THE CIVIS GUIDE TO ANALYTICS MATURITY

HOW TO MAKE THE RIGHT DECISIONS ABOUT HOW YOU MAKE DECISIONS

CIVIS

Your business needs to make the right decisions and you know data, not a gut feeling, is how to make the right decisions with certainty every single day.

If you're reading this, you know the world has completely changed and that making decisions based on gut reaction or anecdotal evidence just won't work anymore.

Whether you are responsible for customer acquisition or engagement, measuring and maximizing returns on a large media spend, understanding drivers of engagement in order to do workforce planning, or turning unstructured data sources into something actionable, you're asking yourself what steps you should take to be as data-driven as possible. You are rightly worried because there are many missteps to take along the way—costly technology adoption, pricey consultations, initiatives without an organization-wide impact—and you don't have a clear vision of the best way to make data an integral part of decision-making at your organization.

At Civis, we have customers who are at different stages of using their data to drive the outcomes they care about and from experience we know that no single action, technology, or model is going to solve all of your problems. Far too many businesses end up with analytics advice, services, or software that don't fit their needs. Each business is different, but one thing is the same: the path to the outcomes you care about always involves a unique mixture of people, data, technology, and scientific tools.

We wrote this guide to accomplish three things:

1. First, we want to help you quickly assess where you are so you can ask the right questions to understand your own needs.
2. Second, we want to impart a structured way of thinking about all of the ingredients for successfully leveraging the data you have to drive the business outcomes you care about.
3. Finally, we want you to be a voice for change in your organization. Take our point of view, and make it your own. Share this document with like-minded individuals and champions for progress

Successful data-driven businesses are products of evolution, not revolution, and our hope is that after reading this guide, you'll have a clearer picture of the steps you need to take to make data an essential part of your business so you can make the right decisions every day.

ABOUT THE AUTHORS

Directors of Data Science Katie Malone and Skipper Seabold lead a team of data scientists responsible for researching and developing new methods to solve complex data problems.

Katie Malone, before joining Civis, worked at the Large Hadron Collider at CERN in Geneva, Switzerland, on Higgs boson searches. She also spent a summer working at the online education startup Udacity, where she launched her podcast Linear Digressions. Katie graduated from Ohio State University with a major in Engineering Physics and received her PhD in Particle Physics from Stanford.

Skipper Seabold is an economist by training and has been a leader in the Python data community for over a decade. Skipper initiated and led the statsmodels project and was a key member of the pandas team, which created a Python software library for data manipulation and analysis. Skipper is a PhD candidate in Economics at American University.

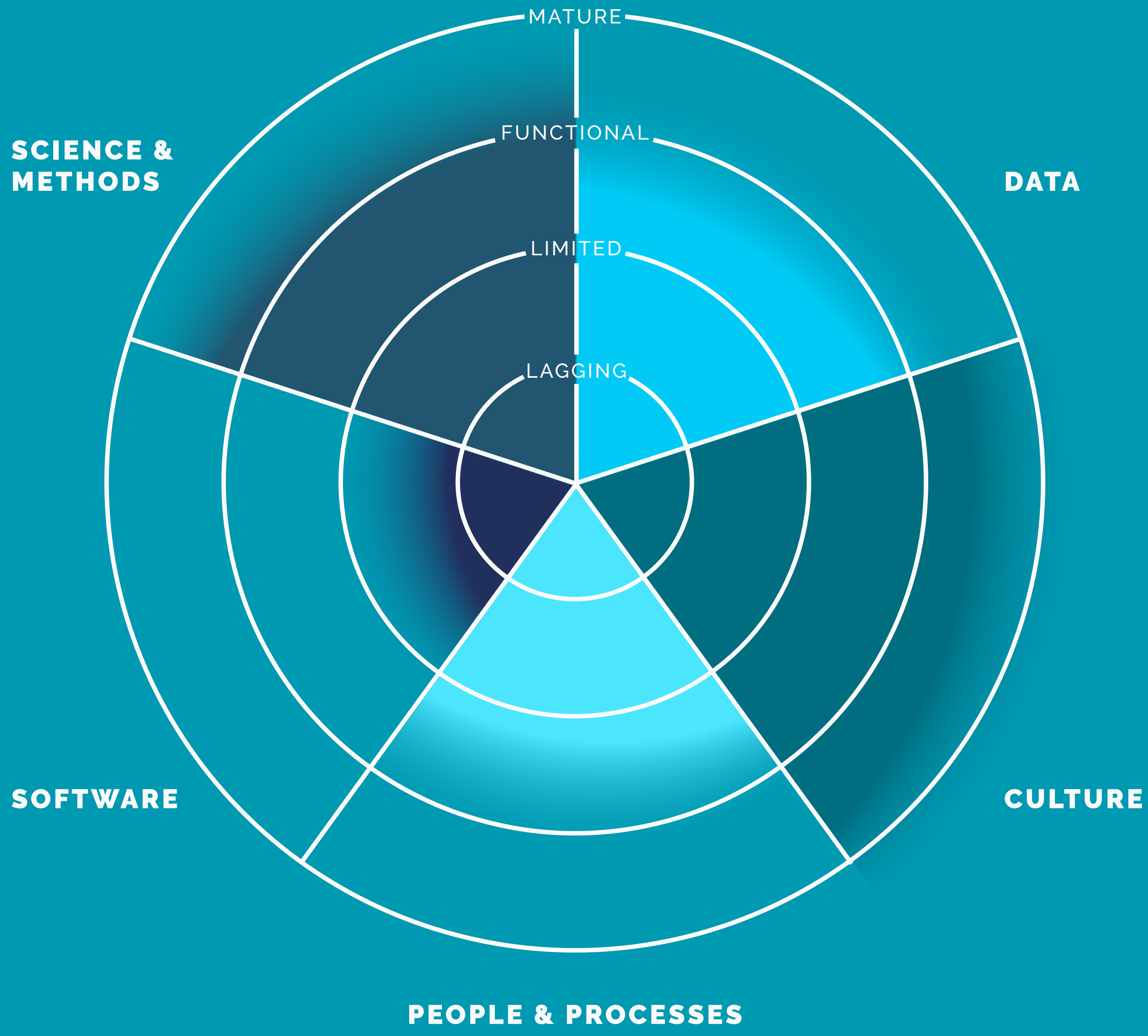
FURTHER READING

Learn more about cultivating your people and processes in Katie's earlier whitepaper for Civis, "Build a Disciplined Data Science Team." You can download it here.

Becoming a data-driven organization is an evolutionary process that unfolds along several axes. To advance, your business needs to:

- Build, maintain, and utilize a great dataset
- Create a culture that appreciates, uses, and prioritizes data
- Employ software that lets work happen and isn't a hindrance
- Empower the right people and introduce and sustain good processes
- Embrace the science and methods that help the organization anticipate change and adapt to it

In the following sections, we'll examine these facets of a data-driven organization across four phases of analytics maturity—Lagging, Limited, Functional, and Mature—so you can diagnose your organization's level of analytics maturity and determine where you need to go next.


MATURE
FUNCTIONAL
LIMITED
LAGGING
SCIENCE & METHODS
DATA
SOFTWARE
CULTURE
PEOPLE & PROCESSES

DATA

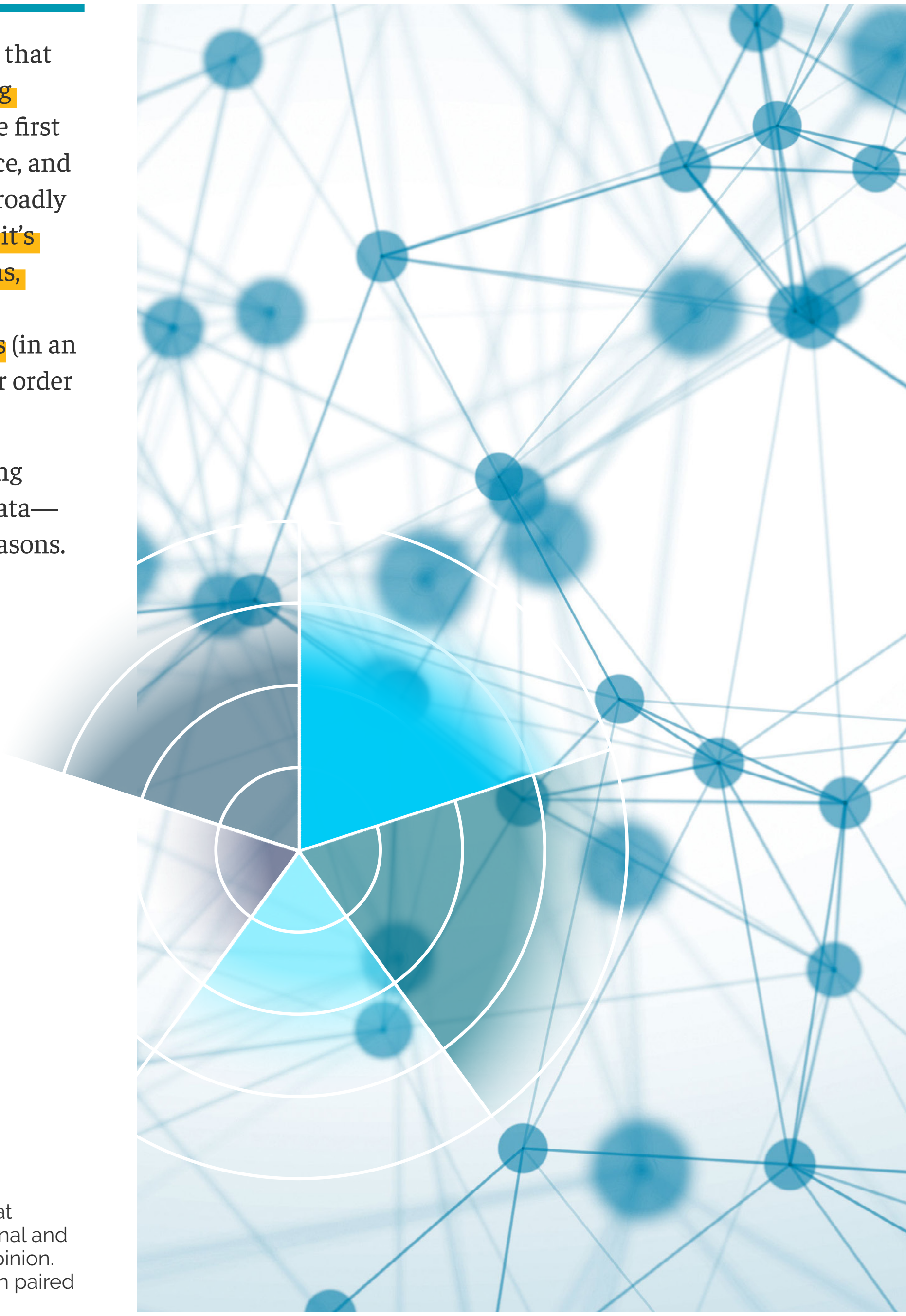
The quickest way to estimate your business's overall analytics maturity is to ask questions about your data.

Where your data lives, how it's maintained, who can access it, and what it'll be used for: these factors reveal truths about your culture, processes, technology, and methods.

Building, maintaining, and using a solid dataset is usually harder and less glamorous than building, maintaining, and using a sophisticated algorithm or a cutting-edge technical stack. Experienced data scientists know that a great dataset, combined with simple analytical methods, is more likely to yield great results than a mediocre dataset and complex methods. Put simply, without data there isn't much analytics can do. The first step your organization needs to take is to gain an understanding of your data.

In our experience, most organizations have data that they create or collect, but having data and having useful data are dramatically different things. The first part of data maturity is recognizing the difference, and the second part is actually having useful data. Broadly speaking, data is usable for business purposes if it's reliably available and useful for making decisions, meaning the data is accessible, clean, regularly updated, and connected across different systems (in an e-commerce organization, for example, customer order data would be easy to join to suppliers data).

It's rare to talk to a business that is not generating any useful data.[1] In reality, everyone has some data—they're just not leveraging it today for varying reasons.



[1] It's not unheard of. We work with many organizations that leverage our national consumer database and our national and international survey capabilities to understand public opinion. The power of this data, however, is really unlocked when paired with and matched to a customer's first-party data.

LAGGING

- Data created as part of doing business being captured partially or not at all
- No identification of data that allows measuring and monitoring of KPIs
- No plan to start capturing the data needed
- Business does not understand what data it has
- Any data being captured is not time-relevant

LIMITED

- Data not discoverable to employees across the organization
- Data in silos with no way to merge or join datasets
- Lack of confidence in data quality because of mistakes and missing values
- Data processing infrastructure does not facilitate fast processing
- Lag in data collection and its availability
- Difficult to articulate relationships between datasets because linkages are unnecessarily complex or not well defined
- Impossible to unify datasets
- Organization trying to solve definition, business, or source-of-truth problems with a piece of data technology[2]

FUNCTIONAL

- Agreement on what data is most important to the business
- Efforts to improve data quality
- Data warehouse not routinely used company-wide
- IT team is data gatekeeper
- IT grants data scientists access to data manually
- Data syncing process slow or manual
- Business logic not consistent or easy to integrate with data
- Data updates happen in batch mode but are automated
- Some process for quality checking new data, updated models, generated results, etc.
- Business decisions constrained by data architecture
- Data stored using technology that enables the data science team to try new methods and workflows

MATURE

- Well-documented business logic: important definitions easily integrated with the data used to calculate them
- Frequent, practically live, batch updates or streaming data support
- Comprehensive and automated data quality control
- Data architecture supports business processes and does not constrain decision making
- Single source of truth exists
- Anticipates out-of-date data and considers it in decision making
- Data maturity not determined by technology or size of dataset[3]

[2] We call this phenomenon "getting Hadoop'd"

[3] When two systems have different answers about something, the organization has a policy governing which one is authoritative and a human being is tasked with owning this decision

- What data do we have?
- Where is it?
- Do we have a competitive advantage around data?
- Is it secure?
- Can my analysts access it?
- Does my business have good data governance?

CASE STUDY

BEFORE / LAGGING

One of the country's largest consumer staples companies had high employee turnover in their distribution centers—the annual churn rate for warehouse picker staff was over 60%. The business wasn't able to confidently determine what was causing employees to churn because of data silos across the organization. Data was largely undiscoverable, and HR data didn't sync with payroll or supply-chain data.

AFTER / FUNCTIONAL

The data science team partnered with Civis to identify the data that was most important and discovered 20 of the most predictive values of whether an individual employee was more likely to churn. The business used the findings to formulate a list of recommendations including improving the onboarding process, conducting exit interviews, and reversing a policy of giving new employees fewer hours during a ramp-up period. Data is now read in or out of a data warehouse, enabling the data science team to try new workflows and methods, yet, the data syncing process is still mostly manual.

CULTURE

If data illuminates, culture enables. Analytics can answer critical questions for your business and be a competitive advantage, but only when your colleagues ask for and appreciate the answers, especially when it challenges their assumptions.

For your business to become data-driven, your culture needs to prioritize truth and scientific rigor over reaction, instinct, and anecdotal evidence. This is easy to say and difficult to do because it's easier and faster to arrive at a decision by gut than by data-driven analysis and because most leaders have far more experience with the former than the latter. However, having a culture of turning to data to guide decisions is a prerequisite for actually getting value out of all the people, processes, data, science, and technology that organizations invest in.

Put bluntly, your culture matters, and it's the hardest thing to give guidance on because it centers around the value structure of your organization. Culture is an ingrained, often unspoken, view of the world (and your organization's place in it) shared by everyone. At its best, a data-driven culture builds on a shared understanding of the right questions to ask, the information needed to make decisions, and how to measure success. Honest—sometimes uncomfortable—conversations are a prerequisite for consensus.

Driving up customer engagement, sales, revenue, and profit may all be objectives for your business, but without agreement on clear and precise business metrics, your efforts can hit a snag if definitions and objectives vary depending on whom you ask. If sales are the figure of merit for a given department, and there's disagreement on whether "sales" includes discounts or taxes, your team will find it extremely difficult to build data pipelines that support many different interpretations of what "sales" mean. Challenges aside, building a data-driven organization is an opportunity to define business metrics: analytics discipline can foster business discipline.

In almost all businesses, but especially in larger and more established organizations, people can be defensive of their domains (and how they define what success means for the business) and opening up to a new way of doing things can feel like giving up some power. This isn't irrational on their part: using data to make decisions means that gut feeling, seniority, personality, and experience won't figure as prominently in the decision-making process. Establishing a good culture in your business means finding a way for your colleagues to feel comfortable with and invested in using data so that they are willing to collaborate with other teams, particularly the data science team. This collaboration is the bedrock of a good, data-driven culture. Without collaboration, your best-case scenario is that your data science team will work in isolation and business opportunities will be left on the floor.

LAGGING

Decisions driven by “gut feeling” throughout the organization

Employees afraid to offer opinions that contradict the collective wisdom, even if those opinions are validated by data

Charismatic or loud personalities wield power

Unclear ownership for making important decisions

Debate and discussions in meetings are not framed around data

There is infrequent or no metrics-driven progress reports for major initiatives—hard to tell when things are succeeding or failing

LIMITED

There is some attention to data in decision-making but only in parts of the organization with the most direct access to data scientists

Data initiatives exist in silos removed from non-technical users

Data scientists are the main advocates for using data to improve decision-making

Some business units deliver more results with the same resources because of their use of analytics, but those initiatives are not used as examples for how to expand analytic capabilities

Confusion around the difference between anecdotes and data: the former is confused for the latter

FUNCTIONAL

Multiple teams are analyzing data, but they use different tools and vocabularies

The organization routinely uses data to understand why initiatives fail and how to improve future projects

Several high-leverage employees are advocates for making decisions based on data, and they coordinate their efforts

There are minimal, explicit assumptions to the decision-making process, and acknowledgment of when assumptions underlie decisions which motivates collecting more information

Important decisions get deep, data-based probing based on who’s asking the questions

MATURE

Shared understanding of the business questions that need to be answered

“Prove it” attitude in making big decisions

Widespread buy-in for using data to make decisions

Consensus around what data-driven decision making looks like in practice

Discussions center around the data company-wide

Discomfort making decisions in the absence of data

Organization turns to automated tools and processes built on data to make decisions

Data teams communicate possible areas of interaction or overlap in their work

Data teams have unified tools and vocabulary and clear ownership

Business uses data to anticipate market shifts and beats the competition

External pitch and sales materials draw upon the strongest supporting data

Sales and marketing activities are fully informed with data

Data teams within or interacting with every team

- Do my colleagues understand the decision-making process?
- Are people across my business versed in how to use data to make decisions?
- Does my organization pursue root causes relentlessly?
- Do people know and recognize they can be wrong?
- Do people change their minds when confronted with facts?
- Do my colleagues recognize when they don't have enough information to make a decision?
- Do people constantly seek out information that to minimizes the assumption to knowledge ratio?[4]

[4] A good explanation of this concept comes from "Discovery-Driven Planning" by McGrath and MacMillan, which ran in the July/August issue of *Harvard Business Review*.

CASE STUDY

BEFORE / LIMITED

A large beverage company wanted to help their distributors strategize about which products to sell to individual retailers. To accomplish this, the business not only needed improved tools and models, but new processes and a cultural shift.

AFTER / FUNCTIONAL

Executive sponsors provided critical support to the small data science team, enabling the team to introduce a data science platform to efficiently build and automate recommendation models for one of the company's largest product lines. While a culture of making data-driven decisions is taking root in one major line of business and the data science team has achieved visibility, there are still numerous opportunities to expand the footprint of the team to achieve success in the company's other lines of business.

PEOPLE & PROCESSES

The right team, given visibility and credibility by your business's leaders and the tools they need, will create a positive feedback loop that can dramatically reshape how you make decisions.

But in a field that moves as fast as data and analytics, it can be particularly challenging to find people with the right skill set and empower them with processes that play to their strengths. A data scientist can't add value to an organization entirely on her own, the way that, say, a salesperson can. A data scientist's impact comes when she creates and deploys solutions that other people in your organization can then use to inform their work. Analytics and data science are inherently team sports, and without the right team in place, it's hard to score wins. Members of your data science team need the right technical skills, but it's also critical they know how to work together and to work with (and effectively communicate with) colleagues who aren't data scientists.

So what are the essential ingredients you need to build a highly effective data science team? First, your organization's leadership needs to understand and appreciate (or at least not undermine) the need to make decisions based on data. If your leadership team advocates for using data in decision making, our experience is that the rest of the organization follows. On the leadership level, important questions include:

- Is my team able to communicate across business units?
- How are my team members spending their time?
- Are we starting new data-driven projects?
- Am I confident analytics initiatives are having a positive effect?
- Am I a leverage point for analytical thinking?
- Are performance expectations aligned with my desired outcomes?
- Do analysts know what they are working to achieve? Do they have regular contact with stakeholders?

Second, your organization needs a team of data scientists[5] to build and maintain data analyses and tools: you need boots on the ground, and they need to be properly equipped to do analytically minded work in service of making better, faster, smarter decisions. Questions to ask about your team:

- Do my analysts have the right technical skills?
- Are my people trained in the right tools? Are there training programs in place?
- Do my analysts have the right business context?
- Are my hiring practices aligned with my needs?
- Are my teams diverse in their skills?

Third, good procedural habits ensure data gets regularly included in the decision-making process. Questions to ask to determine your organization's procedural habits:

- Has the management team identified key targets?
- Do I know what to measure? Am I measuring it?
- Does my business's decision-making process explicitly draw in data that quantifies the costs and rewards of all the options?
- Was there a moment when data conflicted with intuition and my business followed the data over instinct?
- Does my organization have a timeline for implementing changes?
- Am I looking to the past, at current conditions, or making forecasts?
- Do different business units operate in a way that allows them to coordinate, when appropriate?
- Am I enforcing best practices?
- Do my analysts have enough business context to improve outcomes?

[5] There are a lot of job titles other than "data scientist" that could be applicable here. Data analyst, business intelligence associate, machine-learning-minded software engineer, and many other roles and titles might effectively overlap with "data science" at any given organization.

LAGGING

- Leaders decide by gut
- No data scientists, analysts, or people interested in acquiring those skills
- No managers who prioritize data access for their teams
- Leadership does not see value in incorporating data into decision making processes

LIMITED

- Ad-hoc decision making process
- No targets or timelines
- Management lacks data awareness
- Leadership interested in using data, but not taking action to do so
- No training programs to increase data skills for interested employees
- Technically skilled employees not spread throughout the organization
- No communication among technically skilled employees
- Hiring for data skills, but not in a way that's targeted at the needs of the organization (hiring PhD physicist when what you need is a web developer)
- Some data-informed business targets and timelines for meeting those targets
- Local decisions informed by data, but in a non-repeatable fashion

FUNCTIONAL

- Some leadership buy-in
- Short-term data plan
- Team dedicated to analytics
- Analytics team only sporadically communicates with the business units and lacks business context as a result
- Nontechnical employees know that there are people in the organization with data skills and know when to work with them
- Project-based hiring of people with analytics skills, usually at the business unit level
- Training program to upskill employees with analytics interest
- Backward-looking analytics
- Projects internally consistent but don't tie together
- Best practices internally communicated
- Data scientists have a reporting structure and institutionalized contact

MATURE

- Leaders create data and analytics strategies
- Analytics efforts focus on business predictions about the future
- Integrated project teams prioritize business outcomes
- Long-term plan for building, maintaining, and using datasets
- Cross-functional teams include data scientists or analysts
- Positive feedback loops
- Data scientists as engineers
- Best practices enforced

CASE STUDY

BEFORE / LIMITED

Leaders within a multinational manufacturing company recognized that, in order for the company to compete, they needed to start making decisions backed by data and that it was essential to focus on their people and processes to do so. The company had an ad-hoc decision-making process and leaders had interest in using data but there was no forward movement in making it a reality. A data science team existed, but there was a lack of data awareness among management, no training programs were in place to increase employees' data skills, and hiring priorities did not necessarily fit the needs of the organization.

AFTER / FUNCTIONAL

The company partnered with Civis on a customer engagement project, not only to learn more about customer churn, but to upskill members of their data science team and inspire organization-wide confidence in the ability of the data team to help leaders make informed decisions. The partnership helped expand the analytics team's communication with business units and define the team's place within the organizational structure.

SOFTWARE

The software component of analytics maturity is one of the trickiest to get right.

The number of different pieces that underpin analytics capabilities—things like data engineering and storage solutions, statistics and machine learning software, tools analysts use to build workflows, and reporting frameworks—and the even larger number of options (each of those constantly evolving) and buzzwords can be overwhelming. This complexity means decisions about your technology have long-reaching consequences that may not become apparent for months or even years. You risk multi-year vendor lock-in that could force you to live with suboptimal solutions and perhaps even painful licensing audits.[6] Alternatively, you may end up eating costs on unused software down the line.[7]

So should you rely on open-source software or buy proprietary software? Should you select point solutions that are better for particular or specialized needs, or a more general-purpose platform that allows more flexibility if you need it? Do you build it all yourself and commit to supporting, maintaining, and improving these systems going forward, or should you work with a technology partner?

[6] Oracle'd anyone?
[7] Hadoop'd anyone?

Your answer will depend on your culture, processes, and team, and you should aim to balance giving your data science team flexibility to use the software and approaches they want with limiting fragmentation through greater discipline. A few data scientists working with their own individual toolkits is better than nothing, but this way of working can quickly lead to fragmentation of your analytics capabilities: data scientists can't read or review each other's work, reuse isn't possible, work gets repeated, important results get lost, and more effort goes into getting a new functionality to work with what already exists than it took to build the functionality in the first place. Your team should be accelerating as they build, not moving more slowly.

Fighting fragmentation with discipline is the key to building a highly effective team. Limit what your team members can do, up to a point. There should be one format of data that goes into models, one agreed-upon process for getting a model into production, one standard means of validating and monitoring models, and one set of libraries that everyone shares. This probably won't be as fun for your data scientists, and there will be some instances where your team will have to forego a sweet new toy in service of discipline and speed, but getting results and building trust within your business benefits both the organization and your data science team.

LAGGING

Struggles with build vs. buy decision for data science software

No policies or best practices about how to build or deploy models—each one built from scratch

No software support for saving work, or collaborating on projects

Localized open source but not agreed-upon tools and models

Team members working on their own projects and not communicating what they're working on

LIMITED

Data generally accessible, but the process for gaining access is slow and manual

Siloed tools and models that don't leverage existing code

Open communication channels and attempted coordination between collaborators

Commonly used models have well-documented and enforced standard practices

Scattershot version control

FUNCTIONAL

Smooth data access channels through IT (or well-maintained IT workarounds)

Data scientists able to use favorite tools, including open-source solutions

Established process for adding new tools to standard toolbox

Project code under version control and repeatable

New code added to codebase according to written quality standards and code review process

Code is modular and has good unit test coverage so engineers and data scientists don't accidentally introduce breaking changes when they modify the codebase

MATURE

Organization practices polyglot persistence, which means different types of data (which likely serve different business purposes) are stored in different types of storage systems, each of which are chosen based on what's optimal for the data type and usage

Data scientists have access to self-serve computing infrastructure, with minimal or no need to get explicit approval from other parts of the organization to use it (often this means computing infrastructure is hosted on a cloud system like AWS or Azure)

Well-defined standardized pieces of data science workflows, with a defined API between major pieces

Data workflows and pipelines have integration tests that monitor the interactions and interfaces between pieces and systems of code

- Do data storage systems enable the outcomes my organization needs?
- Do analytics solutions make it into business processes?
- Can my analysts deploy solutions?
- Do I have a true solutions architecture?
- Do my IT solutions support business needs, operations, and analytics?

CASE STUDY

BEFORE / LAGGING

A B2C marketing company wasn't able to gain a full understanding of their customers and consultants and take action to increase engagement because of limited data and software capabilities. Because data lived across many different systems, the data science team didn't have a cohesive data science ecosystem to quickly and efficiently provide insights to leadership. The team struggled to make a decision about whether to build or buy data science software due to a reluctance to spend a large amount of time and money constructing a database and cobbling together assorted solutions.

AFTER / FUNCTIONAL

The company implemented a data science platform to enable direct access to data (by merging their data streams with a dataset built into the data science platform), assembled a data science team around a common set of inputs and tools, and empowered the team to create transparent and automated workflows. The company can now set KPIs for targets and easily generate shareable reports to enable colleagues in leadership and marketing to make decisions based on data.

SCIENCE & METHODS

Doing effective data science requires covering the fundamentals.

Once your team has the tools, process, credibility, and support to make data a critical part of how your business makes decisions, your team can start using and developing new methods to solve a wider range of problems. Data scientists are scientists after all, and with a solid foundation in place, your team can use the scientific method to develop increasingly sophisticated techniques tailored to yield higher-impact results for your business.

It can be tempting, however, for those in your business to read about advances in the field and ask why your data science team isn't using a cutting-edge method. It's similarly tempting for data scientists to want to dive into developing cool models with high levels of complexity. While it's a great sign that both decision makers and data scientists in your business want to do sophisticated data science, it's crucial to take care of the basics first (your data, software, culture, people and processes) so your team can iterate on their methods and find the right approaches for your business's unique set of problems.

LAGGING

- Backward-looking measurements of important business objectives
- Measurements do not have uncertainties or error bars
- Inappropriate use of sophisticated or advanced methodologies—neural networks deployed without enough training data
- Confusion between correlation and causation, or between causality and reverse causality

LIMITED

- Algorithms like linear models and decision trees employed to make forward-looking predictions
- Occasional or disorganized use of feature engineering methods
- Scientific understanding of how various model hyperparameters affect important model attributes like bias and variance
- Appropriate statistical methodology deployed when the organization needs answers to causal questions versus predictive questions

FUNCTIONAL

- Uncertainties calculated on most measurements and predictions
- Ensemble machine learning methods used where appropriate
- Routine use of feature engineering methods
- Well-socialized understanding of the limitations of feature engineering methods
- Hyperparameter optimization part of the model building/selection process
- Models selected on the basis of metrics like accuracy, ROC score, or F1-score

MATURE

- Uncertainties calculated on all measurements and predictions
- Uncertainties taken into account when making decisions
- Optimization algorithms used to simulate results of different decisions and suggest the most favorable
- Deep understanding of how estimates and predictions change when underlying distributions or assumptions change
- Deep learning and/or neural network methods used where appropriate
- Black-box machine learning models have associated model interpretability tools
- New methodologies routinely researched to see if they improve upon the organization's existing methodologies

CASE STUDY

BEFORE / FUNCTIONAL

A technology company that helps industrial device purchasers compare device performance and costs needed to build aggregated summaries of each device's history of failures. With approximately 5 million unstructured text descriptions to sift through, the company needed more advanced science and methods to aggregate information of highest value to their customers.

AFTER / MATURE

The company worked with machine learning specialists to build a recurrent neural network model to assign predicted labels for all text descriptions in the database. The team was then able to use labels to break out product features by most common device failure reason and by the severity of device failures—information the company's customers used to make informed purchases.

The good news is that you already have a lot going for you: your people and your data are some of your most powerful assets and your business recognizes the need to unlock that potential. Making informed decisions requires making data science central to how you do business, and making data science part of your business demands being honest and practical about how you do it. Achieving analytics maturity takes time and many small steps, but an evolutionary approach centered on asking good questions and doing what's uniquely right for your business will pay off.

Ask good questions, know where you stand, and be realistic about what you need (and what you don't need) and you'll be well-equipped to make the right decisions about how you make decisions.

KATIE MALONE & SKIPPER SEABOLD

DIRECTORS OF DATA SCIENCE

CIVIS ANALYTICS

FURTHER READING

Learn more about cultivating your people and processes in Katie's earlier whitepaper for Civis, "Build a Disciplined Data Science Team." You can download it here.

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Civis Analytics helps businesses use data to gain a competitive advantage in how they identify, attract, and engage loyal customers and employees. With a powerful combination of best-in-class proprietary data, cutting-edge software solutions, and an interdisciplinary team of data scientists, developers, and survey science experts, Civis works with Fortune 500 companies and the country's largest nonprofits to make data-driven decision-making essential to how the world's best companies do business.

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We look forward to speaking with you!

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