science.

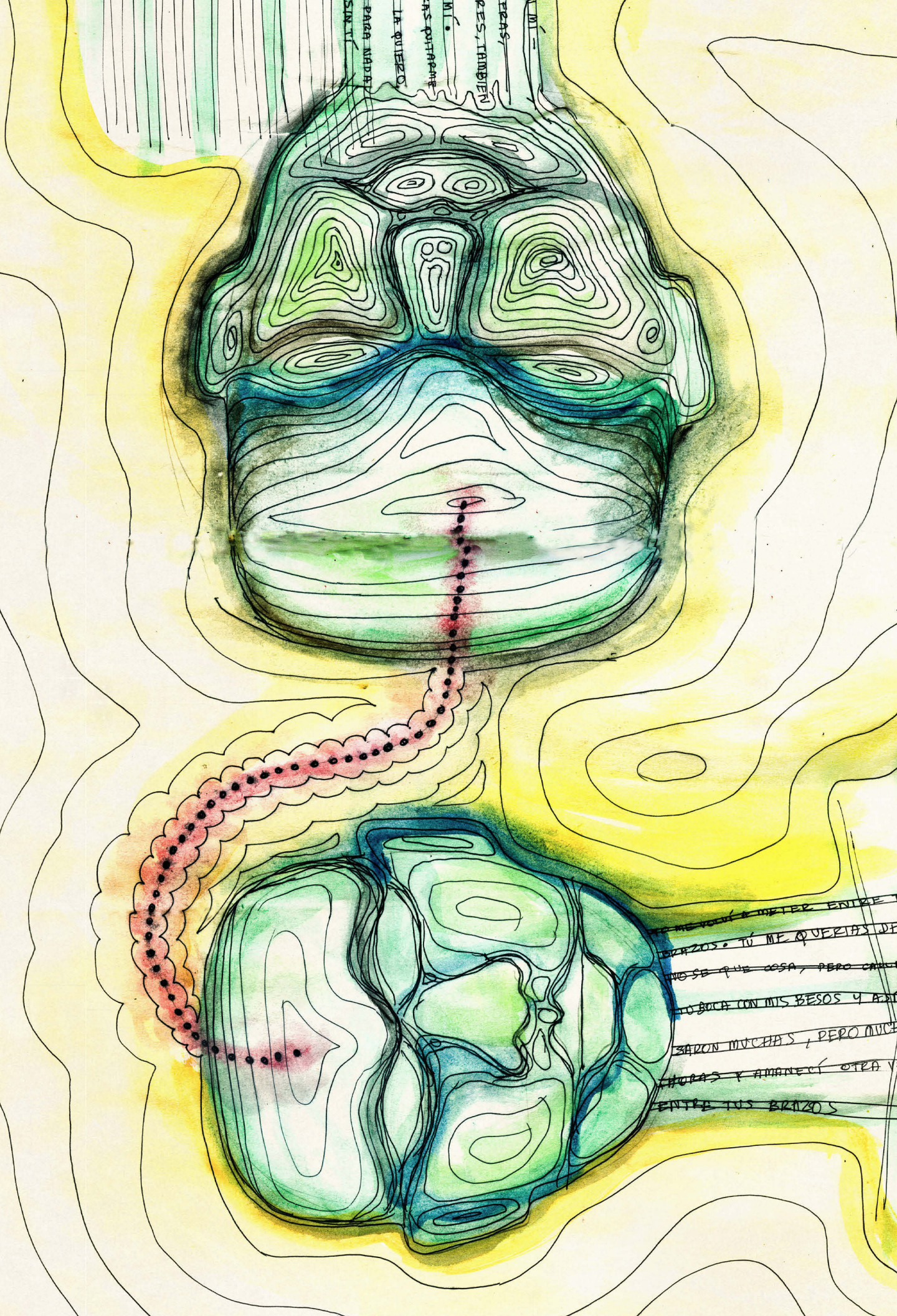
DATA SCIENCE IS NECESSARY...

17-49%	increase in productivity when organizations increase data usability by 10%
11-42%	return on assets (ROA) when organizations increase data access by 10%
241%	increase in ROI when organizations use big data to improve competitiveness
1000%	increase in ROI when deploying analytics across most of the organization, aligning daily operations with senior management's goals, and incorporating big data
5-6%	performance improvement for organizations making data-driven decisions.

...TO COMPETE IN THE FUTURE

Source: Booz Allen Hamilton

The Business Impacts of Data Science (adapted from [7], [8] and [9])


ENTRE TUS BRAZOS

What is Different Now?

For 20 years IT systems were built the same way. We separated the people who ran the business from the people who managed the infrastructure (and therefore saw data as simply another thing they had to manage). With the advent of new technologies and analytic techniques, this artificial – and highly ineffective – separation of critical skills is no longer necessary. For the first time, organizations can directly connect business decision makers to the data. This simple step transforms data from being 'something to be managed' into 'something to be valued.'

In the wake of the transformation, organizations face a stark choice: you can continue to build data silos and piece together disparate information or you can consolidate your data and distill answers.

From the Data Science perspective, this is a false choice: The siloed approach is untenable when you consider the (a) the opportunity cost of not making maximum use of all available data to help an organization succeed, and (b) the resource and time costs of continuing down the same path with outdated processes. The tangible benefits of data products include:

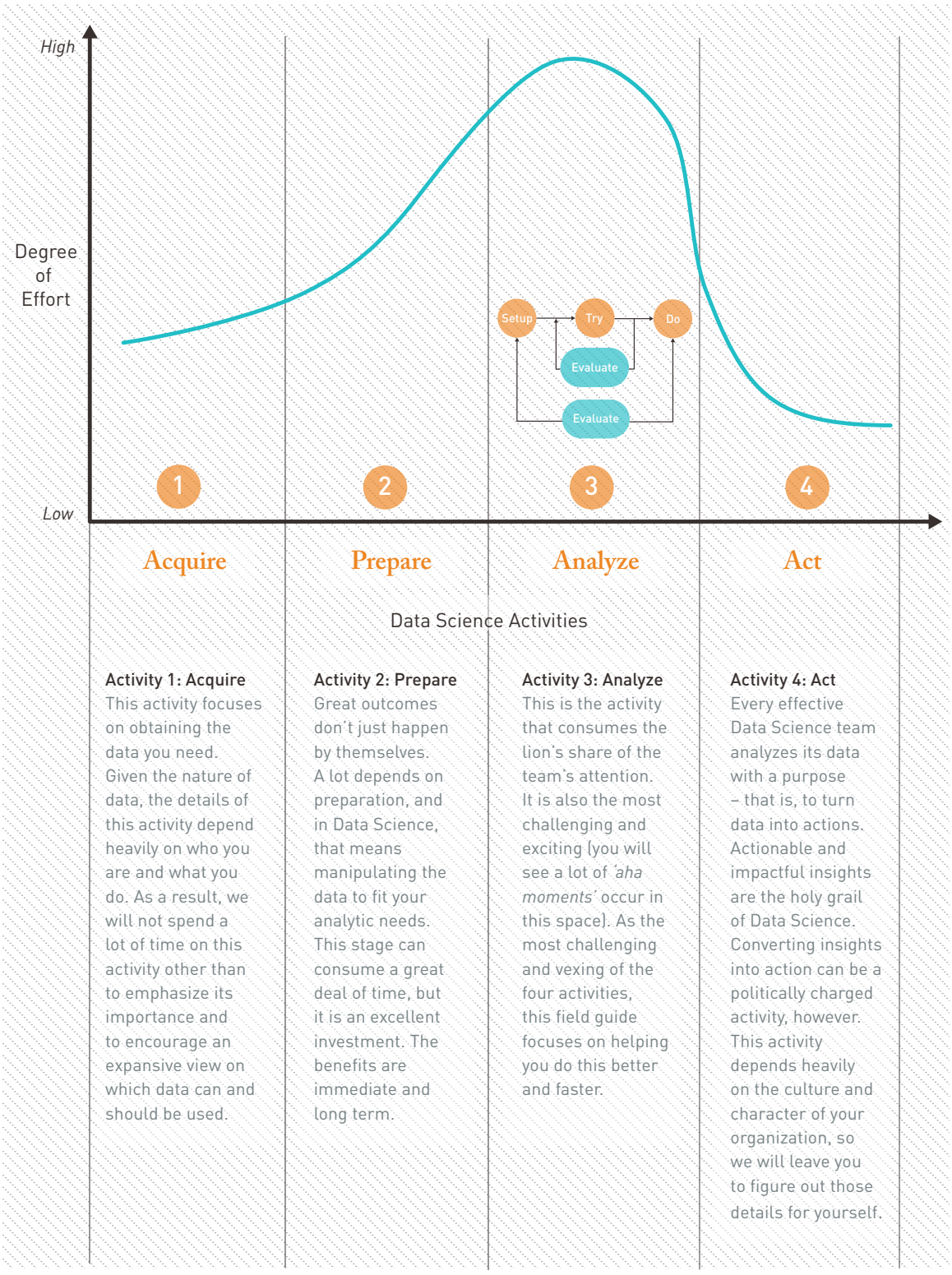
- ***Opportunity Costs:*** Because Data Science is an emerging field, opportunity costs arise when a competitor implements and generates value from data before you. Failure to learn and account for changing customer demands will inevitably drive customers away from your current offerings. When competitors are able to successfully leverage Data Science to gain insights, they can drive differentiated customer value propositions and lead their industries as a result.
- ***Enhanced Processes:*** As a result of the increasingly interconnected world, huge amounts of data are being generated and stored every instant. Data Science can be used to transform data into insights that help improve existing processes. Operating costs can be driven down dramatically by effectively incorporating the complex interrelationships in data like never before. This results in better quality assurance, higher product yield and more effective operations.

How does Data Science Actually Work?

It's not rocket science… it's something better - Data Science

Let's not kid ourselves - Data Science is a complex field. It is difficult, intellectually taxing work, which requires the sophisticated integration of talent, tools and techniques. But as a field guide, we need to cut through the complexity and provide a clear, yet effective way to understand this new world.

To do this, we will transform the field of Data Science into a set of simplified activities as shown in the figure, *The Four Key Activities of a Data Science Endeavor*. Data Science purists will likely disagree with this approach, but then again, they probably don't need a field guide, sitting as they do in their ivory towers! In the real world, we need clear and simple operating models to help drive us forward.



Activity 1: Acquire
This activity focuses on obtaining the data you need. Given the nature of data, the details of this activity depend heavily on who you are and what you do. As a result, we will not spend a lot of time on this activity other than to emphasize its importance and to encourage an expansive view on which data can and should be used.

Activity 2: Prepare
Great outcomes don't just happen by themselves. A lot depends on preparation, and in Data Science, that means manipulating the data to fit your analytic needs. This stage can consume a great deal of time, but it is an excellent investment. The benefits are immediate and long term.

Activity 3: Analyze
This is the activity that consumes the lion's share of the team's attention. It is also the most challenging and exciting (you will see a lot of *'aha moments'* occur in this space). As the most challenging and vexing of the four activities, this field guide focuses on helping you do this better and faster.

Activity 4: Act
Every effective Data Science team analyzes its data with a purpose – that is, to turn data into actions. Actionable and impactful insights are the holy grail of Data Science. Converting insights into action can be a politically charged activity, however. This activity depends heavily on the culture and character of your organization, so we will leave you to figure out those details for yourself.

Source: Booz Allen Hamilton

The Four Key Activities of a Data Science Endeavor

1 Acquire

All analysis starts with access to data, and for the Data Scientist this axiom holds true. But there are some significant differences – particularly with respect to the question of who stores, maintains and owns the data in an organization.

But before we go there, lets look at what is changing. Traditionally, rigid data silos artificially define the data to be acquired. Stated another way, the silos create a filter that lets in a very small amount of data and ignores the rest. These filtered processes give us an artificial view of the world based on the 'surviving data,' rather than one that shows full reality and meaning. Without a broad and expansive data set, we can never immerse ourselves in the diversity of the data. We instead make decisions based on limited and constrained information.

Eliminating the need for silos gives us access to all the data at once – including data from multiple outside sources. It embraces the reality that *diversity is good and complexity is okay*. This mindset creates a completely different way of thinking about data in an organization by giving it a new and differentiated role. Data represents a significant new profit and mission-enhancement opportunity for organizations.

But as mentioned earlier, this first activity is heavily dependent upon the situation and circumstances. We can't leave you with anything more than general guidance to help ensure maximum value:

- ***Look inside first:*** What data do you have current access to that you are not using? This is in large part the data being left behind by the filtering process, and may be incredibly valuable.
- ***Remove the format constraints:*** Stop limiting your data acquisition mindset to the realm of structured databases. Instead, think about unstructured and semi-structured data as viable sources.
- ***Figure out what's missing:*** Ask yourself what data would make a big difference to your processes if you had access to it. Then go find it!
- ***Embrace diversity:*** Try to engage and connect to publicly available sources of data that may have relevance to your domain area.

» Not All Data Is Created Equal

As you begin to aggregate data, remember that not all data is created equally. Organizations have a tendency to collect any data that is available. Data that is nearby (readily accessible and easily obtained) may be cheap to collect, but there is no guarantee it is the right data to collect. Focus on the data with the highest ROI for your organization. Your Data Science team can help identify that data. Also remember that you need to strike a balance between the data that you need and the data that you have. Collecting huge volumes of data is useless and costly if it is not the data that you need.

2 Prepare

Once you have the data, you need to prepare it for analysis.

Organizations often make decisions based on inexact data. Data stovepipes mean that organizations may have blind spots. They are not able to see the whole picture and fail to look at their data and challenges holistically. The end result is that valuable information is withheld from decision makers. Research has shown almost 33% of decisions are made without good data or information.[10]

When Data Scientists are able to explore and analyze all the data, new opportunities arise for analysis and data-driven decision making. The insights gained from these new opportunities will significantly change the course of action and decisions within an organization. Gaining access to an organization's complete repository of data, however, requires preparation.

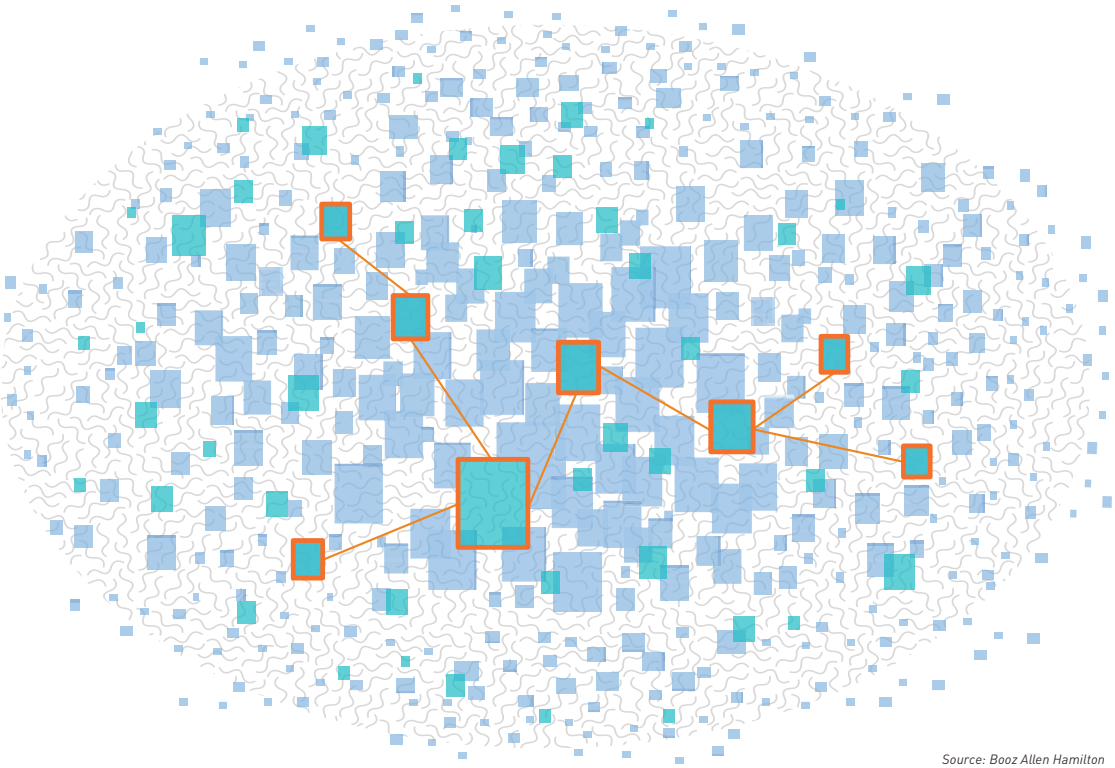
Our experience shows time and time again that the best tool for Data Scientists to prepare for analysis is a lake – specifically, the Data Lake.[11] This is a new approach to collecting, storing and integrating data that helps organizations maximize the utility of their data. Instead of storing information in discrete data structures, the Data Lake consolidates an organization's complete repository of data in a single, large view. It eliminates the expensive and cumbersome data-preparation process, known as Extract/Transform/Load (ETL), necessary with data silos. The entire body of information in the Data Lake is available for every inquiry – and all at once.

3 Analyze

We have acquired the data… we have prepared it… now it is time to analyze it.

The Analyze activity requires the greatest effort of all the activities in a Data Science endeavor. The Data Scientist actually builds the analytics that create value from data. Analytics in this context is an iterative application of specialized and scalable computational resources and tools to provide relevant insights from exponentially growing data. This type of analysis enables real-time understanding of risks and opportunities by evaluating situational, operational and behavioral data.

With the totality of data fully accessible in the Data Lake, organizations can use analytics to find the kinds of connections and patterns that point to promising opportunities. This high-speed analytic connection is done within the Data Lake, as opposed to older style sampling methods that could only make use of a narrow slice of the data. In order to understand what was in the lake, you had to bring the data out and study it. Now you can dive into the lake, bringing your analytics to the data. The figure, *Analytic Connection in the Data Lake,* highlights the concept of diving into the Data Lake to discover new connections and patterns.



Source: Booz Allen Hamilton

Analytic Connection in the Data Lake

Data Scientists work across the spectrum of analytic goals – Describe, Discover, Predict and Advise. The maturity of an analytic capability determines the analytic goals encompassed. Many variables play key roles in determining the difficulty and suitability of each goal for an organization. Some of these variables are the size and budget of an organization and the type of data products needed by the decision makers. A detailed discussion on analytic maturity can be found in *Data Science Maturity within an Organization*.

In addition to consuming the greatest effort, the Analyze activity is by far the most complex. The tradecraft of Data Science is an art. While we cannot teach you how to be an artist, we can share foundational tools and techniques that can help you be successful. The entirety of *Take Off the Training Wheels* is dedicated to sharing insights we have learned over time while serving countless clients. This includes descriptions of a Data Science product lifecycle and the *Fractal Analytic Model* (FAM). The *Analytic Selection Process* and accompanying *Guide to Analytic Selection* provide key insights into one of the most challenging tasks in all of Data Science – selecting the right technique for the job.

4 Act

Now that we have analyzed the data, it's time to take action.

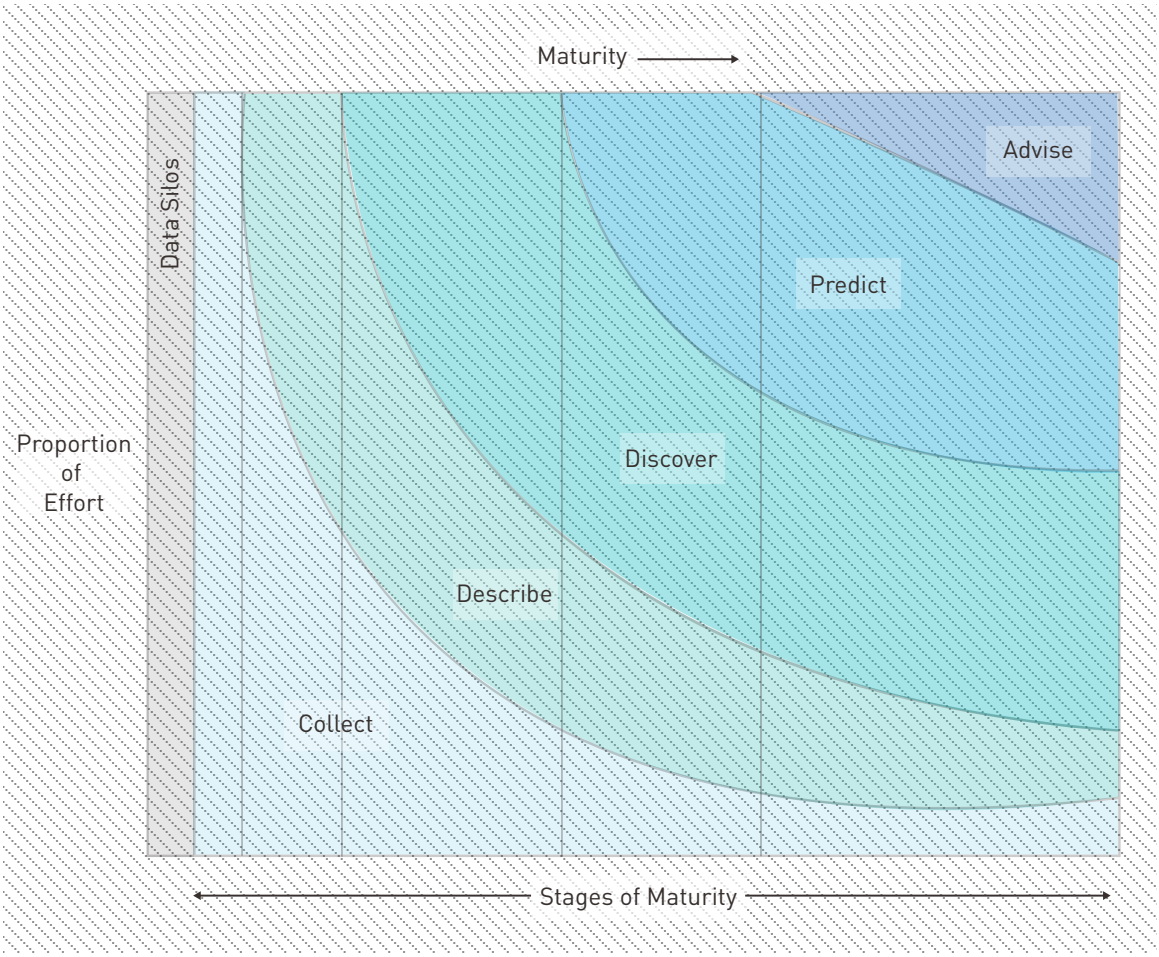
The ability to make use of the analysis is critical. It is also very situational. Like the Acquire activity, the best we can hope for is to provide some guiding principles to help you frame the output for maximum impact. Here are some key points to keep in mind when presenting your results:

1. The finding must make sense with relatively little up-front training or preparation on the part of the decision maker.
2. The finding must make the most meaningful patterns, trends and exceptions easy to see and interpret.
3. Every effort must be made to encode quantitative data accurately so the decision maker can accurately interpret and compare the data.
4. The logic used to arrive at the finding must be clear and compelling as well as traceable back through the data.
5. The findings must answer real business questions.

Data Science Maturity within an Organization

The four activities discussed thus far provide a simplified view of Data Science. Organizations will repeat these activities with each new Data Science endeavor. Over time, however, the level of effort necessary for each activity will change. As more data is Acquired and Prepared in the Data Lake, for example, significantly less effort will need to be expended on these activities. This is indicative of a maturing Data Science capability.

Assessing the maturity of your Data Science capability calls for a slightly different view. We use *The Data Science Maturity Model* as a common framework for describing the maturity progression and components that make up a Data Science capability. This framework can be applied to an organization's Data Science capability or even to the maturity of a specific solution, namely a data product. At each stage of maturity, powerful insight can be gained.



Source: Booz Allen Hamilton

The Data Science Maturity Model

When organizations start out, they have *Data Silos*. At this stage, they have not carried out any broad Aggregate activities. They may not have a sense of all the data they have or the data they need. The decision to create a Data Science capability signals the transition into the *Collect* stage.

All of your initial effort will be focused on identifying and aggregating data. Over time, you will have the data you need and a smaller proportion of your effort can focus on *Collect*. You can now begin to *Describe* your data. Note, however, that while the proportion of time spent on *Collect* goes down dramatically, it never goes away entirely. This is indicative of the four activities outlined earlier – you will continue to Aggregate and Prepare data as new analytic questions arise, additional data is needed and new data sources become available.

Organizations continue to advance in maturity as they move through the stages from *Describe* to *Advise*. At each stage they can tackle increasingly complex analytic goals with a wider breadth of analytic capabilities. As described for *Collect*, each stage never goes away entirely. Instead, the proportion of time spent focused on it goes down and new, more mature activities begin. A brief description of each stage of maturity is shown in the table *The Stages of Data Science Maturity*.

The Stages of Data Science Maturity

Stage	Description	Example
Collect	Focuses on collecting internal or external datasets.	Gathering sales records and corresponding weather data.
Describe	Seeks to enhance or refine raw data as well as leverage basic analytic functions such as counts.	How are my customers distributed with respect to location, namely zip code?
Discover	Identifies hidden relationships or patterns.	Are there groups within my regular customers that purchase similarly?
Predict	Utilizes past observations to predict future observations.	Can we predict which products that certain customer groups are more likely to purchase?
Advise	Defines your possible decisions, optimizes over those decisions, and advises to use the decision that gives the best outcome.	Your advice is to target advertise to specific groups for certain products to maximize revenue.

Source: Booz Allen Hamilton

The maturity model provides a powerful tool for understanding and appreciating the maturity of a Data Science capability. Organizations need not reach maximum maturity to achieve success. Significant gains can be found in every stage. We believe strongly that one does not engage in a Data Science effort, however, unless it is intended to produce an output – that is, you have the intent to *Advise*. This means simply that each step forward in maturity drives you to the right in the model diagram. Moving to the right requires the correct processes, people, culture and operating model – a robust Data Science capability. *What Does it Take to Create a Data Science Capability?* addresses this topic.

We have observed very few organizations actually operating at the highest levels of maturity, the *Predict* and *Advise* stages. The tradecraft of *Discover* is only now maturing to the point that organizations can focus on advanced *Predict* and *Advise* activities. This is the new frontier of Data Science. This is the space in which we will begin to understand how to close the cognitive gap between humans and computers. Organizations that reach *Advise* will be met with true insights and real competitive advantage.

» Where does your organization fall in analytic maturity?

Take the quiz!

1. How many data sources do you collect?

a. Why do we need a bunch of data? *– 0 points, end here.*

b. I don't know the exact number. *– 5 points*

c. We identified the required data and collect it. *– 10 points*

2. Do you know what questions your Data Science team is trying to answer?

a. Why do we need questions? *- 0 points*

b. No, they figure it out for themselves. *– 5 points*

c. Yes, we evaluated the questions that will have the largest impact to the business. *– 10 points*

3. Do you know the important factors driving your business?

a. I have no idea. *– 0 points*

b. Our quants help me figure it out. *– 5 points*

c. We have a data product for that. *– 10 points*

4. Do you have an understanding of future conditions?

a.I look at the current conditions and read the tea leaves. *– 0 points*

b. We have a data product for that. *– 5 points*

5. Do you know the best course of action to take for your key decisions?

a. I look at the projections and plan a course. *– 0 points*

b. We have a data product for that. *– 5 points*

Check your score:

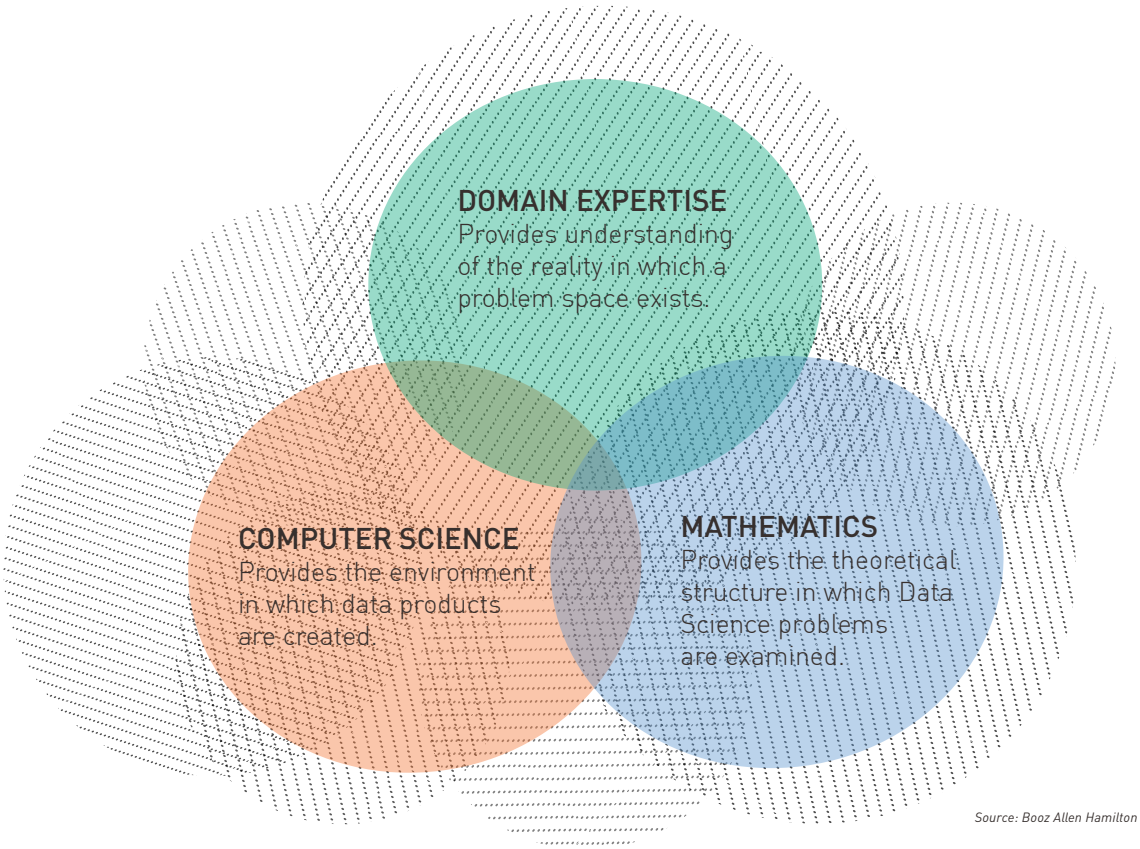
0 – Data Silos, 5-10 – Collect,
10-20 – Describe, 20-30 – Discover,
30-35 – Predict, 35-40 - Advise

Source: Booz Allen Hamilton

What does it Take to Create a Data Science Capability?

Data Science is all about building teams and culture.

As with any team sport, Data Science depends on a diverse set of skills to achieve its objective – winning at the game of improved insights. You need the three skill sets shown in *The Data Science Venn Diagram* to create a winning team in the world of Data Science.



The Data Science Venn Diagram (inspired by [12])

Building Data Science teams is difficult. It requires an understanding of the types of personalities that make Data Science possible, as well as a willingness to establish a culture of innovation and curiosity in your organization. You must also consider how to deploy the team and gain widespread buy-in from across your organization.

Understanding What Makes a Data Scientist

Data Science often requires a significant investment of time across a variety of tasks. Hypotheses must be generated and data must be acquired, prepared, analyzed, and acted upon. Multiple techniques are often applied before one yields interesting results. If that seems daunting, it is because it is. Data Science is difficult, intellectually taxing work, which requires lots of talent: both tangible technical skills as well as the intangible 'x-factors.'

The most important qualities of Data Scientists tend to be the intangible aspects of their personalities. Data Scientists are by nature curious, creative, focused, and detail-oriented.

- ***Curiosity*** is necessary to peel apart a problem and examine the interrelationships between data that may appear superficially unrelated.
- ***Creativity*** is required to invent and try new approaches to solving a problem, which often times have never been applied in such a context before.
- ***Focus*** is required to design and test a technique over days and weeks, find it doesn't work, learn from the failure, and try again.
- ***Attention to Detail*** is needed to maintain rigor, and to detect and avoid over-reliance on intuition when examining data.

Success of a Data Science team requires proficiency in three foundational technical skills: computer science, mathematics and domain expertise, as reflected in *The Data Science Venn Diagram*. Computers provide the environment in which data-driven hypotheses are tested, and as such computer science is necessary for data manipulation and processing. Mathematics provides the theoretical structure in which Data Science problems are examined. A rich background in statistics, geometry, linear algebra, and calculus are all important to understand the basis for many algorithms and tools. Finally, domain expertise contributes to an understanding of what problems actually need to be solved, what kind of data exists in the domain and how the problem space may be instrumented and measured.

» The Triple Threat Unicorn

Individuals who are great at all three of the Data Science foundational technical skills are like unicorns – very rare and if you're ever lucky enough to find one they should be treated carefully. When you manage these people:

- Encourage them to lead your team, but not manage it. Don't bog them down with responsibilities of management that could be done by other staff.
- Put extra effort into managing their careers and interests within your organization. Build opportunities for promotion into your organization that allow them to focus on mentoring other Data Scientists and progressing the state of the art while also advancing their careers.
- Make sure that they have the opportunity to present and spread their ideas in many different forums, but also be sensitive to their time.

Finding the Athletes for Your Team

Building a Data Science team is complex. Organizations must simultaneously engage existing internal staff to create an "anchor" that can be used to recruit and grow the team, while at the same time undergo organizational change and transformation to meaningfully incorporate this new class of employee.

» Don't judge a book by its cover, or a Data Scientist by his or her degree in this case. Amazing Data Scientists can be found anywhere. Just look at the diverse and surprising sampling of degrees held by Our Experts:

- Bioinformatics
- Biomedical Engineering
- Biophysics
- Business
- Computer Graphics
- Computer Science
- English
- Forest Management
- History
- Industrial Engineering
- Information Technology
- Mathematics
- National Security Studies
- Operations Research
- Physics
- Wildlife & Fisheries Management

Building a team starts with identifying existing staff within an organization who have a high aptitude for Data Science. Good candidates will have a formal background in any of the three foundational technical skills we mentioned, and will most importantly have the personality traits necessary for Data Science. They may often have advanced (masters or higher) degrees, but not always. The very first staff you identify should also have good leadership traits and a sense of purpose for the organization, as they will lead subsequent staffing and recruiting efforts. Don't discount anyone – you will find Data Scientists in the strangest places with the oddest combinations of backgrounds.

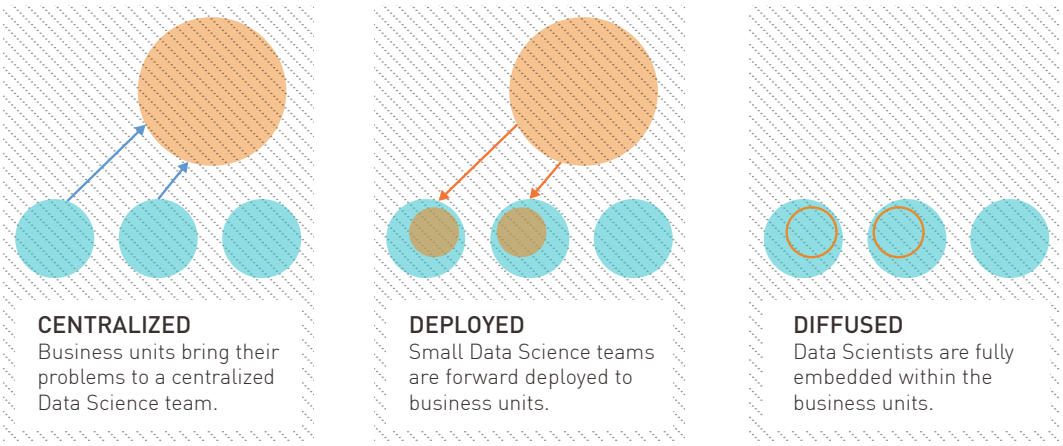
Shaping the Culture

Good Data Science requires a highly academic culture of peer review, where no member of the organization is immune from constructive criticism. As you build your Data Science practice, you should be prepared to subject all aspects of your corporate operations to the curious nature of your Data Science teams. Failure to do so creates a negative image of a culture that fails to "eat its own dog food," and will invite negative reflection on the brand, both internally and externally. You should be conscious of any cultural legacies existing in an organization that are antithetical to Data Science.

Data Scientists are fundamentally curious and imaginative. We have a saying on our team, "We're not nosy, we're Data Scientists." These qualities are fundamental to the success of the project and to gaining new dimensions on challenges and questions. Often Data Science projects are hampered by the lack of the ability to imagine something new and different. Fundamentally, organizations must foster trust and transparent communication across all levels, instead of deference to authority, in order to establish a strong Data Science team. Managers should be prepared to invite participation more frequently, and offer explanation or apology less frequently.

Selecting Your Operating Model

Depending on the size, complexity, and the business drivers, organizations should consider one of three Data Science operating models: Centralized, Deployed, or Diffused. These three models are shown in the figure, *Data Science Operating Models.*



Source: Booz Allen Hamilton

Data Science Operating Models

Centralized Data Science teams serve the organization across all business units. The team is centralized under a Chief Data Scientist. They serve all the analytical needs of an organization and they all co-locate together. The domain experts come to this organization for brief rotational stints to solve challenges around the business.

Deployed Data Science teams go to the business unit or group and reside there for short- or long-term assignments. They are their own entity and they work with the domain experts within the group to solve hard problems. They may be working independently on particular challenges, but they should always collaborate with the other teams to exchange tools, techniques and war stories.

The Diffused Data Science team is one that is fully embedded with each group and becomes part of the long-term organization. These teams work best when the nature of the domain or business unit is already one focused on analytics. However, building a cross-cut view into the team that can collaborate with other Data Science teams is critical to the success.

BALANCING THE DATA SCIENCE TEAM EQUATION

Balancing the composition of a Data Science team is much like balancing the reactants and products in a chemical reaction. Each side of the equation must represent the same quantity of any particular element. In the case of Data Science, these elements are the foundational technical skills computer science (CS), mathematics (M) and domain expertise (DE). The reactants, your Data Scientists, each have their own unique skills composition. You must balance the staff mix to meet the skill requirements of the Data Science team, the product in the reaction. If you don't correctly balance the equation, your Data Science team will not have the desired impact on the organization.

$$2\ CS\ M_2 + 2\ CS + M\ DE \rightarrow CS_4\ M_5\ DE$$

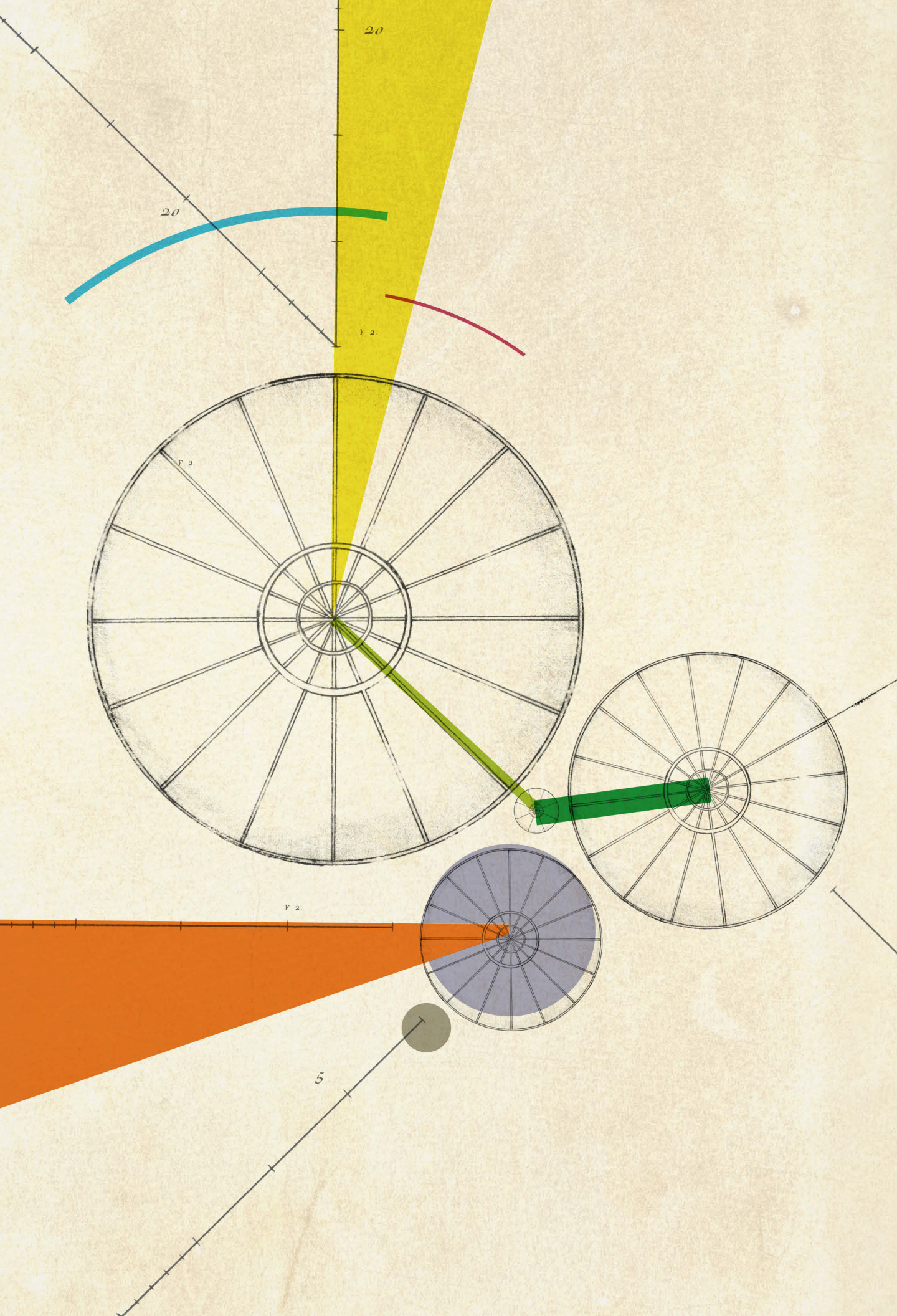
In the example above, your project requires four parts computer science, five parts mathematics and one part domain expertise. Given the skills mix of the staff, five people are needed to balance the equation. Throughout your Data Science project, the skills requirements of the team will change. You will need to re-balance the equation to ensure the reactants balance with the products.

Source: Booz Allen Hamilton

Success Starts at the Top

Data Science teams, no matter how they are deployed, must have sponsorship. These can start as grass roots efforts by a few folks to start tackling hard problems, or as efforts directed by the CEO. Depending on the complexity of the organization, direction from top-down for large organizations is the best for assuaging fears and doubts of these new groups.

Data Science teams often face harder political headwinds when solving problems than any technical hurdles. To prove a Data Science team's value, the team needs to initially focus on the hardest problems within an organization that have the highest return for key stakeholders and will change how the organization approaches challenges in the future. This has the effect of keeping the team motivated and encouraged in the face of difficult challenges. Leaders must be key advocates who meet with stakeholders to ferret out the hardest problems, locate the data, connect disparate parts of the business and gain widespread buy-in.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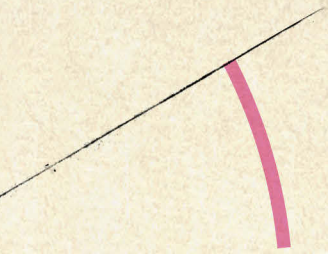
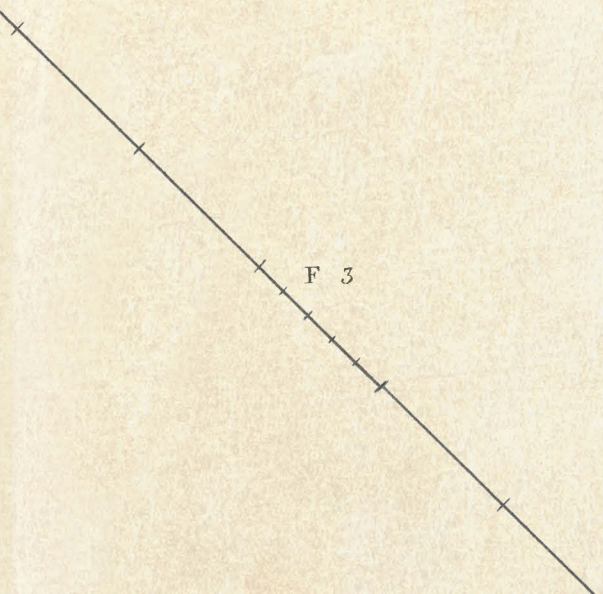
TAKE OFF *the* **TRAINING WHEELS**

THE PRACTITIONER'S GUIDE TO DATA SCIENCE

Read this section to get beyond the hype and learn the secrets of being a Data Scientist.





Guiding Principles

Failing is good; failing quickly is even better.

The set of guiding principles that govern how we conduct the tradecraft of Data Science are based loosely on the central tenets of innovation, as the two areas are highly connected. These principles are not hard and fast rules to strictly follow, but rather key tenets that have emerged in our collective consciousness. You should use these to guide your decisions, from problem decomposition through implementation.

» Tips From the Pros

It can be easier to rule out a solution than confirm its correctness. As a result, focus on exploring obvious shortcomings that can quickly disqualify an approach. This will allow you to focus your time on exploring truly viable approaches as opposed to dead ends.

- ***Be willing to fail.*** At the core of Data Science is the idea of experimentation. Truly innovative solutions only emerge when you experiment with new ideas and applications. Failure is an acceptable byproduct of experimentation. Failures locate regions that no longer need to be considered as you search for a solution.
- ***Fail often and learn quickly.*** In addition to a willingness to fail, be ready to fail repeatedly. There are times when a dozen approaches must be explored in order to find the one that works. While you shouldn't be concerned with failing, you should strive to learn from the attempt quickly. The only way you can explore a large number of solutions is to do so quickly.
- ***Keep the goal in mind.*** You can often get lost in the details and challenges of an implementation. When this happens, you lose sight of your goal and begin to drift off the path from data to analytic action. Periodically step back, contemplate your goal, and evaluate whether your current approach can really lead you where you want to go.

» Tips From the Pros

If the first thing you try to do is to create the ultimate solution, you will fail, but only after banging your head against a wall for several weeks.

- ***Dedication and focus lead to success.*** You must often explore many approaches before finding the one that works. It's easy to become discouraged. You must remain dedicated to your analytic goal. Focus on the details and the insights revealed by the data. Sometimes seemingly small observations lead to big successes.
- ***Complicated does not equal better.*** As technical practitioners, we have a tendency to explore highly complex, advanced approaches. While there are times where this is necessary, a simpler approach can often provide the same insight. Simpler means easier and faster to prototype, implement and verify.

The Importance of Reason

Beware: in the world of Data Science, if it walks like a duck and quacks like a duck, it might just be a moose.

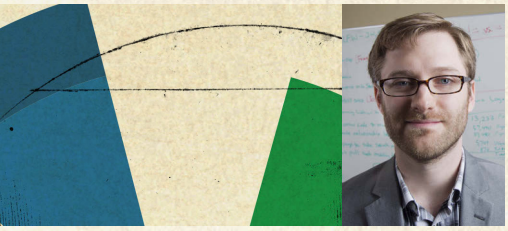
Data Science supports and encourages shifting between deductive (hypothesis-based) and inductive (pattern-based) reasoning. Inductive reasoning and exploratory data analysis provide a means to form or refine hypotheses and discover new analytic paths. Models of reality no longer need to be static. They are constantly tested, updated and improved until better models are found.

The analysis of big data has brought inductive reasoning to the forefront. Massive amounts of data are analyzed to identify correlations. However, a common pitfall to this approach is confusing correlation with causation. Correlation implies but does not prove causation. Conclusions cannot be drawn from correlations until the underlying mechanisms that relate the data elements are understood. Without a suitable model relating the data, a correlation may simply be a coincidence.

» Correlation without Causation

A common example of this phenomenon is the high correlation between ice cream consumption and the murder rate during the summer months. Does this mean ice cream consumption causes murder or, conversely, murder causes ice cream consumption? Most likely not, but you can see the danger in mistaking correlation for causation. Our job as Data Scientists is making sure we understand the difference.

›› The Dangers of Rejection



Paul Yacci

In the era of big data, one piece of analysis that is frequently overlooked is the problem of finding patterns when there are actually no apparent patterns. In statistics this is referred to as Type I error. As scientists, we are always on the lookout for a new or interesting breakthrough that could explain a phenomenon. We hope to see a pattern in our data that explains something or that can give us an answer. The primary goal of hypothesis testing is to limit Type I error. This is accomplished by using small α values. For example, a α value of 0.05 states that there is a 1 in 20 chance that the test will show that there is something significant when in actuality there isn't. This problem compounds when testing multiple hypotheses. When running multiple hypothesis tests, we are likely to encounter Type I error. As more data becomes available for analysis, Type I error needs to be controlled.

One of my projects required testing the difference between the means of two microarray data samples. Microarray data contains thousands of measurements but is limited in the number of observations. A common analysis approach is to measure the same genes under different conditions. If there is a significant enough difference in the amount of gene expression between the two samples, we can say that the gene is correlated with a particular phenotype. One way to do this is to take the mean of each phenotype for a particular gene and formulate a hypothesis to test whether there is a significant difference between the means. Given that we were running thousands of these tests at $\alpha = 0.05$, we found several differences that were significant. The problem was that some of these could be caused by random chance.

Many corrections exist to control for false indications of significance. The Bonferroni correction is one of the most conservative. This calculation lowers the level below which you will reject the null hypothesis (your *p* value). The formula is *alpha/n*, where n equals the number of hypothesis tests that you are running. Thus, if you were to run 1,000 tests of significance at $\alpha = 0.05$, your *p* value should be less than 0.00005 (0.05/1,000) to reject the null hypothesis. This is obviously a much more stringent value. A large number of the previously significant values were no longer significant, revealing the true relationships within the data.

The corrected significance gave us confidence that the observed expression levels were due to differences in the cellular gene expression rather than noise. We were able to use this information to begin investigating what proteins and pathways were active in the genes expressing the phenotype of interest. By solidifying our understanding of the causal relationships, we focused our research on the areas that could lead to new discoveries about gene function and, ultimately to improved medical treatments.

Reason and common sense are foundational to Data Science. Without it, data is simply a collection of bits. Context, inferences and models are created by humans and carry with them biases and assumptions. Blindly trusting your analyses is a dangerous thing that can lead to erroneous conclusions. When you approach an analytic challenge, you should always pause to ask yourself the following questions:

- ***What problem are we trying to solve?*** Articulate the answer as a sentence, especially when communicating with the end-user. Make sure that it sounds like an answer. For example, "Given a fixed amount of human capital, deploying people with these priorities will generate the best return on their time."
- ***Does the approach make sense?*** Write out your analytic plan. Embrace the discipline of writing, as it brings structure to your thinking. Back of the envelope calculations are an existence proof of your approach. Without this kind of preparation, computers are power tools that can produce lots of bad answers really fast.
- ***Does the answer make sense?*** Can you explain the answer? Computers, unlike children, do what they are told. Make sure you spoke to it clearly by validating that the instructions you provided are the ones you intended. Document your assumptions and make sure they have not introduced bias in your work.
- ***Is it a finding or a mistake?*** Be skeptical of surprise findings. Experience says that it if seems wrong, it probably is wrong. Before you accept that conclusion, however, make sure you understand and can clearly explain why it is wrong.
- ***Does the analysis address the original intent?*** Make sure that you are not aligning the answer with the expectations of the client. Always speak the truth, but remember that answers of "your baby is ugly" require more, not less, analysis.
- ***Is the story complete?*** The goal of your analysis is to tell an actionable story. You cannot rely on the audience to stitch the pieces together. Identify potential holes in your story and fill them to avoid surprises. Grammar, spelling and graphics matter; your audience will lose confidence in your analysis if your results look sloppy.
- ***Where would we head next?*** No analysis is every finished, you just run out of resources. Understand and explain what additional measures could be taken if more resources are found.

» Tips From the Pros

Better a short pencil than a long memory. End every day by documenting where you are; you may learn something along the way. Document what you learned and why you changed your plan.

» Tips From the Pros

Test your answers with a friendly audience to make sure your findings hold water. Red teams save careers.

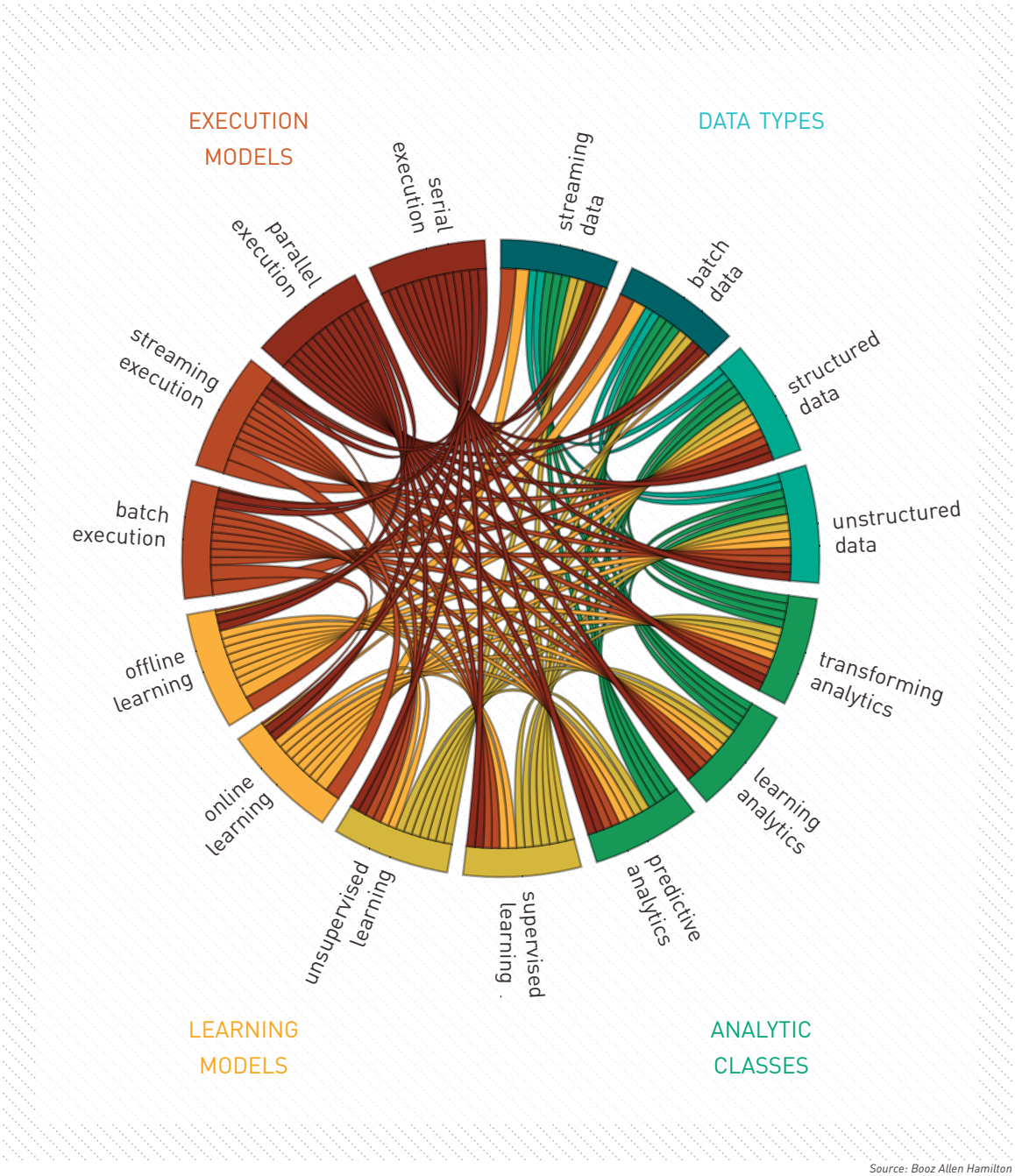
Component Parts of Data Science

There is a web of components that interact to create your solution space. Understanding how they are connected is critical to your ability to engineer solutions to Data Science problems.

The components involved in any Data Science project fall into a number of different categories including the data types analyzed, the analytic classes used, the learning models employed and the execution models used to run the analytics. The interconnection across these components, shown in the figure, *Interconnection Among the Component Parts of Data Science*, speaks to the complexity of engineering Data Science solutions. A choice made for one component exerts influence over choices made for others categories. For example, data types lead the choices in analytic class and learning models, while latency, timeliness and algorithmic parallelization strategy inform the execution model. As we dive deeper into the technical aspects of Data Science, we will begin with an exploration of these components and touch on examples of each.

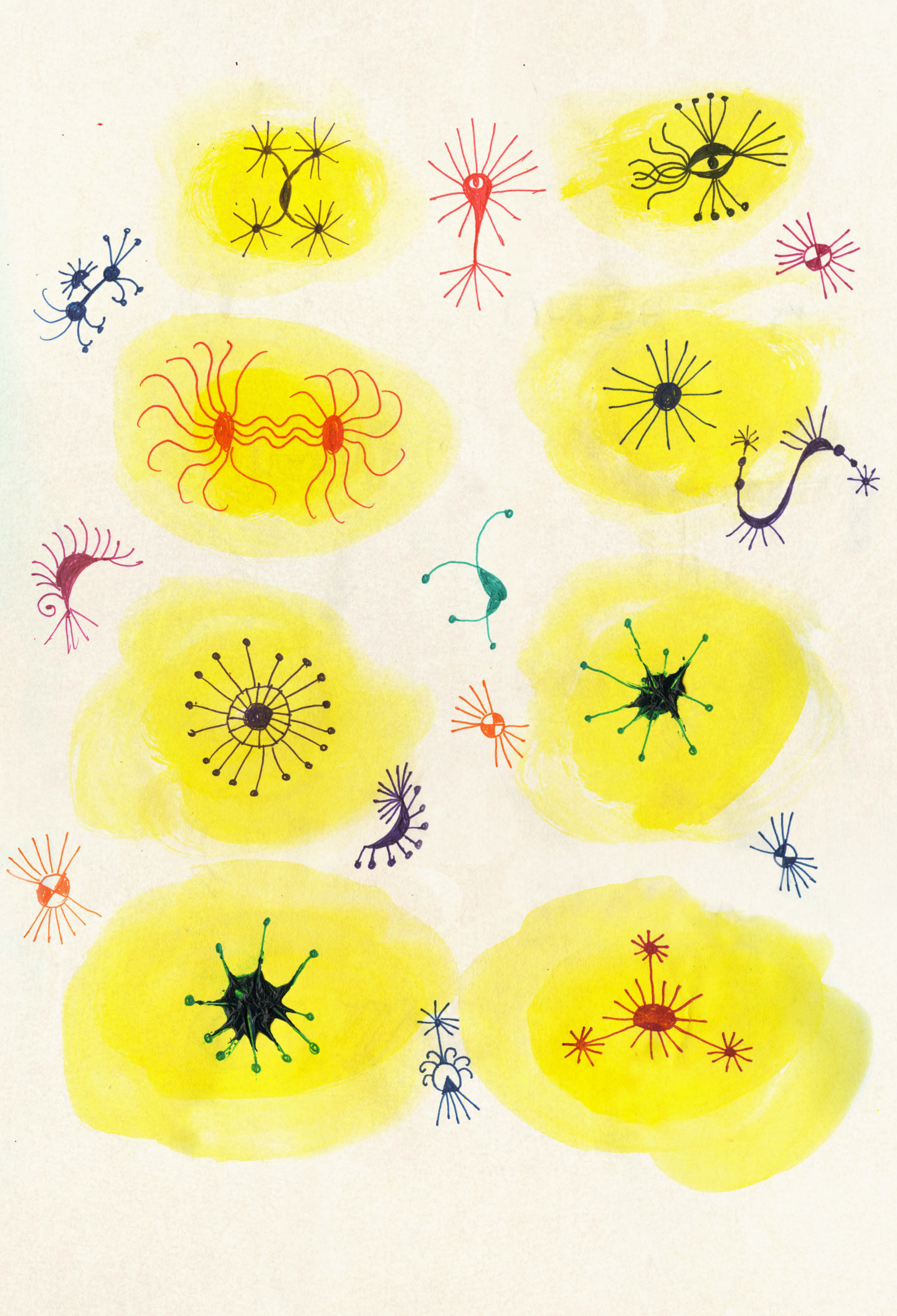
Read this to get the quick and dirty:

When engineering a Data Science solution, work from an understanding of the components that define the solution space. Regardless of your analytic goal, you must consider the *data types* with which you will be working, the *classes of analytics* you will use to generate your data product, how the *learning models* embodied will operate and evolve, and the *execution models* that will govern how the analytic will be run. You will be able to articulate a complete Data Science solution only after considering each of these aspects.



Source: Booz Allen Hamilton

Interconnection Among the Component Parts of Data Science



Data Types

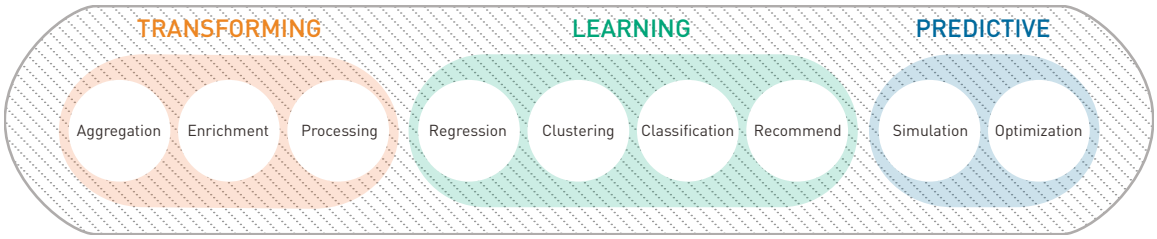
Data types and analytic goals go hand-in-hand much like the chicken and the egg; it is not always clear which comes first. Analytic goals are derived from business objectives, but the data type also influences the goals. For example, the business objective of understanding consumer product perception drives the analytic goal of sentiment analysis. Similarly, the goal of sentiment analysis drives the selection of a text-like data type such as social media content. Data type also drives many other choices when engineering your solutions.

There are a number of ways to classify data. It is common to characterize data as *structured* or *unstructured*. Structured data exists when information is clearly broken out into fields that have an explicit meaning and are highly categorical, ordinal or numeric. A related category, semi-structured, is sometimes used to describe structured data that does not conform to the formal structure of data models associated with relational databases or other forms of data tables, but nonetheless contains tags or other markers. Unstructured data, such as natural language text, has less clearly delineated meaning. Still images, video and audio often fall under the category of unstructured data. Data in this form requires preprocessing to identify and extract relevant 'features.' The features are structured information that are used for indexing and retrieval, or training classification, or clustering models.

Data may also be classified by the rate at which it is generated, collected or processed. The distinction is drawn between streaming data that arrives constantly like a torrent of water from a fire hose, and batch data, which arrives in buckets. While there is rarely a connection between data type and data rate, data rate has significant influence over the execution model chosen for analytic implementation and may also inform a decision of analytic class or learning model.

Classes of Analytic Techniques

As a means for helping conceptualize the universe of possible analytic techniques, we grouped them into nine basic classes. Note that techniques from a given class may be applied in multiple ways to achieve various analytic goals. Membership in a class simply indicates a similar analytic function. The nine analytic classes are shown in the figure, *Classes of Analytic Techniques*.



Source: Booz Allen Hamilton

Classes of Analytic Techniques

» Transforming Analytics

- **Aggregation**: Techniques to summarize the data. These include basic statistics (e.g., mean, standard deviation), distribution fitting, and graphical plotting.
- **Enrichment**: Techniques for adding additional information to the data, such as source information or other labels.
- **Processing**: Techniques that address data cleaning, preparation, and separation. This group also includes common algorithm pre-processing activities such as transformations and feature extraction.

» Learning Analytics

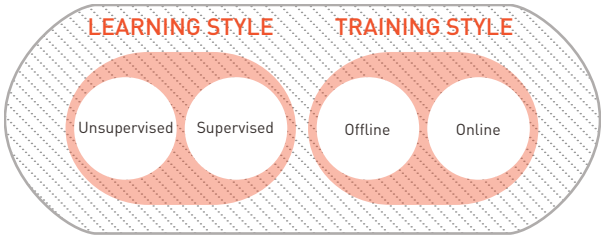
- **Regression**: Techniques for estimating relationships among variables, including understanding which variables are important in predicting future values.
- **Clustering**: Techniques to segment the data into naturally similar groups.
- **Classification**: Techniques to identify data element group membership.
- **Recommendation**: Techniques to predict the rating or preference for a new entity, based on historic preference or behavior.

» Predictive Analytics

- **Simulation**: Techniques to imitate the operation of a real-world process or system. These are useful for predicting behavior under new conditions.
- **Optimization**: Operations Research techniques focused on selecting the best element from a set of available alternatives to maximize a utility function.

Learning Models

Analytic classes that perform predictions such as regression, clustering, classification, and recommendation employ learning models. These models characterize how the analytic is trained to perform judgments on new data based on historic observation. Aspects of learning models describe both the types of judgments performed and how the models evolve over time, as shown in the figure, *Analytic Learning Models*.



Source: Booz Allen Hamilton

Analytic Learning Models

The learning models are typically described as employing unsupervised or supervised learning. Supervised learning takes place when a model is trained using a labeled data set that has a known class or category associated with each data element. The model relates the features found in training instances with the labels so that predictions can be made for unlabeled instances. Unsupervised learning models have no a-priori knowledge about the classes into which data can be placed. They use the features in the dataset to form groupings based on feature similarity.

A useful distinction of learning models is between those that are trained in a single pass, which are known as offline models, and those that are trained incrementally over time, known as online models. Many learning approaches have online or offline variants. The decision to use one or another is based on the analytic goals and execution models chosen.

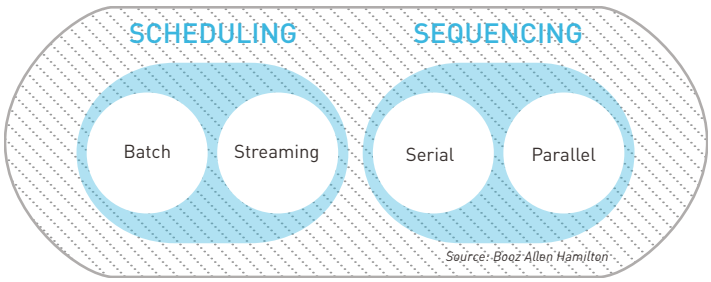
Generating an offline model requires taking a pass over the entire training data set. Improving the model requires making separate passes over the data. These models are static in that once trained, their predictions will not change until a new model is created through a subsequent training stage. Offline model performance is easier to evaluate due to this deterministic behavior. Deployment of the model into a production environment involves swapping out the old model for the new.

Online models have both advantages and disadvantages. They dynamically evolve over time, meaning they only require a single deployment into a production setting. The fact that these models do not have the entire dataset available when being trained, however, is a challenge. They must make assumptions about the data based

on the examples observed; these assumptions may be sub-optimal. This can be offset somewhat in cases where feedback on the model's predictions is available since online models can rapidly incorporate feedback to improve performance.

Execution Models

Execution models describe how data is manipulated to perform an analytic function. They may be categorized across a number of dimensions. Execution Models are embodied by an execution framework, which orchestrates the sequencing of analytic computation. In this sense, a framework might be as simple as a programming language runtime, such as the Python interpreter, or a distributed computing framework that provides a specific API for one or more programming languages such as Hadoop, MapReduce or Spark. Grouping execution models based on how they handle data is common, classifying them as either batch or streaming execution models. The categories of execution model are shown in the figure, *Analytic Execution Models.*



Analytic Execution Models

A batch execution model implies that data is analyzed in large segments, that the analytic has a state where it is running and a state where it is not running and that little state is maintained in memory between executions. Batch execution may also imply that the analytic produces results with a frequency on the order of several minutes or more. Batch workloads tend to be fairly easy to conceptualize because they represent discrete units of work. As such, it is easy to identify a specific series of execution steps as well as the proper execution frequency and time bounds based on the rate at which data arrives. Depending on the algorithm choice, batch execution models are easily scalable through parallelism. There are a number of frameworks that support parallel batch analytic execution. Most famously, Hadoop provides a distributed batch execution model in its MapReduce framework.

Conversely, a streaming model analyzes data as it arrives. Streaming execution models imply that under normal operation, the analytic is always executing. The analytic can hold state in memory and

constantly deliver results as new data arrives, on the order of seconds or less. Many of the concepts in streaming are inherent in the Unix-pipeline design philosophy; processes are chained together by linking the output of one process to the input of the next. As a result, many developers are already familiar with the basic concepts of streaming. A number of frameworks are available that support the parallel execution of streaming analytics such as Storm, S4 and Samza.

The choice between batch and streaming execution models often hinges on analytic latency and timeliness requirements. Latency refers to the amount of time required to analyze a piece of data once it arrives at the system, while timeliness refers to the average age of an answer or result generated by the analytic system. For many analytic goals, a latency of hours and timeliness of days is acceptable and thus lend themselves to the implementation enabled by the batch approach. Some analytic goals have up-to-the-second requirements where a result that is minutes old has little worth. The streaming execution model better supports such goals.

Batch and streaming execution models are not the only dimensions within which to categorize analytic execution methods. Another distinction is drawn when thinking about scalability. In many cases, scale can be achieved by spreading computation over a number of computers. In this context, certain algorithms require a large shared memory state, while others are easily parallelizable in a context where no shared state exists between machines. This distinction has significant impacts on both software and hardware selection when building out a parallel analytic execution environment.

» Tips From the Pros

In order to understand system capacity in the context of streaming analytic execution, collect metrics including: the amount of data consumed, data emitted, and latency. This will help you understand when scale limits are reached.

Fractal Analytic Model

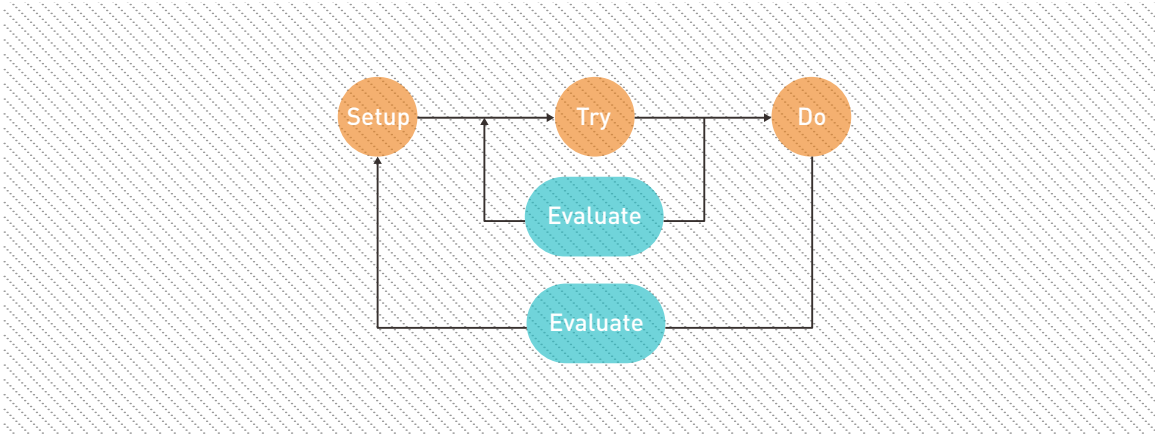
Data Science analytics are a lot like broccoli.

Fractals are mathematical sets that display self-similar patterns. As you zoom in on a fractal, the same patterns reappear. Imagine a stalk of broccoli. Rip off a piece of broccoli and the piece looks much like the original stalk. Progressively smaller pieces of broccoli still look like the original stalk.

Data Science analytics are a lot like broccoli – fractal in nature in both time and construction. Early versions of an analytic follow the same development process as later versions. At any given iteration, the analytic itself is a collection of smaller analytics that often decompose into yet smaller analytics.

Iterative by Nature

Good Data Science is fractal in time — an iterative process. Getting an imperfect solution out the door quickly will gain more interest from stakeholders than a perfect solution that is never completed. The figure, *The Data Science Product Lifecycle,* summarizes the lifecycle of the Data Science product.



Source: Booz Allen Hamilton

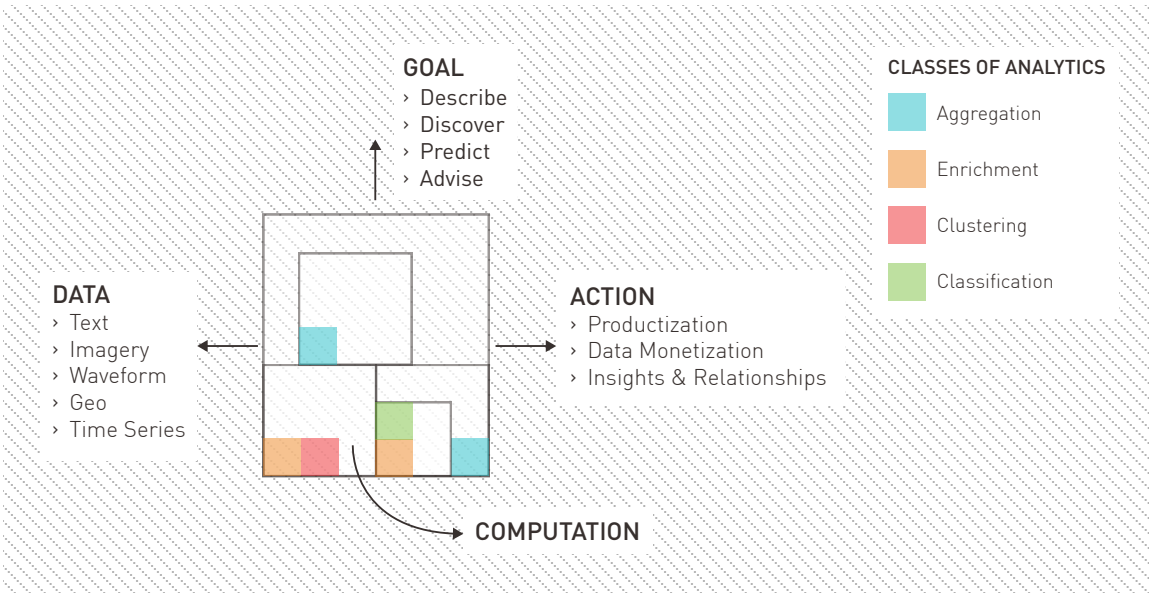
The Data Science Product Lifecycle

Set up the infrastructure, aggregate and prepare the data, and incorporate domain expert knowledge. *Try* different analytic techniques and models on subsets of the data. *Evaluate* the models, refine, evaluate again, and select a model. *Do* something with your models and results – deploy the models to inform, inspire action, and act. *Evaluate* the business results to improve the overall product.

Smaller Pieces of Broccoli: A Data Science Product

Components inside and outside of the Data Science product will change with each iteration. Let's take a look under the hood of a Data Science product and examine the components during one such iteration.

In order to achieve a greater analytic goal, you need to first decompose the problem into sub-components to divide and conquer. The figure, *The Fractal Analytic Model*, shows a decomposition of the Data Science product into four component pieces.



Source: Booz Allen Hamilton

The Fractal Analytic Model

Goal

You must first have some idea of your analytic goal and the end state of the analysis. Is it to Discover, Describe, Predict, or Advise? It is probably a combination of several of those. Be sure that before you start, you define the business value of the data and how you plan to use the insights to drive decisions, or risk ending up with interesting but non-actionable trivia.

Data

Data dictates the potential insights that analytics can provide. Data Science is about finding patterns in variable data and comparing those patterns. If the data is not representative of the universe of events you wish to analyze, you will want to collect that data through carefully planned variations in events or processes through A/B testing or design of experiments. Data sets are never perfect so don't wait for perfect data to get started. A good Data Scientist is adept at handling messy data with missing or erroneous values. Just make sure to spend the time upfront to clean the data or risk generating garbage results.

Computation

Computation aligns the data to goals through the process of creating insights. Through divide and conquer, computation decomposes into several smaller analytic capabilities with their own goals, data, computation and resulting actions, just like a smaller piece of broccoli maintains the structure of the original stalk. In this way, computation itself is fractal. Capability building blocks may utilize different types of execution models such as batch computation or streaming, that individually accomplish small tasks. When properly combined together, the small tasks produce complex, actionable results.

Action

How should engineers change the manufacturing process to generate higher product yield? How should an insurance company choose which policies to offer to whom and at what price? The output of computation should enable actions that align to the goals of the data product. Results that do not support or inspire action are nothing but interesting trivia.

Given the fractal nature of Data Science analytics in time and construction, there are many opportunities to choose fantastic or shoddy analytic building blocks. *The Analytic Selection Process* offers some guidance.

The Analytic Selection Process

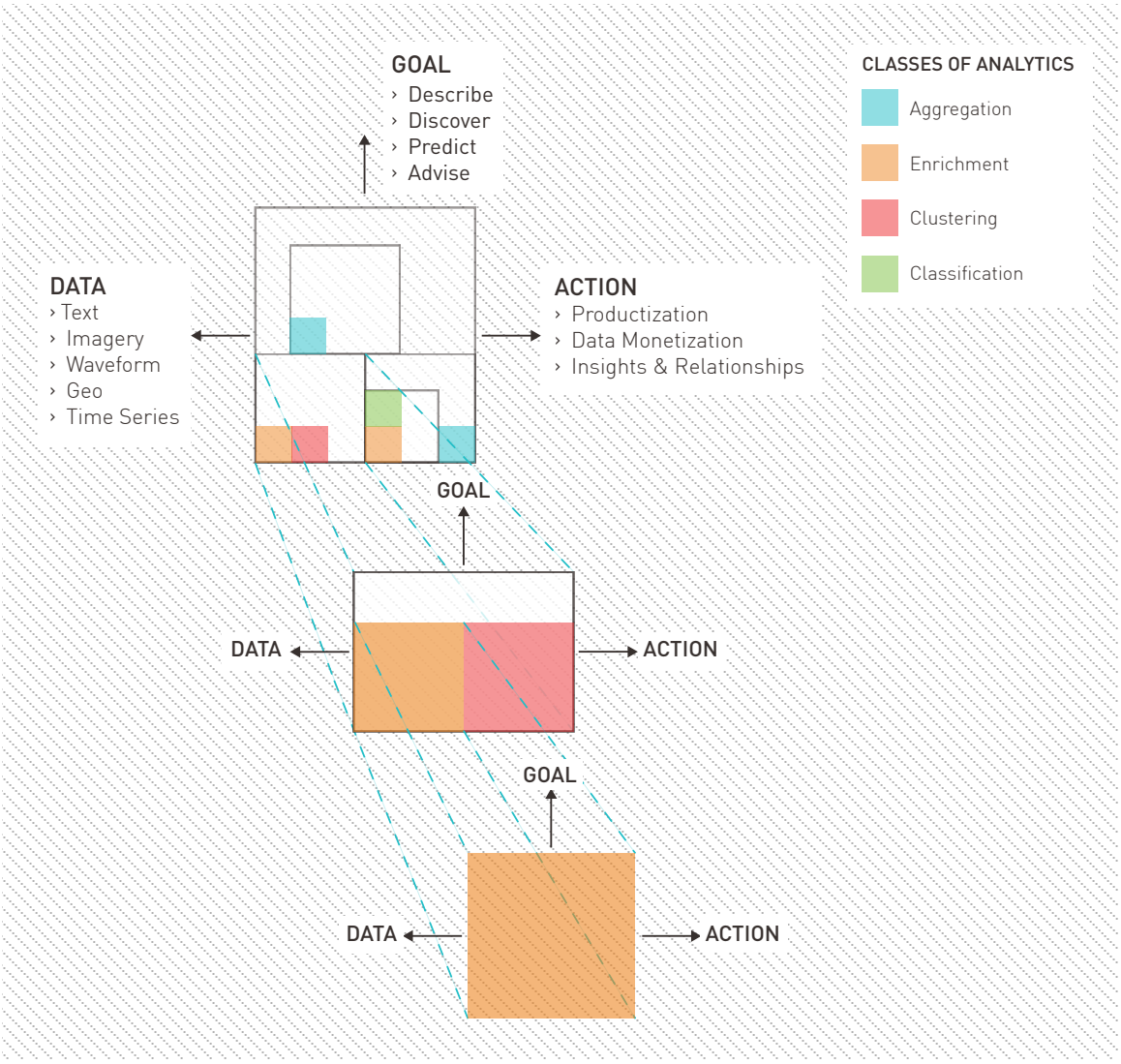
If you focus only on the science aspect of Data Science you will never become a data artist.

A critical step in Data Science is to identify an analytic technique that will produce the desired action. Sometimes it is clear; a characteristic of the problem (e.g., data type) points to the technique you should implement. Other times, however, it can be difficult to know where to begin. The universe of possible analytic techniques is large. Finding your way through this universe is an art that must be practiced. We are going to guide you on the next portion of your journey - becoming a data artist.

Decomposing the Problem

Decomposing the problem into manageable pieces is the first step in the analytic selection process. Achieving a desired analytic action often requires combining multiple analytic techniques into a holistic, end-to-end solution. Engineering the complete solution requires that the problem be decomposed into progressively smaller sub-problems.

The *Fractal Analytic Model* embodies this approach. At any given stage, the analytic itself is a collection of smaller computations that decompose into yet smaller computations. When the problem is decomposed far enough, only a single analytic technique is needed to achieve the analytic goal. Problem decomposition creates multiple sub-problems, each with their own goals, data, computations, and actions. The concept behind problem decomposition is shown in the figure, *Problem Decomposition Using the Fractal Analytic Model*.



Source: Booz Allen Hamilton

Problem Decomposition Using the Fractal Analytic Model

On the surface, problem decomposition appears to be a mechanical, repeatable process. While this may be true conceptually, it is really the performance of an art as opposed to the solving of an engineering problem. There may be many valid ways to decompose the problem, each leading to a different solution. There may be hidden dependencies or constraints that only emerge after you begin developing a solution. This is where art meets science. Although the art behind problem decomposition cannot be taught, we have distilled some helpful hints to help guide you. When you begin to think about decomposing your problem, look for:

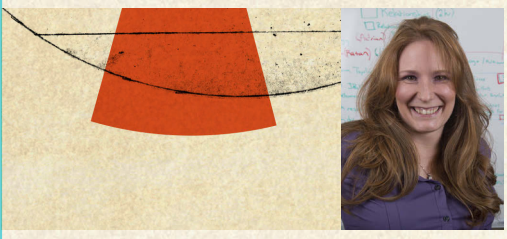
» Tips From the Pros

One of your first steps should be to explore available data sources that have not been previously combined. Emerging relationships between data sources often allow you to pick low hanging fruit.

- ***Compound analytic goals that create natural segmentation.*** For example, many problems focused on predicting future conditions include both Discover and Predict goals.
- ***Natural orderings of analytic goals.*** For example, when extracting features you must first identify candidate features and then select the features set with the highest information value. These two activities form distinct analytic goals.
- ***Data types that dictate processing activities.*** For example, text or imagery both require feature extraction.
- ***Requirements for human-in-the-loop feedback.*** For example, when developing alerting thresholds, you might need to solicit analyst feedback and update the threshold based on their assessment.
- ***The need to combine multiple data sources.*** For example, you may need to correlate two data sets to achieve your broader goal. Often this indicates the presence of a Discover goal.

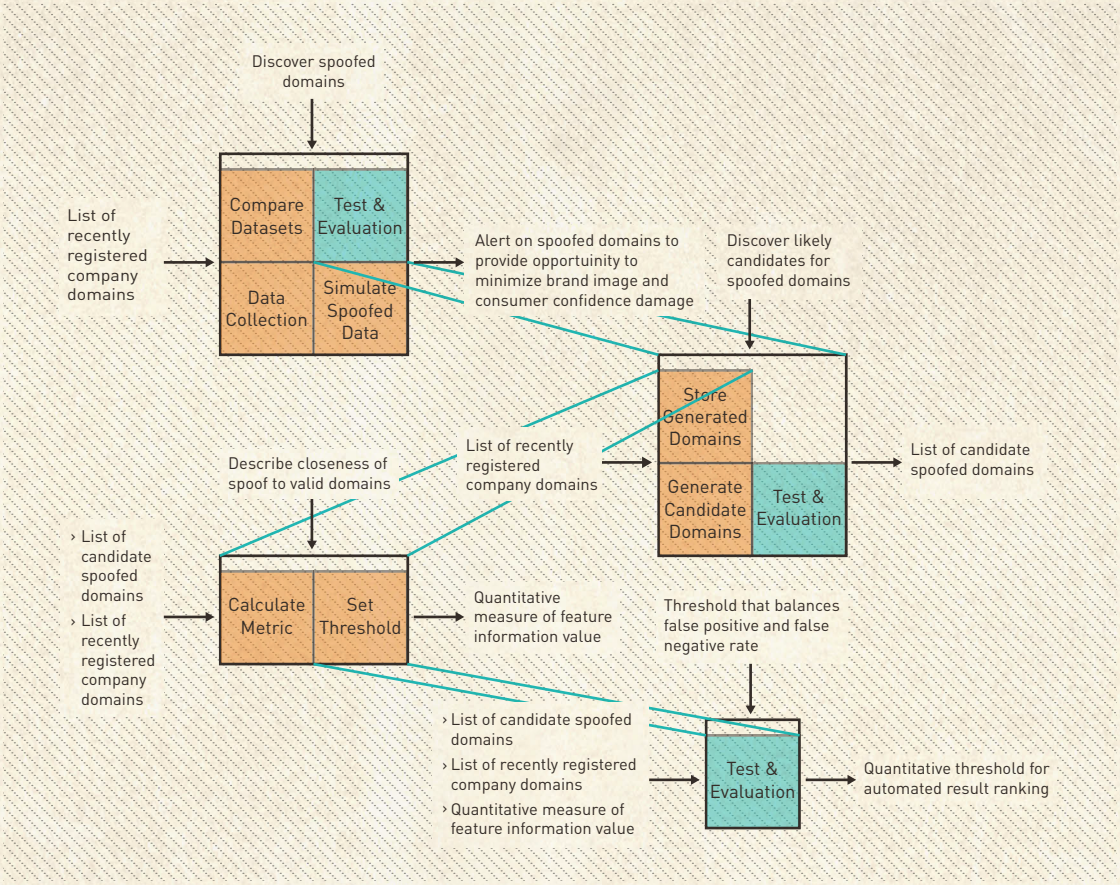
In addition to problem decomposition providing a tractable approach to analytic selection, it has the added benefit of simplifying a highly complex problem. Rather than being faced with understanding the entire end-to-end solution, the computations are discrete segments that can be explored. Note, however, that while this technique helps the Data Scientist approach the problem, it is the complete end-to-end solution that must be evaluated.

›› Identifying Spoofed Domains



Stephanie Rivera

Identifying spoofed domains is important for an organization to preserve their brand image and to avoid eroded customer confidence. Spoofed domains occur when a malicious actor creates a website, URL or email address that users believe is associated with a valid organization. When users click the link, visit the website or receive emails, they are subjected to some type of nefarious activity.



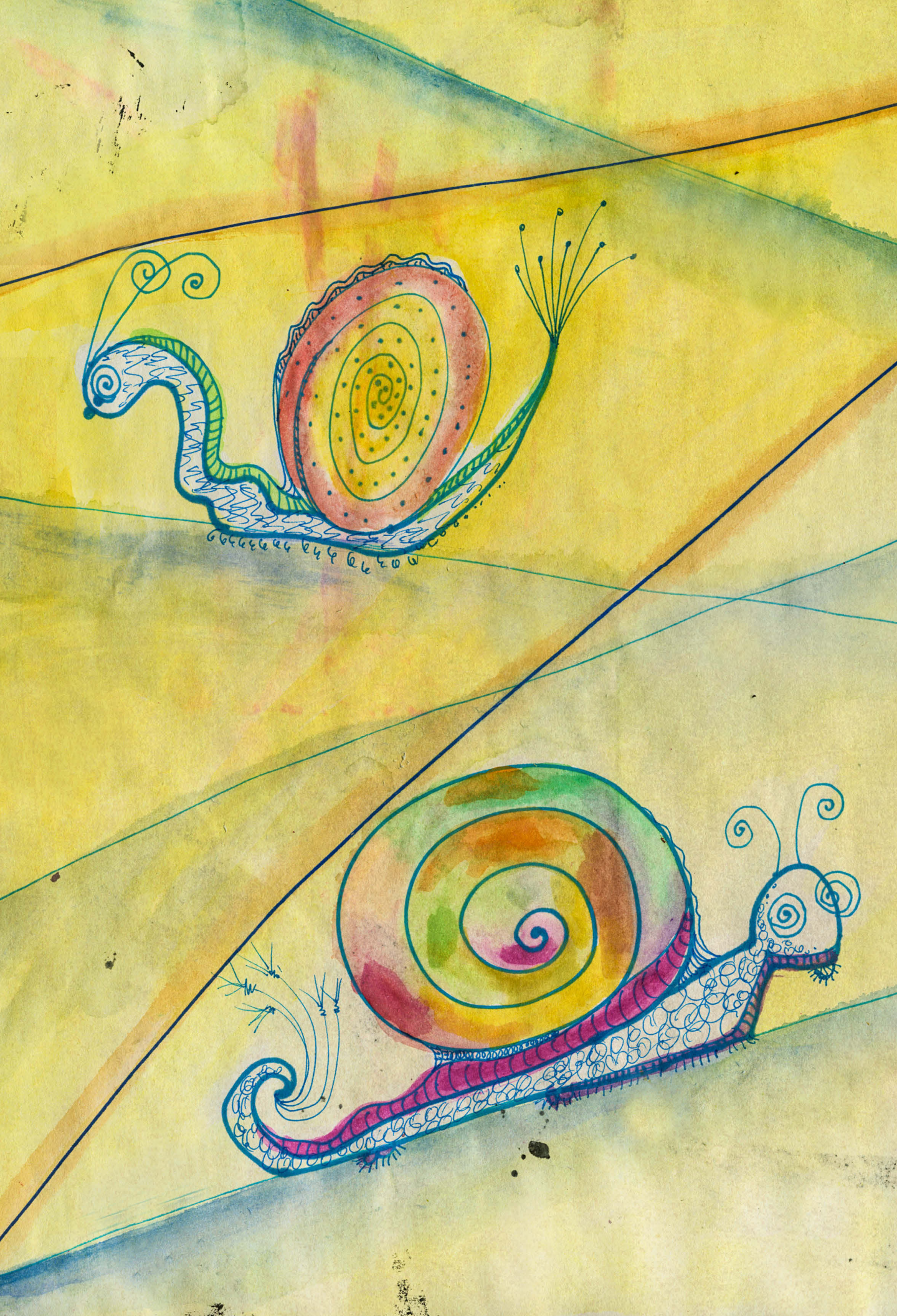
Source: Booz Allen Hamilton

Spoofed Domain Problem Decomposition

Our team was faced with the problem of identifying spoofed domains for a commercial company. On the surface, the problem sounded easy; take a recently registered domain, check to see if it is similar to the company's domain and alert when the similarity is sufficiently high. Upon decomposing the problem, however, the main computation quickly became complicated.

We needed a computation that determined similarity between two domains. As we decomposed the similarity computation, complexity and speed became a concern. As with many security-related problems, fast alert speeds are vital. Result speed created an implementation constraint that forced us to re-evaluate how we decomposed the problem.

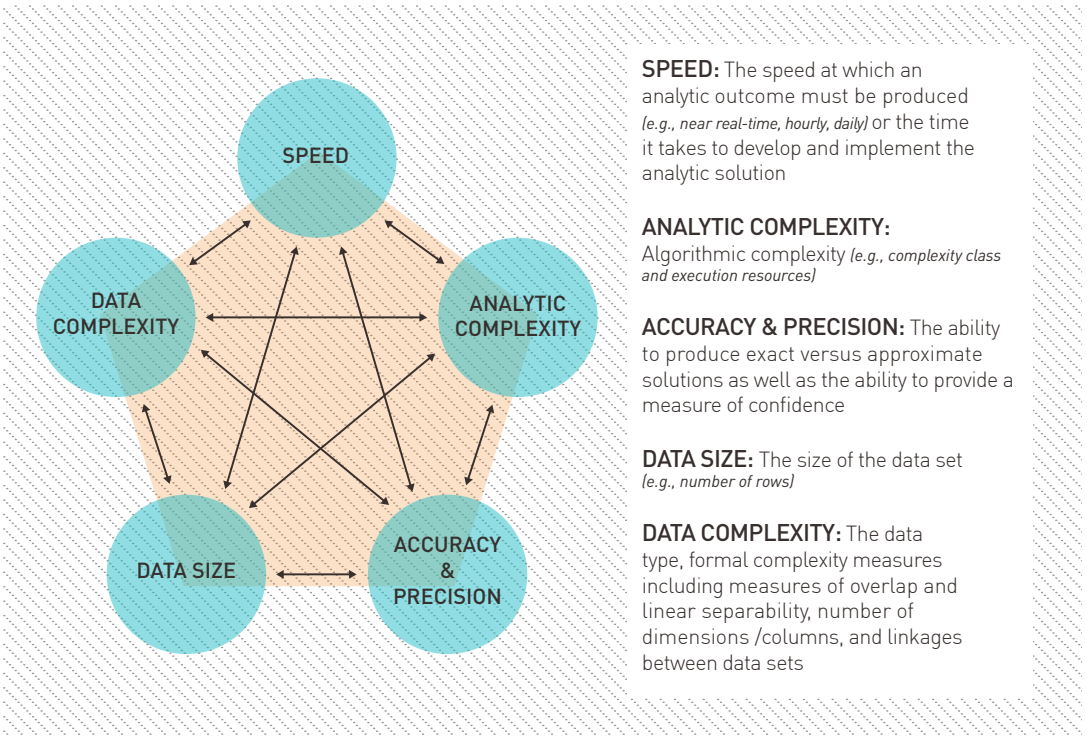
Revisiting the decomposition process led us to a completely new approach. In the end, we derived a list of domains similar to those registered by the company. We then compared that list against a list of recently registered domains. The figure, *Spoofed Domain Problem Decomposition,* illustrates our approach. Upon testing and initial deployment, our analytic discovered a spoofed domain within 48 hours.



Implementation Constraints

In the spoofed domains case study, the emergence of an implementation constraint caused the team to revisit its approach. This demonstrates that analytic selection does not simply mean choosing an analytic technique to achieve a desired outcome. It also means ensuring that the solution is feasible to implement.

The Data Scientist may encounter a wide variety of implementation constraints. They can be conceptualized, however, in the context of five dimensions that compete for your attention: analytic complexity, speed, accuracy & precision, data size, and data complexity. Balancing these dimensions is a zero sum game - an analytic solution cannot simultaneously exhibit all five dimensions, but instead must make trades between them. The figure, *Balancing the Five Analytic Dimensions,* illustrates this relationship.



Source: Booz Allen Hamilton

Balancing the Five Analytic Dimensions

Implementation constraints occur when an aspect of the problem dictates the value for one or more of these dimensions. As soon as one dimension is fixed, the Data Scientist is forced to make trades among the others. For example, if the analytic problem requires actions to be produced in near real-time, the speed dimension is fixed and trades must be made among the other four dimensions. Understanding which trades will achieve the right balance among the five dimensions is an art that must be learned over time.

As we compiled this section, we talked extensively about ways to group and classify implementation constraints. After much discussion we settled on these five dimensions. We present this model in hopes that others weigh in and offer their own perspectives.

» Tips From the Pros

When possible, consider approaches that make use of previously computed results. Your algorithm will run much faster if you can avoid re-computing values across the full time horizon of data.

» Tips From the Pros

Our *Data Science Product Lifecycle* has evolved to produce results quickly and then incrementally improve the solution.

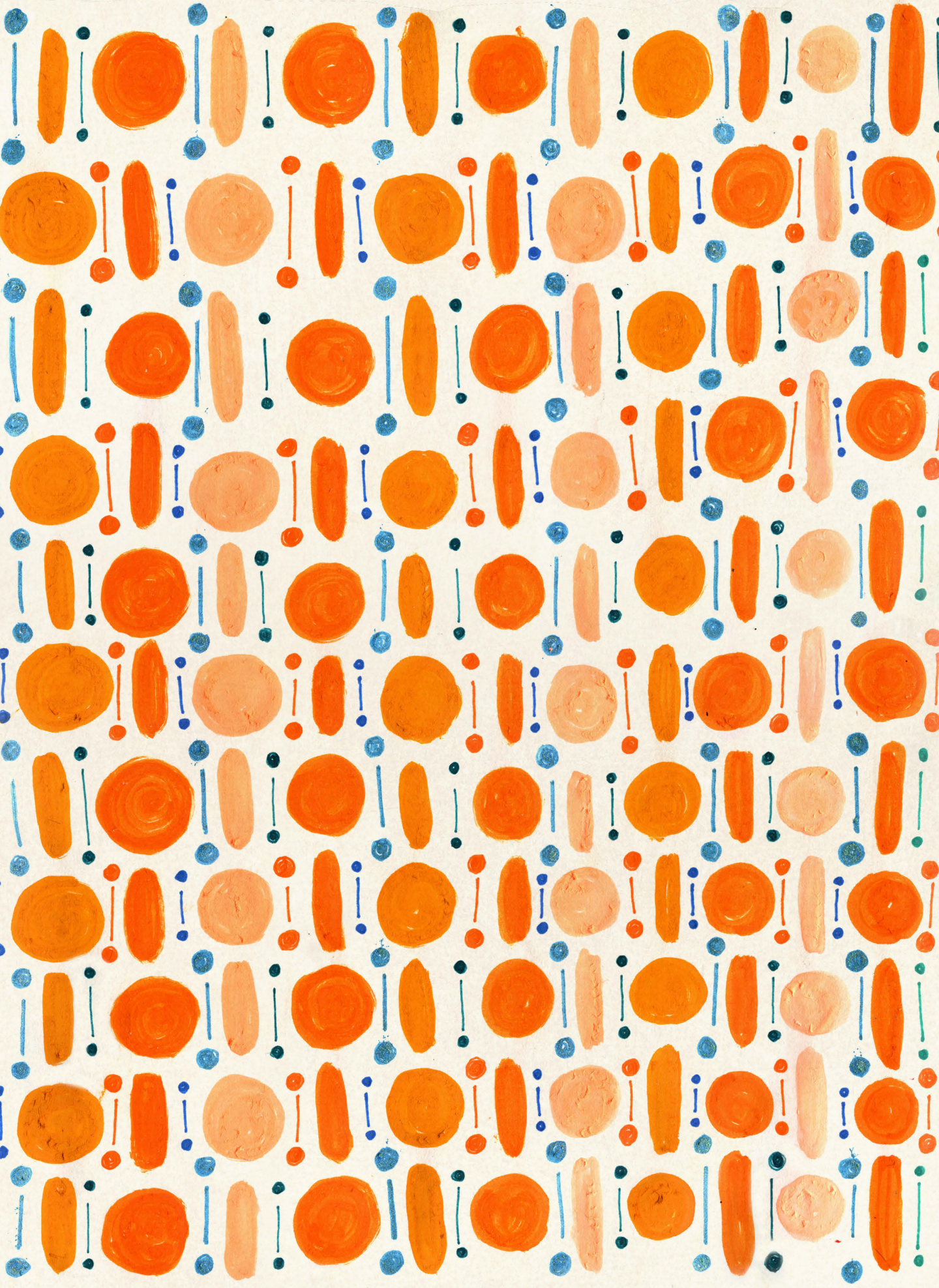
» Tips From the Pros

Streaming approaches may be useful for overcoming storage limitations.

Some common examples of implementation constraints include:

- ***Computation frequency.*** The solution may need to run on a regular basis (e.g., hourly), requiring that computations be completed within a specified window of time. The best analytic is useless if it cannot solve the problem within the required time.
- ***Solution timeliness.*** Some applications require near real-time results, pointing toward streaming approaches. While some algorithms can be implemented within streaming frameworks, many others cannot.
- ***Implementation speed.*** A project may require that you rapidly develop and implement a solution to quickly produce analytic insights. In these cases, you may need to focus on less complex techniques that can be quickly implemented and verified.
- ***Computational resource limitations.*** Although you may be able to store and analyze your data, data size may be sufficiently large that algorithms requiring multiple computations across the full data set are too resource intensive. This may point toward needing approaches that only require a single pass on the data (e.g., canopy cluster as opposed to k-means clustering).
- ***Data storage limitations***. There are times when big data becomes so big it cannot be stored or only a short time horizon can be stored. Analytic approaches that require long time horizons may not be possible.

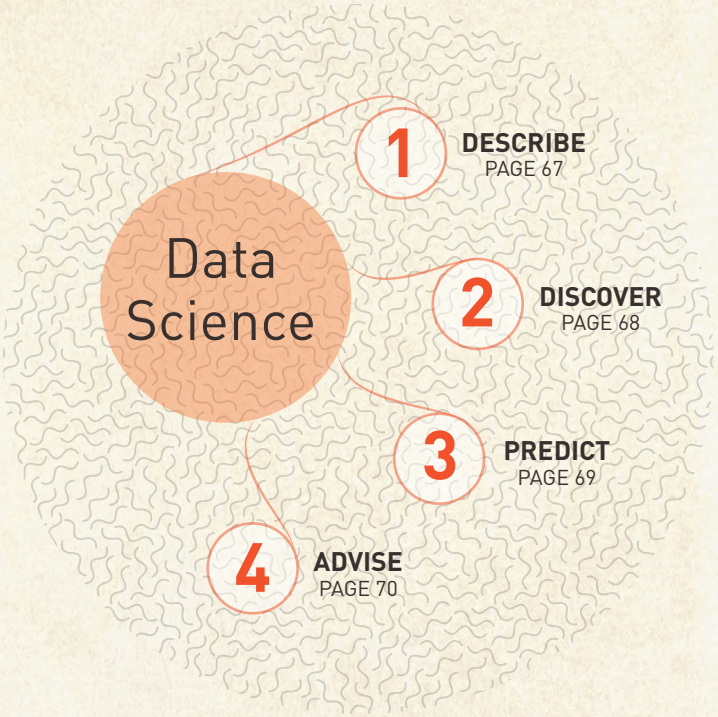
Organizational policies and regulatory requirements are a major source of implicit constraints that merit a brief discussion. Policies are often established around specific classes of data such as Personally Identifiable Information (PII) or Personal Health Information (PHI). While the technologies available today can safely house information with a variety of security controls in a single system, these policies force special data handling considerations including limited retention periods and data access. Data restrictions impact the data size and complexity dimensions outlined earlier, creating yet another layer of constraints that must be considered.



Guide to Analytic Selection

Your senses are incapable of perceiving the entire universe, so we drew you a map.

The universe of analytic techniques is vast and hard to comprehend. We created this diagram to aid you in finding your way from data and goal to analytic action. Begin at the center of the universe (Data Science) and answer questions about your analytic goals and problem characteristics. The answers to your questions will guide you through the diagram to the appropriate class of analytic techniques and provide recommendations for a few techniques to consider.



❶ **TIP:** There are several situations where dimensionality reduction may be needed:
- › Models fail to converge
- › Models produce results equivalent to random chance
- › You lack the computational power to perform operations across the feature space
- › You do not know which aspects of the data are the most important

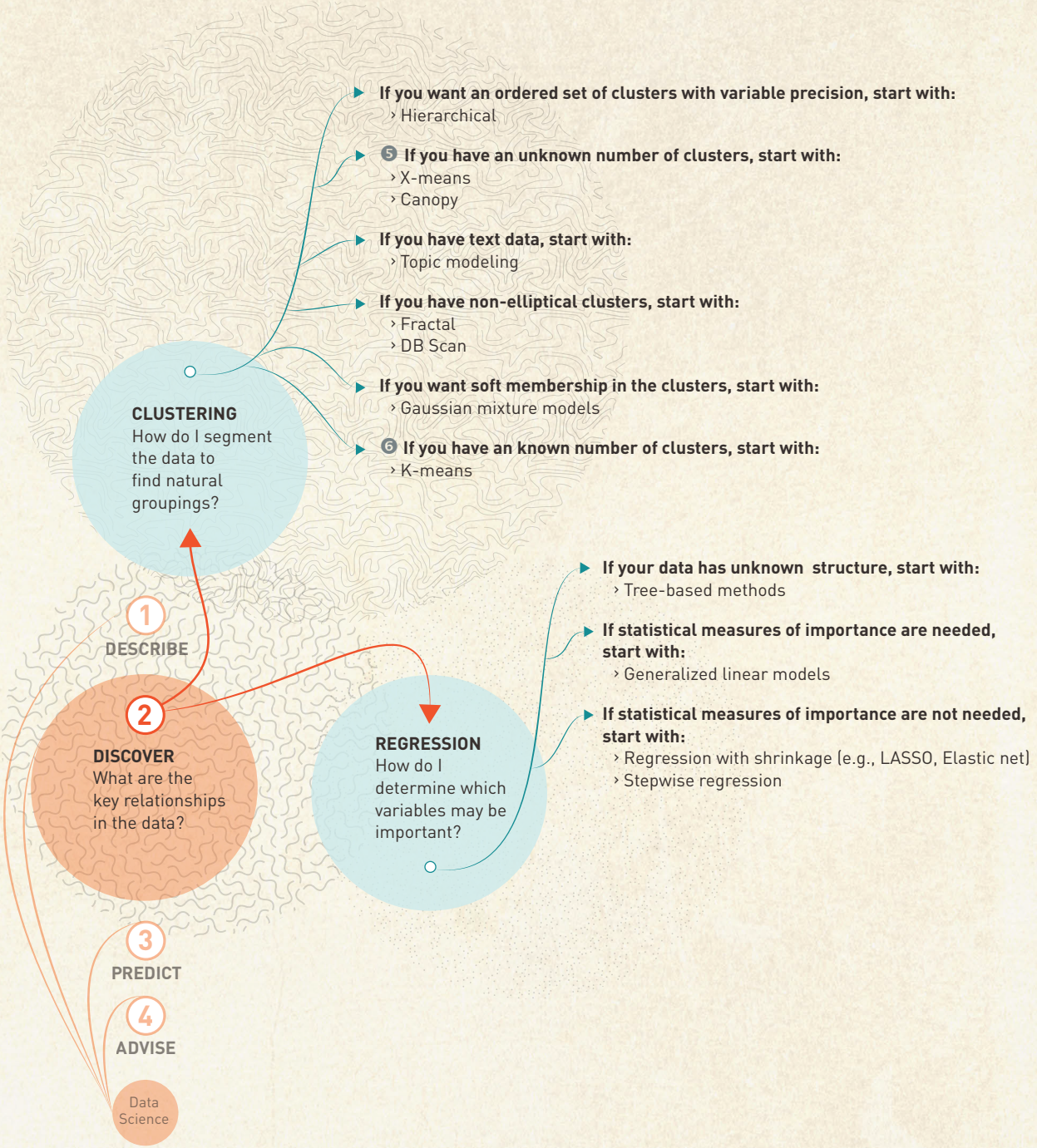
❷ **Feature Extraction** is a broad topic and is highly dependent upon the domain area. This topic could be the subject of an entire book. As a result, a detailed exploration has been omitted from this diagram. See the *Featuring Engineering* and *Feature Selection* sections in the *Life in the Trenches* chapter for additional information.

❸ **TIP:** Always check data labels for correctness. This is particularly true for time stamps, which may have reverted to system default values.

❹ **TIP:** Smart enrichment can greatly speed computational time. It can also be a huge differentiator between the accuracy of different end-to-end analytic solutions.

Source: Booz Allen Hamilton

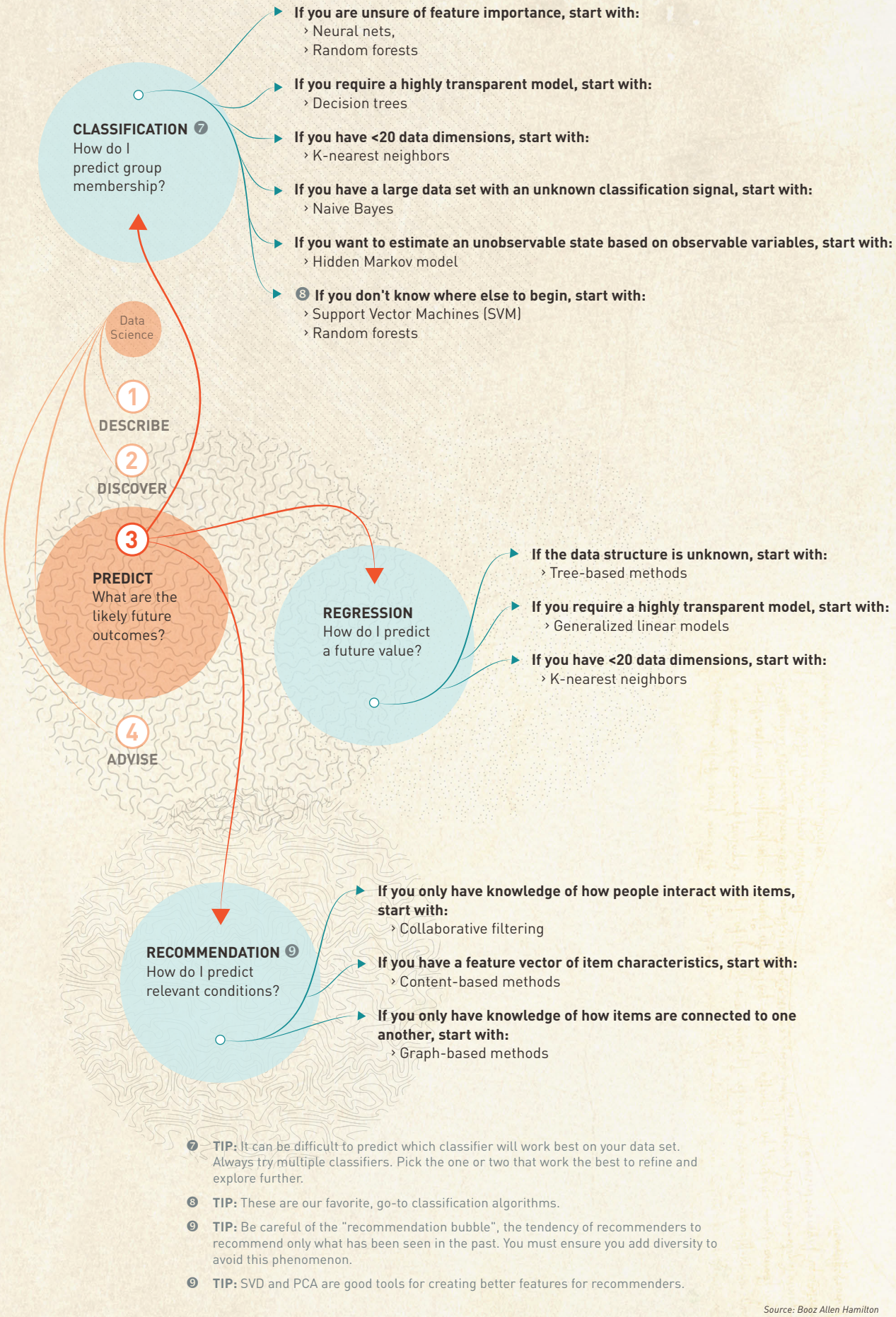
Source: Booz Allen Hamilton



5 **TIP:** Canopy clustering is good when you only want to make a single pass over the data.

6 **TIP:** Use canopy or hierarchical clustering to estimate the number of clusters you should generate.

Source: Booz Allen Hamilton



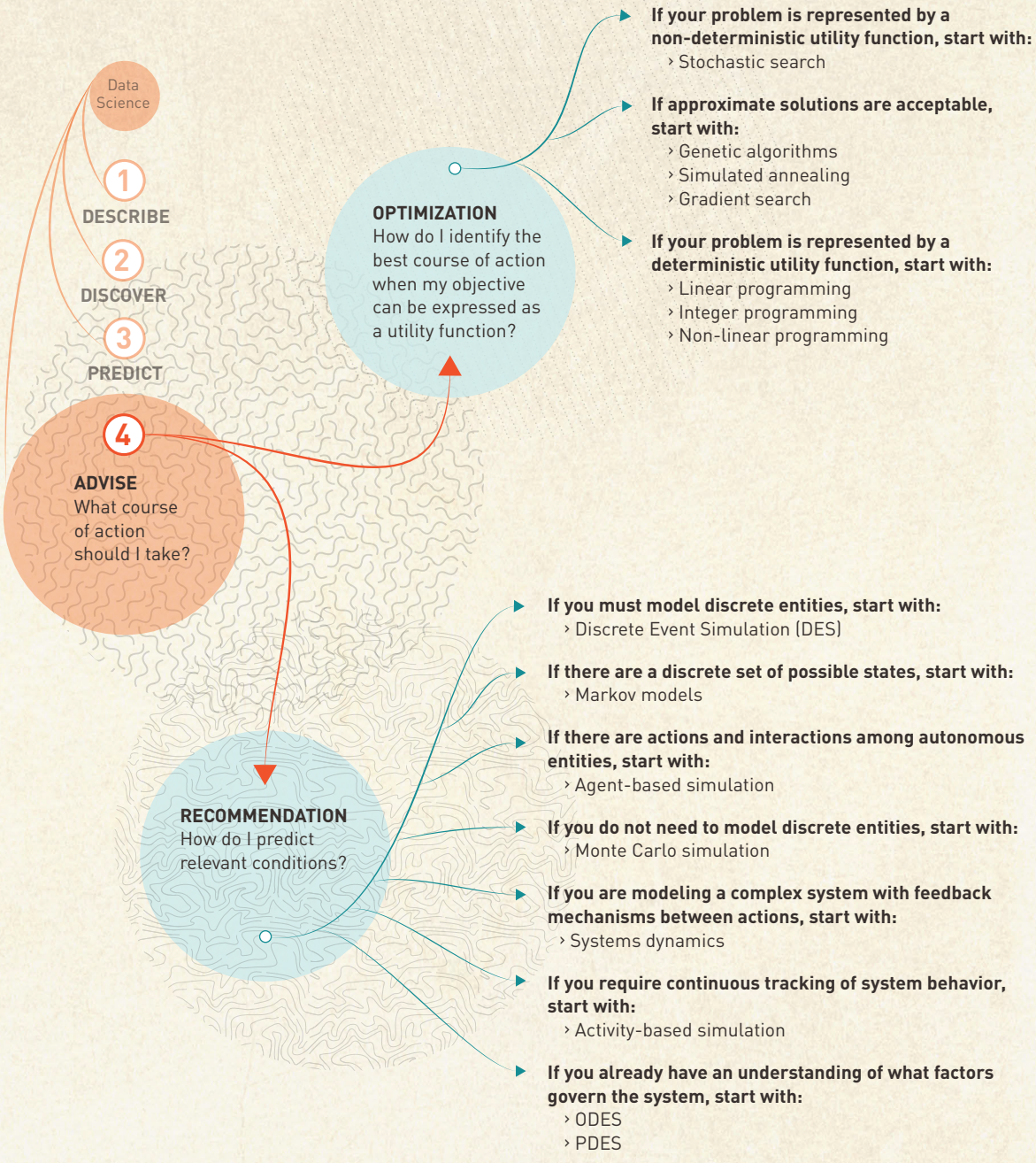
7 **TIP:** It can be difficult to predict which classifier will work best on your data set. Always try multiple classifiers. Pick the one or two that work the best to refine and explore further.

8 **TIP:** These are our favorite, go-to classification algorithms.

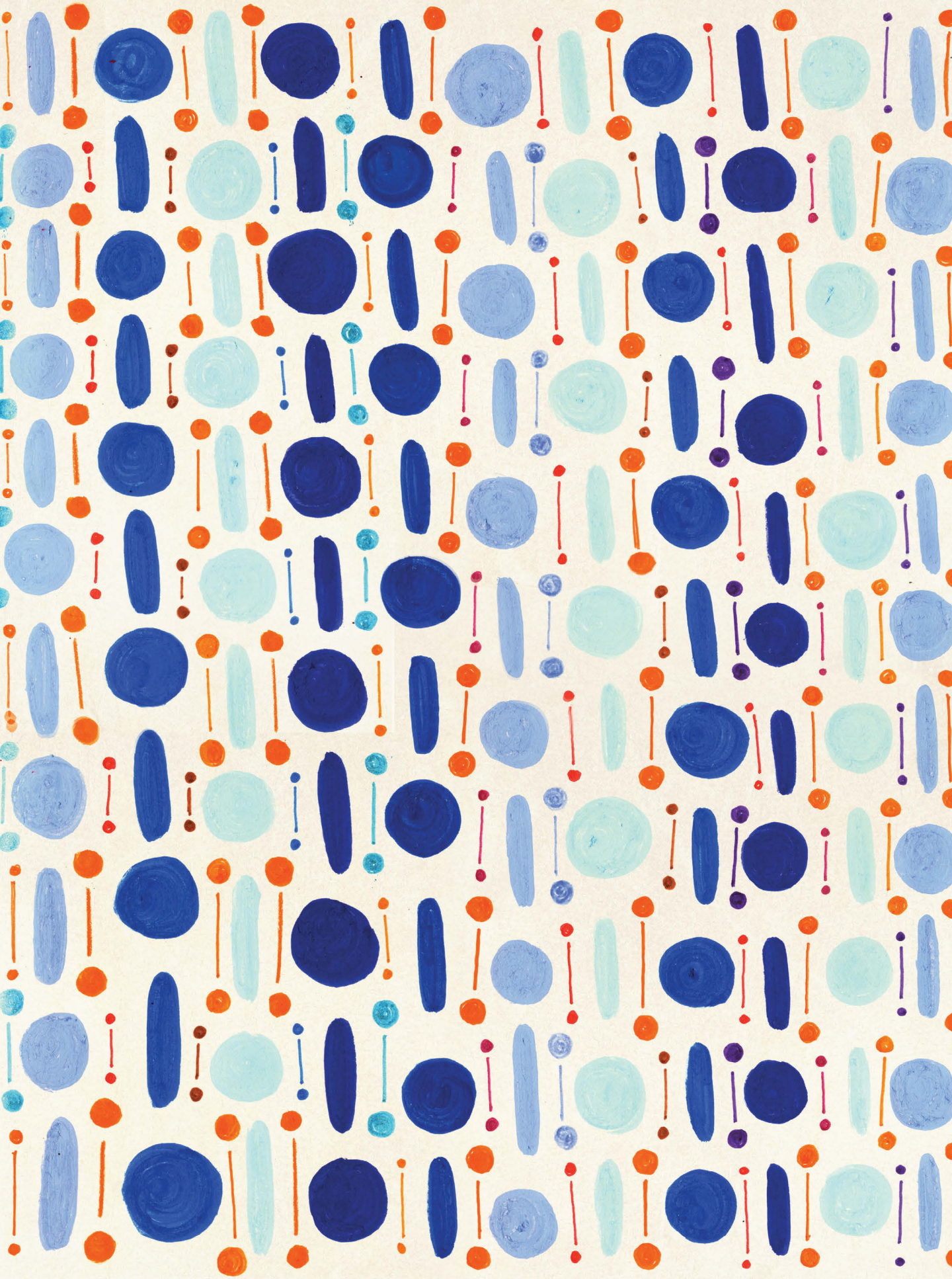
9 **TIP:** Be careful of the "recommendation bubble", the tendency of recommenders to recommend only what has been seen in the past. You must ensure you add diversity to avoid this phenomenon.

9 **TIP:** SVD and PCA are good tools for creating better features for recommenders.

Source: Booz Allen Hamilton



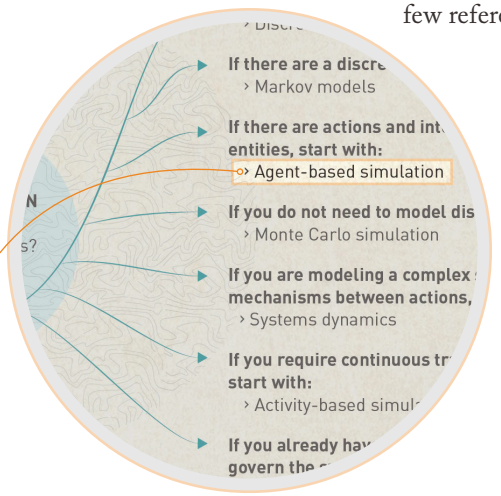
Source: Booz Allen Hamilton



Detailed Table of Analytics

Getting you to the right starting point isn't enough. We also provide a translator so you understand what you've been told.

Identifying several analytic techniques that can be applied to your problem is useful, but their name alone will not be much help. The *Detailed Table of Analytics* translates the names into something more meaningful. Once you've identified a technique in the Guide to Analytic Selection, find the corresponding row in the table. There you will find a brief description of the techniques, tips we've learned and a few references we've found helpful.



Algorithms or Method Name	Description	Tips From the Pros	References and Papers We Love to Read
Agent Based Simulation	Simulates the actions and interactions of autonomous agents.	In many systems, complex behavior results from surprisingly simple rules. Keep the logic of your agents simple and gradually build in sophistication.	Macal, Charles, and Michael North. "Agent-based Modeling and Simulation." Winter Simulation Conference. Dec. 2009. Print.
Collaborative Filtering	Also known as 'Recommendation,' suggest or eliminate items from a set by comparing a history of actions against items performed by users. Finds similar items based on who used them or similar users based on the items they use.	Use Singular Value Decomposition based Recommendation for cases where there are latent factors in your domain, e.g., genres in movies.	Owen, Sean, Robin Anil, Ted Dunning, and Ellen Friedman. *Mahout in Action.* New Jersey: Manning, 2012. Print.
Coordinate Transformation	Provides a different perspective on data.	Changing the coordinate system for data, for example, using polar or cylindrical coordinates, may more readily highlight key structure in the data. A key step in coordinate transformations is to appreciate multidimensionality and to systematically analyze subspaces of the data.	Abbott, Edwin. A. *Flatland: A Romance of Many Dimensions.* United Kingdom: Seely & Co, 1884. Print.
Design of Experiments	Applies controlled experiments to quantify effects on system output caused by changes to inputs.	Fractional factorial designs can significantly reduce the number of different types of experiments you must conduct.	Montgomery, Douglas. *Design and Analysis of Experiments.* New Jersey: John Wiley & Sons, 2012. Print.

Compiled by: Booz Allen Hamilton

Algorithms or Method Name	Description	Tips From the Pros	References and Papers We Love to Read
Differential Equations	Used to express relationships between functions and their derivatives, for example, change over time.	Differential equations can be used to formalize models and make predictions. The equations themselves can be solved numerically and tested with different initial conditions to study system trajectories.	Zill, Dennis, Warren Wright, and Michael Cullen. *Differential Equations with Boundary-Value Problems.* Connecticut: Cengage Learning, 2012. Print.
Discrete Event Simulation	Simulates a discrete sequence of events where each event occurs at a particular instant in time. The model updates its state only at points in time when events occur.	Discrete event simulation is useful when analyzing event based processes such as production lines and service centers to determine how system level behavior changes as different process parameters change. Optimization can integrate with simulation to gain efficiencies in a process.	Cassandras, Christopher, and Stephanie Lafortune. *Introduction to Discrete Event Systems.* New York: Springer, 1999. Print.
Discrete Wavelet Transform	Transforms time series data into frequency domain preserving locality information.	Offers very good time and frequency localization. The advantage over Fourier transforms is that it preserves both frequency and locality.	Burrus, C.Sidney, Ramesh A. Gopinath, Haitao Guo, Jan E. Odegard, and Ivan W. Selesnick. Introduction to Wavelets and Wavelet Transforms: A Primer. New Jersey: Prentice Hall, 1998. Print.
Exponential Smoothing	Used to remove artifacts expected from collection error or outliers.	In comparison to a using moving average where past observations are weighted equally, exponential smoothing assigns exponentially decreasing weights over time.	Chatfield, Chris, Anne B. Koehler, J. Keith Ord, and Ralph D. Snyder. "A New Look at Models for Exponential Smoothing." *Journal of the Royal Statistical Society: Series D (The Statistician)* 50.2 (July 2001): 147-159. Print.
Factor Analysis	Describes variability among correlated variables with the goal of lowering the number of unobserved variables, namely, the factors.	If you suspect there are inmeasurable influences on your data, then you may want to try factor analysis.	Child, Dennis. *The Essentials of Factor Analysis.* United Kingdom: Cassell Educational, 1990. Print.
Fast Fourier Transform	Transforms time series from time to frequency domain efficiently. Can also be used for image improvement by spatial transforms.	Filtering a time varying signal can be done more effectively in the frequency domain. Also, noise can often be identified in such signals by observing power at aberrant frequencies.	Mitra, Partha P., and Hemant Bokil. *Observed Brain Dynamics.* United Kingdom: Oxford University Press, 2008. Print.
Format Conversion	Creates a standard representation of data regardless of source format. For example, extracting raw UTF-8 encoded text from binary file formats such as Microsoft Word or PDFs.	There are a number of open source software packages that support format conversion and can interpret a wide variety of formats. One notable package is Apache Tikia.	Ingersoll, Grant S., Thomas S. Morton, and Andrew L. Farris. *Taming Text: How to Find, Organize, and Manipulate It.* New Jersey: Manning, 2013. Print.
Gaussian Filtering	Acts to remove noise or blur data.	Can be used to remove speckle noise from images.	Parker, James R. *Algorithms for Image Processing and Computer Vision.* New Jersey: John Wiley & Sons, 2010. Print.
Generalized Linear Models	Expands ordinary linear regression to allow for error distribution that is not normal.	Use if the observed error in your system does not follow the normal distribution.	MacCullagh, P., and John A. Nelder. *Generalized Linear Models.* Florida: CRC Press, 1989. Print.
Genetic Algorithms	Evolves candidate models over generations by evolutionary inspired operators of mutation and crossover of parameters.	Increasing the generation size adds diversity in considering parameter combinations, but requires more objective function evaluation. Calculating individuals within a generation is strongly parallelizable. Representation of candidate solutions can impact performance.	De Jong, Kenneth A. *Evolutionary Computation - A Unified Approach.* Massachusetts: MIT Press, 2002. Print.
Grid Search	Systematic search across discrete parameter values for parameter exploration problems.	A grid across the parameters is used to visualize the parameter landscape and assess whether multiple minima are present.	Kolda, Tamara G., Robert M. Lewis, and Virginia Torczon. "Optimization by Direct Search: New Perspectives on Some Classical and Modern Methods." *SIAM Review* 45.3 (2003): 385-482. Print.

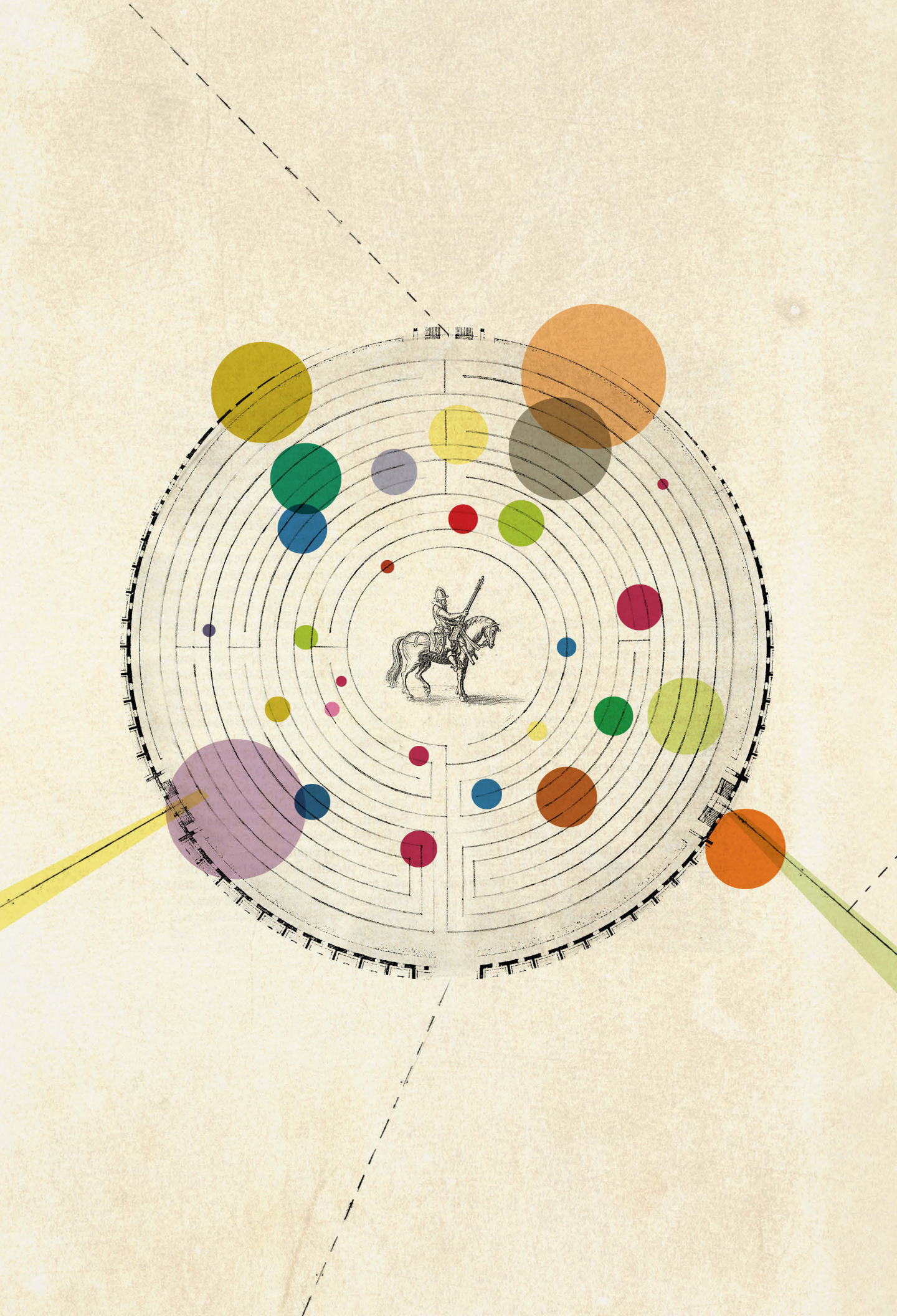
Compiled by: Booz Allen Hamilton

Algorithms or Method Name	Description	Tips From the Pros	References and Papers We Love to Read
Hidden Markov Models	Models sequential data by determining the discrete latent variables, but the observables may be continuous or discrete.	One of the most powerful properties of Hidden Markov Models is their ability to exhibit some degree of invariance to local warping (compression and stretching) of the time axis. However, a significant weakness of the Hidden Markov Model is the way in which it represents the distribution of times for which the system remains in a given state.	Bishop, Christopher M. *Pattern Recognition and Machine Learning.* New York: Springer, 2006. Print.
Hierarchical Clustering	Connectivity based clustering approach that sequentially builds bigger (agglomerative) or smaller (divisive) clusters in the data.	Provides views of clusters at multiple resolutions of closeness. Algorithms begin to slow for larger data sets due to most implementations exhibiting $O(N^3)$ or $O(N^2)$ complexity.	Rui Xu, and Don Wunsch. *Clustering.* New Jersey: Wiley-IEEE Press, 2008. Print.
K-means and X-means Clustering	Centroid based clustering algorithms, where with K means the number of clusters is set and X means the number of clusters is unknown.	When applying clustering techniques, make sure to understand the shape of your data. Clustering techniques will return poor results if your data is not circular or ellipsoidal shaped.	Rui Xu, and Don Wunsch. *Clustering.* New Jersey: Wiley-IEEE Press, 2008. Print.
Linear, Non-linear, and Integer Programming	Set of techniques for minimizing or maximizing a function over a constrained set of input parameters.	Start with linear programs because algorithms for integer and non-linear variables can take much longer to run.	Winston, Wayne L. *Operations Research: Applications and Algorithms.* Connecticut: Cengage Learning, 2003. Print.
Markov Chain Monte Carlo (MCMC)	A method of sampling typically used in Bayesian models to estimate the joint distribution of parameters given the data.	Problems that are intractable using analytic approaches can become tractable using MCMC, when even considering high-dimensional problems. The tractability is a result of using statistics on the underlying distributions of interest, namely, sampling with Monte Carlo and considering the stochastic sequential process of Markov Chains.	Andrieu, Christophe, Nando de Freitas, Amaud Doucet, and Michael I. Jordan. "An Introduction to MCMC for Machine Learning." *Machine Learning*, 50.1 (January 2003): 5-43. Print.
Monte Carlo Methods	Set of computational techniques to generate random numbers.	Particularly useful for numerical integration, solutions of differential equations, computing Bayesian posteriors, and high dimensional multivariate sampling.	Fishman, George S. *Monte Carlo: Concepts, Algorithms, and Applications.* New York: Springer, 2003. Print.
Naïve Bayes	Predicts classes following Bayes Theorem that states the probability of an outcome given a set of features is based on the probability of features given an outcome.	Assumes that all variables are independent, so it can have issues learning in the context of highly interdependent variables. The model can be learned on a single pass of data using simple counts and therefore is useful in determining whether exploitable patterns exist in large data sets with minimal development time.	Ingersoll, Grant S., Thomas S. Morton, and Andrew L. Farris. *Taming Text: How to Find, Organize, and Manipulate It.* New Jersey: Manning, 2013. Print.
Neural Networks	Learns salient features in data by adjusting weights between nodes through a learning rule.	Training a neural network takes substantially longer than evaluating new data with an already trained network. Sparser network connectivity can help to segment the input space and improve performance on classification tasks.	Haykin, Simon O. *Neural Networks and Learning Machines.* New Jersey: Prentice Hall, 2008. Print.
Outlier Removal	Method for identifying and removing noise or artifacts from data.	Be cautious when removing outliers. Sometimes the most interesting behavior of a system is at times when there are aberrant data points.	Maimon, Oded, and Lior Rockach. *Data Mining and Knowledge Discovery Handbook: A Complete Guide for Practitioners and Researchers.* The Netherlands: Kluwer Academic Publishers, 2005. Print.
Principal Components Analysis	Enables dimensionality reduction by identifying highly correlated dimensions.	Many large datasets contain correlations between dimensions; therefore part of the dataset is redundant. When analyzing the resulting principal components, rank order them by variance as this is the highest information view of your data. Use skree plots to infer the optimal number of components.	Wallisch, Pascal, Michael E. Lusignan, Marc D. Benayoun, Tanya I. Baker, Adam Seth Dickey, and Nicholas G. Hatsopoulos. *Matlab for Neuroscientists.* New Jersey: Prentice Hall, 2009. Print.

Compiled by: Booz Allen Hamilton

Algorithms or Method Name	Description	Tips From the Pros	References and Papers We Love to Read
Regression with Shrinkage (Lasso)	A method of variable selection and prediction combined into a possibly biased linear model.	There are different methods to select the lambda parameter. A typical choice is cross validation with MSE as the metric.	Tibshirani, Robert. "Regression Shrinkage and Selection via the Lasso." *Journal of the Royal Statistical Society. Series B (Methodological)* 58.1 (1996): 267-288. Print.
Sensitivity Analysis	Involves testing individual parameters in an analytic or model and observing the magnitude of the effect.	Insensitive model parameters during an optimization are candidates for being set to constants. This reduces the dimensionality of optimization problems and provides an opportunity for speed up.	Saltelli, A., Marco Ratto, Terry Andres, Francesca Campolongo, Jessica Cariboni, Debora Gatelli, Michaela Saisana, and Stefano Tarantola. *Global Sensitivity Analysis: the Primer.* New Jersey: John Wiley & Sons, 2008. Print.
Simulated Annealing	Named after a controlled cooling process in metallurgy, and by analogy using a changing temperature or annealing schedule to vary algorithmic convergence.	The standard annealing function allows for initial wide exploration of the parameter space followed by a narrower search. Depending on the search priority the annealing function can be modified to allow for longer explorative search at a high temperature.	Bertsimas, Dimitris, and John Tsitsiklis. "Simulated Annealing." *Statistical Science.* 8.1 (1993): 10-15. Print.
Stepwise Regression	A method of variable selection and prediction. Akaike's information criterion *AIC* is used as the metric for selection. The resulting predictive model is based upon ordinary least squares, or a general linear model with parameter estimation via maximum likelihood.	Caution must be used when considering Stepwise Regression, as over fitting often occurs. To mitigate over fitting try to limit the number of free variables used.	Hocking, R. R. "The Analysis and Selection of Variables in Linear Regression." *Biometrics.* 32.1 (March 1976): 1-49. Print.
Stochastic Gradient Descent	General-purpose optimization for learning of neural networks, support vector machines, and logistic regression models.	Applied in cases where the objective function is not completely differentiable when using sub-gradients.	Witten, Ian H., Eibe Frank, and Mark A. Hall. *Data Mining: Practical Machine Learning Tools and Techniques.* Massachusetts: Morgan Kaufmann, 2011. Print.
Support Vector Machines	Projection of feature vectors using a kernel function into a space where classes are more separable.	Try multiple kernels and use k-fold cross validation to validate the choice of the best one.	Hsu, Chih-Wei, Chih-Chung Chang, and Chih-Jen Lin. "A Practical Guide to Support Vector Classification." *National Taiwan University.* 2003. Print.
Term Frequency Inverse Document Frequency	A statistic that measures the relative importance of a term from a corpus.	Typically used in text mining. Assuming a corpus of news articles, a term that is very frequent such as "the" will likely appear many times in many documents, having a low value. A term that is infrequent such as a person's last name that appears in a single article will have a higher TD IDF score.	Ingersoll, Grant S., Thomas S. Morton, and Andrew L. Farris. *Taming Text: How to Find, Organize, and Manipulate It.* New Jersey: Manning, 2013. Print.
Topic Modeling (Latent Dirichlet Allocation)	Identifies latent topics in text by examining word co-occurrence.	Employ part-of-speech tagging to eliminate words other than nouns and verbs. Use raw term counts instead of TF/IDF weighted terms.	Blei, David M., Andrew Y. Ng, and Michael I Jordan. "Latent Dirichlet Allocation." *Journal of Machine Learning Research.* 3 (March 2003): 993-1022. Print.
Tree Based Methods	Models structured as graph trees where branches indicate decisions.	Can be used to systematize a process or act as a classifier.	James, G., D. Witten, T. Hastie, and R Tibshirani. *Tree-Based Methods. In An Introduction to Statistical Learning.* New York: Springer, 2013. Print.
Wrapper Methods	Feature set reduction method that utilizes performance of a set of features on a model, as a measure of the feature set's performance. Can help identify combinations of features in models that achieve high performance.	Utilize k-fold cross validation to control over fitting.	John, G. H, R Kohavi, and K. Pfleger. "Irrelevant Features and the Subset Selection Problem." Proceedings of ICML-94, 11th International Conference on Machine Learning. New Brunswick, New Jersey. 1994. 121-129. 59. Conference Presentation.

Compiled by: Booz Allen Hamilton



LIFE *in* THE TRENCHES

NAVIGATING NECK DEEP IN DATA

Our Data Science experts have learned and developed new solutions over the years from properly framing or reframing analytic solutions. In this section, we list a few important topics to Data Science coupled with firsthand experience from our experts.

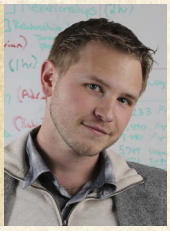
Feature Engineering

Feature engineering is a lot like oxygen. You can't do without it, but you rarely give it much thought.

Feature engineering is the process by which one establishes the representation of data in the context of an analytic approach. It is *the* foundational skill in Data Science. Without feature engineering, it would not be possible to understand and represent the world through a mathematical model. Feature engineering is a challenging art. Like other arts, it is a creative process that manifests uniquely in each Data Scientist. It will be influenced substantially by the scientist's experiences, tastes and understanding of the field.

As the name suggests, feature engineering can be a complex task that may involve chaining and testing different approaches. Features may be simple such as "bag of words," a popular technique in the text processing domain, or or may be based on more complex representations derived through activities such as machine learning. You make use of the output of one analytic technique to create the representation that is consumed by another. More often than not, you will find yourself operating in the world of highly complex activities.

›› Chemoinformatic Search



Ed Kohlwey

On one assignment, my team was confronted with the challenge of developing a search engine over chemical compounds. The goal of chemoinformatic search is to predict the properties that a molecule will exhibit as well as to provide indices over those predicted properties to facilitate data discovery in chemistry-based research. These properties may either be discreet (e.g., "a molecule treats disease x well") or continuous (e.g., "a molecule may be dissolved up to 100.21 g/ml").

Molecules are complex 3D structures, which are typically represented as a list of atoms joined by chemical bonds of differing lengths with varying electron domain and molecular geometries. The structures are specified by the 3-space coordinates and the electrostatic potential surface of the atoms in the molecule. Searching this data is a daunting task when one considers that naïve approaches to the problem bear significant semblance to the Graph Isomorphism Problem.[13]

The solution we developed was based on previous work in molecular fingerprinting (sometimes also called hashing or locality sensitive hashing). Fingerprinting is a dimensionality reduction technique that dramatically reduces the problem space by summarizing many features, often with relatively little regard to the importance of the feature. When an exact solution is likely to be infeasible, we often turn to heuristic approaches such as fingerprinting.

Our approach used a training set where all the measured properties of the molecules were available. We created a model of how molecular structural similarities might affect their properties. We began by finding all the sub-graphs of each molecule with length ***n***, resulting in a representation similar to the bag-of-words approach from natural language processing. We summarized each molecule fragment in a type of fingerprint called a "Counting Bloom Filter."

Next, we used several exemplars from the set to create new features. We found the distance from each member of the full training set to each of the exemplars. We fed these features into a non-linear regression algorithm to yield a model that could be used on data that was not in the original training set. This approach can be conceptualized as a "hidden manifold," whereby a hidden surface or shape defines how a molecule will exhibit a property. We approximate this shape using a non-linear regression and a set of data with known properties. Once we have the approximate shape, we can use it to predict the properties of new molecules.

Our approach was multi-staged and complex – we generated sub-graphs, created bloom filters, calculated distance metrics and fit a linear-regression model. This example provides an illustration of how many stages may be involved in producing a sophisticated feature representation. By creatively combining and building "features on features," we were able to create new representations of data that were richer and more descriptive, yet were able to execute faster and produce better results.

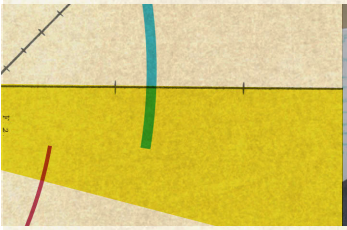
Feature Selection

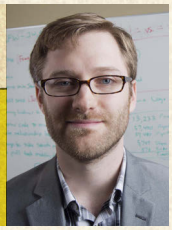
Models are like honored guests; you should only feed them the good parts.

Feature selection is the process of determining the set of features with the highest information value to the model. Two main approaches are filtering and wrapper methods. Filtering methods analyze features using a test statistic and eliminate redundant or non-informative features. As an example, a filtering method could eliminate features that have little correlation to the class labels. Wrapper methods utilize a classification model as part of feature selection. A model is trained on a set of features and the classification accuracy is used to measure the information value of the feature set. One example is that of training a neural network with a set of features and evaluating the accuracy of the model. If the model scores highly on the test set, then the features have high information value. All possible combinations of features are tested to find the best feature set.

There are tradeoffs between these techniques. Filtering methods are faster to compute since each feature only needs to be compared against its class label. Wrapper methods, on the other hand, evaluate feature sets by constructing models and measuring performance. This requires a large number of models to be trained and evaluated (a quantity that grows exponentially in the number of features). Why would anyone use a wrapper method? Feature sets may perform better than individual features.[14] With filter methods, a feature with weak correlation to its class labels is eliminated. Some of these eliminated features, however, may have performed well when combined with other features.

›› Cancer Cell Classification





Paul Yacci

On one project, our team was challenged to classify cancer cell profiles. The overarching goal was to classify different types of Leukemia, based on Microarray profiles from 72 samples[15] using a small set of features. We utilized a hybrid Artificial Neural Network (ANN)[16] and Genetic Algorithm[17] to identify subsets of 10 features selected from thousands.[18] We trained the ANN and tested performance using cross-fold validation. The performance measure was used as feedback into the Genetic Algorithm. When a set of features contained no useful information, the model performed poorly and a different feature set would be explored. Over time, this method selected a set of features that performed with high accuracy. The down-selected feature set increased speed and performance as well as allowed for better insight into the factors that may govern the system. This allowed our team to design a diagnostic test for only a few genetic markers instead of thousands, substantially reducing diagnostic test complexity and cost.

Data Veracity

We're Data Scientists, not data alchemists. We can't make analytic gold from the lead of data.

While most people associate data volume, velocity, and variety with big data, there is an equally important yet often overlooked dimension – data veracity. Data veracity refers to the overall quality and correctness of the data. You must assess the truthfulness and accuracy of the data as well as identify missing or incomplete information. As the saying goes, "Garbage in, garbage out." If your data is inaccurate or missing information, you can't hope to make analytic gold.

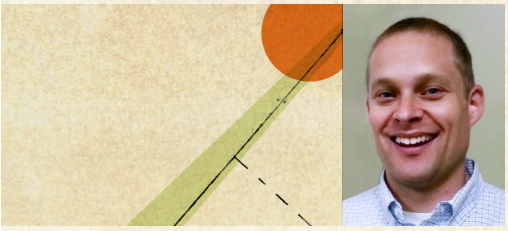
Assessing data truthfulness is often subjective. You must rely on your experience and an understanding of the data origins and context. Domain expertise is particularly critical for the latter. Although data accuracy assessment may also be subjective, there are times that quantitative methods may be used. You may be able to re-sample from the population and conduct a statistical comparison against the stored values, thereby providing measures of accuracy.

The most common issues you will encounter are missing or incomplete information. There are two basic strategies for dealing with missing values – deletion and imputation. In the former, entire observations are excluded from analysis, reducing sample size and potentially introducing bias. Imputation, or replacement of missing or erroneous values, uses a variety of techniques such as random sampling (hot deck imputation) or replacement using the mean, statistical distributions or models.

»Tips From the Pros

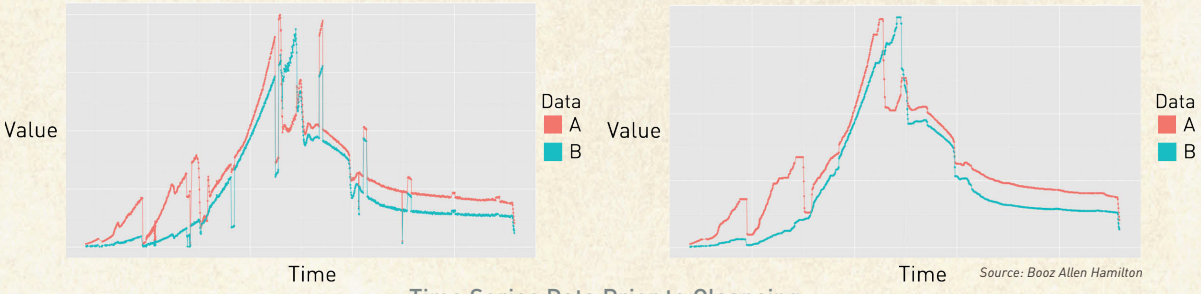
Find an approach that works, implement it, and move on. You can worry about optimization and tuning your approaches later during incremental improvement.

›› Time Series Modeling



Brian Keller

On one of our projects, the team was faced with correlating the time series for various parameters. Our initial analysis revealed that the correlations were almost non-existent. We examined the data and quickly discovered data veracity issues. There were missing and null values, as well as negative-value observations, an impossibility given the context of the measurements (see the figure, *Time Series Data Prior to Cleansing*). Garbage data meant garbage results.

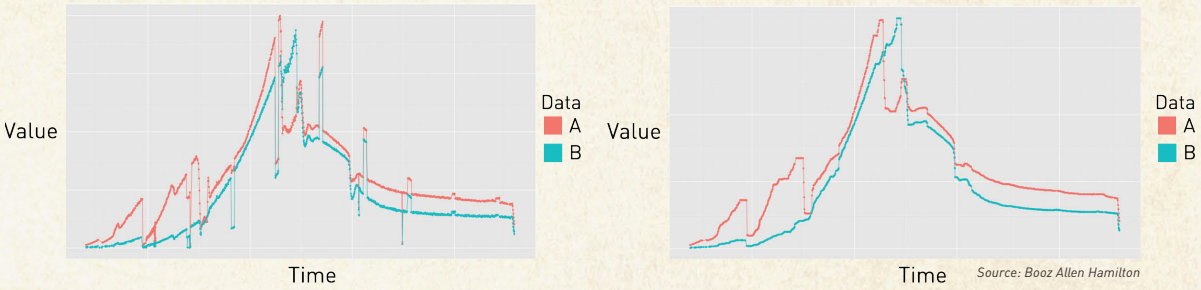


Time Series Data Prior to Cleansing

Because sample size was already small, deleting observations was undesirable. The volatile nature of the time series meant that imputation through sampling could not be trusted to produce values in which the team would be confident. As a result, we quickly realized that the best strategy was an approach that could filter and correct the noise in the data.

We initially tried a simplistic approach in which we replaced each observation with a moving average. While this corrected some noise, including the outlier values in our moving-average computation shifted the time series. This caused undesirable distortion in the underlying signal, and we quickly abandoned the approach.

One of our team members who had experience in signal processing suggested a median filter. The median filter is a windowing technique that moves through the data point-by-point, and replaces it with the median value calculated for the current window. We experimented with various window sizes to achieve an acceptable tradeoff between smoothing noise and smoothing away signal. The figure, *Time Series Data After Cleansing*, shows the same two time series after median filter imputation.



Time Series Data After Cleansing

The application of the median filter approach was hugely successful. Visual inspection of the time series plots reveals smoothing of the outliers without dampening the naturally occurring peaks and troughs (no signal loss). Prior to smoothing, we saw no correlation in our data, but afterwards, Spearman's Rho was ~0.5 for almost all parameters.

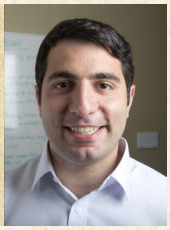
By addressing our data veracity issues, we were able to create analytic gold. While other approaches may also have been effective, implementation speed constraints prevented us from doing any further analysis. We achieved the success we were after and moved on to address other aspects of the problem.

Application of Domain Knowledge

We are all special in our own way. Don't discount what you know.

Knowledge of the domain in which a problem lies is immensely valuable and irreplaceable. It provides an in-depth understanding of your data and the factors influencing your analytic goal. Many times domain knowledge is a key differentiator to a Data Science team's success. Domain knowledge influences how we engineer and select features, impute data, choose an algorithm, and determine success. One person cannot possibly be a domain expert in every field, however. We rely on our team, other analysts and domain experts as well as consult research papers and publications to build an understanding of the domain.

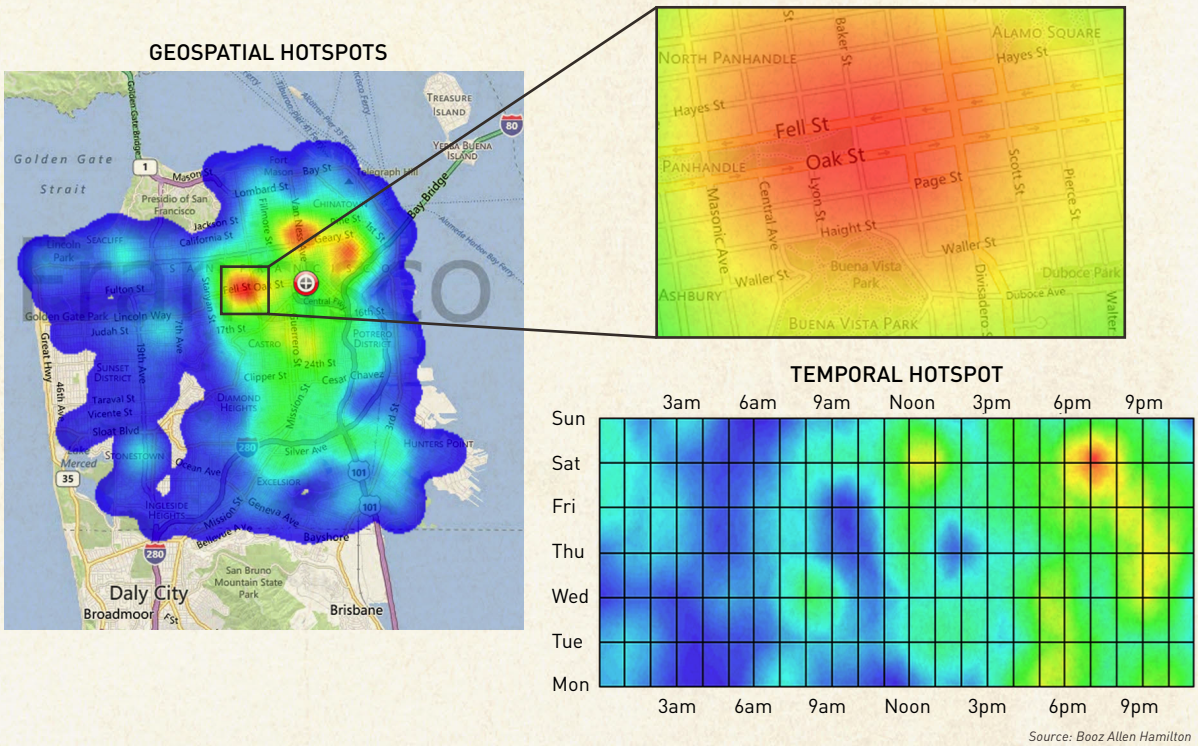
›› Motor Vehicle Theft



Armen Kherlopian

On one project, our team explored how Data Science could be applied to improve public safety. According to the FBI, approximately $8 Billion is lost annually due to automobile theft. Recovery of the one million vehicles stolen every year in the U.S. is less than 60%. Dealing with these crimes represents a significant investment of law enforcement resources. We wanted to see if we could identify how to reduce auto theft while efficiently using law enforcement resources.

Our team began by parsing and verifying San Francisco crime data. We enriched stolen car reporting with general city data. After conducting several data experiments across both space and time, three geospatial and one temporal hotspot emerged (see figure, *Geospatial and Temporal Car Theft Hotspots*). The domain expert on the team was able to discern that the primary geospatial hotspot corresponded to an area surrounded by parks. The parks created an urban mountain with a number of over-foot access points that were conducive to car theft.



Source: Booz Allen Hamilton

Geospatial and Temporal Car Theft Hotspots

Our team used the temporal hotspot information in tandem with the insights from the domain expert to develop a Monte Carlo model to predict the likelihood of a motor vehicle theft at particular city intersections. By prioritizing the intersections identified by the model, local governments would have the information necessary to efficiently deploy their patrols. Motor vehicle thefts could be reduced and law enforcement resources could be more efficiently deployed. The analysis, enabled by domain expertise, yielded actionable insights that could make the streets safer.

The Curse of Dimensionality

There is no magical potion to cure the curse, but there is PCA.

The "curse of dimensionality" is one of the most important results in machine learning. Most texts on machine learning mention this phenomenon in the first chapter or two, but it often takes many years of practice to understand its true implications.

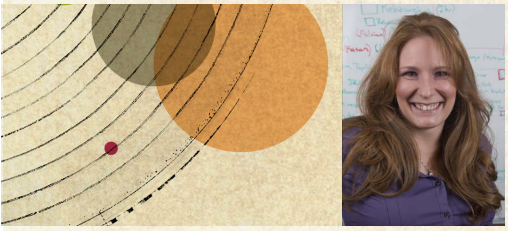
Classification methods, like most machine learning methods, are subject to the implications of the curse of dimensionality. The basic intuition in this case is that as the number of data dimensions increases, it becomes more difficult to create generalizable classification models (models that apply well over phenomena not observed in the training set). This difficulty is usually impossible to overcome in real world settings. There are some exceptions in domains where things happen to work out, but usually you must work to minimize the number of dimensions. This requires a combination of clever feature engineering and use of dimensionality reduction techniques (see *Feature Engineering* and *Feature Selection Life in the Trenches*). In our practical experience, the maximum number of dimensions seems to be ~10 for linear model-based approaches. The limit seems to be in the tens of thousands for more sophisticated methods such as support vector machines, but the limit still exists nonetheless.

A counterintuitive consequence of the curse of dimensionality is that it limits the amount of data needed to train a classification model. There are roughly two reasons for this phenomenon. In one case, the dimensionality is small enough that the model can be trained on a single machine. In the other case, the exponentially expanding complexity of a high-dimensionality problem makes it (practically) computationally impossible to train a model. In our experience, it is quite rare for a problem to fall in a "sweet spot" between these two extremes.

This observation is not to say that such a condition never arises. We believe it is rare enough, however, that practitioners need not concern themselves with how to address this case. Rather than trying to create super-scalable algorithm implementations, focus your attention on solving your immediate problems with basic methods. Wait until you encounter a problem where an algorithm fails to converge or provides poor cross-validated results, and then seek new approaches. Only when you find that alternate approaches don't already exist, should you begin building new implementations. The expected cost of this work pattern is lower than over-engineering right out of the gate.

Put otherwise, "Keep it simple, stupid".

›› Baking the Cake



Stephanie Rivera

I was once given a time series set of roughly 1,600 predictor variables and 16 target variables and asked to implement a number of modeling techniques to predict the target variable values. The client was challenged to handle the complexity associated with the large number of variables and needed help. Not only did I have a case of the curse, but the predictor variables were also quite diverse. At first glance, it looked like trying to bake a cake with everything in the cupboard. That is not a good way to bake or to make predictions!

The data diversity could be partially explained by the fact that the time series predictors did not all have the same periodicity. The target time series were all daily values whereas the predictors were daily, weekly, quarterly, and monthly. This was tricky to sort out, given that imputing zeros isn't likely to produce good results. For this specific reason, I chose to use neural networks for evaluating the weekly variable contributions.

Using this approach, I was able to condition upon week, without greatly increasing the dimensionality. For the other predictors, I used a variety of techniques, including projection and correlation, to make heads or tails of the predictors. My approach successfully reduced the number of variables, accomplishing the client's goal of making the problem space tractable. As a result, the cake turned out just fine.

Model Validation

Repeating what you just heard does not mean that you learned anything.

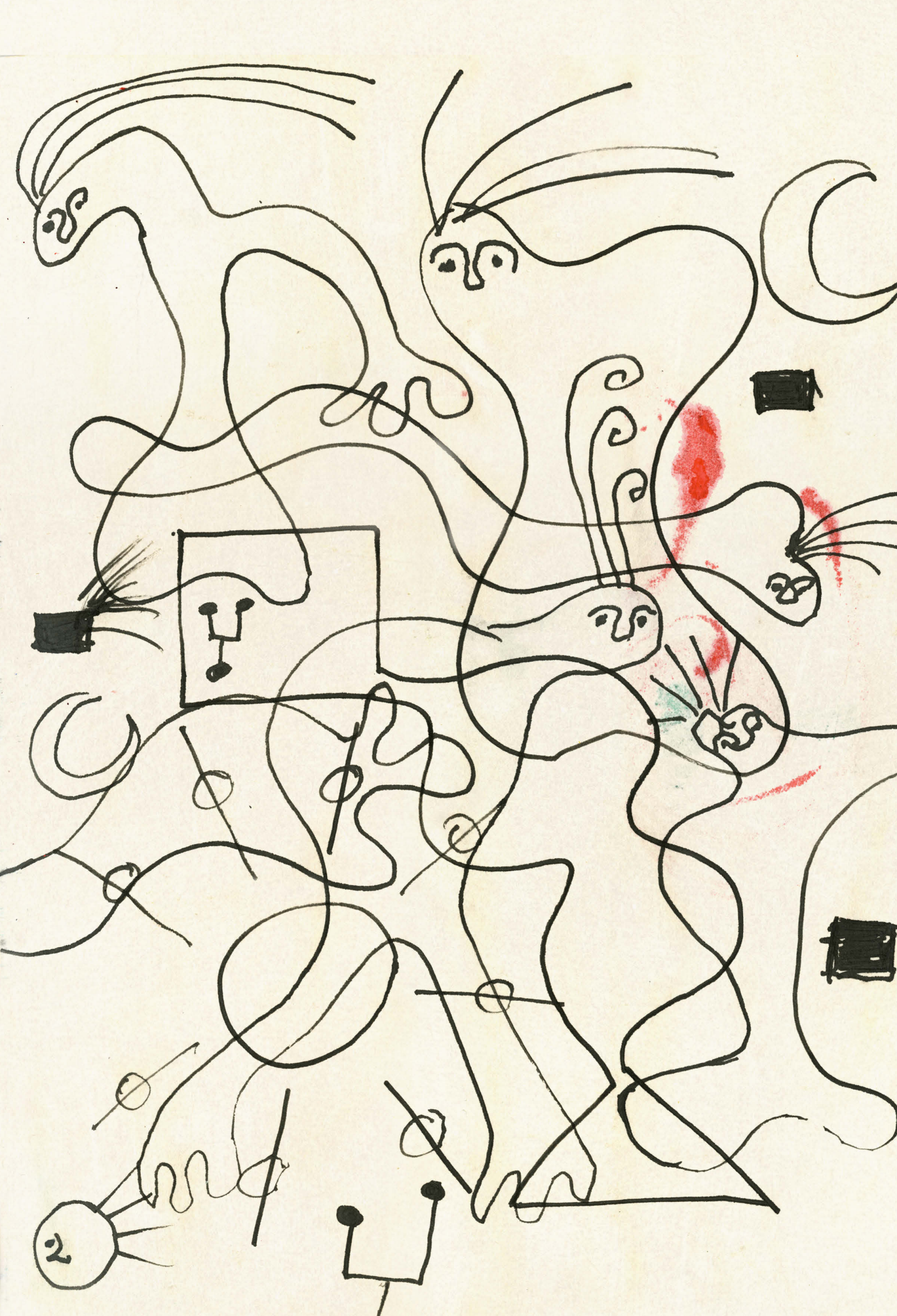
Model validation is central to construction of any model. This answers the question "How well did my hypothesis fit the observed data?" If we do not have enough data, our models cannot connect the dots. On the other hand, given too much data the model cannot think outside of the box. The model learns specific details about the training data that do not generalize to the population. This is the problem of model over fitting.

Many techniques exist to combat model over fitting. The simplest method is to split your data set into training, testing and validation sets. The training data is used to construct the model. The model constructed with the training data is then evaluated with the testing data. The performance of the model against the testing set is used to further reduce model error. This indirectly includes the testing data within model construction, helping to reduce model over fit. Finally, the model is evaluated on the validation data to assess how well the model generalizes.

A few methods where the data is split into training and testing sets include: *k*-fold cross-validation, Leave-One-Out cross-validation, bootstrap methods, and resampling methods. Leave-One-Out cross-validation can be used to get a sense of ideal model performance over the training set. A sample is selected from the data to act as the testing sample and the model is trained on the rest of the data. The error on the test sample is calculated and saved, and the sample is returned to the data set. A different sample is then selected and the process is repeated. This continues until all samples in the testing set have been used. The average error over the testing examples gives a measure of the model's error.

»Do we really need a case study to know that you should check your work?

There are other approaches for testing how well your hypothesis reflects the data. Statistical methods such as calculating the coefficient of determination, commonly called the *R*-squared value are used to identify how much variation in the data your model explains. Note that as the dimensionality of your feature space grows, the *R*-squared value also grows. An adjusted *R*-squared value compensates for this phenomenon by including a penalty for model complexity. When testing the significance of the regression as a whole, the F-test compares the explained variance to unexplained variance. A regression result with a high F-statistic and an adjusted *R*-squared over 0.7 is almost surely significant.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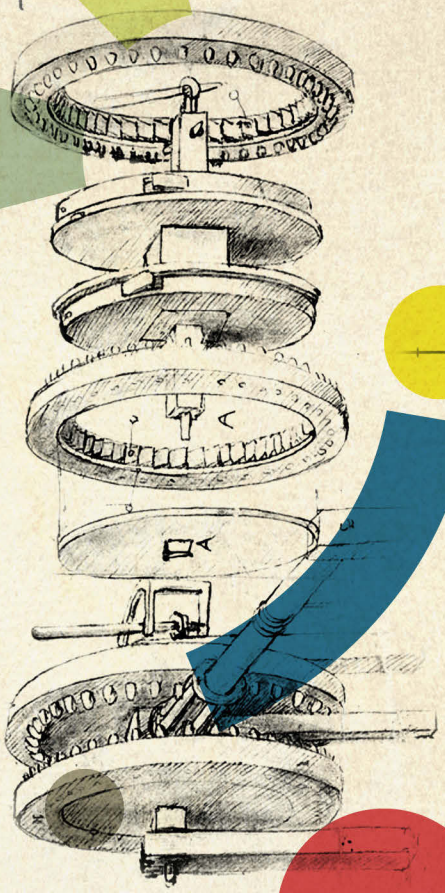


PUTTING *it* ALL TOGETHER

›› Consumer Behavior Analysis from a Multi-Terabyte Dataset

» Our Case Studies

Hey, we have given you a lot of really good technical content. We know that this section has the look and feel of marketing material, but there is still a really good story here. Remember, storytelling comes in many forms and styles, one of which is the marketing version. You should read this chapter for what it is – great information told with a marketing voice.

Analytic Challenge

After storing over 10 years' worth of retail transaction in the natural health space, a retail client was interested in employing advanced machine learning techniques to mine the data for valuable insights. The client wanted to develop a database structure for long term implementation of retail supply chain analytics and select the proper algorithms needed to develop insights into supplier, retailer, and consumer interactions. Determining the actual worth of applying big data analytics to the end-to-end retail supply chain was also of particular interest.

Our Approach

The client's data included 3TBs of product descriptions, customer loyalty information and B2B and B2C transactions for thousands of natural health retailers across North America. Because the data had been stored in an ad-hoc fashion, the first step was creating a practical database structure to enable analytics. We selected a cloud environment in order to quickly implement analytics on the client's disparate and sometimes redundant datasets. Once we created a suitable analytics architecture, we moved on to identifying appropriate machine learning techniques that would add value across three key focus areas: product receptivity, loyal program analysis, and market basket analysis.

For product receptivity, our team used Bayesian Belief Networks (BBN) to develop probabilistic models to predict the success, failure, and longevity of a new or current product. We joined transaction data with attribute data of both successful and failed products to

transform the data into usable form. Once we created this data file, we used it to train BBNs and create a predictive model for future products.

For loyalty program analysis, we joined transactional data and customer attribute data, which included location information and shopping trends. We used *k*-means clustering to segment customers based on their behavior over time. This allowed us to cluster and characterize groups of customers that exhibited similar loyalty patterns.

For market basket analysis, we employed Latent Dirichlet Allocation (LDA), a natural language processing technique, to create consistent product categorization. The client's product categorization was ad-hoc, having been entered by individual suppliers and retailers. As a result, it was inconsistent and often contained typographical errors or missing values. LDA allowed our team to use the existing text to derive new, consistent customer categories for the market basket analysis. After joining the new product categorization data with transaction data, we used Association Rules Learning to identify sets of product categories that customers tended to purchase together at individual retailer locations.

Our Impact

Our team provided key findings and recommendations to describe how the machine learning techniques could be operationalized to provide real-time reporting to retailers. The client received suggestions for improving product nomenclature, product promotions, and end-to-end visibility of the product and process lifecycle. As an example, we used our market basket analysis to create product recommendations for individual retail locations. Our recommendations have the potential to improve sales within certain product categories by up to 50% across the retail network. Together with time savings realized from automated data processing (such as a 300x increase in product categorization speed), these insights demonstrated the clear value of big data analytics to the client's organization.

›› Strategic Insights within Terabytes of Passenger Data

Analytic Challenge

A commercial airline client was faced with increasing market competition and challenges in profitability. They wanted to address these challenges with rapid deployment of advanced, globalized analytical tools within their private electronic data warehouse. In the past, the client had analyzed smaller datasets in-house. Because smaller datasets are filtered or diluted subsets of the full data, the airline had not been able to extract the holistic understanding it was seeking.

Booz Allen was engaged to create capabilities to analyze hundreds of gigabytes of client data. The ultimate goal was to generate insights into airline operations, investment decisions and consumer preferences that may not have been apparent from studying data subsets. Specifically, the airline wanted to be able to understand issues such as: how they perform in different city-pair markets relative to competitors; how booking behaviors change, based on passenger and flight characteristics; and how connection times impact demand.

Our Solution

Due to data privacy issues, our team set up a cloud environment within the client's electronic data warehouse. Leveraging this analytic environment, analysis proceeded with an approach that focused on the client's three priorities: market performance, booking behavior, and passenger choice.

We performed probabilistic analysis using machine learning techniques, particularly Bayesian Belief Networks (BBN). We merged passenger booking and other data to create a BBN training file. Our team developed and validated comprehensive BBN models to represent significant customer behavior and market-based factors that influence passenger preference, with respect to selection of flights by connection times. Finally, our team developed custom big data visualizations to convey the findings to technical and non-technical audiences alike.

Our Impact

We demonstrated the ability to rapidly deploy big data analytical tools and machine learning on massive datasets located inside a commercial airline's private cloud environment. Results included insights that seemed counterintuitive, but could improve financial performance nonetheless. An example of one such finding was that under certain circumstances, passengers are willing to pay a premium to book itineraries with modified connection times. This translates into a potential revenue increase of many millions of dollars. These insights, often at the level of named customers, can be acted upon immediately to improve financial performance.

›› Savings Through Better Manufacturing

Analytic Challenge

A manufacturing company engaged Booz Allen to explore data related to chemical compound production. These processes are quite complex. They involve a long chain of interconnected events, which ultimately leads to high variability in product output. This makes production very expensive.

Understanding the production process is not easy – sensors collect thousands of time series variables and thousands of point-in-time measurements, yielding terabytes of data. There was a huge opportunity if the client could make sense of this data. Reducing the variance and improving the product yield by even a small amount could result in significant cost savings.

Our Solution

Due to the size and complexity of the process data, prior analysis efforts that focused on data from only a single sub-process had limited success. Our Data Science team took a different approach: analyzing *all* the data from *all* the sub-processes with the goal of identifying the factors driving variation. Once we understood those factors, we could develop recommendations on how to control them to increase yield. The client's process engineers had always wanted to pursue this approach but lacked the tools to carry out the analysis.

We decomposed the problem into a series of smaller problems. First, it was necessary to identify which time series parameters likely affected product yield. We engaged the client's domain experts to identify their hypotheses surrounding the process. Once we discerned a set of hypotheses, we identified the sensors that collected the relevant data.

We began initial data processing, which included filtering bad values and identifying patterns in the time series. We then needed to segment the data streams into individual production runs. We identified a sensor that stored the high-level information indicating when a production process began. This sensor provided exactly what we needed, but we quickly noticed that half of the expected data was missing. Examining the data more closely, we realized the sensor had only been used within recent years. We had to take a step back and reassess our plan. After discussions with the domain experts, we identified a different sensor

that gave us raw values directly from the production process. The raw values included a tag that indicated the start of a production run. The sensor was active for every production run and could be used reliably to segment the data streams into production runs.

Next, we had to determine which time series parameters affected product yield. Using the cleaned and processed data and a non-parametric correlation technique, we compared each time series in a production run to all other time series in that same run. Given the pair-wise similarities, we estimated correlation of the similarities to final product yield. We then used the correlations as input into a clustering algorithm to find clusters of time series parameters that correlated with each other in terms of product yield, not in terms of the time series themselves. This data analysis was at a scale not previously possible – millions of comparisons for whole production runs. Engineers were able to look at *all* the data for the first time, and to see impacts of specific parameters across different batches and sensors.

In addition to identifying the key parameters, the engineers needed to know how to control the parameters to increase product yield. Discussions with domain experts provided insight into which time series parameters could be easily controlled. This limited the candidate parameters to only those that the process engineers could influence. We extracted features from the remaining time series signals and fed them into our models to predict yield. The models quantified the correlation between the pattern of parameter values and yield, providing insights on how to increase product yield.

Our Impact

With controls identified and desirable patterns quantified, we provided the engineers with a set of process control actions to improve product output. The raw sensor data that came directly from the production process drove our analysis and recommendations, thus providing the client with confidence in the approach. The reduction in product yield variability will enable the client to produce a better product with lower risk at a reduced cost.

›› Realizing Higher Returns Through Predictive Analytics

Analytic Challenge

A major investment house wanted to explore whether the application of Data Science techniques could yield increased investment returns. In particular, the company wanted to predict future commodity value movements based on end-of-day and previous-day equity metrics. The client hoped the predictions could be used to optimize their trading activities. By translating the approach across their entire portfolio, they could dramatically improve the yield curve for their investors.

Several challenges were immediately apparent. The data volume was very large, consisting of information from tens of thousands of equities, commodities, and options across most major world markets across multiple time intervals. The need to recommend a predictive action (go short, go long, stay, increase position size, or engage in a particular option play) with very low latency was an even greater challenge. The team would need to develop an approach that addressed both of these implicit constraints.

Our Solution

The client challenged Booz Allen to use 3,500 independent variables to predict the daily price movements of 16 financial instruments. The client hid the meaning and context of the independent variables, however, forcing our team to perform analysis without qualitative information. The team immediately began searching for supplemental data sources. We identified unstructured data from other companies, financial institutions, governments and social media that could be used in our analysis. The team paid considerable attention to database access efficiency and security as well as the speed of computation.

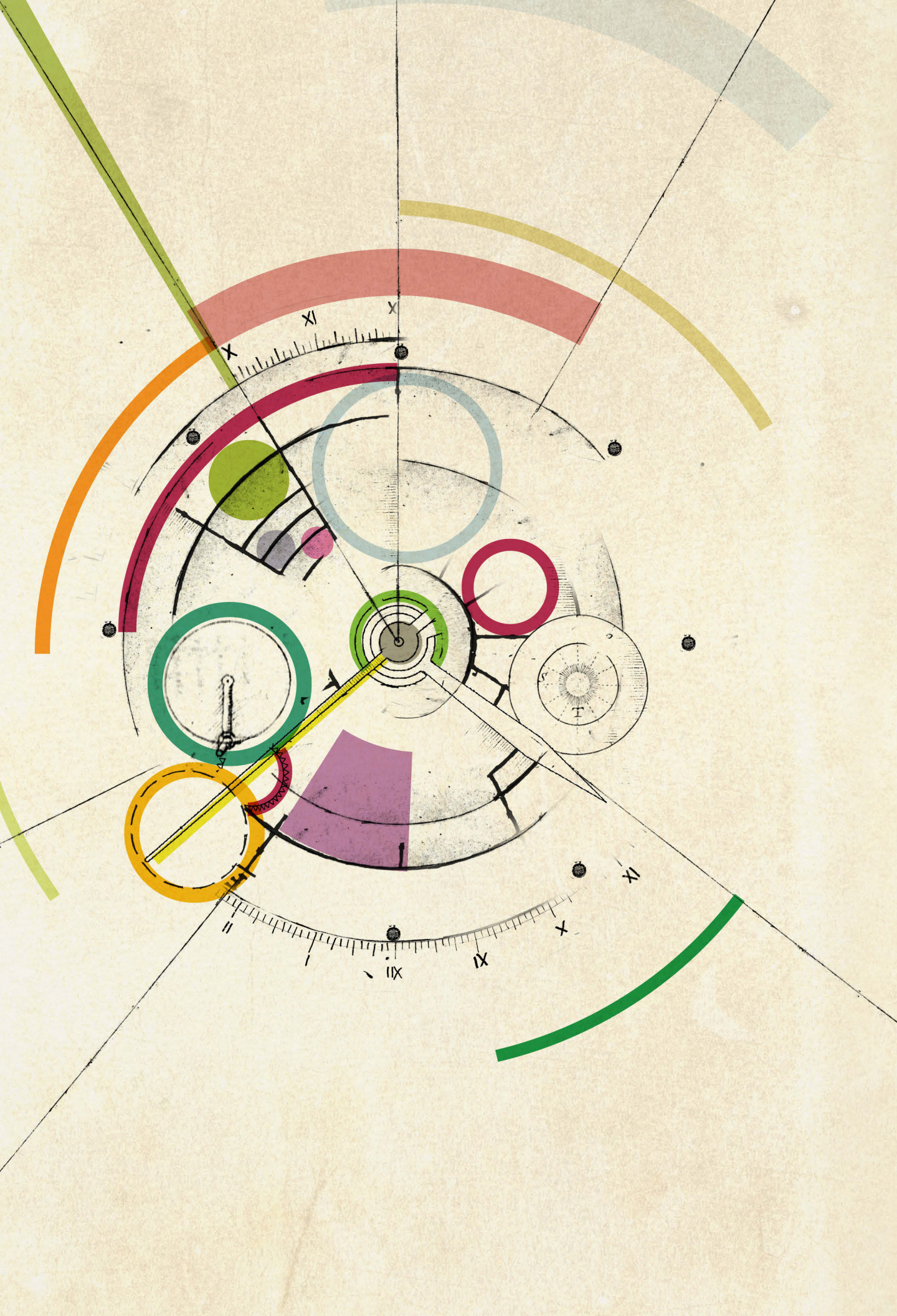
Our team implemented a multifaceted approach, including a mix of neural network optimization and a variety of principal component, regression, and unsupervised learning techniques. We were able to infer insight into small-scale exogenous events that provided a richer basis for predicting localized fluctuations in the equity prices. Our team was able to use these predictions to determine the optimal combination of actions

that would generate the best aggregate return over 12 months of trading. Careful consideration of the residuals and skilled modeling of the variance added additional value to the outcome for this client.

Our Impact

Our Data Science team conducted an experiment to determine the efficacy of our approach. We used our model to generate buy/sell recommendations based on training data provided by the client. The test cases converged on a set of recommendations in less than ten minutes, satisfying the solution timeliness constraint. The experiment revealed a true positive accuracy of approximately 85% with a similar outcome for true negative accuracy when compared against optimal recommendations based on perfect information. The typical return on investment was, as desired, quite large.

The ability to determine the position to take, not just for a single financial instrument but also for a complete portfolio, is invaluable for this client. Achieving this outcome required predictive analytics and the ability to rapidly ingest and process large data sets, including unstructured data. This could not have been accomplished without a diverse team of talented Data Scientists bringing the entirety of their tradecraft to bear on the problem.



CLOSING **TIME**

PARTING THOUGHTS

Data Science capabilities are creating data analytics that are improving every aspect of our lives, from life-saving disease treatments, to national security, to economic stability, and even the convenience of selecting a restaurant. We hope we have helped you truly understand the potential of your data and how to become extraordinary thinkers by asking the right questions of your data. We hope we have helped drive forward the science and art of Data Science. Most importantly, we hope you are leaving with a newfound passion and excitement for Data Science.

Thank you for taking this journey with us. Please join our conversation and let your voice be heard. Email us your ideas and perspectives at **data_science@bah.com** or submit them via a pull request on the **Github repository**.

Tell us and the world what you know. Join us. Become an author of this story.

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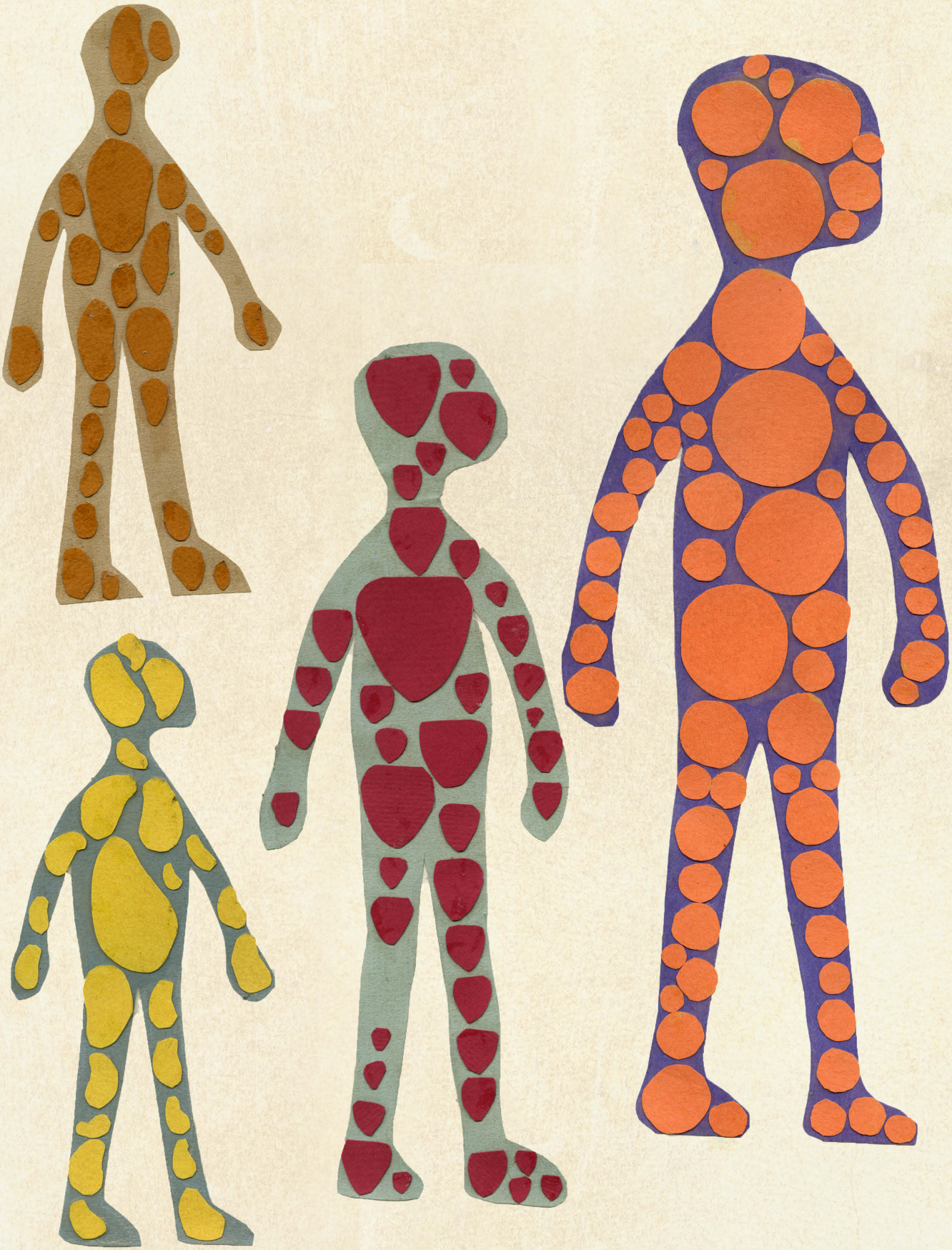


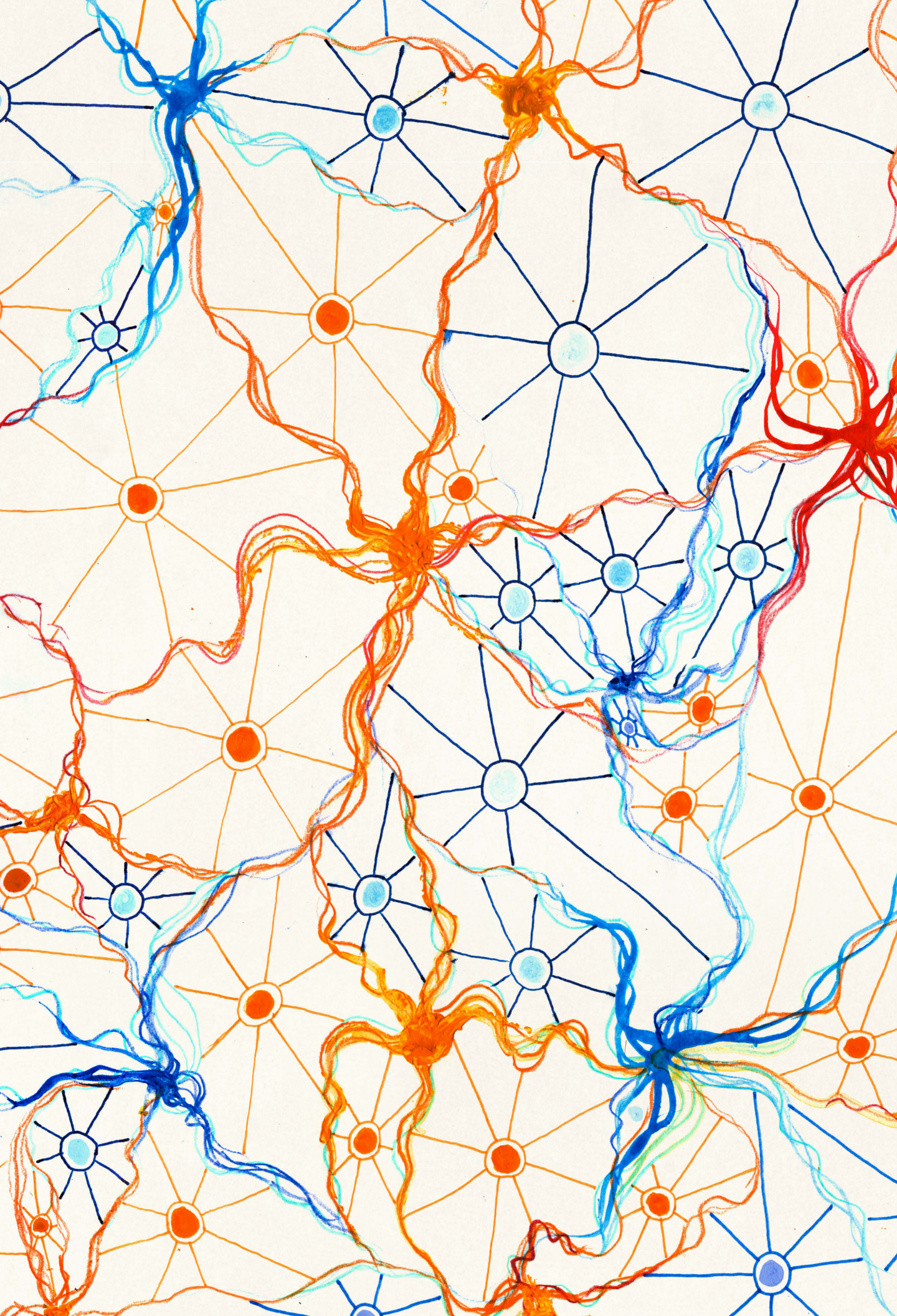
›› *About*

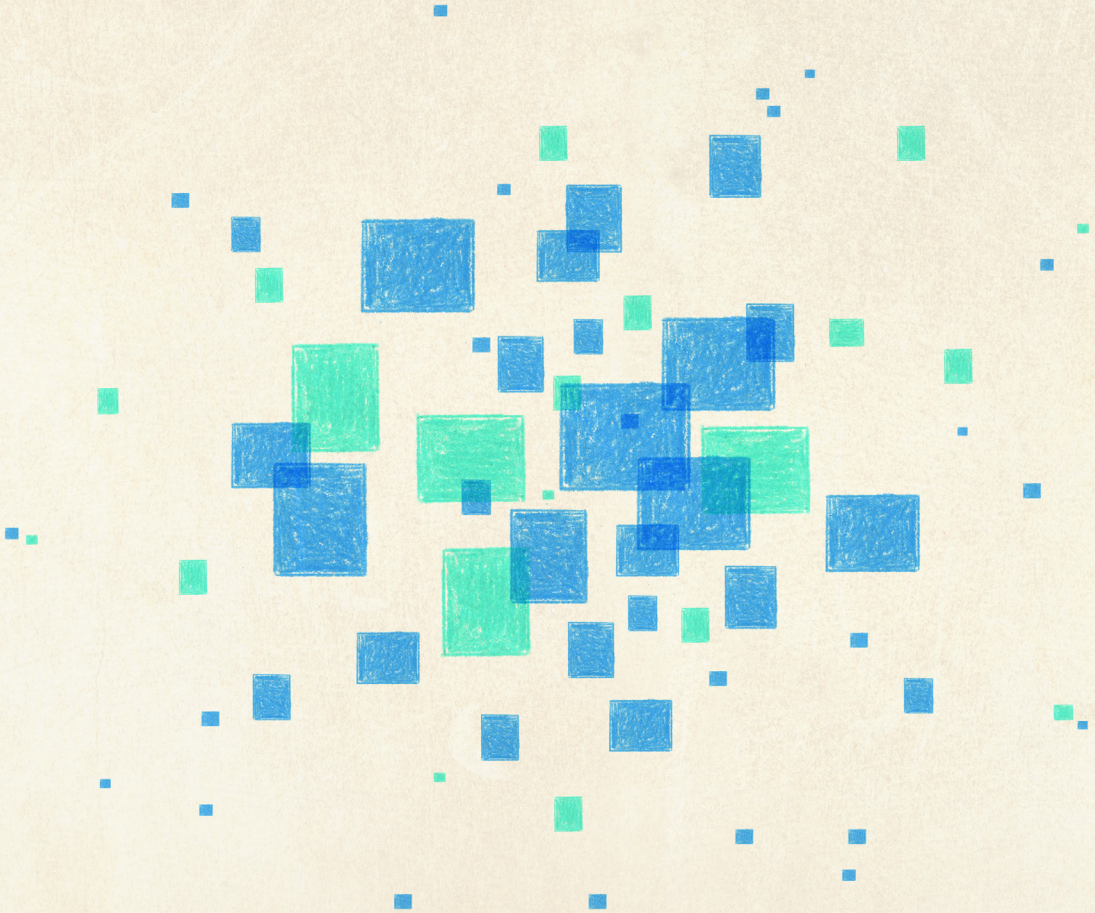
BOOZ ALLEN HAMILTON

Booz Allen Hamilton has been at the forefront of strategy and technology consulting for nearly a century. Today, Booz Allen is a leading provider of management consulting, technology, and engineering services to the US government in defense, intelligence, and civil markets, and to major corporations, institutions, and not-for-profit organizations. In the commercial sector, the firm focuses on leveraging its existing expertise for clients in the financial services, healthcare, and energy markets, and to international clients in the Middle East. Booz Allen offers clients deep functional knowledge spanning consulting, mission operations, technology, and engineering—which it combines with specialized expertise in clients' mission and domain areas to help solve their toughest problems.

The firm's management consulting heritage is the basis for its unique collaborative culture and operating model, enabling Booz Allen to anticipate needs and opportunities, rapidly deploy talent and resources, and deliver enduring results. By combining a consultant's problem-solving orientation with deep technical knowledge and strong execution, Booz Allen helps clients achieve success in their most critical missions—as evidenced by the firm's many client relationships that span decades. Booz Allen helps shape thinking and prepare for future developments in areas of national importance, including cybersecurity, homeland security, healthcare, and information technology.

Booz Allen is headquartered in McLean, Virginia, employs more than 23,000 people, and had revenue of $5.76 billion for the 12 months ended March 31, 2013. For over a decade, Booz Allen's high standing as a business and an employer has been recognized by dozens of organizations and publications, including Fortune, Working Mother, G.I. Jobs, and DiversityInc. More information is available at www.boozallen.com. (NYSE: BAH)





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