THE DATAOPS COOKBOOK

Methodologies and Tools That Reduce Analytics Cycle Time While Improving Quality

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The DataOps Cookbook

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Foreword

In the early 2000s, Chris and Gil worked at a company that specialized in analytics for the pharmaceutical industry. It was a small company that offered a full suite of services related to analytics — data engineering, data integration, visualization and what is now called “data science.” Their customers were marketing and sales executives who tend to be challenging because they are busy, need fast answers and don’t understand or care about the underlying mechanics of analytics. They are business people, not technologists.

When a request from a customer came in, Chris and Gil would gather their team of engineers, data scientists and consultants to plan out the how to get the project done. After days of planning, they would propose their project plan to the customer. “It will take two weeks.” The customer would shoot back, “I need it in two hours!”

Walking back to their office, tail between their legs, they would pick up the phone. It was a customer boiling over with anger. There was a data error. If it wasn’t fixed immediately the customer would find a different vendor.

The company had hired a bunch of smart people to deliver these services. “ I want to innovate — Can I try out this new open source tool,” the team members would ask. “No,” the managers would have to answer. “We can’t afford to introduce technical risk.”

They lived this life for many years. How do you create innovative data analytics? How do you not have embarrassing errors? How do you let your team easily try new ideas? There had to be a better way.

They found their answer by studying the software and manufacturing industries which had been struggling with these same issues for decades. They discovered that data-analytics cycle time and quality can be optimized with a combination of tools and methodologies that they now call ***DataOps***. They decided to start a new company. The new organization adopted the kitchen metaphor for data analytics. After all, cooking up charts and graphs requires the right *ingredients* and *recipes*.

The DataKitchen founders (Chris, Gil and Eric) built their own DataOps Platform. What happened next was remarkable. When analytics go faster, users embrace analytics and innovate. Rapid, high-quality analytics can unlock an organization's creative potential.

Having experienced this transformation, the DataKitchen founders sought a way to help other data professionals. There are so many talented people stuck in no-win situations. This book is for data professionals who are living the nightmare of slow, buggy analytics and frustrated users. It will explain why working weekends isn't the answer. It provides you with practical steps that you can take tomorrow to improve your analytics cycle time.

DataKitchen markets a DataOps Platform that will help analytics organizations implement DataOps. However, this book isn't really about us and our product. It is about you, your challenges, your potential and getting your analytics team back on track.

The values and principles that are central to DataOps are listed in the DataOps Manifesto which you can read below. If you agree with it, please join the thousands of others who share these beliefs by signing the manifesto. There may be aspects of the manifesto that require further explanation. Please read on. By the end of this book, it should all make sense.

You'll also notice that we've included some real recipes in this book. These are some of our favorites. We hope you enjoy them!

Please reach out to us at info@datakitchen.io with any comments or questions.

Chris, Gil and Eran

The DataOps Manifesto

Background

Through firsthand experience working with data across organizations, tools, and industries we have uncovered a better way to develop and deliver analytics that we call DataOps. Whether referred to as data science, data engineering, data management, big data, business intelligence, or the like, through our work we have come to value in analytics:

- Individuals and interactions over processes and tools
- Working analytics over comprehensive documentation
- Customer collaboration over contract negotiation
- Experimentation, iteration, and feedback over extensive upfront design
- Cross-functional ownership of operations over siloed responsibilities

DataOps Principles

1. CONTINUALLY SATISFY YOUR CUSTOMER

Our highest priority is to satisfy the customer through the early and continuous delivery of valuable analytic insights from a couple of minutes to weeks.

2. VALUE WORKING ANALYTICS

We believe the primary measure of data analytics performance is the degree to which insightful analytics are delivered, incorporating accurate data, atop robust frameworks and systems.

3. EMBRACE CHANGE

We welcome evolving customer needs, and in fact, we embrace them to generate competitive advantage. We believe that the most efficient, effective, and agile method of communication with customers is face-to-face conversation.

4. IT'S A TEAM SPORT

Analytic teams will always have a variety of roles, skills, favorite tools, and titles.

5. DAILY INTERACTIONS

Customers, analytic teams, and operations must work together daily throughout the project.

6. SELF-ORGANIZE

We believe that the best analytic insight, algorithms, architectures, requirements, and designs emerge from self-organizing teams.

7. REDUCE HEROISM

As the pace and breadth of need for analytic insights ever increases, we believe analytic teams should strive to reduce heroism and create sustainable and scalable data analytic teams and processes.

8. REFLECT

Analytic teams should fine-tune their operational performance by self-reflecting, at regular intervals, on feedback provided by their customers, themselves, and operational statistics.

9. ANALYTICS IS CODE

Analytic teams use a variety of individual tools to access, integrate, model, and visualize data. Fundamentally, each of these tools generates code and configuration which describes the actions taken upon data to deliver insight.

10. ORCHESTRATE

The beginning-to-end orchestration of data, tools, code, environments, and the analytic team's work is a key driver of analytic success.

11. MAKE IT REPRODUCIBLE

Reproducible results are required and therefore we version everything: data, low-level hardware and software configurations, and the code and configuration specific to each tool in the toolchain.

12. DISPOSABLE ENVIRONMENTS

We believe it is important to minimize the cost for analytic team members to experiment by giving them easy to create, isolated, safe, and disposable technical environments that reflect their production environment.

13. SIMPLICITY

We believe that continuous attention to technical excellence and good design enhances agility; likewise simplicity—the art of maximizing the amount of work not done—is essential.

14. ANALYTICS IS MANUFACTURING

Analytic pipelines are analogous to lean manufacturing lines. We believe a fundamental concept of DataOps is a focus on process-thinking aimed at achieving continuous efficiencies in the manufacture of analytic insight.

15. QUALITY IS PARAMOUNT

Analytic pipelines should be built with a foundation capable of automated detection of abnormalities (jidoka) and security issues in code, configuration, and data, and should provide continuous feedback to operators for error avoidance (poka yoke).

16. MONITOR QUALITY AND PERFORMANCE

Our goal is to have performance, security and quality measures that are monitored continuously to detect unexpected variation and generate operational statistics.

17. REUSE

We believe a foundational aspect of analytic insight manufacturing efficiency is to avoid the repetition of previous work by the individual or team.

18. IMPROVE CYCLE TIMES

We should strive to minimize the time and effort to turn a customer need into an analytic idea, create it in development, release it as a repeatable production process, and finally refactor and reuse that product.

Join the Thousands of People Who Have Already Signed The Manifesto

DataOps Ribeye

by Christopher Bergh

INGREDIENTS AND TOOLS

- Rib eye steaks 1 ½-2" thick
- Large baking potatoes
- Corn on the husk
- Olive oil
- Ground sea salt & Fresh coarse ground pepper or Penzey's Chicago Steak Seasoning
- Green Egg or another charcoal grill
- Instapen thermometer

PREPARE CORN AND POTATOES

1. Season/marinade steaks to your liking, but I now like the 'TRex way of prepping/grilling my steaks (see below): coat the steaks with olive oil, liberally apply salt and pepper (or Penzey's Chicago Steak Seasoning) and rub the mixture into the steaks on both sides.
2. Soak corn in water for at least 30 minutes or more.
3. Brush potatoes with olive oil and salt on both sides. Heat Green Egg to 400 degrees with a few chunks of Hickory wood and put potatoes directly on grill grid, direct heat, turning once after 30 minutes. About 20-25 minutes before the potatoes are done, put the corn on the grill grid. Turn the corn about every 8-10 minutes or just enough to keep the corn from getting burned (a little charring of the corn is okay, though).
4. Remove the potatoes and corn and wrap in aluminum foil and place in a warming oven or drawer at 170 degrees.

PREPARE THE STEAKS

1. TRex method of grilling/cooking steaks: Crank the draft door and daisy wheel open all the way on the Egg for maximum temperature. When you get the Green Egg up to at least over 600 degrees (be careful to "burp" the Egg at this high temp), put the steaks on and sear for 90 seconds per side.
2. Take the steaks off the Egg and let sit/rest for 20 minutes. Shut down the lower vent and Daisy Wheel to get the Green Egg back down to 425 degrees.
3. Throw some more chunks of Hickory wood on the fire and try and maintain a temp around 400 degrees. After 10 minutes of letting the steaks sit/rest put back on the Green Egg and cook for approximately 4-5 minutes per side for a medium-rare/medium result. Check internal temperature of steak so that it is 120 degrees

Eight Challenges of Data Analytics

Companies increasingly look to analytics to drive growth strategies. As the leader of the data-analytics team, you manage a group responsible for supplying business partners with the analytic insights that can create a competitive edge. Customer and market opportunities evolve quickly and drive a relentless series of questions. Analytics, by contrast, move slowly, constrained by development cycles, limited resources and brittle IT systems. The gap between what users need and what IT can provide can be a source of conflict and frustration. Inevitably this mismatch between expectations and capabilities can cause dissatisfaction, leaving the data-analytics team in an unfortunate position and preventing a company from fully realizing the strategic benefit of its data.

As a manager overseeing analytics, it's your job to understand and address the factors that prevent the data-analytics team from achieving peak levels of performance. If you talk to your team, they will tell you exactly what is slowing them down. You'll likely hear variations of the following eight challenges:

1 – The Goalposts Keep Moving

Users are demanding customers for a data-analytics team. Their requirements change constantly. They require immediate responses, and no matter how much the analytics team delivers, users keep generating new requests. It's enough to overwhelm any data-analytics team.

They don't know what they want. Users are not data experts. They don't know what insights are possible until someone from your team shows them. Sometimes they don't know what they want until after they see it in production (and maybe not even then). Often, business stakeholders do not know what they will need next week, let alone next quarter or next year. It's not their fault. It's the nature of pursuing opportunities in a fast-paced marketplace.

They need everything ASAP. Business is a competitive endeavor. When an opportunity opens, the company needs to move on it faster than the competition. When users bring a question to the data-analytics team, they expect an immediate response. They can't wait weeks or months — the opportunity will close as the market seeks alternative solutions.

The questions never end. Sometimes providing business stakeholders with analytics generates more questions than answers. Analytic insights enable users to understand the business in new ways. This spurs creativity, which leads to requests for more analytics. A healthy relationship between the analytics and users will foster a continuous series of questions that drive demand for new analytics. However, this relationship can sour quickly if the delivery of new analytics can't meet the required time frames.

2 – Data Lives in Silos

In pursuit of business objectives, companies collect an enormous amount of data: orders, deliveries, returns, website page views, mobile app navigations, downloads, clicks, metrics, audio logs, social media and more. Further, this data can be combined with demographic, psychographic or other third-party market data. All of this data is collected in separate databases which typically do not talk to each other. They utilize numerous platforms, APIs and technologies. Accessing all of this data is a daunting task requiring such a wide range of skills that it is rare to find a single person who can do it all. Integrating data from these myriad sources becomes a major undertaking.

Business stakeholders want fast answers. Meanwhile, the data-analytics team has to work with IT to gain access to operational systems, plan and implement architectural changes, and develop/test/deploy new analytics. This process is complex, lengthy and subject to numerous bottlenecks and blockages.

3 – Data Formats are not Optimized

Data in operational systems is usually *not* structured in a way that lends itself to the efficient creation of analytics. For example, an ERP system might have a schema that is optimized for inserts, updates, and for display in a web user interface. For operational systems, these are the actions that need to happen in real time.

A database optimized for data analytics is structured to optimize reads and aggregations. It's also important for the schema of an analytics database to be easily understood by humans. For example, the field names would be descriptive of their contents and data tables would be linked in ways that make intuitive sense.

4 – Data Errors

Whether your data sources are internal or from external third parties, data will eventually contain errors. Data errors can prevent your data pipeline from flowing correctly. Errors may also be subtle, such as duplicate records or individual fields that contain erroneous data. Data errors could be caused by a new algorithm that doesn't work as expected, a database schema change that broke one of your feeds, an IT failure or one of many other possibilities. Data errors can be difficult to trace and resolve quickly.

5 – Bad Data Ruins Good Reports

When data errors work their way through the data pipeline into published analytics, internal stakeholders can become dissatisfied. This causes unplanned work, which diverts your key contributors from the highest priority projects. Bad data also harms the hard-won credibility of the data-analytics team. If business colleagues repeatedly see bad data in analytics reports, they might learn not to trust or value the work product of the data-analytics team.

6 – Data Pipeline Maintenance Never Ends

Data-analytics is a pipeline process that executes a set of operations and attempts to produce a consistent output at a high level of quality. Every new or updated data source, schema enhancement, analytics improvement or other change triggers an update to the pipeline. The data-analytics team is continuously making changes and improvements to the data pipeline. Each one of these changes must be made carefully so that it doesn't break operational analytics. The effort required to validate and verify changes often takes longer than the time required to create the changes in the first place. You may not realize it, but your analysts, data scientists and engineers may be spending 80% of their time updating, maintaining and assuring the quality of the data pipeline. This is necessary work, but much of it is behind the scenes and unappreciated when viewed against the growing backlog of new requests from business customers.

7 – Manual Process Fatigue

Data integration, cleansing, transformation, quality assurance and deployment of new analytics must be performed flawlessly day in and day out. The data-analytics team may have automated a portion of these tasks, but some teams perform numerous manual processes on a regular basis. These rote procedures are error prone, time consuming and tedious.

Further, manual processes can also lead to high employee turnover. Many managers have watched high-performing data-analytics team members burn out due to having to repeatedly execute manual data procedures. Manual processes strain the productivity of the data team in numerous ways.

8 – The Trap of "Hope and Heroism"

The landscape is littered with projects and initiatives cancelled or deferred due to changing requirements, slipped schedules, disappointed users, inflexibility, poor quality, low ROI, and irrelevant features.

According to the research firm Gartner, Inc., half of all chief data officers (CDO) in large organizations will not be deemed a *success* in their role. Per Forrester Research, 60% of the data and analytics decision-makers surveyed said they *are not very confident* in their analytics insights. Only ten percent responded that their organizations sufficiently *manage the quality of data and analytics.* Just sixteen percent believe they perform well in producing *accurate models.*

Many CDO's and data-analytics professionals respond to these challenges in one of three ways:

Heroism - Data-analytics teams work long hours to compensate for the gap between performance and expectations. When a deliverable is met, the data-analytics team is considered heroes. However, yesterday's heroes are quickly forgotten when there is a new deliverable to meet. Also, this strategy is difficult to sustain over a long period of time, and it, ultimately, just resets expectations at a higher level without providing additional resources. The heroism approach is also difficult to scale up as an organization grows.

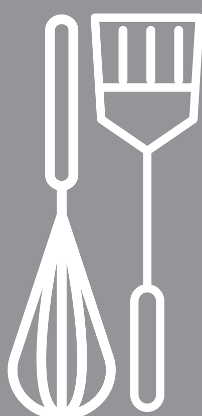
Hope - When a deadline must be met, it is tempting to just quickly produce a solution with minimal testing, push it out to the users and *hope* it does not break. This approach has inherent risks. Eventually, a deliverable will contain data errors, upsetting the users and harming the hard-won credibility of the data-analytics team.

Caution - The team decides to give each data-analytics project a longer development and test schedule. Effectively, this is a decision to deliver higher quality, but fewer features to users. One difficulty with this approach is that users often don't know what they want until they see it, so a detailed specification might change considerably by the end of a project. The slow and methodical approach might also make the users unhappy because the analytics are delivered more slowly than their stated delivery requirements and as requests pile up, the data-analytics team risks being viewed as bureaucratic and inefficient.

None of these approaches adequately serve the needs of both users and data-analytics professionals, but there is a way out of this bind. The challenges above are not unique to analytics, and in fact, are shared by other organizations.

Overcoming the Challenges

Some say that an analytics team can overcome these challenges by buying a new tool. While it is true that new tools are helpful, they are not enough by themselves. You cannot truly transform your staff into a high-performance team without an overhaul of the methodologies and processes that guide your workflows. In this book, we will discuss how to combine tools and new processes in a way that improves the productivity of your data analytics team by orders of magnitude.



DataOps Chili Mole

by Gil Benghiat

INGREDIENTS AND TOOLS

- 1 pound ground beef (90% lean or leaner)
- 1 diced onion
- 2 diced Jalapeño or 2 Serrano or 1 habanero pepper
- 2 pounds frozen sweet corn
- 28 oz can crushed tomatoes
- 15.5 oz can of black beans, NOT drained
- 15.5 oz can of black beans, drained
- 15.5 oz can of red beans, drained
- 15.5 oz can of white beans, drained
- 7 cloves of crushed garlic
- ½ cup sugar
- 3 ½ table spoons of unsweetened cocoa powder
- 3 table spoons of chili powder
- 1 teaspoon of salt

INSTRUCTIONS

1. Crock Pot: Combine all ingredients and cook on high for 5-8 hours. Stir occasionally.
2. Stove Top: Combine ground beef, onion, and pepper. Cook on medium high until beef is cooked through. Add the remaining ingredients and cook on low-simmer for 1-2 hours. Stir occasionally.
3. For vegan chili: Substitute 5 tablespoons of canola oil for the ground beef.
4. Serve with rice.

“What Is DataOps”

You can view DataOps in the context of a century-long evolution of ideas that improve how people manage complex systems. It started with pioneers like W. Edwards Deming and statistical process control - gradually these ideas crossed into the technology space in the form of Agile, DevOps and now, DataOps. In the next section we will examine how these methodologies impact productivity, quality and reliability in data analytics.

Delivering Analytics at *Amazon Speed*

The world changed in February 2005 when Amazon Prime brought flat-rate, unlimited, two-day shipping into a world where people expected to pay extra to receive packages in four to six business days. Since its launch, Amazon Prime has completely transformed the retail market, making low-cost, predictable shipping an integral part of consumer expectations. This business model, which some have called the “on-demand economy,” is popping up in many industries and markets across the globe.

For example, some may remember video stores where movies were rented for later viewing. Today, 65 percent of global respondents to a recent Nielsen survey watch video on demand (VOD), many of them daily. With VOD, a person’s desire to watch a movie is fulfilled within seconds. Amazon participates in the VOD market with their Amazon Prime Video service.

Instant fulfillment of customer orders seems to be part of Amazon’s business model. They have even brought that capability to IT. About 10 years ago, Amazon Web Services (AWS) began offering computing, storage, and other IT infrastructure on an as-needed basis. Whether the need is for one server or thousands and whether for hours, days, or months, you only pay for what you use, and the resources are available in just a few minutes.

To successfully compete in today’s on-demand economy, companies need to deliver their products and services just as Amazon has done—in other words, at *Amazon speed*. What might be surprising to many is how the expectations of instant fulfillment are crossing over into data analytics, which, along with everything else in the digital economy, is now expected to happen at Amazon speed and with Amazon predictability.

A typical example: the VP of sales enters the office of the chief data officer (CDO). She'd like to cross-reference the customer database with some third-party consumer data. The CDO asks for time to study the problem and, days later, has planned the project. Resources will be allocated and configured, schemas will be updated, reports will be elegantly designed, and the delivery pipeline will be thoroughly tested. The changes will take several weeks. "Not acceptable," the VP of sales fires back. The new analytics are needed for a meeting with the board later in the week. "The competition is ahead of us; we can't wait weeks." This scenario is playing out in one form or another in corporations around the globe.

ANALYTICS IN THE ON-DEMAND ECONOMY

Analytics must be delivered rapidly in order to meet user expectations in the on-demand economy. This is simply not possible with an approach that depends upon "hope and heroism" or "caution."

In order to deliver value consistently, quickly and accurately, data-analytics teams must learn to create and publish analytics in a new way. We call this new approach DataOps. DataOps is a combination of tools and methods, which streamline the development of new analytics while ensuring impeccable data quality. DataOps helps shorten the cycle time for producing analytic value and innovation, while avoiding the trap of "hope, heroism and caution."

Data Analytics Can Learn from Agile

If you were managing 100 software developers, you would have to choose the best way to maximize their productivity. Since the dawn of the computer era many software project management approaches have been tried. The waterfall model dominated software project management up until the 1990's. In the early days of computing, project management was adapted from the manufacturing and construction industries, which required detailed planning and a great degree of structure. Projects were organized into phases (conception, initiation, analysis, design, construction, testing, production/implementation and maintenance) and progressed through these phases sequentially. Once a phase was done, the team moved forward to the next phase.

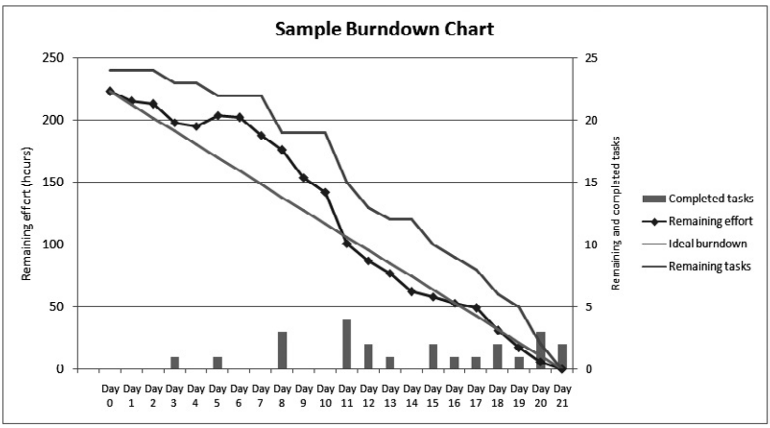


Figure 1: In Agile development, a burndown chart shows work remaining over time.

The waterfall model is better suited to situations where the requirements are fixed and well understood up front. This is nothing like the technology industry where the competitive environment evolves rapidly. In the 1980's a typical software project required about 12 calendar months. In technology-driven businesses (i.e. nearly everyone these days) customers demand new features and services, and competitive pressures change priorities on a seemingly daily basis. The waterfall model has no mechanism to respond to these changes. In waterfall, changes trigger a seemingly endless cycle of replanning causing delays and resulting in project budget overruns.

In the early 2000's, the software industry embraced a new approach to code production called Agile Development. Agile is an umbrella term for several different iterative and incremental software development methodologies.

In Agile Software Development, the team and its processes and tools are organized around the goal of publishing releases to the users every few weeks (or at most every few months). A development cycle is called a *sprint* or an *iteration*. At the beginning of an iteration, the team commits to completing working and (the most) valuable changes to the code base. Features are associated with *user stories*, which help the development team understand the context behind requirements. User stories include descriptions of features and acceptance criteria. The Agile methodology is particularly good for non-sequential product development where market requirements are quickly evolving. This is similar to the data-analytics environment where each new analysis and report of the data inspires requests for additional queries.

Agile is widely credited with boosting software productivity. One study sponsored by the Central Ohio Agile Association and Columbus Executive Agile Special Interest Group found that Agile projects were completed 31 percent faster and with a 75 percent lower defect rate than the industry norm. The vast majority of companies are getting on-board. In a survey of 400 IT professionals by TechBeacon, two-thirds described their company as either "pure agile" or "leaning towards agile. Among the remaining one third of companies, most use a hybrid approach, leaving only nine percent using a pure waterfall approach.

In an increasingly competitive marketplace, Agile methods allow companies to become more responsive to customer requirements and accelerate time to market. Agile also improves ROI because features delivered in each iteration can be immediately monetized instead of waiting months for a big release. Agile is the major reason that release frequency improved from around 3 months in the 1990's to about 3 weeks in the 2000's. However, improvements didn't stop there. Today releases are occurring every few seconds using an updated approach which builds upon Agile.

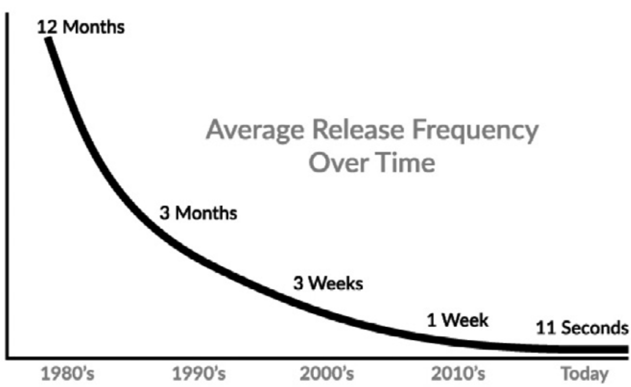


Figure 2: The decrease in release cycle time as software development evolved from waterfall to Agile to DevOps.

Data Analytics Can Learn from DevOps

Before the advent of on-demand cloud services, the various groups in software development (design, development, test, quality, support, ...) had to set-up their own infrastructure. Whatever components were needed (physical servers, networks, storage, software, ...) had to be ordered, installed, configured and managed by the IT department. Servers would be ordered at different times and from different vendors, each slightly different from the other.

Depending on the task at hand, different machines could have a different array of software applications with revisions of each app being continuously updated. Target devices could range from embedded IoT (Internet of Things) to the largest, most powerful severs. With all of this variability, it was quite common for individuals within the company to be running code in different environments. Outside the four walls of the company, customers could be running in yet another environment. This situation presented challenges.

The software development pipeline can be organized as follows: planning, resourcing, development, testing, quality assurance, and deployment. Continuous delivery requires automation from planning all the way through to delivery/deployment. Previously, software development, testing, quality assurance, and customers could each be running in different environments. This hampered their ability to communicate and led to misunderstandings and delays.

If, for example, the customer reported a problem, it might not be replicable in the support, test or development groups due to differences in the hardware and software environments being run. This lack of alignment fostered misunderstandings and delays and often led to a lack of trust and communication between the various stakeholders.

In a complex world requiring the physical provisioning of servers, installation of stacks and frameworks, and numerous target devices, the standardization and control of the run-time environment has been difficult and slow. It became necessary to break down barriers between the respective teams in the software development pipeline. This merging of development and IT/Operations is widely known as DevOps, which also has had enormous impact on the world of software development. DevOps improves collaboration between employees from the planning through the deployment phases of software. It seeks to reduce time to deployment, decrease time to market, minimize defects, and shorten the time required to fix problems.

About a decade ago, Amazon Web Services (AWS) and other cloud providers, began offering computing, storage and other IT resources as an on-demand service. No more waiting weeks or months for the IT department to fulfill a request for servers. Cloud providers now allow you to order computing services, paying only for what you use, whether that is one processor for an hour or thousands of processors for months. These on-demand cloud services have enabled developers to write code that provisions processing resources with strictly specified environments, on-demand, in just a few minutes. This capability has been called *Infrastructure as Code (IaC)*. IaC has made it possible for everyone in the software development pipeline, all the different groups mentioned above, to use an identical environment tailored to application requirements. With IaC, design, test, QA and support

can easily get *on the same page*. This leads to much better collaboration between the groups and breaks down barriers that prevented open communication. In other words, no more finger pointing.

With IT infrastructure being defined by code, the hard divisions between IT operations and software development are able to blur. The merger of development and operations is how the term *DevOps* originated.

With the automated provisioning of resources, DevOps paved the way for a fully automated test and release process. The process of deploying code that used to take weeks, could now be completed in minutes. Major organizations including Amazon, Facebook and Netflix are now operating this way. At a recent conference, Amazon disclosed that their AWS team performs 50,000,000 code releases per year. This is more than one per second! This methodology of rapid releases is called *continuous delivery* or alternatively, *continuous deployment*, when new features (and fixes) are not only delivered internally but fully deployed to customers.

DevOps starts with continuous delivery and Agile development and adds automated provisioning of resources (infrastructure as code) and cloud services (platform as a service) to ensure that the same environment is being utilized at every stage of the software development pipeline. The cloud provides a natural platform that allows individuals to create and define identical run-time environments. DevOps is beginning to achieve critical mass in terms of its adoption within the world of software development.

DevOps improves collaboration between employees from the planning through the deployment phases of software. It seeks to reduce time to deployment, decrease time to market, minimize defects, and shorten the time required to fix problems.

The impact of DevOps on development organizations was shown in a 2014 survey, "The 2014 State of DevOps Report" by Puppet Labs, IT Revolution Press and ThoughtWorks, based on 9,200 survey responses from technical professionals. The survey found that IT organizations implementing DevOps were deploying code 30 times more frequently and with 50 percent fewer failures. Further, companies with these higher performing IT organizations tended to have stronger business performance, greater productivity, higher profitability and larger market share. In other words, DevOps is not just something that engineers are doing off in a dark corner. It is a core competency that helps good companies become better.

The Data analytics team transforms raw data into actionable information that improves decision making and provides market insight. Imagine an organization with the best data analytics in the industry. That organization would have a tremendous advantage over competitors. That could be you.

Data Analytics Can Learn from Manufacturing

What could data analytics professionals possibly learn from industrial manufacturers? It turns out, a lot. Automotive giant Toyota pioneered a set of methods, later folded into a discipline called *lean manufacturing*, in which employees focus relentlessly on improving quality and reducing non-value-add activities. This culture enabled Toyota to grow into the one of the world's leading car companies. The Agile and DevOps methods that have led to stellar improvements in coding velocity are really just an example of lean manufacturing principles applied to software development.

Conceptually, manufacturing is a pipeline process. Raw materials enter the manufacturing floor through the stock room, flow to different work stations as work-in-progress and exit as finished goods. In data-analytics, data progresses through a series of steps and exits in the form of reports, models and visualizations. Each step takes an input from the previous step, executes a complex procedure or set of instructions and creates output for the subsequent step. At an abstract level, the data-analytics pipeline is analogous to a manufacturing process. Like manufacturing, data analytics executes a set of operations and attempts to produce a consistent output at a high level of quality. In addition to lean-manufacturing-inspired methods like Agile and DevOps, there is one more useful tool that can be taken from manufacturing and applied to data-analytics process improvement.

W. Edwards Deming championed statistical process control (SPC) as a method to improve manufacturing quality. SPC uses real-time product or process measurements to monitor and control quality during manufacturing processes. If the process measurements are maintained within specific limits, then the manufacturing process is deemed to be functioning properly. When SPC is applied to the data-analytics pipeline, it leads to remarkable improvements in efficiency and quality. For example, Google executes over one hundred million automated test scripts per day to validate any new code released by software developers. In the Google consumer surveys group, code is deployed to customers eight minutes after a software engineer finishes writing and testing it.

In data analytics, tests should verify that the results of each intermediate step in the production of analytics matches expectations. Even very simple tests can be useful. For example, a simple row-count test could catch an error in a join that inadvertently produces a Cartesian product. Tests can also detect unexpected trends in data, which might be flagged as warnings. Imagine that the number of customer transactions exceeds its historical average by 50%. Perhaps that is an anomaly that upon investigation would lead to insight about business seasonality.

Tests in data analytics can be applied to data or models either at the input or output of a phase in the analytics pipeline. Tests can also verify business logic.

Business logic tests validate assumptions about the data. For example:

- Customer Validation – Each customer should exist in a dimension table
- Data Validation – At least 90 percent of data should match entries in a dimension table

Input tests check data prior to each stage in the analytics pipeline. For example:

- Count Verification – Check that row counts are in the right range, ...
- Conformity – US Zip5 codes are five digits, US phone numbers are 10 digits, ...
- History – The number of prospects always increases, ...
- Balance – Week over week, sales should not vary by more than 10%, ...
- Temporal Consistency – Transaction dates are in the past, end dates are later than start dates, ...
- Application Consistency – Body temperature is within a range around 98.6F/37C, ...
- Field Validation – All required fields are present, correctly entered, ...

Output tests check the results of an operation, like a Cartesian join. For example:

- Completeness – Number of customer prospects should increase with time
- Range Verification – Number of physicians in the US is less than 1.5 million

The data analytics pipeline is a complex process with steps often too numerous to be monitored manually. SPC allows the data analytics team to monitor the pipeline end-to-end from a big-picture perspective, ensuring that everything is operating as expected. As an automated test suite grows and matures, the quality of the analytics is assured without adding cost. This makes it possible for the data analytics team to move quickly — enhancing analytics to address new challenges and queries — without sacrificing quality.

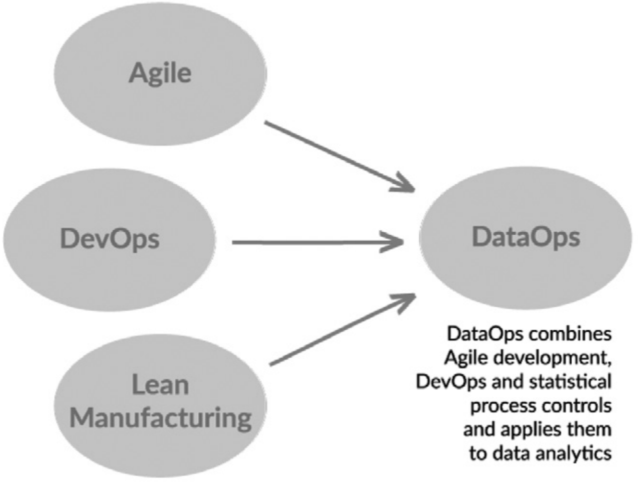


Figure 3: DataOps has evolved from lean manufacturing and software methodologies.

DataOps for Data Analytics

The speed and flexibility achieved by Agile and DevOps, and the quality control attained by SPC, can be applied to data analytics. Leading edge proponents of this approach are calling it *DataOps*. DataOps, simply stated, is Agile development and DevOps with statistical process control, for data analytics. DataOps applies Agile methods, DevOps, and manufacturing quality principles, methodologies and tools, to the data-analytics pipeline. The result is a rapid-response, flexible and robust data-analytics capability, which is able to keep up with the creativity of internal stakeholders and users.

DataOps is an analytic development method that emphasizes communication, collaboration, integration, automation, measurement and cooperation between data scientists, analysts, data/ETL (extract, transform, load) engineers, information technology (IT), and quality assurance/governance. The method acknowledges the interdependence of the entire end-to-end analytic process. It aims to help organizations rapidly produce insight, turn that insight into operational tools, and continuously improve analytic operations and performance. It enables the whole analytic team involved in the analytic process to follow the values laid out in the DataOps Manifesto.

When DataOps is implemented correctly, it addresses many of the issues discussed earlier that have plagued data-analytics teams.

Challenge	DataOps Approach
Changing Requirements	The team delivers something of value to users at each iteration. If the requirements change, it is simple to put new requirements on the request list for a future iteration.
Slipped schedules	Iterations occur in rapid succession allowing greater visibility to the progress that is being made. As a team gains experience with DataOps, their forecasting improves.
Disappointed users	Users receive new features quickly and give feedback to the development team about how to keep improving the data analytics with even more new features.
Inflexibility	DataOps enables teams to respond quickly to change. The team can pivot at the beginning of the next iteration, which by definition is always relatively soon.
Poor quality	Extensive, automated testing, in the form of statistical process control, is a key element in DataOps.
Low ROI	With features being delivered in short increments, the monetization of the data-analytics investment begins much earlier, improving ROI.
Irrelevant features	The data-analytics team is churning out management's highest priority features in quick succession.

Table 1: Challenge/DataOps Approach

DataOps views the data-analytics pipeline as a process and as such focuses on how to make the entire process run more rapidly and with higher quality, rather than optimizing the productivity of any single individual or tool by itself.

Key Benefits of DataOps

DataOps can accelerate the ability of data-analytics teams to create and publish new analytics to users. It requires an Agile mindset and must also be supported by an automated platform which incorporates existing tools into a DataOps development pipeline. DataOps spans the entire analytic process, from data acquisition to insight delivery. Its goal is to achieve more insight and better analysis, while still being faster, cheaper and higher quality.

The key business benefits of adopting DataOps are:

- Reduce time to insight
- Improve analytic quality
- Lower the marginal cost to ask the next business question
- Improve analytic team morale by going beyond hope, heroism and caution
- Promote team efficiency through agile process, reuse and refactoring

DataKitchen markets an automated DataOps platform that helps companies accelerate their DataOps implementation, but this book is about DataOps not us. This book is not trying to sell you anything. You can implement DataOps all by yourself, using your existing tools, by implementing the seven steps described in the next section. If you desire assistance, there is an ecosystem of DataOps vendors who offer a variety of innovative solutions and services.

The Seven Steps to Implement DataOps

Data analytics has become business critical, but requirements quickly evolve and data-analytics teams that respond to these challenges in the traditional ways often end up facing disappointed users. DataOps offers a more effective approach that optimizes the productivity of the data analytics pipeline by an order of magnitude.

Imagine the next time that the Vice President of Marketing requests a new customer segmentation, by tomorrow. With DataOps, the data-analytics team can respond 'yes' with complete confidence that the changes can be accomplished quickly, efficiently and robustly. How then does an organization implement DataOps? You may be surprised to learn that an analytics team can migrate to DataOps in seven simple steps.

STEP 1 - ADD DATA AND LOGIC TESTS

If you make a change to an analytic pipeline, how do you know that you did not break anything? Automated testing insures that a feature release is of high quality without requiring time-consuming, manual testing. The idea in DataOps is that every time a data-analytics team member makes a change, he or she adds a test for that change. Testing is added incrementally, with the addition of each feature, so testing gradually improves and quality is literally built in. In a big run, there could be hundreds of tests at each stage in the pipeline.

Adding tests in data analytics is analogous to the statistical process control that is implemented in a manufacturing operations flow. Tests insure the integrity of the final output by verifying that work-in-progress (the results of intermediate steps in the pipeline) matches expectations. Testing can be applied to data, models and logic. The figure below shows examples of tests in the data-analytics pipeline.

For every step in the data-analytics pipeline, there should be at least one test. The philosophy is to start with simple tests and grow over time. Even a simple test will eventually catch an error before it is released out to the users. For example, just making sure that row counts are consistent throughout the process can be a very powerful test. One could easily make a mistake on a *join* and make a *cross product* which fails to execute correctly. A simple row-count test would quickly catch that.

Tests can detect warnings in addition to errors. A warning might be triggered if data exceeds certain boundaries. For example, the number of customer transactions in a week may be OK if it is within 90% of its historical average. If the transaction level exceeds that, then a warning could be flagged. This might not be an error. It could be a seasonal occurrence for example, but the reason would require investigation. Once recognized and understood, the users of the data could be alerted.

DataOps is not about being perfect. In fact, it acknowledges that code is imperfect. It's natural that a data-analytics team will make a best effort, yet still miss something. If so, they can determine the cause of the issue and add a test so that it never happens again. In a rapid release environment, a fix can quickly propagate out to the users.

With a suite of tests in place, DataOps allows you to move fast because you can make changes and quickly rerun the test suite. If the changes pass the tests, then the data-analytics team member can be confident and release it. The knowledge is built into the system and the process stays under control. Tests catch potential errors and warnings before they are released so the quality remains high.

Automated tests continuously monitor the data pipeline for errors and anomalies. They work nights, weekends and holidays without taking a break. If you build a DataOps dashboard, you can view the high-level state of your data operations at any time. If warning and failure alerts are automated, you don't have to constantly check your dashboard. Automated testing frees the data-analytics team from the drudgery of manual testing, so they can focus on higher value-add activities.

Figure 4: Tests enable the data professional to apply statistical process controls to the data pipeline

STEP 2 - USE A VERSION CONTROL SYSTEM

There are many processing steps that turn raw data into useful information for stakeholders. To be valuable, data must progress through these steps, linked together in some way, with the ultimate goal of producing a data-analytics output. Data may be preprocessed, cleaned, checked, transformed, combined, analyzed, and reported. Conceptually, the data-analysis pipeline is a set of stages implemented using a variety of tools including ETL tools, data science tools, self-service data prep tools, reporting tools, visualization tools and more. The stages may be executed serially, but many stages can be parallelized. The pipeline is deterministic because the pipeline stages are defined by scripts, source code, algorithms, html, configuration files, parameter files, containers and other files. All of these items are *essentially* just code. Code controls the entire data-analytics pipeline from end to end in a reproducible fashion.

The artifacts (files) that make this reproducibility possible are usually subject to continuous improvement. Like other software projects, the source files associated with the data pipeline should be maintained in a version control (source control) system such as Git. A version control tool helps teams of individuals organize and manage the changes and revisions to code. It also keeps code in a known repository and facilitates disaster recovery. However, the most important benefit of version control relates to a process change that it facilitates. It allows data-analytics team members to *branch and merge*.

STEP 3 - BRANCH AND MERGE

In a typical software project, developers are continuously updating various code source files. If a developer wants to work on a feature, he or she pulls a copy of all relevant code from the version control tool and starts to develop changes on a local copy. This local copy is called a *branch*. This approach can help data-analytics teams maintain many coding changes to the data-analytics pipeline in parallel. When the changes to a branch are complete and tested, the code from the branch is *merged* back into the trunk, where the code came from.

Branching and merging can be a major productivity boost for data analytics because it allows teams to make changes to the same source code files in parallel without slowing each other down. Each individual team member has control of his or her work environment. They can run their own tests, make changes, take risks and experiment. If they wish, they can discard their changes and start over. Another key to allowing team members to work well in parallel relates to providing them with an isolated machine environment.

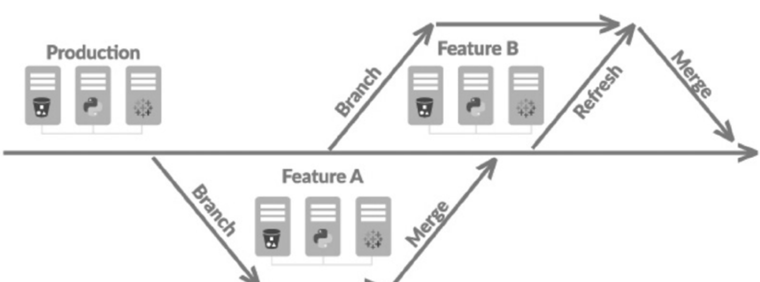
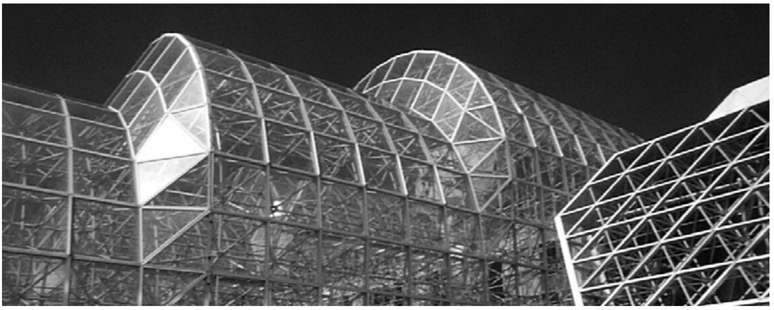


Figure 5: Branching and merging enables parallel development in data analytics.

STEP 4 - USE MULTIPLE ENVIRONMENTS

Every data-analytics team member has their own development tools on their own laptop. Version control tools allow team members to work on their own private copy of the source code while still staying coordinated with the rest of the team. In data analytics, a team member can't be productive unless they also have a copy of the data that they need. Most use cases can be covered in less than a Terabyte (TB). Historically, disk space has been prohibitively expensive, but today, at less than $25 per TB per month (cloud storage), costs are now less significant than the opportunity cost of a team member's time. If the data set is still too large, then a team member can take only the subset of data that is needed. Often the team member only needs a representative copy of the data for testing or developing one set of features.

When many team members work on the production database, it can lead to conflicts. A database engineer changing a schema may break reports. A data scientist developing a new model might get confused as new data flows in. Giving team members their own *Environment* isolates the rest of the organization from being impacted by their work.



STEP 5 - REUSE & CONTAINERIZE

Another productivity boosting method for teams is the ability to reuse and containerize code. Each middle step in the data-analytics pipeline receives output from a prior stage and provides input to the next stage. It is cumbersome to work with an entire data-analytics pipeline as one monolith, so it is common to break it down into smaller components. It's easiest for other team members to reuse smaller components if they can be segmented or containerized. One popular container technology is Docker.

Some steps in the data-analytics pipeline are messy and complicated. For example, one operation might call a custom tool, run a python script, use FTP and other specialized logic. This operation might be hard to set up (because it requires a specific set of tools) and difficult to create (because it requires a specific skill set). This scenario is another common use case for creating a container. Once the code is placed in a container, it is much easier to use by other programmers who aren't familiar with the custom tools inside the container but know how to use the container's external interfaces. It is also easier to deploy that code to each environment.

STEP 6 - PARAMETERIZE YOUR PROCESSING

There are cases when the data-analytic pipeline needs to be flexible enough to incorporate different run-time conditions. Which version of the raw data should be used? Is the data directed to production or testing? Should records be filtered according to some criterion (such as private health care data)? Should a specific set of processing steps in the workflow be included or not? To increase development velocity, these options need to be built into the pipeline. A robust pipeline design will allow the engineer or analyst to invoke or specify these options using parameters. In software development, a parameter is some information (e.g. a name, a number, an option) that is passed to a program that affects the way that it executes. If the data-analytic pipeline is designed with the right flexibility, it will be ready to accommodate different run-time circumstances.

For example, imagine a pharmaceutical company that obtains prescription data from a 3rd party company. The data is incomplete, so the data producer uses algorithms to fill in those gaps. In the course of improving their product, the data producer develops a different algorithm to the fill in the gaps. The data has the same shape (rows and columns), but certain fields are modified using the new algorithm. With the correct built-in parameters, an engineer or analyst can easily build a parallel data mart with the new algorithm and have both the old and new versions accessible through a parameter change.

STEP 7: WORK WITHOUT FEAR OR HEROISM

Many data analytics professionals live in fear. In data analytics there are two common ways to be professionally embarrassed (or get fired):

- Allow poor quality data to reach users
- Deploy changes that break production systems

Data engineers, scientists and analysts spend an excessive amount of time and energy working to avoid these disastrous scenarios. They attempt “heroism” — working weekends. They do a lot of hoping and praying. They devise creative ways to avoid overcommitting. The problem is that heroic efforts are eventually overcome by circumstances. Without the right controls in place, a problem will slip through and bring the company’s critical analytics to a halt.

The DataOps enterprise puts the right set of tools and processes in place to enable data and new analytics to be deployed with a high level of quality. When an organization implements DataOps, engineers, scientists and analysts can relax because quality is assured. They can *Work Without Fear or Heroism*. DataOps accomplishes this by optimizing two key workflows.

The Value Pipeline

Data analytics seeks to extract value from data. We call this the Value Pipeline. The diagram below shows the Value Pipeline progressing horizontally from left to right. Data enters the pipeline and moves into production processing. Production is generally a series of stages: access, transforms, models, visualizations, and reports. When data exits the pipeline, in the form of useful analytics, value is created for the organization. DataOps utilizes toolchain workflow automation to optimize operational efficiency in the Value Pipeline. Data in the Value Pipeline is updated on a continuous basis, but code is kept constant. Step 2 in the seven steps of implementing DataOps — using version control — serves as the foundation for controlling the code deployed.

As mentioned above, the worst possible outcome is for poor quality data to enter the Value Pipeline. DataOps prevents this by implementing data tests (step 1). Inspired by the statistical process control in a manufacturing workflow, data tests ensure that data values lay within an acceptable statistical range. Data tests validate data values at the inputs and outputs of each processing stage in the pipeline. For example, a US phone number should be ten digits. Any other value is incorrect or requires normalization.

Once data tests are in place, they work 24x7 to guarantee the integrity of the Value Pipeline. Quality becomes *literally* built in. If anomalous data flows through the pipeline, the data tests catch it and take action — in most cases this means firing off an alert to the data analytics team who can then investigate. The tests can even, in the spirit of auto manufacturing, “stop the line.” Statistical process control eliminates the need to worry about what might happen. With the right data tests in place, the data analytics team can *Work Without Fear or Heroism*. This frees DataOps engineers to focus on their other major responsibility — the Innovation Pipeline.

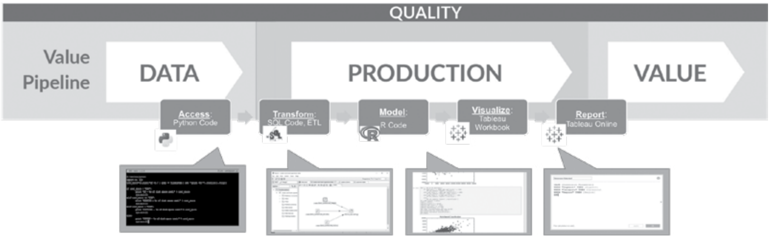


Figure 6: The value pipeline

The Innovation Pipeline

The Innovation Pipeline seeks to improve analytics by implementing new ideas that yield analytic insights. As the diagram illustrates, a new feature undergoes development before it can be deployed to production systems. The Innovation Pipeline creates a feedback loop. Innovation spurs new questions and ideas for enhanced analytics. This requires more development leading to additional insight and innovation. During the development of new features, code changes, but data is kept constant. Keeping data static prevents changes in data from being falsely attributed to the impact of the new algorithm. A fixed data set can be set-up when creating a development environment — step 4 in the seven steps of implementing DataOps.

DataOps implements continuous deployment of new ideas by automating the workflow for building and deploying new analytics. It reduces the overall cycle time of turning ideas into innovation. While doing this, the development team must avoid introducing new analytics that break production. The DataOps enterprise uses logic tests (step 1) to validate new code before it is deployed. Logic tests ensure that data matches business assumptions. For example, a field that identifies a customer should match an existing entry in a customer dimension table. A mismatch should trigger some type of follow-up.

With logic tests in place, the development pipeline can be automated for continuous deployment, simplifying the release of new enhancements and enabling the data analytics team to focus on the next valuable feature. With DataOps the dev team can deploy without worrying about breaking the production systems — they can *Work Without Fear or Heroism*. This is a key characteristic of a fulfilled, productive team.

The Value-Innovation Pipeline

In real world data analytics, the Value Pipeline and Innovation Pipeline are not separate. The same team is often responsible for both. The same assets are leveraged. Events in one affect the other. The two workflows are shown combined into the Value-Innovation Pipeline in the figure below. The Value-Innovation Pipeline captures the interplay between development and production and between data and code. DataOps breaks down this barri-

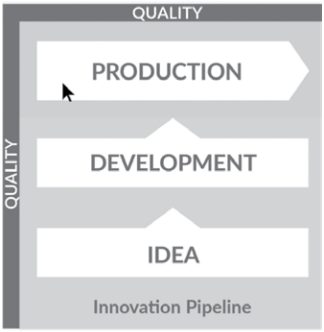


Figure 7: The innovation pipeline

er so that cycle time, quality and creativity can all be improved. The DataOps enterprise masters the orchestration of data to production and the deployment of new features both while maintaining impeccable quality. Reduced cycle time enables DataOps engineers to impact the organization in highly visible ways. Improved quality enables the team to move forward with confidence. DataOps speeds the extraction of value from data and improves the velocity of new development while ensuring the quality of data and code in production systems. With confidence in the Value-Innovation pipeline that stems from DataOps, the data analytics team avoids the anxiety and over-caution that characterizes a non-DataOps enterprise. *Work Without Fear or Heroism*!

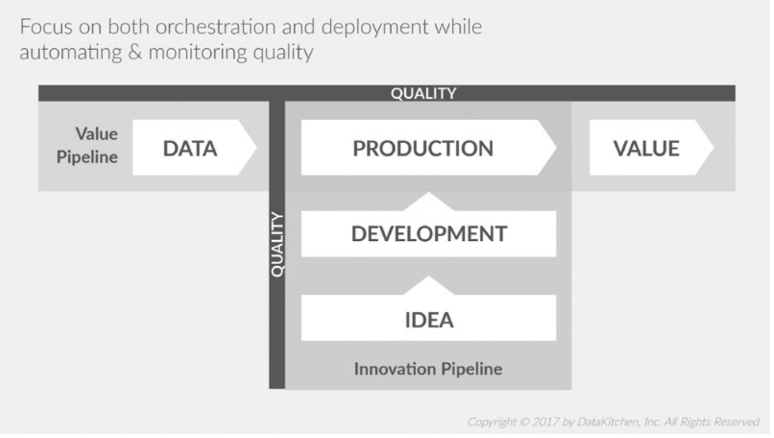


Figure 8: The Value and Innovation Pipelines illustrate how new analytics are introduced into data operations.

DataOps is NOT Just DevOps for Data

One common misconception about DataOps is that it is just DevOps *applied to data analytics*. While a little semantically misleading, the name “DataOps” has one positive attribute. It communicates that data analytics can achieve what software development attained with DevOps. That is to say, DataOps can yield an order of magnitude improvement in quality and cycle time when data teams utilize new tools and methodologies. The specific ways that DataOps achieves these gains reflect the unique people, processes and tools characteristic of data teams (versus software development teams using DevOps). Here’s our in-depth take on both the pronounced and subtle differences between DataOps and DevOps.

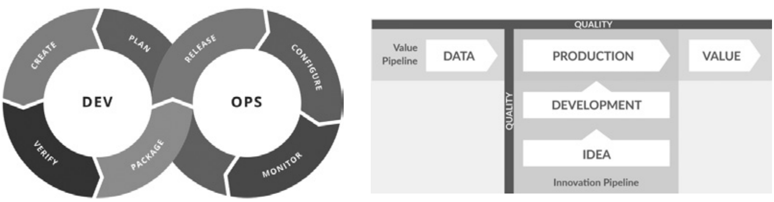


Figure 9: DevOps is often depicted as an infinite loop, while DataOps is illustrated as intersecting Value and Innovation Pipelines

The Intellectual Heritage of DataOps

DevOps is an approach to software development that accelerates the build lifecycle (formerly known as release engineering) using automation. DevOps focuses on continuous integration and continuous delivery of software by leveraging on-demand IT resources (infrastructure as code) and by automating integration, test and deployment of code. This merging of software development and IT operations (“DEVelopment” and “OPerationS”) reduces time to deployment, decreases time to market, minimizes defects, and shortens the time required to resolve issues.

Using DevOps, leading companies have been able to reduce their software release cycle time from months to (literally) seconds. This has enabled them to grow and lead in fast-paced, emerging markets. Companies like Google, Amazon and many others now release software many times per day. By improving the quality and cycle time of code releases, DevOps deserves a lot of credit for these companies’ success.

Optimizing code builds and delivery is only one piece of the larger puzzle for data analytics. DataOps seeks to reduce the end-to-end cycle time of data analytics, from the origin of ideas to the literal creation of charts, graphs and models that create value. The data lifecycle relies upon people in addition to tools. For DataOps to be effective, it must manage collaboration and innovation. To this end, DataOps introduces Agile Development into data analytics so that data teams and users work together more efficiently and effectively.

In Agile Development, the data team publishes new or updated analytics in short increments called “sprints.” With innovation occurring in rapid intervals, the team can continuously reassess its priorities and more easily adapt to evolving requirements. This type of responsiveness is impossible using a Waterfall project management methodology which locks a team into a long development cycle with one "big-bang" deliverable at the end.

Studies show that Agile software development projects complete faster and with fewer defects when Agile Development replaces the traditional Waterfall sequential methodology. The Agile methodology is particularly effective in environments where requirements are quickly evolving — a situation well known to data analytics professionals. In a DataOps setting, Agile methods enable organizations to respond quickly to customer requirements and accelerate time to value.

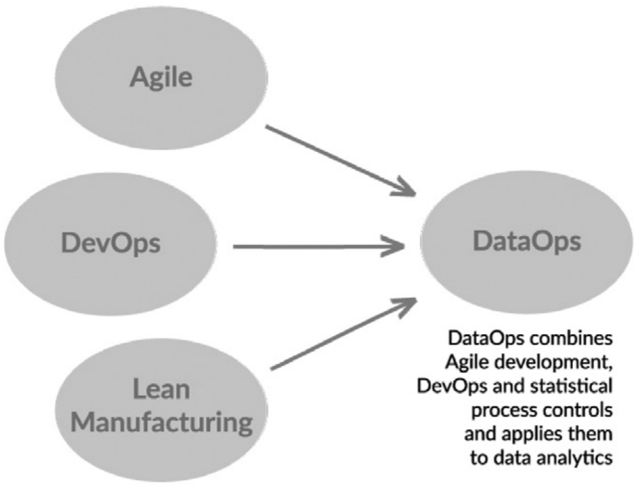


Figure 10: DataOps has evolved from lean manufacturing and software methodologies.

Agile development and DevOps add significant value to data analytics, but there is one more major component to DataOps. Whereas Agile and DevOps relate to analytics development and deployment, data analytics also manages and orchestrates a data pipeline. Data continuously enters on one side of the pipeline, progresses through a series of steps and exits in the form of reports, models and views. The data pipeline is the "operations" side of data analytics. It is helpful to conceptualize the data pipeline as a manufacturing line where quality, efficiency, constraints and uptime must be managed. To fully embrace this manufacturing mindset, we call this pipeline the *"data factory."*

In DataOps, the flow of data through operations is an important area of focus. DataOps orchestrates, monitors and manages the data factory. One particularly powerful lean-manufacturing tool is statistical process control (SPC). SPC measures and monitors data and operational characteristics of the data pipeline, ensuring that statistics remain within acceptable ranges. When SPC is applied to data analytics, it leads to remarkable improvements in efficiency, quality and transparency. With SPC in place, the data flowing through the operational system is verified to be working. If an anomaly occurs, the data analytics team will be the first to know, through an automated alert.

While the name “DataOps” implies that it borrows most heavily from DevOps, it is all three of these methodologies - Agile, DevOps and statistical process control — that comprise the intellectual heritage of DataOps. Agile governs analytics development, DevOps optimizes code verification, builds and delivery of new analytics and SPC orchestrates and monitors the data factory. Figure 10 illustrates how Agile, DevOps and statistical process control flow into DataOps.

You can view DataOps in the context of a century-long evolution of ideas that improve how people manage complex systems. It started with pioneers like Deming and statistical process control — gradually these ideas crossed into the technology space in the form of Agile, DevOps and now, DataOps.

DevOps vs. DataOps — The Human Factor

As mentioned above, DataOps is as much about managing people as it is about tools. One subtle difference between DataOps and DevOps relates to the needs and preferences of stakeholders.

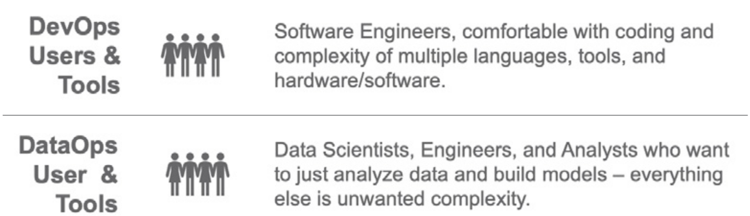


Figure 11: DataOps and DevOps users have different mindsets

DevOps was created to serve the needs of software developers. Dev engineers love coding and embrace technology. The requirement to learn a new language or deploy a new tool is an opportunity, not a hassle. They take a professional interest in all the minute details of code creation, integration and deployment. DevOps embraces complexity.

DataOps users are often the opposite of that. They are data scientists or analysts who are focused on building and deploying models and visualizations. Scientists and analysts are typically not as technically savvy as engineers. They focus on domain expertise. They are interested in getting models to be more predictive or deciding how to best visually render data. The technology used to create these models and visualizations is just a means to an end. Data professionals are happiest using one or two tools — anything beyond that adds unwelcome complexity. In extreme cases, the complexity grows beyond their ability to manage it. DataOps accepts that data professionals live in a multi-tool, heterogeneous world and it seeks to make that world more manageable for them.

DevOps vs. DataOps - Process Differences

We can begin to understand the unique complexity facing data professionals by looking at data analytics development and lifecycle processes. We find that data analytics professionals face challenges both similar and unique relative to software developers.

The DevOps lifecycle is commonly illustrated using a diagram in the shape of an infinite symbol — See Figure 12. The end of the cycle ("plan") feeds back to the beginning ("create"), and the process iterates indefinitely.

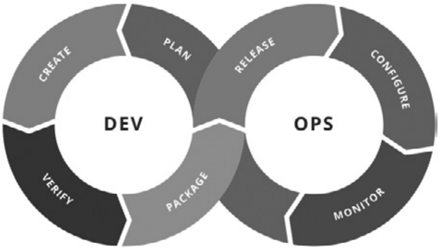


Figure 12: The DevOps lifecycle is often depicted as an infinite loop

The DataOps lifecycle shares these iterative properties, but an important difference is that DataOps consists of two active and intersecting pipelines (Figure 13). The data factory, described above, is one pipeline. The other pipeline governs how the data factory is updated — the creation and deployment of new analytics into the data pipeline.

The data factory takes raw data sources as input and through a series of orchestrated steps produces analytic insights that create *"value"* for the organization. We call this the "*Value Pipeline*." DataOps automates orchestration and, using SPC, monitors the quality of data flowing through the Value Pipeline.

The "*Innovation Pipeline*" is the process by which new analytic ideas are introduced into the Value Pipeline. The Innovation Pipeline conceptually resembles a DevOps development process, but upon closer examination, several factors make the DataOps development process more challenging than DevOps. Figure 13 shows a simplified view of the Value and Innovation Pipelines.

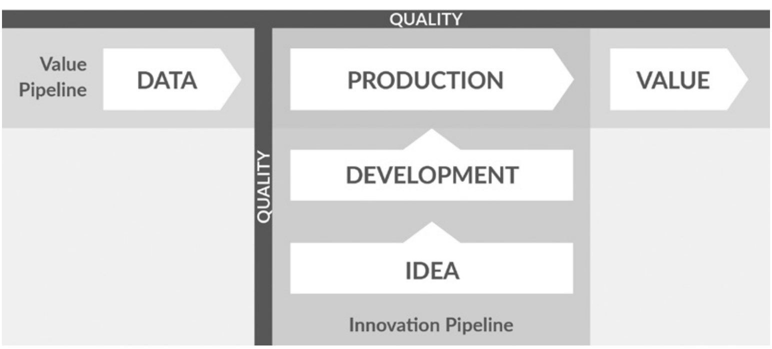


Figure 13: The DataOps lifecycle — the Value and Innovation Pipelines

DevOps vs. DataOps — Development and Deployment Processes

DataOps builds upon the DevOps development model. As shown in Figure 14, the DevOps process flow includes a series of steps that are common to software development projects:

- **Develop** – create/modify an application
- **Build** – assemble application components
- **Test** – verify the application in a test environment
- **Deploy** – transition code into production
- **Run** – execute the application

DevOps introduces two foundational concepts: Continuous Integration (CI) and Continuous Deployment (CD). CI continuously builds, integrates and tests new code in a development environment. Build and test are automated so they can occur rapidly and repeatedly. This allows issues to be identified and resolved quickly. Figure 14 illustrates how CI encompasses the build and test process stages of DevOps.

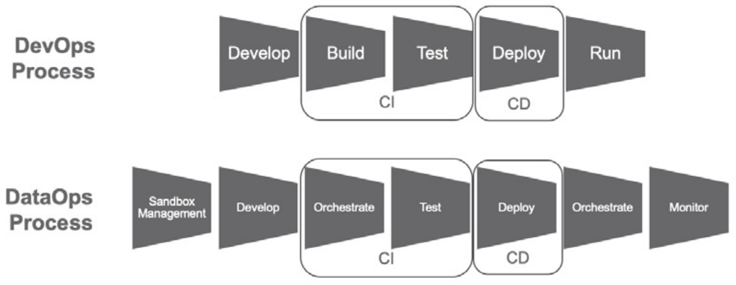


Figure 14: Comparing the DataOps and DevOps processes

CD is an automated approach to deploying or delivering software. Once an application passes all qualification tests, DevOps deploys it into production. Together CI and CD resolve the main constraint hampering Agile development. Before DevOps, Agile created a rapid succession of updates and innovations that would stall in a manual integration and deployment process. With automated CI and CD, DevOps has enabled companies to update their software many times per day.

The Duality of Orchestration in DataOps

It's important to note that "orchestration" occurs twice in the DataOps process shown in Figure 14. As we explained above, DataOps orchestrates the data factory (the Value Pipeline). The data factory consists of a pipeline process with many steps. Imagine a complex directed acyclic graph (DAG). The "orchestrator" could be a software entity which controls the execution of the steps, traverses the DAG, and handles exceptions. For example, the orchestrator might create containers, invoke runtime processes with context-sensitive parameters, transfer data from stage to stage, and "monitor" pipeline execution. Orchestration of the data factory is the second "orchestration" in the DataOps process in Figure 15.

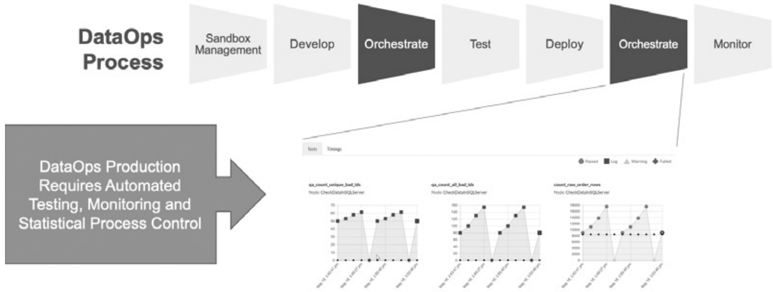


Figure 15: DataOps orchestrates the data factory.

As noted above, the [Innovation Pipeline]() has a representative copy of the data pipeline which is used to [test]() and verify new analytics before deployment into production. This is the orchestration that occurs in conjunction with "testing" and prior to "deployment" of new analytics — as shown in Figure 16.

Orchestration occurs in both the Value and Innovation Pipelines. Similarly, testing fulfills a dual role in DataOps.

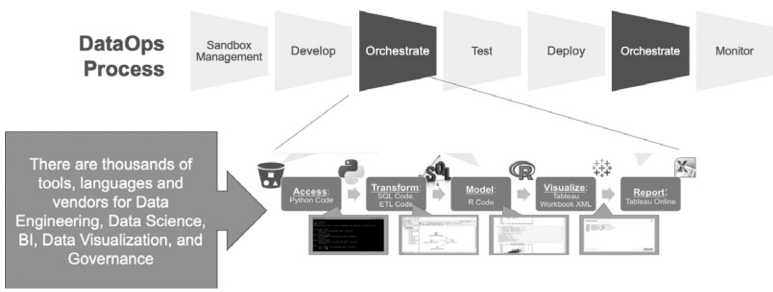


Figure 16: DataOps orchestration controls the numerous tools that access, transform, model, visualize and report data

The Duality of Testing in DataOps

Tests in DataOps have a role in both the Value and Innovation Pipelines. In the Value Pipeline, tests monitor the data values flowing through the data factory to catch anomalies or flag data values outside statistical norms. In the Innovation Pipeline, tests validate new analytics before deploying them.

In DataOps, tests target either data or code. Figure 17 below illustrates this concept. Data that flows through the Value Pipeline is variable and subject to statistical process control and monitoring. Tests target the data which is continuously changing. Analytics in the Value Pipeline, on the other hand, are fixed and change only using a formal release process. In the Value Pipeline, analytics are revision controlled to minimize any disruptions in service that could affect the data factory.

In the Innovation Pipeline code is variable and data is fixed. The analytics are revised and updated until complete. Once the sandbox (analytics development environment) is set-up, the data doesn't usually change. In the Innovation Pipeline, tests target the code (analytics), not the data. All tests must pass before promoting (merging) new code into production. A good test suite serves as an automated form of impact analysis that runs on any and every code change before deployment.

Some tests are aimed at both data and code. For example, a test that makes sure that a database has the right number of rows helps your data and code work together. Ultimately both data tests and code tests need to come together in an integrated pipeline as shown in Figure 13. DataOps enables code and data tests to work together so all around quality remains high.

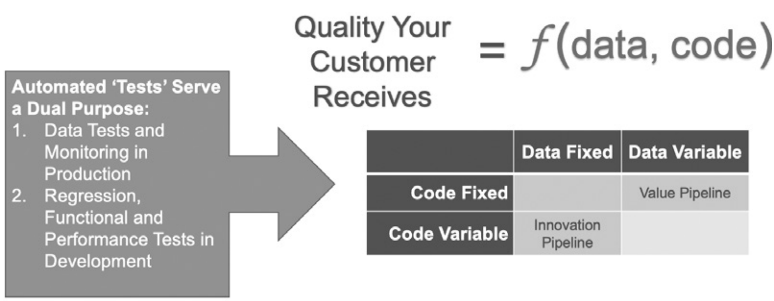


Figure 17: In DataOps, analytics quality is a function of data and code testing

DataOps Complexity — Sandbox Management

When an engineer joins a software development team, one of their first steps is to create a "sandbox." A sandbox is an isolated development environment where the engineer can write and test new application features, without impacting teammates who are developing other features in parallel. Sandbox creation in software development is typically straightforward — the engineer usually receives a bunch of scripts from teammates and can configure a sandbox in a day or two. This is the typical mindset of a team using DevOps.

Sandboxes in data analytics are often more challenging from a tools and data perspective. First of all, data teams collectively tend to use many more tools than typical software dev teams. There are literally thousands of tools, languages and vendors for data engineering, data science, BI, data visualization, and governance. Without the centralization that is characteristic of most software development teams, data teams tend to naturally diverge with different tools and data islands scattered across the enterprise.

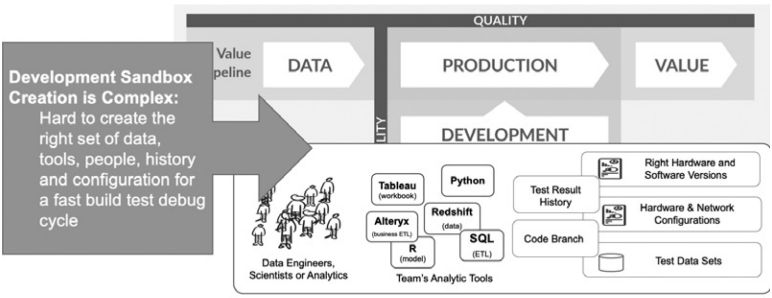


Figure 18: A "sandbox" is an isolated development environment where the data professional can write and test new analytics without impacting teammates.

DataOps Complexity - Test Data Management

In order to create a dev environment for analytics, you have to create a copy of the data factory. This requires the data professional to replicate data which may have security, governance or licensing restrictions. It may be impractical or expensive to copy the entire data set, so some thought and care is required to construct a representative data set. Once a multi-terabyte data set is sampled or filtered, it may have to be cleaned or redacted (have sensitive information removed). The data also requires infrastructure which may not be easy to replicate due to technical obstacles or license restrictions.

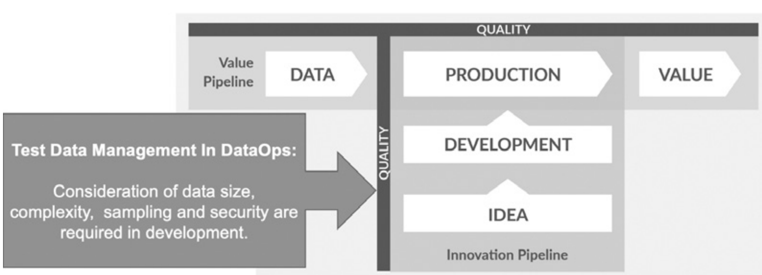


Figure 19: The concept of test data management is a first order problem in DataOps.

The concept of test data management is a first order problem in DataOps whereas in most DevOps environments, it is an afterthought. To accelerate analytics development, DataOps has to automate the creation of development environments with the needed data, software, hardware and libraries so innovation keeps pace with Agile iterations.

DataOps Connects the Organization in Two Ways

DevOps strives to help development and operations (information technology) teams work together in an integrated fashion. In DataOps, this concept is depicted in Figure 20. The development team are the analysts, scientists, engineers, architects and others who create data warehouses and analytics.

In data analytics, the operations team supports and monitors the data pipeline. This can be IT, but it also includes customers — the users who create and consume analytics. DataOps brings these groups together so they can work together more closely.

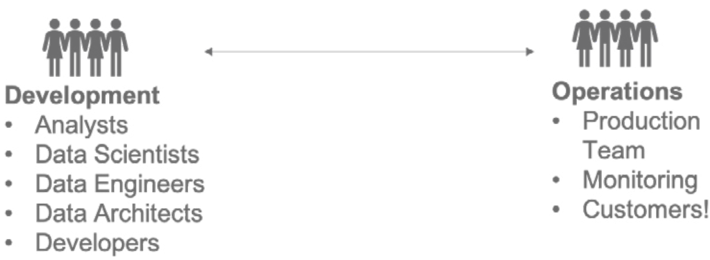


Figure 20: DataOps combines data analytics development and data operations

Freedom vs. Centralization

DataOps also brings the organization together across another dimension. A great deal of data analytics development occurs in remote corners of the enterprise, close to business units, using self-service tools like Tableau, Alteryx, or Excel. These local teams, engaged in decentralized, distributed analytics creation play an essential role in delivering innovation to users. Empowering these pockets of creativity maintains the enterprise's competitiveness, but frankly, a lack of top-down control can lead to unmanaged chaos.

Centralizing analytics development under the control of one group, such as IT, enables the organization to standardize metrics, control data quality, enforce security and governance, and eliminate islands of data. The issue is that too much centralization chokes creativity.

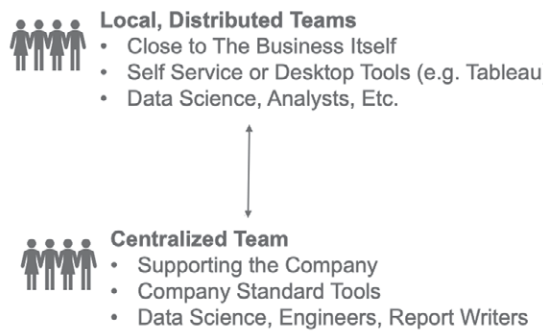


Figure 21: DataOps brings together centralized and distributed development

One important benefit of DataOps is its ability to harmonize the back-and-forth between the decentralized and centralized development of data analytics—the tension between centralization and freedom. In a DataOps enterprise, new analytics originate and undergo refinement in the local pockets of innovation. When an idea proves useful or is worthy of wider distribution, it is promoted to a centralized development group who can more efficiently and robustly implement it at scale.

DataOps brings localized and centralized development together enabling organizations to reap the efficiencies of centralization while preserving localized development—the tip of the innovation spear. DataOps brings the enterprise together across two dimensions as shown in Figure 22 — development/operations as well as distributed/centralized development.

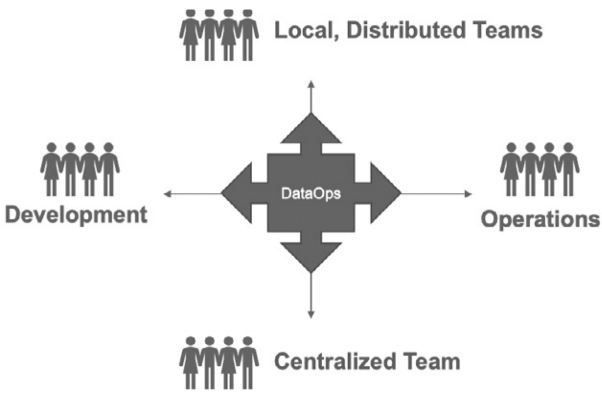


Figure 22: DataOps brings teams together across two dimensions — development/operations as well as distributed/centralized development.

DataOps brings three cycles of innovation between core groups in the organization: centralized production teams, centralized [data engineering](#)/analytics/science/governance development teams, and groups using self-service tools distributed into the lines business closest to the customer. Figure 23 shows the interlocking cycles of innovation.

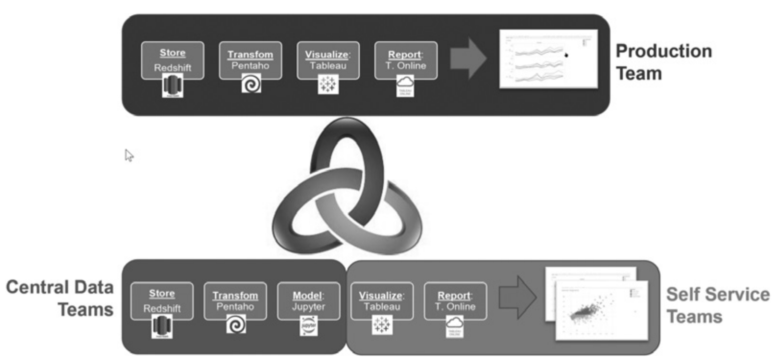


Figure 23: DataOps brings three cycles of innovation between production, central data, and self-service teams.

Enterprise Example - Data Analytics Lifecycle Complexity

Having examined the DataOps development process at a high level, let's look at the development lifecycle in the enterprise context. Figure 24 illustrates the complexity of analytics progression from inception to production. Analytics are first created and developed by an individual and then merged into a team project. After completing unit acceptance testing (UAT), analytics move into production. The goal of DataOps is to create analytics in the individual development environment, advance into production, receive feedback from users and then continuously improve through further iterations. This can be challenging due to the differences in personnel, tools, code, versions, manual procedures/automation, hardware, operating systems/libraries and target data. The columns in Figure 24 show the varied characteristics for each of these four environments.

The challenge of pushing analytics into production across these four quite different environments is daunting without DataOps. It requires a patchwork of manual operations and scripts that are in themselves complex to manage. Human processes are error-prone so data professionals compensate by working long hours, mistakenly relying on hope and heroism for success. All of this results in unnecessary complexity, confusion and a great deal of wasted time and energy. Slow progression through the lifecycle shown in Figure 24 coupled with high-severity errors finding their way into production can leave a data analytics team little time for innovation.

	Individual Development Environment	Team Development Environment	Test/UAT Environment	Production Environment
Who	Data Scientist	Data Scientist, Engineer & Analyst	Production and UAT Team	Production Team
Development Tool	Jupyter Notebook	Jupyter Notebook, SQL Editor & ...	None	None
Code	Python	Python, SQL, & others	Python, SQL, & others	Python, SQL, & others ....
Code Version	Version 1	Version 2 & 3	Version 3	Version 3
Run, Test, & Monitor	Ad hoc run: check unit tests	Ad hoc run: check unit, functional tests	Ad hoc run: check functional & monitor tests	Scheduled run: check monitor tests
Hardware	Laptop & test data	Development Servers & DB	Test Servers & DB	Production Servers & DB
Operating System & Libraries	Windows + libraries	Unix + Various libraries	Unix + Various libraries	Unix + Various libraries
Data	Small Development Data	Development Data	Copy Production Data	Production Data

Figure 24: Data Analytics Development Lifecycle Complexities

Implementing DataOps

DataOps simplifies the complexity of data analytics creation and operations. It aligns data analytics development with user priorities. It streamlines and automates the analytics development lifecycle — from the creation of sandboxes to deployment. DataOps controls and monitors the data factory so data quality remains high, keeping the data team focused on adding value.

You can get started with DataOps by implementing the seven steps in the last section. You can also adopt a DataOps Platform which will support DataOps methods within the context of your existing tools and infrastructure.

A DataOps Platform automates the steps and processes that comprise DataOps: sandbox management, orchestration, monitoring, testing, deployment, the data factory, dashboards, Agile, and more. A DataOps Platform is built for data professionals with the goal of simplifying all of the tools, steps and processes that they need into an easy-to-use, configurable, end-to-end system. This high degree of automation eliminates a great deal of manual work, freeing up the team to create new and innovative analytics that maximize the value of an organization's data.

DataOps Resolves the Struggle Between Centralization and Freedom in Analytics

Freedom and employee empowerment are essential to innovation, but a lack of top-down control leads to chaos. Self-service tools enable data analysts to create new analytics very quickly, but they can drift in different directions. Imagine a team of analysts building reports that tally sales figures and each come up with a different result. One approach includes drop shipments and sales from distributors/subsidiaries. Another report might consist of product sales, but not services. These different approaches each have their use case, but from a manager's perspective inconsistency creates the appearance of inaccuracy. You can't establish a shared reality when everyone has different numbers.

Some managers respond to this challenge by centralizing analytics. With data and analytics under the control of one group, such as IT, you can standardize metrics, control data quality, enforce security and governance, and eliminate islands of data. All worthy endeavors, however forcing analytic updates through a heavyweight IT development process is a sure way to stifle innovation. It is one of the reasons that some companies take three months to deploy ten lines of SQL into production. Analytics have to be able to evolve and iterate quickly to keep up with user demands and fast-paced markets. Managers instinctively understand that data analytics teams must be free to innovate. The fast-growing self-service tools market (Tableau, Looker, etc.) addresses this market.

Centralizing analytics brings it under control but granting analysts free reign is necessary to stay competitive. How do you balance the need for centralization and freedom? How do you empower your analysts to be innovative without drowning in the chaos and inconsistency that a lack of centralized control inevitably produces? Visit any modern enterprise, and you will find this challenge playing out repeatedly in budget discussions and hiring decisions. You might say, it is a *struggle between centralization and freedom*.

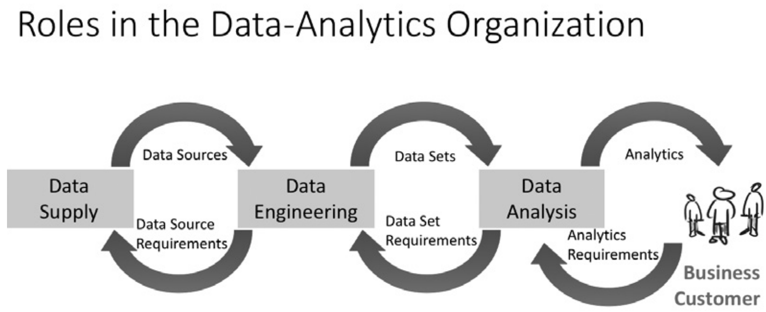


Figure 25: Data Supply, Data Engineering and Data Analysis work together in a supply chain to fulfill the analytics requirements of customers (business users).

The Analytics Supply Chain

DataOps processes and tools offer you a way to harmonize these opposing forces, empowering data analysts, while exerting a measured amount of centralization and control on your end-to-end process. To explore these ideas further, we need to review the structure of the analytics supply chain, and how the various roles relate to each other. The analytics organization in a DataOps enterprise consists of three essential job functions: data analysts, data engineers and data suppliers. You can think of the three roles as groups forming a supply chain. Data suppliers extract data for data engineers who create targeted data sets. Data analysts consume these data sets and generate analytics for business use cases. As figure 25 shows, the three functions work together in an interlinked fashion with data and analytics flowing to the right and feedback and requirements flowing to the left. Each group focuses on its immediate customer (its right neighbor), but together they share the mission of delivering analytic insights to business users. While they share a common underlying mission, the three groups operate in different business contexts.

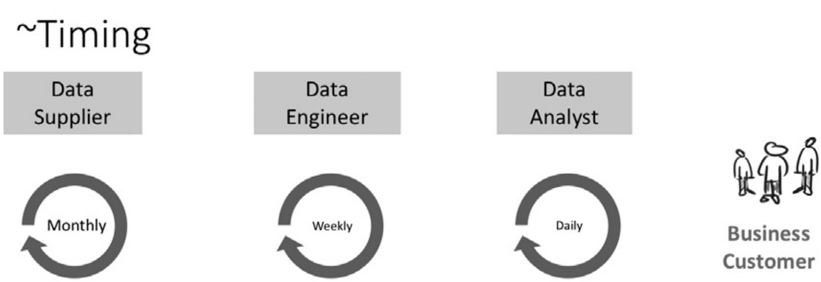


Figure 26: Data suppliers, engineers and analysts use different cycle times driven mainly by their tools, methods and proximity to demanding users.

Data Analysts

Data analysts directly support business users who work in fast-paced markets, which continuously evolve. A successful analyst finds ways to respond quickly to user requests. If new analytics are needed, the analyst pulls that together. New charts and graphs, updates, changes to calculated fields, integrations of new data sets — top-performing analysts do whatever it takes to address user requirements.

Analysts choose tools and processes oriented toward this business context. They use powerful, self-service tools, such as Tableau, Alteryx, and Excel, to quickly create or iterate on charts, graphs, and dashboards. They organize their work into daily sprints (figure 26), so they can deliver value regularly and receive feedback from users immediately. Agile tools like Jira are an excellent way to manage the productivity of analyst daily sprints.

The data analyst is the tip of the innovation spear. Organizations must give data analysts maximum freedom to experiment. There are a lot more data in the world than companies can analyze. Not everything can be placed in data warehouses. Not all data *should* be operationalized. Companies need data analysts to play around with different data sets to establish what is predictive and relevant.

When Freedom is Not Free

As their body of analytics grows, data analysts can get bogged down in non-value-add tasks. Self-service tools do not include mechanisms that promote and enable reuse. The data analyst may end up copying a calculated field into many reports and then have to manage changes to that algorithm manually. It becomes a revision control nightmare. New data sets are often integrated using labor-intensive and error-prone manual steps. This becomes a heavy burden on data analysts, consuming more than 75% of their time. Help and support from data engineering addresses these challenges for the team.

Some companies mistakenly ask data engineering to create data sets for every idea. It is best to let analysts lead on implementing new analytic ideas and proving them out before considering how data engineering can help. For example, consider the following:

1. Have the new analytics proven to be useful to many users?
2. Have calculations been reused in many reports/charts/dashboards?
3. Can automation reduce duplication of effort or manual integration errors?
4. Does data quality need improvement?

By this standard, the organization focuses its data engineering resources on those items that give the most *bang for the buck*. Keep in mind that when analytics are moved into a data warehouse, some of the benefits of centralization come at the expense of reduced freedom — it is slower to update a data warehouse than a Tableau worksheet. It's important to wait until analytics have *earned the right* to make this transition. The value created by centralizing must outweigh the restriction of freedom.

Data Engineers

Data engineers choose tools and processes which facilitate their objectives — to produce quality-checked data sets like data lakes, data warehouses and data marts for Data Analysts. These data sets include field calculations that analysts can leverage, promoting reuse. Data engineers can also automate data integration and other processes, minimizing manual steps for the data analyst. With the added centralization offered by data engineering, analysts can mitigate non-value add tasks and keep innovating rapidly.

Data engineers utilize programmable platforms such as AWS, S3, EC2 and Redshift. These tools require programming in a high-level language and offer greater potential functionality than the tools used by analysts. The relative complexity of the tools and scope of projects in data engineering fit best in weekly Agile iterations (figure 26). DataOps platforms like DataKitchen enable the data engineer to streamline the quality control, orchestration and data operations aspects of their duties. With automated support for agile development, impact analysis, and data quality, the data engineer can stay focused on creating and improving data sets for analysts.

After data sets have proven their value, it's worth considering whether the benefits of further centralization outweigh the cost of a further reduction in freedom. Data suppliers fulfill the function of greater centralization by providing data sources or data extracts for data engineering.

There are several reasons that a project may have earned the right to transition to data suppliers. Analytics may provide functionality that executives wish to make available to the entire corporation, not just one business unit. It could also be a case of standardization — for example, the company wants to standardize on an algorithm for calculating market share. In another example, perhaps data engineering has implemented quality control on a data set and wishes to achieve efficiencies by pushing this functionality upstream to the data supplier. A data supplier may be an external third party or an internal group, such as an IT master data management (MDM) team.

Master Data Management

In MDM, an enterprise links all of its critical data to a common reference. For example, in the pharmaceutical industry, there are 20-30 public data sets that describe physicians, payers and products. The initial merging and mastery of the data sets may, and in some cases should, be performed by the data engineering team, for example, for the purpose of business analytics.

After the usefulness of the mastered data is established, the company might decide that the data has broader uses. They may want the customer or partner list to be available for a portal or tied into a billing system. This use case requires a higher standard of accuracy for the mastered data than was necessary for the analytic data warehouse. It's appropriate at this point to consider moving the MDM to a data supplier, such as a corporate IT team, who are adept at tackling more extensive, development initiatives. Put another way, initial data mastery may have been good enough for analytic insights, but data must be perfect when it is being used in a billing system. The data supplier takes the MDM to the next level.

Function	Data Supply	Data Engineering	Data Analysis
Iteration Cycle Time	Monthly	Weekly	Daily
Deliverables	Data Extracts	Organized, quality-checked data sets	Produce insights via charts, graphs, dashboards
Customer	Data Engineers	Data Analysts	Business users
Technical tools	RDBS, MDM, Salesforce, etc.	AWS, DataKitchen, GIT	Self-service tools
Process management tools	MS Office and others	Jira	Jira

Table 2: Data Supply, Data Engineering and Data Analysis prefer different tools and methods which influence their optimal cycle times

Data Suppliers

Projects transitioned to data suppliers tend to incorporate more process and tool complexity than those in data engineering, leading to a more extended iteration period of one or more months (figure 26). These projects use tools such as RDBS, MDM, Salesforce, Excel, sFTP, etc., and rely upon waterfall project management and MS Project tracking. Table 2 summarizes tools and processes preferred by data suppliers as contrasted with engineers and analysts.

The Centralization-Freedom Spectrum

Data analysts, data engineers and data suppliers sit on a centralization-innovation (freedom) spectrum with data suppliers offering the most centralization capabilities, data analysts producing the fastest innovation and data engineering serving as a transition space in the center. The characteristic strengths and weaknesses of each of these groups are strongly influenced by their daily, weekly and monthly iteration periods. By organizing the various groups in this way, the company has access to the full spectrum of development; fast innovation, medium-scope development and longer-term, complex projects. For every need, the project has a home. The principle of granting analysts as much freedom as possible ensures that the innovation engine continues to turn. Waiting for analytics to stabilize and *earn the right* to be transitioned ensures that centralization adds value where it should and doesn't infringe on freedom and creativity.

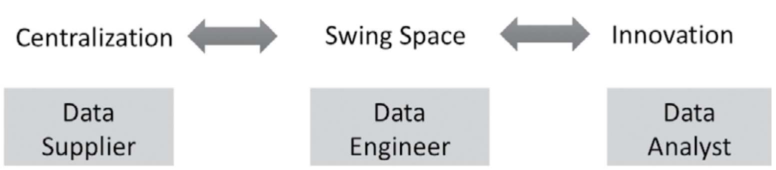


Figure 27: Data Suppliers, Data Engineers and Data Analysts sit on a spectrum of centralization and innovation/freedom.

The DataOps Framework for Innovation Management

The supply chain model that we have discussed illustrates how DataOps processes and tools help enterprises empower data analysts while exerting a measured amount of centralization and control on the end-to-end data pipeline. The special sauce behind DataOps is automated orchestration, continuous deployment and testing/monitoring of the data pipeline. DataOps reduces manual effort, enforces data quality and streamlines the orchestration of the data pipeline.

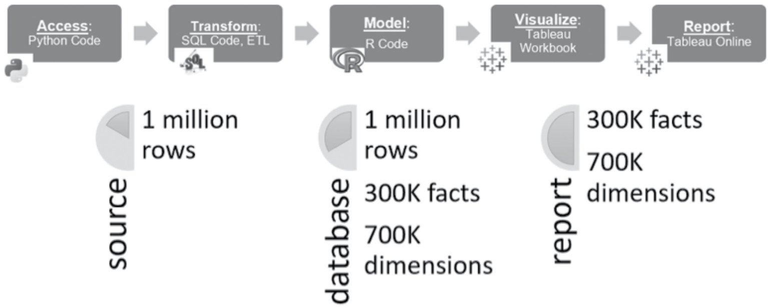


Figure 28: Tests verify that data rows, facts and dimensions match business logic throughout the data pipeline

For example, Figure 28 shows how the DataOps platform orchestrates, tests and monitors every step of the data operations pipeline, freeing up the team from significant manual effort. The test verifies that the quantity of data matches business logic at each stage of the data pipeline. If a problem occurs at any point in the pipeline, the analytics team is alerted and can resolve the issue before it develops into an emergency. With 24x7 monitoring of the data pipeline, the team can rest easy and focus on customer requirements for new/updated analytics.

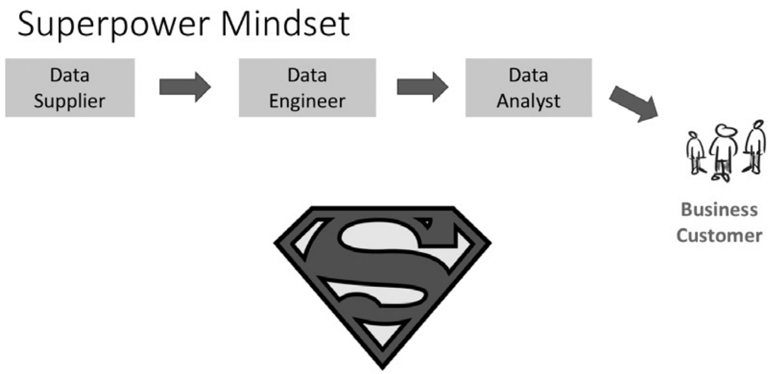


Figure 29: DataOps enables a superpower mindset — make your customer awesome

Giving Your Team Superpowers

The goal of DataOps is to minimize overhead and free data engineers and analysts to focus on delivering analytics to customers. With automation, DataOps enables data professionals to improve their productivity by an order of magnitude. A single data engineer supports ten data analysts, who in turn support 100 business professionals. It's like gaining *superpowers*. Data suppliers, engineers and analysts then concentrate their energy on their primary objective — *making customers awesome*.

DataOps Chicken Wings

by Nick Bracy

INGREDIENTS AND TOOLS

- 1/4 cup of soy sauce
- 3 tbsp of sesame oil
- 1 1/2 tbsp siracha sauce
- Freshly grated ginger and garlic
  (I use about 2-3 tsp of minced garlic — 2 cloves)
- Ginger *(can be overpowering, a grated piece of ginger that is about a square inch is good, about the size of the top part of your thumb—from knuckle to the top of your thumb)*
- 1 tbsp of rice wine vinegar
- A generous tbsp of organic honey or agave
- Black pepper to taste
- 1/2 cup of ketchup (optional)

INSTRUCTIONS

1. Place chicken drums and wings in a large zip-lock back, add marinade, seal zip-lock bag, mix contents of the bag around gently (you don't want to accidentally open the bag and marinate your kitchen floor or counter), make sure your chicken is well coated inside the bag.
2. Refrigerate your chicken in the marinade for 8-24 hours *(You can also just cook them right away if you don't have the time)*
3. Best slow cooked for 5-6 hours in a crockpot or on 225 degrees in a conventional oven—use all the contents in the bag. *(If you don't have that kind of time, bake at 400 degrees Fahrenheit.)* 3.5 lbs. of chicken should bake for 55-60 minutes; 4.5 lbs. of chicken requires 60-65 minutes.

Recipe inspired by Joe DeFran

DataOps for the Chief Data Officer

Prove Your Awesomeness with Data: The CDO DataOps Dashboard

Do you deserve a promotion? You may think to yourself that your work is exceptional. Could you prove it?

As a Chief Data Officer (CDO) or Chief Analytics Officer (CAO), you serve as an advocate for the benefits of data-driven decision making. Yet, many CDO's are surprisingly unanalytical about the activities relating to their own department. Why not use analytics to shine a light on yourself?

Internal analytics could help you pinpoint areas of concern or provide a big-picture assessment of the state of the analytics team. We call this set of analytics the *CDO Dashboard*. If you are as good as you think you are, the CDO Dashboard will show how simply awesome you are at what you do. You might find it helpful to share this information with your boss when discussing the data analytics department and your plans to take it to the next level. Below are some reports that you might consider including in your *CDO dashboard*:

BURNDOWN CHART

The burndown chart graphically represents the completion of backlog tasks over time. It shows whether a team is on schedule and sheds light on the productivity achieved in each development iteration. It can also show a team's accuracy in forecasting its own schedule.

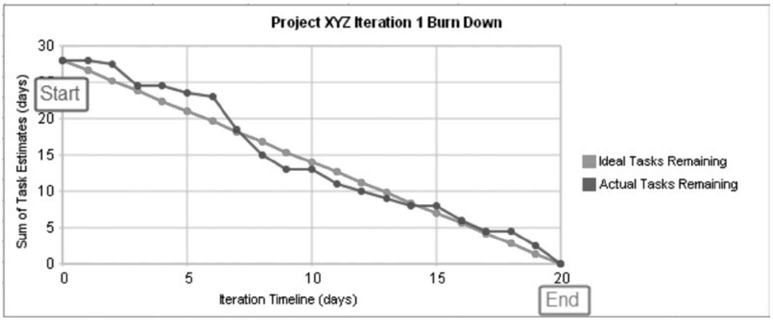


Figure 30: Sample Burndown chart

VELOCITY CHART

The velocity chart shows the amount of work completed during each sprint — it displays how much work the team is doing week in and week out. This chart can illustrate how improved processes and indirect investments (training, tools, process improvements, ...) increase velocity over time.

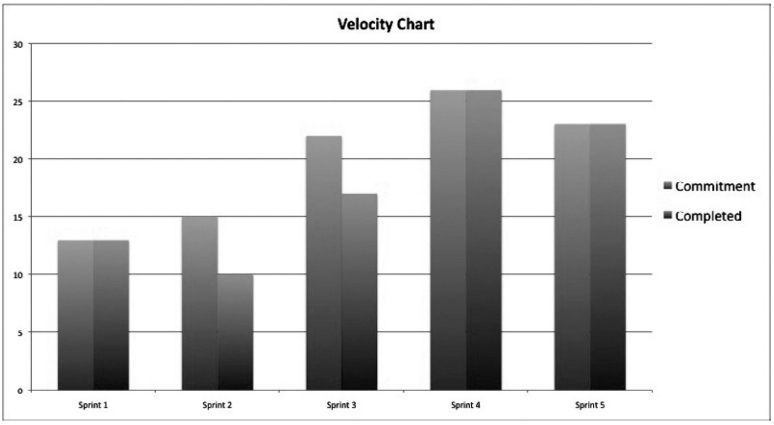


Figure 31: Sample Velocity chart

TORNADO REPORT

The [Tornado Report](#) is a stacked bar chart that displays a weekly representation of the operational impact of production issues and the time required to resolve them. The Tornado Report provides an easy way to see how issues impacted projects and development resources.

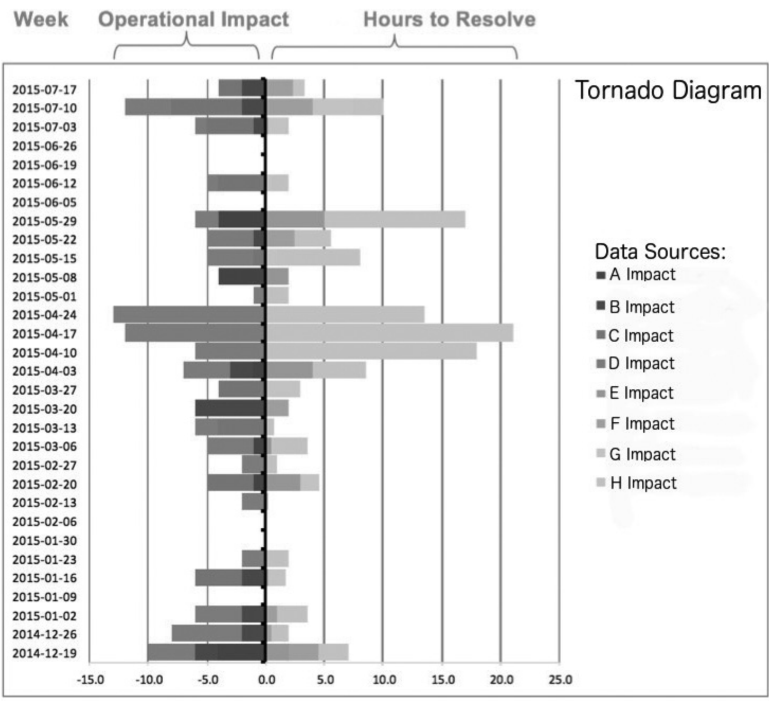


Figure 32: Sample Tornado report

DATA ARRIVAL REPORT

A large organization might receive hundreds of data sets from suppliers and each one could represent dozens of files. All of the data has to arrive error-free in order to, for example, build the critical Friday afternoon report. The Data Arrival report tracks how vendors perform relative to their respective service level agreements (SLA).

The Data Arrival report enables you to track data suppliers and quickly spot delivery issues. Any partner that causes repeated delays can be targeted for coaching and management. The Tornado Report mentioned above can help quantify how much time is spent managing these issues in order to articulate impact. These numbers are quite useful when coaching a peer organization or vendor to improve its quality.

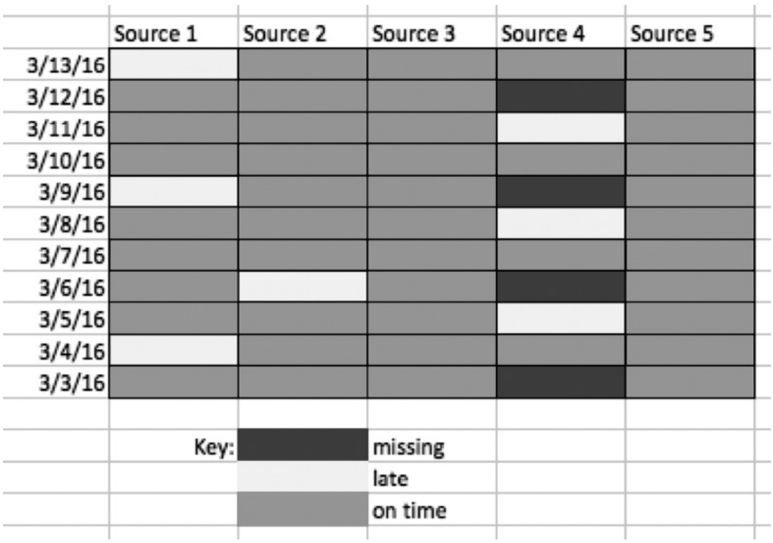


Figure 33: Sample Data Arrival Report

TEST COVERAGE AND INVENTORY

The Test Coverage and Inventory Reports show the degree of test coverage of the data analytics pipeline. It shows the percent of tables and data covered by tests and how test coverage improves over time. The report can also provide details on each test. In a DataOps enterprise, results from tests run on the production pipeline are linked to real-time alerts. If a process fails with an error, the analytics team can troubleshoot the problem by examining test coverage before or after the point of interest.

STATISTICAL PROCESS CONTROLS

The data analytics pipeline is a complex process with steps often too numerous to be monitored manually. Statistical Process Control (SPC) allows the data analytics team to monitor the pipeline end-to-end from a big-picture perspective, ensuring that everything is operating as expected.

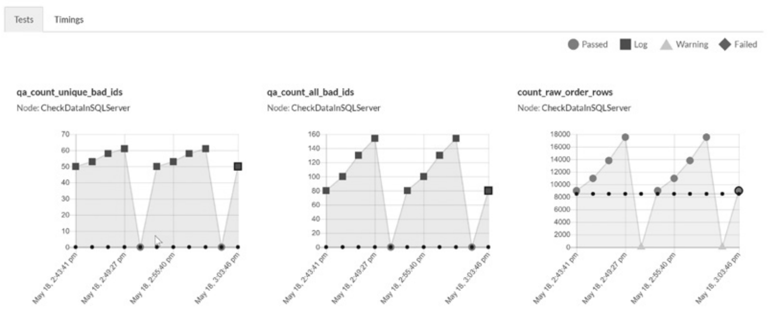


Figure 34: Sample Statistical Process Controls

NET PROMOTER SCORE

A Net Promoter Score is a customer satisfaction metric that gauges a team's effectiveness. For a data team, this is often a survey of internal users who are served by analytics. The Net Promoter Score can show that the data analytics team is effective at meeting the needs of its internal customer constituency or that satisfaction is improving.

One of the main goals of analytics is to improve decision-making. The CDO Dashboard puts information at the fingertips of executives, so they have a complete picture of what is happening in the data analytics domain. When it's time to review performance, the CDO Dashboard can help you show others that the analytics department is a well-oiled machine. *Now, about that promotion…*

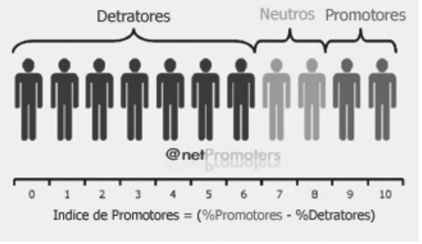


Figure 35: Net Promoter Score

Surviving Your Second Year as CDO

As the Chief Data Officer (or Chief Analytics Officer) of your company, you manage a team, oversee a budget and a hold a mandate to set priorities and lead organizational change. The bad news is that everything that could possibly go wrong from a security, governance and risk perspective is your responsibility. If you do a perfect job, then no one on the management team ever hears your name.

The average tenure of a CDO or CAO is about 2.5 years. In our conversations with data and analytics executives, we find that CDOs and CAOs often fall short of expectations because they fail to add sufficient value in an acceptable time frame. If you are a CDO looking to survive well beyond year two, we recommend avoiding three common *traps* that we have seen ensnare even the best and brightest.

1) THE TRAP OF DATA DEFENSE

Babson College professor Tom Davenport classifies data and analytics projects as either *defense or offense*. Data defense seeks to resolve issues, improve efficiency or mitigate risks. Data quality, security, privacy, governance, compliance — these are all critically important endeavors, but they are in essence, just enabling activities. You could think of data defense as providing *indirect* value.

Data offense expands top-line revenue, builds the brand, grows the company and in general puts *points on the board*. Using data analytics to help marketing and sales is data offense. Companies may acknowledge the importance of defense, but they care passionately about offense and focus on it daily. Data offense provides the organization with *direct* value and it is *what gets CDOs and CAOs promoted*.

The challenge for a CDO is that data defense is hard. A company's shortcomings in governance, security, privacy, or compliance may be glaringly obvious. In some cases, new regulations like GDPR (General Data Protection Regulation, EU 2016/679) demand immediate action. Data defense has a way of consuming more than its fair share of attention and staff. If not put in perspective, data defense is a trap that can divert the CDO's attention and resources away from offensive activities that create value for the organization.

2) THE TRAP OF DEFERRED VALUE

Projects that implement new platforms and solutions can require months, if not years, of integration and oversight. If conceived as a waterfall project, with a *big-bang* deliverable at the end, these projects produce little to no value until they are complete. We call this the trap of *deferred value*, and it is possibly the main reason that many CDOs never make it past year three of their tenure.

In a fast-paced, competitive environment, an 18-month integration project can seem like the remote future. Also, success is uncertain until you deliver. Your C-level peers know that big software integration projects fail half the time. Projects frequently turn out to be more complex than anticipated, and they often miss the mark. For example, you may have thought you needed ten new capabilities, but your internal customers only really require seven, and two of them were not on your original list. The issue is that you won't know which seven features are critical until around the time of your second annual performance review and by then it might be too late to right the ship.

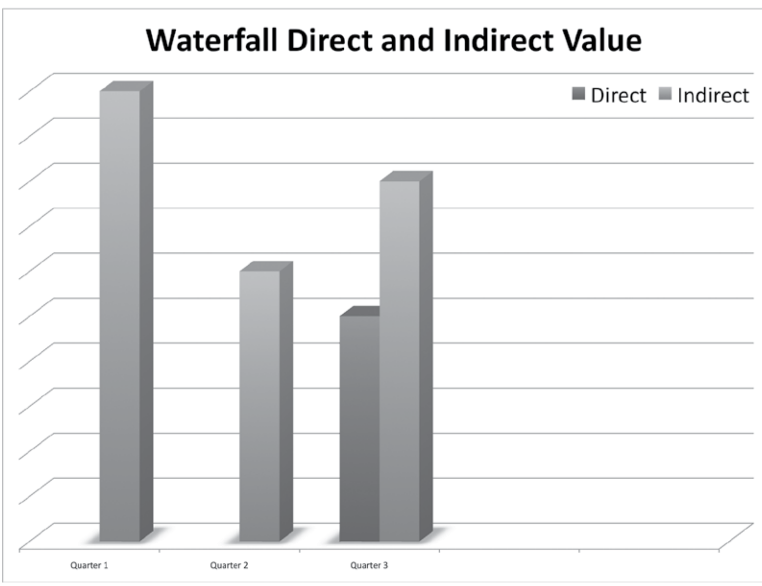


Figure 36: CDO's often make the dual mistake of (1) focusing too much on delivering indirect value (governance, security, privacy, or compliance, ...) and (2) using a waterfall project methodology which defers the delivery of value to the end of a long project cycle. In the case shown, it takes several months to deliver direct value

3) THE TRAP OF DATA VALUATION

Industry analysts and the media have long touted the strategic value of data. Following the advice of analysts, a CDO may decide to embark on a project to quantify the monetary value of the company's data. This seems like a worthy endeavor that some say should attain a high level of visibility.

A data valuation project can take months of effort and consumes the attention of the CDO and her staff on what is essentially an internally-focused, intellectual exercise. In the end, you have a beautiful PowerPoint presentation with detailed spreadsheets to back it up. *Your data has tremendous value that can and should be carried on the balance sheet*. You tell everyone all about it — why don't they care?

Don't confuse data valuation with data offense. Knowing the theoretical value of data is not data offense. While data valuation may be useful and important in certain cases, it is often a distraction. All of the time and resources devoted to creating and populating the valuation model could have been spent on higher value-add activities.

DIRECT VS. INDIRECT VALUE

Investments in data analytics can create value either directly or indirectly. Sales growth is an example of direct value. Indirect value lays the foundation for future growth and productivity. In both cases, value is delivered either quickly or in a longer time frame. One common mistake is to focus too heavily on indirect-value, long-term projects.

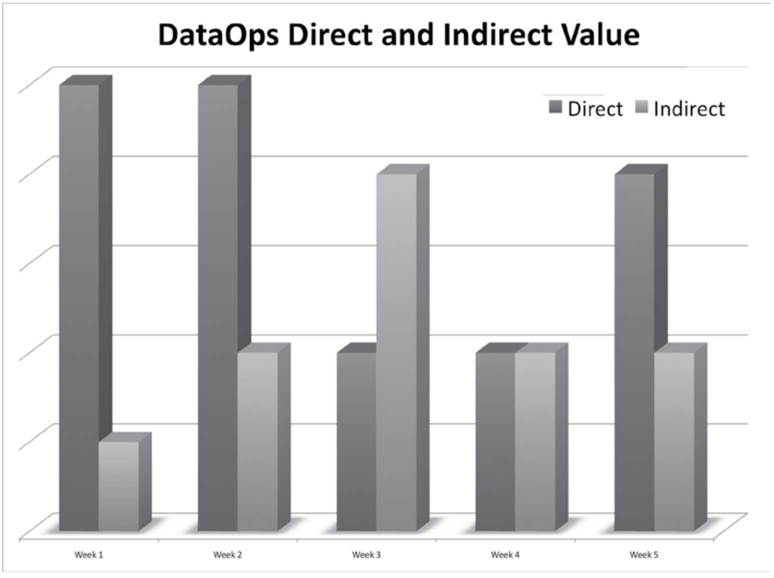


Figure 37: DataOps uses an iterative product management methodology (Agile development) that enables the CDO to rapidly deliver direct value (growing the top line).

That's not to say indirect or long-term projects don't have their place. They can be important and worthwhile. For example, a CDO may wisely invest in employee training or building technical infrastructure. It's essential to create the right mix, investing in enough indirect value-creators to support long-term growth and enough direct-value and short-term projects to maintain a high level of visibility.

DATAOPS ACCELERATES VALUE CREATION

The trick is to reorganize the data and analytics teams to be responsive and adaptable to the needs of internal customers and users. DataOps can help here. DataOps subscribes to an Agile, iterative approach. Deliver something of value in a few weeks and build on that in successive intervals. DataOps combines Agile with DevOps and lean manufacturing methods to provide a data and analytics team with the processes and tools needed to accelerate the value-creation cycle. *Raise a glass to year two!*

CAOs and CDOs: Earn the Trust of your CEO

One of the greatest challenges in analytics is earning the trust of your organization's CEO and management team. A lot of people in the business world make decisions with their gut. They rely on experience and intuition, but many companies would prefer to depend upon data. You cannot walk through an airport these days and not see some version of an advertisement saying *we are the company who is going to help you to be more data-driven*.

People do not always trust data. Imagine you are an executive and an employee walks into your office and shows you charts and graphs that contradict strongly held assumptions about your business. A lot of managers in this situation favor their own instincts. Data-analytics professionals, who tend to be doers, not talkers, are sometimes unable to convince an organization to trust its data.

BUILDING TRUST IN THE DATA

We've discovered that the best way for data-analytics professionals to build trust with their management team is to deliver value consistently, quickly and accurately. To accomplish this, you need to create and publish analytics in a new way. We call this new approach *DataOps*. DataOps is a combination of tools and methods, which streamline the development of new analytics while ensuring impeccable data quality. DataOps helps shorten the cycle time for producing analytic value and innovation, addressing some of the fundamental challenges that prevent organizations from trusting their data.

EARN TRUST BY DELIVERING A JOURNEY OF VALUE

DataOps uses the Agile Development methodology to create valuable new analytics for the business or organization. Agile accepts that people don't necessarily know what they want until they see it. The data-analytics team delivers new analytics in a short time frame and receives immediate feedback from users. This tight feedback loop steers the development of new analytics to the features that are most valuable to the business. Users aren't expected to take a *leap of faith*. They are gradually introduced to their own data and direct the journey of each future improvement in analytics through their feedback. This feedback both improves the analytics and draws them into the process as an active and invested stakeholder. When users grow to appreciate the value provided, it is time to operationalize the analytics and deliver them on a continuous basis.

EARN TRUST BY DELIVERING QUICKLY

In DataOps automated tests enable the data-analytics team to deploy new analytics quickly and with confidence. Minimizing the cycle time of new analytics is critical to earning the trust of users. The relevance of a question asked, at any given moment, decays rapidly as the situation facing the organization quickly evolves. Customers and prospects do not stand still. If analytics take too long, frustration builds, and the answer to a question might be delivered long after the question has ceased to be relevant.

DataOps relies upon the data lake design pattern, which enables data analytics teams to update schemas and transforms quickly to create new data warehouses that promptly address pressing business questions. DataOps incorporates the continuous-deployment methodology that is characteristic of DevOps. This reduces the cycle time of new analytics by an order of magnitude. When users get used to quick answers, it builds trust in the data-analytics team, and stimulates the type of creativity and teamwork that leads to breakthroughs.

EARN TRUST BY DELIVERING ACCURATELY

Trust is tough to earn and easy to squander. If bad data makes its way through your data pipeline, the users might not ever again trust the data. DataOps tests and monitors business logic and data validity by testing data at each stage of the data-analytics pipeline. We liken this testing to the statistical process control used in lean manufacturing. The tests can start simple, but over time they are expanded in breadth until they become a formidable check on quality. If a problem occurs with an internal or external dataset, or at any processing stage, the data-analytics team will be alerted immediately by the automated tests. DataOps protects the integrity of the data, so the data itself is worthy of user trust.

THE BENEFIT OF TRUSTED ANALYTICS

Earning your organization's trust makes the job of the data-analytics team a lot easier, but much more is at stake. Companies that don't trust their data will be outcompeted in the marketplace. Managers will make decisions based on instinct, past experience or preconceived notions. In cases like this, managers sometimes develop different versions of reality and can't agree on the facts, let alone strategic plans.

A company that trusts its data develops a unified view of reality and can formulate a shared vision of how to achieve its goals. Data-driven companies deliver higher growth and ultimately higher valuations than their peers. As a CAO or CDO, leading the organization to become more data-driven is your mission. DataOps makes that easier by helping the data-analytics team deliver quickly and robustly, creating value that is recognized and trusted by the organization.

The Four Stage Journey to Analytics Excellence

First, we walk, then we run. The same is true in data analytics. In our many discussions, we have encountered companies that are just starting out with data analytics and others with substantial organizations handling petabytes of data. Everyone that we meet is somewhere along this spectrum of maturity. We've found that just because an enterprise's data analytics organization is large does not mean that it is *excellent*. In fact, the flaws in a process or methodology become particularly noticeable when a team grows beyond the initial stages.

We view every company as being somewhere on a journey towards achieving excellence. In our experience, the journey is divided into four stages. That said, some get there faster by taking a shortcut. We'll discuss the four-stage journey and the shortcut to excellence below.

STAGE 1 - DATA DESERT

Companies generate data from a variety of enterprise applications. This data can help organizations gain a better understanding of customers, products, and markets. If your company is not reaping value from your data, then you live in a data desert. In a data desert, the data is underutilized or lays dormant. Like a mineral resource that remains in the ground, the data could have enormous potential, but without data analytics that potential goes unrealized.

This situation could have implications for the company's future. What if competitors have devised a way to use data analytics to garner a competitive advantage? Without a comprehensive data strategy, a company risks missing the market.

STAGE 2- BOUTIQUE ANALYTICS

Some organizations are engaged in analytics but do so in a decentralized fashion or on a small scale. Some enterprises are just getting started in analytics. Whether or not a person has programming skills, it is possible to do a fair amount of analytics using everyday tools like spreadsheets. One can accomplish even more using data visualization software. We call this Boutique Analytics. In a boutique shop, data analytics professionals are akin to artisans.

Boutique Analytics tend to be ad hoc or create one-off reports that answer questions posed by a manager. For example, a global enterprise may wish to know how much of its revenue it derives from one customer. Data is exported from CRMs or operations systems and pulled into a spreadsheet for analysis. The term Boutique Analytics may make it sound small in scale, but some large enterprises are known to rely solely upon this approach. A large enterprise might run weekly reports exporting sales data into a flat file. The global sales and marketing team can then easily manipulate the data in a spreadsheet. The sharing of data using flat files can be used to complement an enterprise's operational analytics.

There is nothing inherently wrong with Boutique Analytics. It is a great way to explore the best ways to deliver value based on data. The eventual goal should be to operationalize the data and deliver that value on a regular basis. This can be time-consuming and error-prone if executed manually.

STAGE 3- WATERFALL ANALYTICS

If an analytics initiative is successful and the team grows, a company will eventually begin to manage analytics more formally. Companies usually have a deeply entrenched project management culture based upon the methodology used by their research and development teams. Often project management is based on the Waterfall method so it is natural for these organizations to implement Waterfall Analytics.

In the Waterfall world, development cycles are long and rigidly controlled. Projects pass through a set of sequential phases: architecture, design, test, deployment, and maintenance. Changes in the project plan at any stage cause modifications to the scope, schedule or budget of the project. As a result, Waterfall projects are resistant to change. This is wholly appropriate when you are building a bridge or bringing a new drug to market, but in the field of data analytics, changes in requirements occur on a continuous basis. Teams that use Waterfall analytics often struggle with development cycle times that are much longer than their users expect and demand. Waterfall analytics also tends to be labor intensive, which makes every aspect of the process slow and susceptible to error. Most data-analytics teams today are in the Waterfall analytics stage and are often unaware that there is a better way.

Stage	Name	Model	Data Pipeline	Cycle Time
1	**Data Desert**	N/A	None	N/A
2	**Boutique Analytics**	Individual Artisan	One-Off or Ad Hoc	Custom
3	**Waterfall Analytics**	Waterfall Project Management	Manual Process	Long
4	**DataOps Analytics**	Agile Development, DevOps, Lean Manufacturing	Automated Process	Short

Table 3: Four Stages of Analytics

STAGE 4 - DATAOPS ANALYTICS

DataOps is a new approach to data analytics, which is superior to Waterfall Analytics in terms of flexibility, quality, and development cycle time. DataOps adopts key concepts from lean manufacturing. It views data analytics as a continuously operating pipeline, which can be automated, monitored and controlled. New analytics are created using Agile Development, a methodology created in the software engineering field. Agile manages the development of new analytics by delivering valuable features in short increments. This allows an organization to quickly adapt to new requirements or change course based on the demands of the marketplace. Analytics are deployed using the continuous deployment methodology pioneered by DevOps. Automated orchestration replaces labor-intensive manual processes. This means that new analytics can be published continuously, on-demand with minimal human intervention. Data quality flowing through the data analytics pipeline is monitored using automated data and logic tests executed as part of the continuous deployment automation. These tests are inspired by the statistical process control widely used in modern manufacturing operations.

TAKE THE SHORTCUT

The mistake that many companies make is that they languish in stage 3. The better approach is to take a shortcut, skip stage 3 entirely, and move directly to stage 4. If your organization is already in stage 3, then it's advantageous to advance as quickly as possible.

THE JOURNEY TO EXCELLENCE

DataOps provides the foundation for data analytics excellence. It streamlines the development of new analytics, shortens cycle time, and automates the data-analytics pipeline, freeing the team to focus on value-adding activities. It also controls the quality of data flowing through the pipeline so users can trust their data. With DataOps in place, the team is productive, responsive and efficient. They will race far ahead of competitors whose analytics are less nimble and less impactful. DataOps shortens your journey to analytics excellence.

DataOps Healthy Hearty Banana Oatmeal Bread

by Andrew Sadoway

INGREDIENTS AND TOOLS

- 1 1/4 cups whole wheat flour
- 1 1/4 old-fashioned oats
- 1 teaspoon baking powder
- 1/2 teaspoon baking soda
- 1/4 teaspoon salt
- 1 teaspoon cinnamon
- Dash of nutmeg (approx. 1/8 teaspoon)
- 3 medium-*largeish* bananas, mashed (defrosted from freezer OK)
- 1/2 cup low fat plain yogurt + 1 teaspoon vanilla
- 2 tablespoons honey, 1/3 cup brown sugar
- 1 large egg
- Splash of milk, as needed
- 3/4 cup dried cranberries
- 3/4 cup chopped walnuts + 1/4 cup chopped walnuts

INSTRUCTIONS

Preheat oven to 350. Combine dry ingredients (flour through nutmeg) in a small bowl. In a separate bowl, mix together yogurt, vanilla, brown sugar and honey. Add egg. Add mashed up bananas. Slowly fold dry ingredients into wet. Stir in cranberries and 3/4 cup walnuts gently. Pour mixture into buttered loaf pan. Sprinkle remaining walnuts on top of loaf. Bake about 45 minutes, or until lightly browned and knife comes out clean.

DataOps for the Data Engineer and the Data Scientist

DataOps Puts Agility into Agile Data Warehousing

Data analytics professionals get used to being in no-win situations. Internal customers make a simple request; for example, add a new file to the database. Users expect requests like these to take days, yet, in many large organizations, they require months to complete. At DataKitchen, we repeatedly hear from companies that they need to improve their cycle time for new analytics. One approach, *Agile Data Warehousing*, applies Agile principles to data warehouse projects in an attempt to speed innovation. However, many companies quickly discover that simply implementing Scrum is not sufficient to attain results.

Imagine that you oversee a fifty-person team managing numerous large integrated databases (DB) for a big insurance or financial services company. You have 300 terabytes (TB) of data which you manage using a proprietary database. Between software, licensing, maintenance, support and associated hardware, you pay $10M per year in annual fees. Even putting another single CPU into production could cost hundreds of thousands of dollars.

Someday these large databases will move to the cloud at a fraction of the cost. New databases will be turned on and off like light bulbs with the enterprise only paying for the resources they consume. That's a long-term goal. In the short term, the team has to produce results using the existing platform.

You can't afford separate instantiations of the entire data set for development, quality assurance (QA), performance testing and production so non-production machines are given subsets of the data. The necessity of provisioning physically separate hardware instantiations is one barrier to greater Agility.

The machine environments are different and have to be managed and maintained separately. New analytics are tested on each machine in turn — first in dev, then QA and finally production. You may not catch every problem in dev and QA since they aren't using the same data and environment as production.

Running regression tests manually is time-consuming so it can't be done often. This creates risk whenever new code is deployed. Also, when changes are made on one machine they have to be manually installed on the others. The steps in this procedure are detailed in a 30-page text document, which is updated by a committee through a cumbersome series of reviews and meetings. It is a very siloed and fractured process, not to mention inefficient; during upgrades, the DB is offline, so new work is temporarily on hold.

In our hypothetical company, the organization of the workforce is also a factor in slowing the team's velocity. Everyone is assigned a fixed role. Adding a table to a database involves several discrete functions: a Data Quality person who analyzes the problem, a Schema/Architect who designs the schema, an ETL engineer who writes the ETL, a Test Engineer that writes tests and a Release Engineer who handles deployment. Each of these functions is performed sequentially and requires considerable documentation and committee review before any action is taken. Hand-off meetings mark the transition from one stage to the next.

The team wants to move faster but is prevented from doing so due to heavyweight processes, serialization of tasks, overhead, difficulty in coordination and lack of automation. They need a way to increase collaboration and streamline the many inefficiencies of their current process without having to abandon their existing tools.

HOW DATAOPS HELPS

DataOps is a new approach to data analytics that automates the orchestration of data to production and the deployment of new features, both while maintaining impeccable quality. DataOps does not mandate the use of any particular tool or technology, but support in the following areas can be critical to Agile Data Warehousing in large teams, such as the one described:

Shared Workspace – DataOps creates a shared workspace so team members have visibility into each other's work. This enables the team to work more collaboratively and seamlessly outside the formal structure of the hand-off meeting. DataOps also streamlines documentation and reduces the need for formal meetings as a communication forum.

Orchestration – DataOps deploys code updates to each machine instantiation and automates the execution of tests along each stage of the data analytics pipeline. This includes data and logic tests that validate both the production and feature deployment pipelines. Tests are parameterized so they can run in the subset database of each particular machine environment equally well. As the test suite improves, it grows to reflect the full breadth of the production environment. Automated tests are run repeatedly so you can be confident that new features have not broken old ones.

These tools and process changes together break down the organizational and technology barriers that prevent the team from implementing Agile methods in data analytics. DataOps unburdens the team from non-value-add tasks and empowers them to self-organize around new creative initiatives. When the team is free to innovate, the continuous improvement culture built into DataOps will begin working to reduce the cycle time of new analytics from months to days (and less). This ultimately puts the Agility back into Agile Data Warehousing by delivering high-quality analytics to users in a timely fashion.

Speed Up Innovation with DataOps

LEVERAGING DATA LAKES, DATA WAREHOUSES AND SCHEMAS FOR FASTER ANALYTICS

Analytics professionals often strain to make one change to their analytic pipeline per month. DataOps increases their productivity by an order of magnitude. DataOps accelerates innovation by automating and orchestrating the data analytics pipeline and speeding ideas to production. It does this by applying Agile Development, DevOps and statistical process controls to data analytics. This enables the DataOps Engineer to quickly respond to requests for new analytics while guaranteeing a high level of quality. In order to understand this, it is helpful to know a little about the role of data lakes, schemas and data warehouses in DataOps.

DATAOPS REQUIRES EASY ACCESS TO DATA

When data is moved from disparate silos into a common repository, it is much easier for a data analytics team to work with it. The common store is called a data lake. To optimize DataOps, it is often best to move data into a data lake using on-demand simple storage.

People often speak about data lakes as a repository for raw data. It can also be helpful to move processed data into the data lake. There are several important advantages to using data lakes. First and foremost, the data analytics team controls access to it. Nothing can frustrate progress more than having to wait for access to an operational system (ERP, CRM, MRP, …). Additionally, a data lake brings data together in one place. This makes it much easier to process. Imagine buying items at garage sales all over town and placing them in your backyard. When you need the items, it is much easier to retrieve them from the backyard rather than visiting each of the garage sale sites. A data lake serves as a common store for all of the organization's critical data. Easy, unrestricted access to data eliminates restrictions on productivity that slow down the development of new analytics.

Note that if you put public company financial data in a data lake, everyone who has access to the data lake is an "insider." If you have confidential data, HIPAA data (Health Insurance Portability and Accountability Act of 1996) or Personally identifiable information (PII) — these must be managed in line with government regulations, which vary by country.

The structure of a data lake is designed to support efficient data access. This relates to how data is organized and how software accesses it. A database schema establishes the relationship between the entities of data.

UNDERSTANDING SCHEMAS

A database schema is a collection of tables. It dictates how the database is structured and organized and how the various data relate to each other. Below is a schema that might be used in a pharmaceutical-sales analytics use case. There are tables for products, payers, period, prescribers and patients with an integer ID number for each row in each table. Each sale recorded has been entered in the fact table with the corresponding IDs that identify the product, payer, period, and prescriber respectively. Conceptually, the IDs are pointers into the other tables.

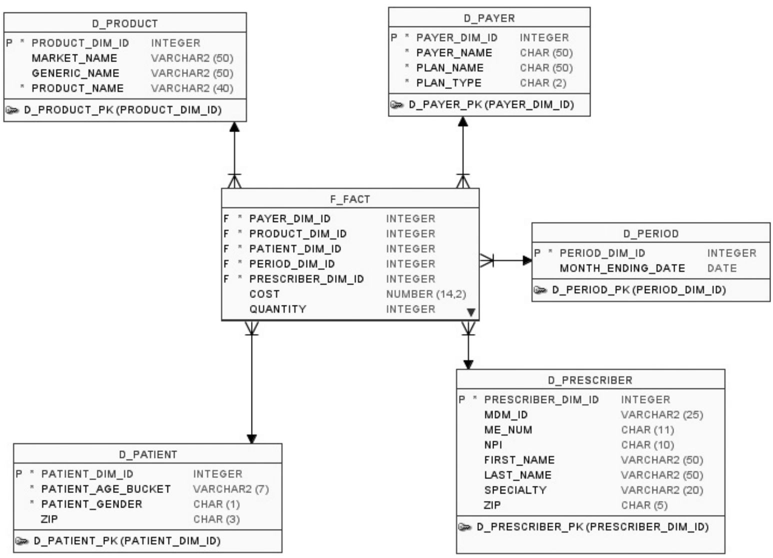


Figure 38: The Schema of a Pharmaceutical-Sales Analytics System

The schema establishes the basic relationships between the data tables. A schema for an operational system is optimized for inserts and updates. The schema for an analytics system, like the star schema shown here, is optimized for reads, aggregations, and is easily understood by people.

Suppose that you want to do analysis of patients based on their MSA (metropolitan service area). An MSA is a metropolitan region usually clustered near a large city. For example, Cambridge, Massachusetts is in the Greater Boston MSA. The prescriber table has a zip-code field. You could create a zip-code-to-MSA lookup table or just add MSA as an attribute to the patient table. Both of these are schema changes. In one case you add a table and in the other case you add a column.

TRANSFORMS CREATE DATA WAREHOUSES

The data lake provides easier access, but lacks the optimizations needed for visualizations or modeling. For example, data often enters the data lake in the format of the source system and not using an optimized schema that facilitates analysis. Data warehouses better address analytic-specific requirements. For example, the data warehouse could have a schema that supports specific visualization, modeling or other features.

You might hear the term *data mart* in relation to data analytics. Data marts are a streamlined form of data warehouses. The two are conceptually very similar.

Data transforms (scripts, source code, algorithms, ...) create data warehouses from data lakes. In DataOps this process is optimized by keeping transform code in source control and by automating the deployment of data warehouses. An automated deployment process is significantly faster, more robust and more productive than a manual deployment process.

THE DATAOPS PIPELINE

The automation of the pipeline that transforms the schemas of data lakes, creating data warehouses and data marts, is a key reason that DataOps is able to improve the speed and quality of the data analytic pipeline. Without using a data lake, data is highly dispersed, and difficult to access. Schemas of operational systems are difficult to navigate and most likely not optimized for analytics.

DataOps moves the enterprise beyond slow, inflexible, disorganized and error-prone manual processes. The DataOps pipeline leverages data lakes and transforms them into well-crafted data warehouses using continuous deployment techniques. This speeds the creation and deployment of new analytics by an order of magnitude. Additionally, the DataOps pipeline is constantly monitored using statistical process control so the analytics team can be confident of the quality of data flowing through the pipeline. Work Without Fear or Heroism. With these tools and process improvements, DataOps compresses the cycle time of innovation while ensuring the robustness of the analytic pipeline. Faster and higher quality analytics ultimately lead to better insights that enable an enterprise to thrive in a dynamic environment.

How to Inspire Code Reuse in Data Analytics

In DataOps, the data analytics team moves at lightning speed using highly optimized tools and processes. One of the most important productivity tools is the ability to reuse and containerize code.

When we talk about reusing code, we mean reusing data analytics components. All of the files that comprise the data analytics pipeline — scripts, source code, algorithms, html, configuration files, parameter files — we think of these as code. Like other software development, code reuse can significantly boost coding velocity.

Code reuse saves time and resources by leveraging existing tools, libraries or other code in the extension or development of new code. If a software component has taken several months to develop, it effectively saves the organization several months of development time when another project reuses that component. This practice can be used to decrease projects budgets. In other cases, code reuse makes it possible to complete projects that would have been impossible if the team were forced to start from scratch.

Containers make code reuse much simpler. A container packages everything needed to run a piece of software — code, runtimes, tools, libraries, configuration files — into a stand-alone executable. Containers are somewhat like virtual machines but use fewer resources because they do not include full operating systems. A given hardware server can run many more containers than virtual machines.

A container eliminates the problem in which code runs on one machine, but not on another, because of slight differences in the set-up and configuration of the two servers or software environments. A container enables code to run the same way on every machine by automating the task of setting up and configuring a machine environment. This is one DataOps techniques that facilitates moving code from development to production — the run-time environment is the same for both. One popular open-source container technology is Docker.

Each step in the data-analytics pipeline is the output of the prior stage and the input to the next stage. It is cumbersome to work with an entire data-analytics pipeline as one monolith, so it is common to break it down into smaller components. On a practical level, smaller components are much easier to reuse by other team members.

Some steps in the data-analytics pipeline are messy and complicated. For example, one operation might call a custom tool, run a python script, use FTP and other specialized logic. This operation might be both hard to set up, because it requires a specific set of tools, and difficult to create, because it requires a specific skill set. This scenario is another common use case for creating a container. Once the code is placed in a container, it is much easier to use by other programmers who aren't familiar with the custom tools inside the container but know how to use the container's external interfaces. All of the complexity is embedded inside the container. It is also easier to deploy that code to different environments. Containers make code reuse much more turnkey and allow developers much greater flexibility in sharing their work with each other.

What Data Scientists Really Need

Kurt Cagle's perceptive analysis of data science titled "Why You Don't Need Data Scientists" explains the many reasons that data science falls short of the high expectations usually placed on it:

- Fancy dashboards are pretty but are only as valuable as the data behind them. Data quality often....stinks.
- Data sets are quirky and difficult to work with.
- Users/stakeholders know their business domain but little about what data can do for them.
- A multimillion-dollar initiative to rebuild the data pipeline from the ground up is generally *off the table*.
- The people who own the databases won't give data scientists access.
- Everyone agrees that integrating data from disparate databases is really, really hard, but in reality, it's much harder than people think.

These are all excellent points and often the conversation ends here — in exasperation. We can tell you that we have been there and have the PTSD to prove it. Fortunately, a few years ago, we found a way out of what may seem at times like a no-win situation. We believe that the secret to successful data science is a little about *tools* and a lot about *people and processes*.

DON'T BOIL THE OCEAN

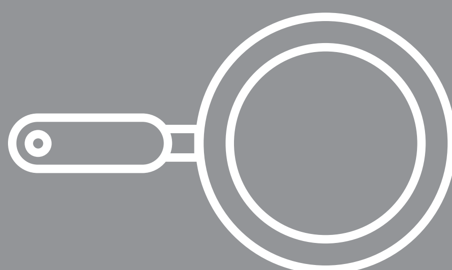
Use Agile methods to create new analytics. Leverage infrastructure that enables teams to work together in an Agile way. Start small and simple. Create something quickly that adds value. Get feedback from your stakeholders. Repeat iteratively.

TESTS ARE BEST

Implement automated process controls that monitor data at every stage of your data analytics pipeline. Think of your data analytics as a lean manufacturing pipeline where the quality of data cannot drift outside statistical and logical bounds. Let your tools work 24x7 so data scientists can stay focused on creating analytics that add value.

AUTOMATE AND ORCHESTRATE

Data Scientists spend 75% of their time doing data engineering. It's about time that data professionals took a page from DevOps. Automate workflow and the deployment of new analytics. Orchestrate the end-to-end data pipeline so we stop sucking the life out of data scientists. A single data engineer should be able to support ten data analysts and scientists, who in turn should be supporting 100 business professionals. An automated pipeline can get you there.



DataOps No-Knead Bread

by Gil Benghiat

INGREDIENTS AND TOOLS

- 3 cups bread flour
- 1/4 teaspoons instant yeast
- ½ teaspoon salt
- 1 ½ cups very warm, almost hot water
- Oil for work surface (canola)

INSTRUCTIONS

1. Combine flour, yeast and salt in a large bowl and stir with your DataKitchen spoon. Add water and stir until blended; dough will be shaggy. You may need an extra ¼ cup of water to get all the flour to blend in. Cover bowl with plastic wrap. Let dough rest at least 4 hours (12-18 hours is good too) at warm room temperature, about 70 degrees.
2. Lightly oil a work surface and place dough on it; fold it over on itself once or twice. Cover loosely with plastic wrap and let rest 30 minutes more. This is a good time to turn the oven on to 425°F.
3. Put a 6-to-8-quart heavy covered pot (cast iron, enamel, Pyrex or ceramic) in the oven as it heats. When dough is ready, carefully remove pot from oven. Slide your hand under dough and put it into pot, seam side up. Shake pan once or twice if dough is unevenly distributed; it will straighten out as it bakes.
4. Cover with lid and bake 30 minutes, then remove lid and bake another 15 to 30 minutes, until loaf is beautifully browned. Cool on a rack.

NOTES

In a convection oven, cook 23 minutes with the lid on, and then 5 minutes with the lid off.

You don't need to pre-heat the pot. You can put the dough on a cookie sheet. The only difference is the crust will not be as crunchy or as beautifully browned. You can experiment with a round shape or Italian or French loaf shapes. The longer shapes will take less time to cook.

You can also cook at a lower temperature (e.g. 350°F). In all cases, take the bread out when the internal temperature reaches 190°F - 200°F. Use a meat thermometer to check.

Derived from New York Times Speedy No-Knead Bread

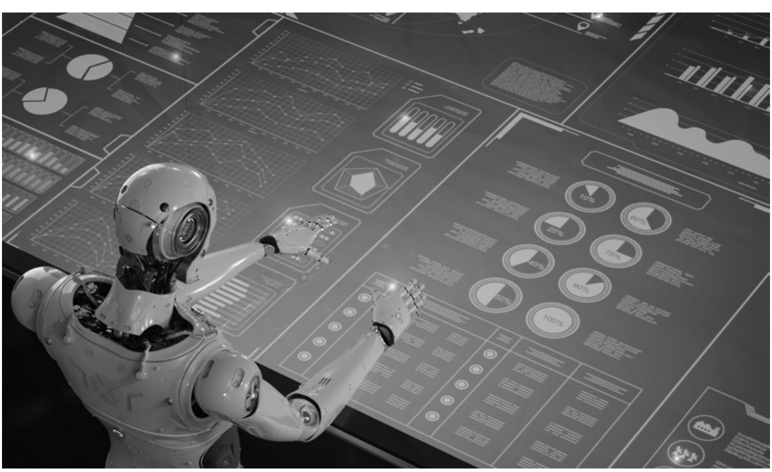
DataOps for Data Quality

Disband Your Impact Review Board: Automate Analytics Testing

Some companies take six months to write 20 lines of SQL and move it into production.

The last thing that an analytics professional wants to do is introduce a change that breaks the system. Nobody wants to be the object of scorn, the butt of jokes, or a cautionary tale. If that 20-line SQL change is misapplied, it can be a “career-limiting move” for an analytics professional.

Analytics systems grow so large and complex that no single person in the company understands them from end to end. A large company often institutes slow, bureaucratic procedures for introducing new analytics in order to reduce fear and uncertainty. They create a waterfall process with specific milestones. There is a lot of documentation, checks and balances, and meetings — lots of meetings.



IMPACT ANALYSIS

One of the bottlenecks in an analytics release process is called "impact analysis." Impact analysis gathers experts on all of the various subsystems (data feeds, databases, transforms, data lakes/warehouses, tools, reports, ...) so they can review the proverbial 20 lines of SQL and try to anticipate if/how it will adversely impact data operations.

Imagine you are building technical systems that integrate data and do models and visualizations. How does a change in one area affect other areas? In a traditional established company, that information is locked in various people's heads. The company may think it has no choice but to gather these experts together in one room to discuss and analyze proposed changes. This is called an "impact analysis meeting." The process includes the company's most senior technical contributors; the backbone of data operations. Naturally, these individuals are extremely busy and subject to high-priority interruptions. Sometimes it takes weeks to gather them in one room. It can take additional weeks or months for them to approve a change.

The impact analysis team is a critical bottleneck that slows down updates to analytics. A DataOps approach to improving analytics cycle time adopts process optimization techniques from the manufacturing field. In a factory environment, a small number of bottlenecks often limit throughput. This is called the Theory of Constraints. Optimize the throughput of bottlenecks and your end-to-end cycle time improves (check out *"The Goal"* by Eliyahu M. Goldratt).

GET OUT OF YOUR HEAD

The Impact Analysis Meeting is a bottleneck because it relies upon your top technical experts — one of the most oversubscribed resources in the company. What if you could extract all the knowledge and experience trapped in the brains of your company's experts and code it into a series of tests that would perform the impact analysis for you? This would give you a quick way to test out changes to analytics without requiring bureaucratic procedures and meetings. If the tests pass, you could deploy with confidence. No more waiting on the impact review team. With a comprehensive test suite, you reduce reliance on the impact analysis bottleneck and move a lot faster.

AUTOMATING IMPACT ANALYSIS

Manual testing moves the bottleneck from impact review to the testing team. Manual testing is performed step-by-step, by a person. This tends to be expensive as it requires someone to create an environment and run tests one at a time. It can also be prone to human error.

DataOps automates testing. Environments are spun up under machine control and test scripts, written in advance, are executed in batch. Automated testing is much more cost-effective and reliable than manual testing, but the effectiveness of automated testing depends on the quality and breadth of the tests. In a DataOps enterprise, members of the analytics team spend 20% of their time writing tests. Whenever a problem is encountered, a new test is added. New tests accompany every analytics update. The breadth and depth of the test suite continuously grow.

One advantage of automated testing is that it's easier to run so it's executed repeatedly and regularly. Manual testing is often too expensive and slow to run on a regular basis. To ensure high quality, you have to be able to consistently and regularly test your data and code.

These concepts are new to many data teams, but they are well established in the software industry. As figure 39 shows, the cycle time of software development releases has been (and continues to be) reduced by orders of magnitude through automation and process improvements. The automation of impact analysis can have a similar positive effect on your organization's analytics cycle time.

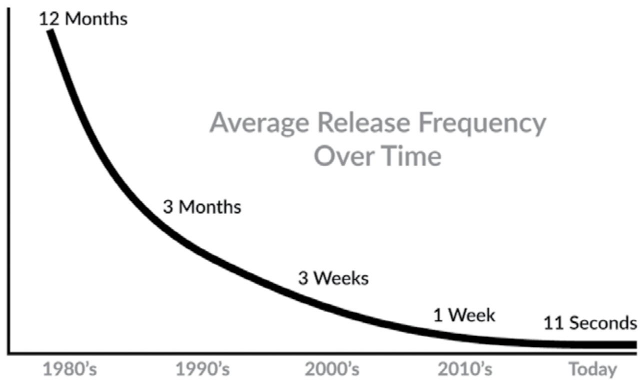


Figure 39: Software developers have reduced the cycle time for new releases by orders of magnitude using automation and process improvements

ANALYTICS IS CODE

At this point some of you are thinking *this has nothing to do with me. I am a data analyst/scientist, not a coder. I am a tool expert. What I do is just a sophisticated form of configuration.* This is a common point of view in data analytics. However, it leads to a mindset that slows down analytics cycle time.

Tools vendors have a business interest in perpetuating the myth that if you stay within the well-defined boundaries of their tool, you are protected from the complexity of software development. This is ill-considered.

Don't get us wrong. We *love our tools*, but don't buy into this falsehood.

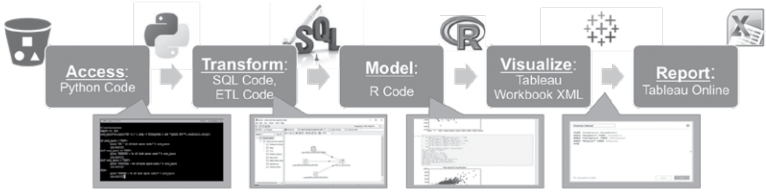


Figure 40: From data access to visualization to reports, there is code running at every stage of the data operations pipeline

The $100B analytics market is divided into two segments: tools that create code and tools that run code. The point is — data analytics is code. The data professional creates code and must own, embrace and manage the complexity that comes along with it.

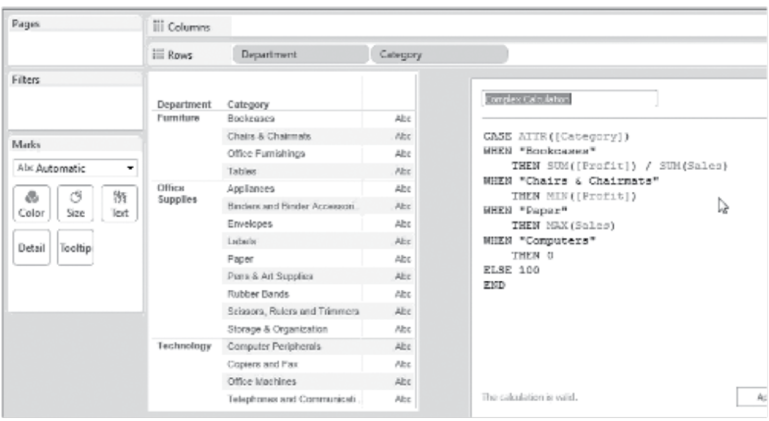


Figure 41: Tableau files are stored as XML, and can contain conditional branches, loops and embedded code.

Figure 40 shows a data operations pipeline with code at every stage of the pipeline. Python, SQL, R — these are all code. The tools of the trade (Informatica, Tableau, Excel, ...) these too are code. If you open an Informatica or Tableau file, it's XML. It contains conditional branches (if-then-else constructs), loops and you can embed Python or R in it.

Remember our 20-line SQL change that took six months to implement? The problem is that analytics systems become so complex that they can easily break if someone makes one misbegotten change. The average data-analytics pipeline encompasses many tools (code generators) and runs lots of code. Between all of the code and people involved, data operations becomes a *combinatorially* complex hairball of systems that could come crashing down with one little mistake.

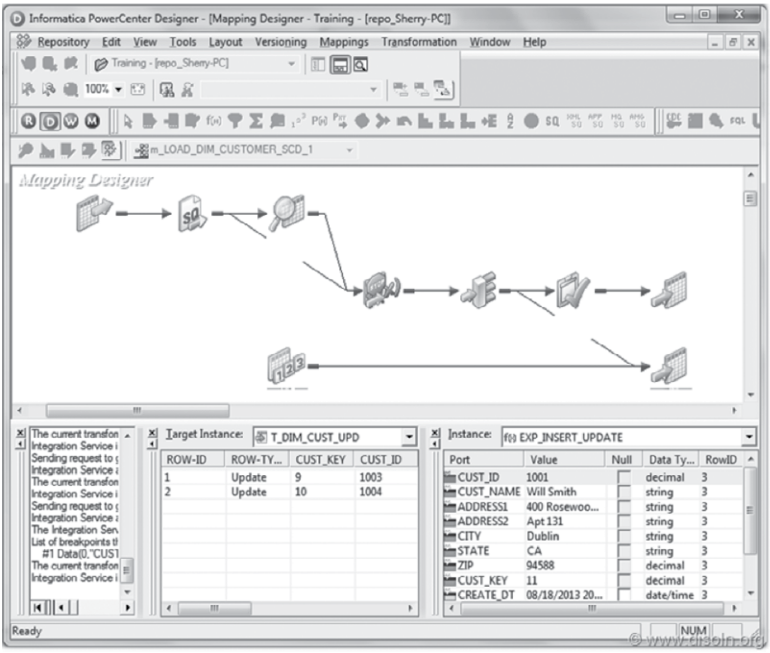


Figure 42: Informatica presents a UI that creates ETL in an XML format that is then converted to Java and executed on the machine.

For example, imagine that you have analytics that sorts customers into five bins based on some conditional criterion. Deep inside your tool's XML file is an if-then-else construct that is responsible for sorting the customers correctly. You have numerous reports based off of a template that contains this logic. They provide information to your business stakeholders: top customers, middle customers, gainers, decliners, whales, profitable customers, ...

There's a team of IT engineers, database developers, data engineers, analysts and data scientists that manage the end to end system that supports these analytics. One of these individuals makes a change. They convert the sales volume field from an integer into a decimal. Perhaps they convert a field that was US dollars into a different currency. Maybe they rename a column. Everything in the analytics pipeline is so interdependent; the change breaks all of the reports that contain the if-then-else logic upon which the original five categories are built. All of a sudden, your five customer categories become one category, or the wrong customers are sorted into the wrong bins. None of the dependent analytics are correct, reports are showing incorrect data, and the VP of Sales is calling you hourly.

At an abstract level, every analytic insight produced, every deliverable, is an interconnected chain of code modules delivering value. The data analytics pipeline is best represented by a directed acyclic graph (DAG). For example, see Figure 43.

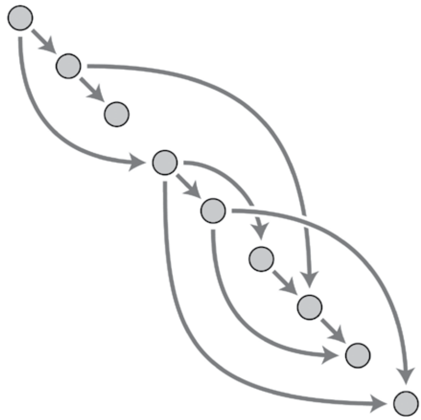


Figure 43: The Directed Acyclic Graph (DAG) models the steps in the data analytics pipeline

Whether you use an analytics tool like Informatica or Tableau, an Integrated Development Environment (IDE) like Microsoft Visual Studio (Figure 44) or even a text editor like Notepad, you are creating code. The code that you create interacts with all of the other code that populates the DAG that represents your data pipeline.

To automate impact analysis, think of the end-to-end data pipeline holistically. Your test suite should verify software entities on a stand-alone basis as well as how they interact.

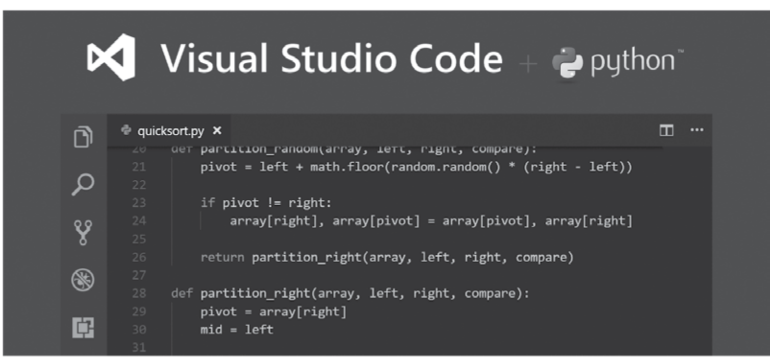


Figure 44: Developers write SQL, Python and other code using an integrated development environment or sometimes a simple editor like Notepad.

TYPES OF TESTS

The software industry has decades of experience ensuring that code behaves as expected. Each type of test has a specific goal. If you spend any time discussing testing with your peers, these terms are sure to come up:

- **Unit Tests** – testing aimed at each software component as a stand-alone entity
- **Integration Tests** – focus on the interaction between components to ensure that they are interoperating correctly
- **Functional Tests** – verification against functional specification or user stories.
- **Regression Tests** – rerun every time a change is made to prove that an application is still functioning
- **Performance Tests** – verify a system's responsiveness, stability and availability under a given workload
- **Smoke Tests** – quick, preliminary validation that the major system functions are operational

TESTS TARGET DATA OR CODE OR BOTH

It's also helpful to frame the purpose and context of a test. Tests can target data or code and run as part of the data operations pipeline. Location balance, historical balance and statistical process controls (time balance) tests are directed at the data flowing through an operations pipeline. The code that runs the data processing steps in the pipeline is fixed. The code is tightly controlled and only changed via a release process. Data that moves through operations, on the other hand, is variable. New data flows through the pipeline continuously. As Figure 45 shows, the data operations pipeline delivers value to users. DataOps terms this the *Value Pipeline*.

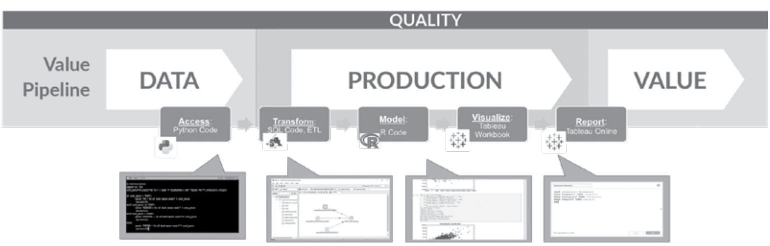


Figure 45: Data Operations: The Value Pipeline

The development of new analytics follows a different path, which is shown in Figure 46 as the Innovation Pipeline. The Innovation Pipeline delivers new insights to the data operations pipeline, regulated by the release process. To safely develop new code, the analyst needs an isolated development environment. When creating new analytics, the developer creates an environment analogous to the overall system. If the database is terabytes in size, the data professional might copy it for test purposes. If the data is petabytes in size, it may make sense to sample it; for example, take 10% of the overall data. If there are concerns about privacy or other regulations, then sensitive information is removed. Once the environment is set up, the data typically remains stable.

	Data Fixed	Data Variable
Code Fixed		Value Pipeline
Code Variable	Innovation Pipeline	

Table 4: In the Value Pipeline code is fixed and data is variable. In the Innovation Pipeline, data is fixed, and code is variable.

In the Innovation Pipeline code is variable, but data is fixed. Tests target the code, not the data. The unit, integration, functional, performance and regression tests that were mentioned above are aimed at vetting new code. All tests are run before promoting (merging) new code to production. Code changes should be managed using a version control system, for example GIT. A good test suite serves as an automated form of impact analysis that can be run on any and every code change before deployment.

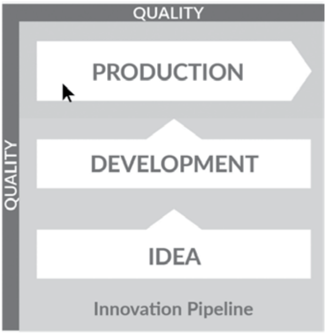


Figure 46: New analytics are developed in the Innovation Pipeline

Some tests are aimed at both data and code. For example, a test that makes sure that a database has the right number of rows helps your data and code work together. Ultimately both data tests and code tests need to come together in an integrated pipeline as shown in Figure 47. DataOps enables code and data tests to work together so all around quality remains high.

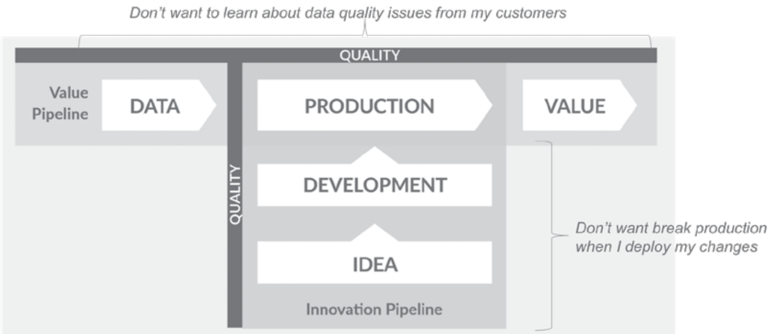


Figure 47: Ultimately the Value and Innovation Pipelines work together to maintain data and code quality

A unified, automated test suite that tests/monitors both production data and analytic code is the linchpin that makes DataOps work. Robust and thorough testing removes or minimizes the need to perform manual impact analysis, which avoids a bottleneck that slows innovation. Removing constraints helps speed innovation and improve quality by minimizing analytics cycle time. With a highly optimized test process you'll be able to expedite new analytics into production with a high level of confidence.

20 new lines of SQL? You'll have it right away.

Build Trust Through Test Automation and Monitoring

"Trust takes years to build, seconds to break, and forever to repair."

We recently talked to a data team in a financial services company that lost the trust of their users. They lacked the resources to implement quality controls so bad data sometimes leaked into user analytics. After several high-profile episodes, department heads hired their own people to create reports. For a data-analytics team, this is the nightmare scenario, and it could have been avoided.

Organizations trust their data when they believe it is accurate. A data team can struggle to produce high-quality analytics when resources are limited, business logic keeps changing and data sources have *less-than-perfect* quality themselves. Accurate data analytics are the product of quality controls and sound processes.

The data team can't spend 100% of its time checking data, but if data analysts or scientists spend 10-20% of their time on quality, they can produce an automated testing and monitoring system that does the work for them. Automated testing can work 24x7 to ensure that bad data never reaches users, and when a mishap does occur, it helps to be able to assure users that new tests can be written to make certain that an error never happens again. Automated testing and monitoring greatly multiplies the effort that a data team invests in quality.

DATA FLOW AS A PIPELINE

Think of data analytics as a manufacturing pipeline. There are inputs (data sources), processes (transformations) and outputs (analytics). A typical manufacturing process includes tests at every step in the pipeline that attempt to identify problems as early as possible. As every manufacturer knows, it is much more efficient and less expensive to catch a problem in incoming inspection as opposed to finished goods.

Figure 48 depicts the data-analytics pipeline. In this diagram, databases are accessed and then data is transformed in preparation for being input into models. Models output visualizations and reports that provide critical information to users.

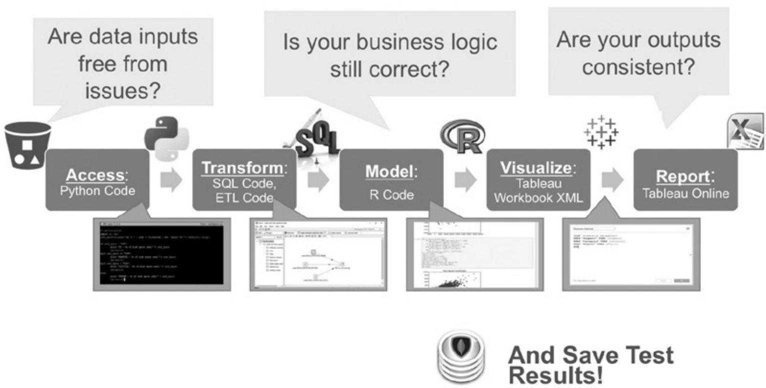


Figure 48: Testing each stage of the data-analytic pipeline

Along the way, tests ask important questions. Are data inputs free from issues? Is business logic correct? Are outputs consistent? As in lean manufacturing, tests are performed at every step in the pipeline. For example, data input tests are analogous to manufacturing incoming quality control. Figure 49 shows examples of data input, output and business logic tests.

Data input tests strive to prevent any bad data from being fed into subsequent pipeline stages. Allowing bad data to progress through the pipeline wastes processing resources and increases the risk of never catching an issue. It also focuses attention on the quality of data sources, which must be actively managed — manufacturers call this *supply chain management*.

Data output tests verify that a pipeline stage executed correctly. Business logic tests validate data against tried and true assumptions about the business. For example, perhaps all European customers are assigned to a member of the Europe sales team.

Test results saved over time provide a way to check and monitor quality versus historical levels.

Inputs	**Verifying the inputs to an analytics processing stage**	
	Count Verification - Check that row counts are in the right range, ...	
	Conformity - US Zip5 codes are five digits, US phone numbers are 10 digits, ...	
	History - The number of prospects always increases, ...	
	Balance - Week over week, sales should not vary by more than 10%, ...	
	Temporal Consistency - Transaction dates are in the past, end dates are later than start dates, ...	
	Application Consistency - Body temperature is within a range around 98.6F/37C, ...	
	Field Validation - All required fields are present, correctly entered, ...	
Business Logic	**Checking that the data matches business assumptions**	
	Customer Validation - Each customer should exist in a dimension table	
	Data Validation - 90 percent of data should match entries in a dimension table	
Output	**Checking the result of an operation, for example, a cross-product join**	
	Completeness - Number of customer prospects should increase with time	
	Range Verification - Number of physicians in the US is less than 1.5 million	

Figure 49: Tests validate data inputs and outputs and verify that data is consistent with business logic.

FAILURE MODES

A disciplined data production process classifies failures according to severity level. Some errors are fatal and require the data analytics pipeline to be stopped. In a manufacturing setting, the most severe errors "stop the line."

Some test failures are warnings. They require further investigation by a member of the data analytics team. Was there a change in a data source? Or a redefinition that affects how data is reported? A warning gives the data-analytics team time to review the changes, talk to domain experts, and find the root cause of the anomaly.

Many test outputs will be informational. They help the data engineer, who oversees the pipeline, to monitor routine pipeline activity or investigate failures.

Severity	Required Action
Error	Stop the pipeline
Warning	Investigate the failure
Informational	Be aware of information

Table 5: Actions required for different failure modes

TYPES OF TESTS

The data team may sometimes feel that its work product is *under a microscope*. If the analytics look "off," users can often tell immediately. They are experts in their own domain and will often see problems in analytics with only a quick glance.

Finding issues before your internal customers do is critically important for the data team. There are three basic types of tests that will help you find issues before anyone else: location balance, historical balance and statistical process control.

LOCATION BALANCE TESTS

Location Balance tests ensure that data properties match business logic at each stage of processing. For example, an application may expect 1 million rows of data to arrive via FTP. The Location Balance test could verify that the correct quantity of data arrived initially, and that the same quantity is present in the database, in other stages of the pipeline and finally, in reports.

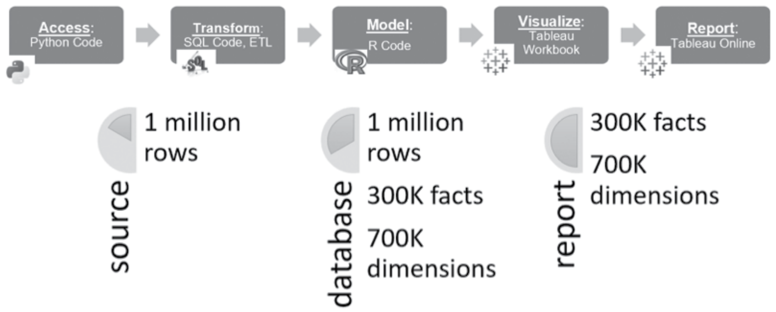


Figure 50: Location Balance Tests verify 1M rows in raw source data, and the corresponding 1M rows / 300K facts / 700K dimension members in the database schema, and 300K facts / 700K dimension members in a Tableau report

HISTORICAL BALANCE

Historical Balance tests compare current data to previous or expected values. These tests rely upon historical values as a reference to determine whether data values are reasonable (or within the range of reasonable). For example, a test can check the top fifty customers or suppliers. Did their values unexpectedly or unreasonably go up or down relative to historical values?

It's not enough for analytics to be correct. Accurate analytics that *"look wrong"* to users raise credibility questions. Figure 51 shows how a change in allocations of SKUs, moving from pre-production to production, affects the sales volumes for product groups G1 and G2. You can bet that the VP of sales will notice this change immediately and will report back that the analytics look *wrong*. This is a common issue for analytics — the report is correct, but it reflects poorly on the data team because it *looks wrong* to users. *What has changed?* When confronted, the data-analytics team has no ready explanation. *Guess who is in the hot seat.*

Historical Balance tests could have alerted the data team ahead of time that product group sales volumes had shifted unexpectedly. This would give the data-analytics team a chance to investigate and communicate the change to users in advance. Instead of hurting credibility, this episode could help build it by showing users that the reporting is under control and that the data team is on top of changes that affect analytics. *"Dear sales department, you may notice a change in the sales volumes for G1 and G2. This is driven by a reassignment of SKUs within the product groups."*

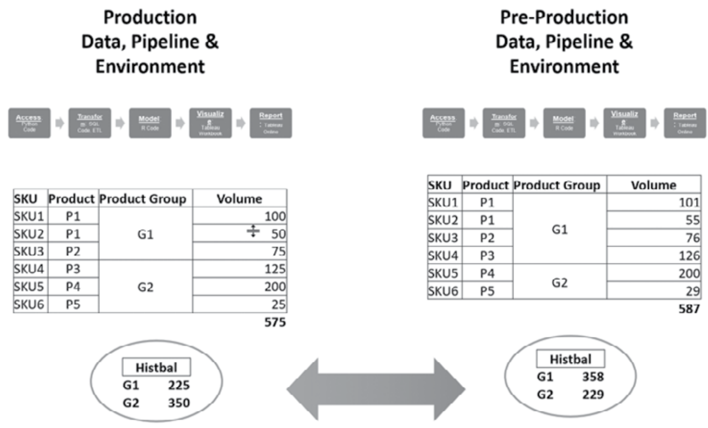


Figure 51: It's not enough for analytics to be correct. Accurate analytics that "look wrong" to users raise credibility questions.

STATISTICAL PROCESS CONTROL

Lean manufacturing operations measure and monitor every aspect of their process in order to detect issues as early as possible. These are called Time Balance tests or more commonly, statistical process control (SPC). SPC tests repeatedly measure an aspect of the data pipeline screening for error or warning patterns. SPC offers a critical tool for the data team to catch failures before users see them in reports.

Figure 52: Statistical Process Control tests apply numerical criteria to data-analytics pipeline measurements

NOTIFICATIONS

A complex process could have thousands of tests running continuously. When an error or warning occurs, a person on the data team should be alerted in real-time through email, text or a notification service like slack. This frees the data team from the distraction of having to periodically poll test results. If and when an event takes place, they'll be notified and can take action.

Test Results

```
Tests: Failed
        No Tests Failed

Tests: Warning
   Step (create-m-location)
      1. compare_raw_rosters (19 equal-to 0)


Tests: Log
        No Tests

Tests: Passed
   Step (put-raw-alignment)
      1. test-T_RHEUM_STRUCTURE-local-row-count (231 equal-to 231)
      2. test-pso-territory-id-in-structure (0 equal-to 0)
      3. test-duplicate-t-zip-terr (0 equal-to 0)
      4. test-T_ZIP_TERR-local-row-count (41294 equal-to 41294)
      5. test-hybrid-territory-id-in-structure (0 equal-to 0)
      6. test-size structure history (235 greater-than 230)
```

Figure 53: Example data test result notification email

Automated tests and alerts enforce quality and greatly lessen the day-to-day burden of monitoring the pipeline. The organization's trust in data is built and maintained by producing consistent, high-quality analytics that help users understand their operational environment. That trust is critical to the success of an analytics initiative. After all, trust in the data is really trust in the data team.

How Data Analytics Professionals Can Sleep Better

LEAN MANUFACTURING SECRETS THAT YOU CAN APPLY TO DATA ANALYTICS

What could data analytics professionals possibly learn from car manufacturers? It turns out, a lot. Automotive giant Toyota pioneered a set of methods, later folded into a discipline called *lean manufacturing*, in which employees focus relentlessly on improving quality and reducing non-value-add activities. This culture enabled Toyota to grow into the one of the world's leading car companies. The Agile and DevOps methods that have led to stellar improvements in coding velocity are really just an example of lean manufacturing principles applied to software development.

Conceptually, manufacturing is a pipeline process. Raw materials enter the manufacturing floor through the stock room, flow to different work stations as work-in-progress and exit as finished goods. In data-analytics, data progresses through a series of steps and exits in the form of reports, models and visualizations. Each step takes an input from the previous step, executes a complex procedure or set of instructions and creates output for the subsequent step. At an abstract level, the data-analytics pipeline is analogous to a manufacturing process. Like manufacturing, data analytics executes a set of operations and attempts to produce a consistent output at a high level of quality. In addition to lean-manufacturing-inspired methods like Agile and DevOps, there is one more useful tool that can be taken from manufacturing and applied to data-analytics process improvement.

W. Edwards Deming championed statistical process control (SPC) as a method to improve manufacturing quality. SPC uses real-time product or process measurements to monitor and control quality during manufacturing processes. If the process measurements are maintained within specific limits, then the manufacturing process is deemed to be functioning properly. When SPC is applied to the data-analytics pipeline, it leads to remarkable improvements in efficiency and quality. For example, Google executes over one hundred million automated test scripts per day to validate any new code released by software developers. In the Google consumer surveys group, code is deployed to customers eight minutes after a software engineer finishes writing and testing it.

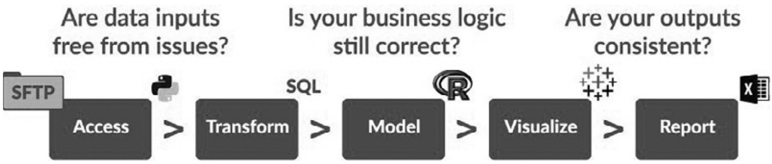


Figure 54: Tests verify the results for each intermediate step in the analytics pipeline.

In data analytics, tests should verify that the results of each intermediate step in the production of analytics matches expectations. Even very simple tests can be useful. For example, a simple row-count test could catch an error in a join that inadvertently produces a Cartesian product. Tests can also detect unexpected trends in data, which might be flagged as warnings. Imagine that the number of customer transactions exceeds its historical average by 50%. Perhaps that is an anomaly that upon investigation would lead to insight about business seasonality.

Tests in data analytics can be applied to data or models either at the input or output of a phase in the analytics pipeline. Tests can also verify business logic.

Inputs	**Verifying the inputs to an analytics processing stage** Count Verification - Check that row counts are in the right range, ... Conformity - US Zip5 codes are five digits, US phone numbers are 10 digits, ... History - The number of prospects always increases, ... Balance - Week over week, sales should not vary by more than 10%, ... Temporal Consistency - Transaction dates are in the past, end dates are later than start dates, ... Application Consistency - Body temperature is within a range around 98.6F/37C, ... Field Validation - All required fields are present, correctly entered, ...
Business Logic	**Checking that the data matches business assumptions** Customer Validation - Each customer should exist in a dimension table Data Validation - 90 percent of data should match entries in a dimension table
Output	**Checking the result of an operation, for example, a cross-product join** Completeness - Number of customer prospects should increase with time Range Verification - Number of physicians in the US is less than 1.5 million

Figure 55: Tests are applied to inputs, outputs or business logic.

The data analytics pipeline is a complex process with steps often too numerous to be monitored manually. SPC allows the data analytics team to monitor the pipeline end-to-end from a big-picture perspective, ensuring that everything is operating as expected. As an automated test suite grows and matures, the quality of the analytics is assured without adding cost. This makes it possible for the data analytics team to move quickly — enhancing analytics to address new challenges and queries — without sacrificing quality.

DataOps Trail Mix Cookies

by Mike Beaverson

INGREDIENTS AND TOOLS

- 1 cup butter, room temperature
- 1 1/4 cup brown sugar
- 1/4 cup honey
- 1 tbsp vanilla extract
- 2 large eggs
- 2 1/4 cups all purpose flour
- 1/2 tsp baking soda
- 1 tsp salt
- Dash of cinnamon
- 1 bag (8-12oz) trail mix (dark chocolate, dried fruit, candy bits, nuts are all good choices)

Instructions

1. Preheat oven to 325F. Line a baking sheet with parchment paper.
2. In a large bowl, cream together butter and sugar until light and fluffy.
3. Beat in honey, vanilla, and both eggs, adding the eggs in one at a time.
4. In a medium bowl, whisk together flour, baking soda, cinnamon, and salt.
5. Working by hand or at a low speed, gradually incorporate flour mixture into honey mixture.
6. Stir in trail mix.
7. Shape cookie dough into 1-inch balls and place onto prepared baking sheet, leaving about 2 inches between each cookie to allow for the dough to spread.
8. Bake for 12-15 minutes, until cookies are golden brown.
9. Cool for 3-4 minutes on the baking sheet, then transfer to a wire rack to cool completely.

Makes about 4-dozen cookies

DataOps and Your Career

DataOps Engineer Will Be the Sexiest Job in Analytics

Years ago, prior to the advent of Agile Development, a friend of mine worked as a release engineer. His job was to ensure a seamless build and release process for the software development team. He designed and developed builds, scripts, installation procedures and managed the version control and issue tracking systems. He played a mean mandolin at company parties too.

The role of release engineer was (and still is) critical to completing a successful software release and deployment, but as these things go, my friend was valued less than the software developers who worked beside him. The thinking went something like this — developers could make or break schedules and that directly contributed to the bottom line. Release engineers, on the other hand, were never noticed, unless something went wrong. As you might guess, in those days the job of release engineer was compensated less generously than development engineer. Often, the best people vied for positions in development where compensation was better.

RISING FORTUNES

Today, the fortunes of release engineers have risen sharply. In companies that are implementing DevOps there is no more important person than the release engineer. The job title has been renamed DevOps engineer and it is one of the most highly compensated positions in the field of software engineering. According to salary surveys, experienced DevOps engineers make six figure salaries. DevOps specialists are so hard to find that firms are hiring people without college degrees, if they have the right experience.

Whereas a release engineer used to work off in a corner tying up loose ends, the DevOps engineer is a high-visibility role coordinating the development, test, IT and operations functions. If a DevOps engineer is successful, the wall between development and operations melts away and the dev team becomes more agile, efficient and responsive to the market. This has a huge impact on the organization's culture and ability to innovate. With so much at stake, it makes sense to get the best person possible to fulfill the DevOps engineer role and compensate them accordingly. When DevOps came along, the release engineer went from fulfilling a secondary supporting role to occupying the most sought-after position in the department. Many release engineers have successfully rebranded themselves as DevOps engineers and significantly upgraded their careers.

DATAOPS FOR DATA ANALYTICS

A similar change, called DataOps, is transforming the roles on the data analytics team. DataOps is a better way to develop and deliver analytics. It applies Agile development, DevOps and lean manufacturing principles to data analytics producing a transformation in data-driven decision making.

Data engineers, data analysts, data scientists — these are all important roles, but they will be valued even more under DataOps. Too often, data analytics professionals are trapped into relying upon non-scalable methods: heroism, hope or caution. DataOps offers a way out of this no-win situation.

The capabilities unlocked by DataOps impacts everyone that uses data analytics — all the way to the top levels of the organization. DataOps breaks down the barriers between data analytics and operations. It makes data more easily accessible to users by redesigning the data analytics pipeline to be more flexible and responsive. It will completely change what people think of as possible in data analytics.

In many organizations, the DataOps engineer will be a separate role. In others, it will be a shared function. In any case, the opportunity to have a high-visibility impact on the organization will make DataOps engineering one of the most desirable and highly compensated functions. Like the release engineer whose career was transformed by DevOps, DataOps will boost the fortunes of data analytics professionals. DataOps will offer select members of the analytics team a chance to reposition their roles in a way that significantly advances their career. If you are looking for an opportunity for growth as a DBA, ETL Engineer, BI Analyst, or another role look into DataOps as the next step.

And watch out Data Scientist, the real sexiest job of the 21st century is DataOps Engineer.

Building a DataOps Team

Picture what you could accomplish if your organization had accurate and detailed information about products, processes, customers and the market. If your company does not have a data analytics function, you need to start one. Better yet, if data analytics is not serving as a competitive advantage in your organization, you need to *step up your game* and establish a DataOps team.

Data analytics analyzes internal and external data to create value and actionable insights. Analytics is a positive force that is transforming organizations around the globe. It helps cure diseases, grow businesses, serve customers better and improve operational efficiency.

In analytics there is mediocre and there is *better*. A typical data analytics team works slowly, all the while living in fear of a high-visibility data quality issue. A high-performance data analytics team rapidly produces new analytics and flexibly responds to marketplace demands while maintaining impeccable quality. We call this a DataOps team. A DataOps team can *Work Without Fear or Heroism* because they have automated controls in place to enforce a high level of quality even as they shorten the cycle time of new analytics by an order of magnitude. Want to upgrade your data analytics team to a DataOps team? It comes down to roles, tools and processes.

MEET THE DATAOPS TEAM

There are four key roles in any DataOps team. Note that larger organizations will tend to have many people in each role. Smaller companies might have one person performing multiple roles. *See the table down below for some key tools associated with each of the roles described as well as alternate job titles.* Most of these roles are familiar to data analytics professionals, but DataOps adds an essential ingredient that makes the team much more productive.

DATA ENGINEER

The data engineer is a software or computer engineer that lays the groundwork for other members of the team to perform analytics. The data engineer moves data from operational systems (ERP, CRM, MRP, ...) into a data lake and writes the transforms that populate schemas in data warehouses and data marts. The data engineer also implements data tests for quality.

DATA ANALYST

The data analyst takes the data warehouses created by the data engineer and provides analytics to stakeholders. They help summarize and synthesize massive amounts of data. The data analyst creates visual representations of data to communicate information in a way that leads to insights either on an ongoing basis or by responding to ad-hoc questions. Some say that a data analyst summarizes data that reflects past performance (*descriptive analytics*) while future predictions are the domain of the data scientist.

DATA SCIENTIST

Data scientists perform research and tackle open-ended questions. A data scientist has domain expertise, which helps him or her create new algorithms and models that address questions or solve problems.

For example, consider the inventory management system of a large retailer. The company has a limited inventory of snow shovels, which have to be allocated among a large number of stores. The data scientist could create an algorithm that uses weather models to predict buying patterns. When snow is forecasted for a particular region it could trigger the inventory management system to move more snow shovels to the stores in that area.

Roles	Other Job Titles	Responsibilities	Skills	Tools
Data Engineer	Database Architect Data Modeler, Database Administrator, Data QA Engineer, ETL Engineer	Data lakes, Data warehouses, Data marts, Schema design	Databases, Programming, Cloud infrastructure, Simple storage	SQL, Informatica, DataStage, SSIS, Talend
Data Analyst	Data Visualization Designer, Business Data Analyst, BI Tableau Developer, Reporting Analyst, Business Intelligence Engineer	Visualizations: Charts, Graphs, Dashboards, Tables, Reports	Programming, Statistics, Machine learning, Data cleaning, Data visualization	Excel, Looker, Tableau, Qlik View, Altryx, Spotfire
Data Scientist	Machine Learning Researcher, Machine Learning Engineer, Quantitative Analyst, AI Programmer Actuary	Algorithms, Models	Domain subject matter expert, Advanced mathematics, Machine learning, Data mining tools, Programming	R, Python, SAS, SPSS
DataOps Engineer		Orchestrating the analytic pipeline, Promoting features to production, Automating quality	Agile Development, DevOps, Statistical Process Control	DataKitchen, data test frameworks, python, shell scripts

Table 6: The DataOps Team

DATAOPS IS THE PROCESS AND THE TOOLS

Many data analytics teams fail because they focus on people and tools and ignore process. This is similar to fielding a sports team with players and equipment, but no game plan describing how everyone will work together. The game plan in data analytics is included in something that we call DataOps.

DataOps is a combination of tools and process improvements that enable rapid-response data analytics, at a high level of quality. Producing analytics that are responsive, flexible, continuously deployed and quality controlled requires data analytics to draw upon techniques learned in other fields.

- **Agile Development –** an iterative project management methodology that completes software projects faster and with far fewer defects.
- **DevOps –** a software development process that leverages on-demand IT resources and automated test and deployment of code to eliminate the barriers between development (Dev) and operations (Ops). DevOps reduces time to deployment, decreases time to market, minimizes defects, and shortens the time required to resolve issues. DevOps techniques help analytics teams break down the barriers between data and ops (DataOps).
- **Lean Manufacturing –** DataOps utilizes statistical process control (SPC) to monitor and control the data analytics pipeline. When SPC is applied to data analytics, it leads to remarkable improvements in efficiency and quality. With quality continuously monitored and controlled, data analytics professionals can Work Without Fear or Heroism.

The process and tools enhancements described above can be implemented by anyone on the analytics team or a new role may be created. We call this role the DataOps Engineer.

DATAOPS ENGINEER

The DataOps Engineer applies Agile Development, DevOps and statistical process controls to data analytics. He or she orchestrates and automates the data analytics pipeline to make it more flexible while maintaining a high level of quality. The DataOps Engineer uses tools to break down the barriers between operations and data analytics, unlocking a high level of productivity from the entire team.

As DataOps breaks down the barriers between data and operations, it makes data more easily accessible to users by redesigning the data analytics pipeline to be more responsive, efficient and robust. This new function will completely change what people think of as possible in data analytics. The opportunity to have a high-visibility impact on the organization will make DataOps engineering one of the most desirable and highly compensated functions on the data-analytics team.

DataOps Triple Chocolate Peanut Butter Cookies

by Aarthy Kannan Adityan

INGREDIENTS AND TOOLS

- 1 cup butter
- 3/4 cup brown sugar
- 3/4 cup white sugar
- 1 1/2 teaspoon vanilla extract
- 3/4 cup chocolate peanut butter
- 2 eggs
- 2 1/3 cup flour
- 1 teaspoon baking soda
- 3/4 cup cocoa powder
- 1 cup semi-sweet chocolate chips
- 1 cup peanut butter chips

INSTRUCTIONS

1. Preheat oven to 350°F
2. Soften butter to room temperature
3. Line a baking sheet with parchment paper
4. In a large bowl, cream together softened butter, brown sugar and white sugar
5. Add vanilla extract, chocolate peanut butter and eggs and mix well
6. Stir in flour, baking soda and cocoa powder and combine until blended
7. Fold chocolate chips and peanut butter chips into batter
8. Scoop batter onto prepared baking sheet using a cookie or ice-cream scoop, leaving enough space in-between for cookies to expand
9. Bake for 14-16 minutes
10. Transfer cookies to a wire rack to cool

Serving size: about 20 cookies

DataOps Examples and Case Studies

Grow Sales Using a DataOps-Powered Customer Data Platform

Data analytics can help drive corporate growth by providing customer analytics and ultimately actionable insights to the sales and marketing teams. Unfortunately, the fast-paced, dynamic nature of sales makes it difficult for the customer-facing teams to tolerate the slow and deliberate manner in which analytics is typically produced. In an earlier chapter, we identified eight major challenges of data analytics:

- **The Goalposts Keep Moving** – Sales and marketing requirements change constantly and the requests for new analytics never cease.
- **Data Lives in Silos** – Data is collected in separate operational systems and typically, none of these systems talk to each other.
- **Data Formats are not Optimized** – Data in operational systems is usually not structured in a way that lends itself to the efficient creation of analytics.
- **Data Errors** – Data will eventually contain errors, which can be difficult to resolve quickly.
- **Bad Data Ruins Good Reports** – When data errors work their way through the data pipeline into published analytics, internal stakeholders can become dissatisfied. These errors also harm the hard-won trust in the analytics team.
- **Data Pipeline Maintenance Never Ends** – Every new or updated data source, schema enhancement, analytics improvement or other change triggers an update to the data pipeline. These updates may be consuming 80% of your team's time.
- **Manual Process Fatigue** – Manual procedures for data integration, cleansing, transformation, quality assurance and deployment of new analytics are error-prone, time-consuming and tedious.
- **The Trap of "Hope and Heroism"** – To cope with the above challenges, data professionals work long hours, make changes (without proper testing) and "hope" for the best or just retreat into a posture of over-caution in which projects just execute more slowly.

OVERCOMING THE EIGHT CHALLENGES

If you have managed an analytics team for any period of time, you have likely encountered these and similar challenges. However, you don't have to accept the status quo. It is possible to implement processes and methodologies that address these challenges and enable your data-analytics team to improve their productivity by an order of magnitude while achieving a higher level of data quality. In this new approach to customer and market analytics, the data-analytics team executes at previously unimaginable speed, efficiency and quality:

Rapid-Response Analytics – The sales and marketing team will continue to demand a never-ending stream of new and changing requirements, but the data-analytics team will delight your sales and marketing colleagues with rapid responses to their requests. New analytics will inspire new questions that will, in turn, drive new requirements for analytics. The feedback loop between analytics and sales/marketing will iterate so quickly that it will infuse excitement and creativity throughout the organization. This will lead to breakthroughs that vault the company to a leadership position in its markets.

Data Under Your Control – Data from all of the various internal and external sources will be integrated into a consolidated database that is under the control of the data-analytics team. Your team will have complete access to it at all times, and they will manage it independently of IT, using their preferred tools. With data under its control, the data-analytics team can modify the format and architecture of data to meet its own operational requirements.

Impeccable Data Quality – As data flows through the data-analytics pipeline, it will pass through tests and filters that ensure that it meets quality guidelines. Data will be monitored for anomalies 24x7, preventing bad data from ever reaching sales and marketing analytics. You'll have a dashboard providing visibility into your data pipeline with metrics that delineate problematic data sources or other issues. When an issue occurs, the system alerts the appropriate member of your team who can then fix the problem before it ever receives visibility. As the manager of the data-analytics team, you'll spend far less time in uncomfortable meetings discussing issues and anomalies related to analytics.

Automated Efficiency – Data feeds and new analytics will be deployed using automation, freeing the data-analytics team from tedious manual processes. The analytics team will be able to focus on its highest priorities — creating new analytics for sales and marketing that create value for the company.

The processes, methodologies and tools required to realize these efficiencies combine two powerful ideas: The Customer Data Platform (CDP) and a revolutionary new approach to analytics called DataOps. **Below we'll explain how you can implement your own DataOps-powered CDP that improves both your analytics cycle time and data-pipeline quality by 10X or more.**

CUSTOMER DATA PLATFORM

A Customer Data Platform (CDP) provides sales and marketing with a unified view of all customer-related data whether internal or external, in a single integrated database. Once setup, a CDP enables the analytics team to create and manage customer data themselves, without reliance upon resources from IT or other departments. This helps sales and marketing better leverage the company's valuable data while responding to market demands quickly and proactively. The figure below shows how a CDP consolidates data from numerous databases. Each operational database becomes a data source that continuously feeds a copy of its data into a centralized CDP database.

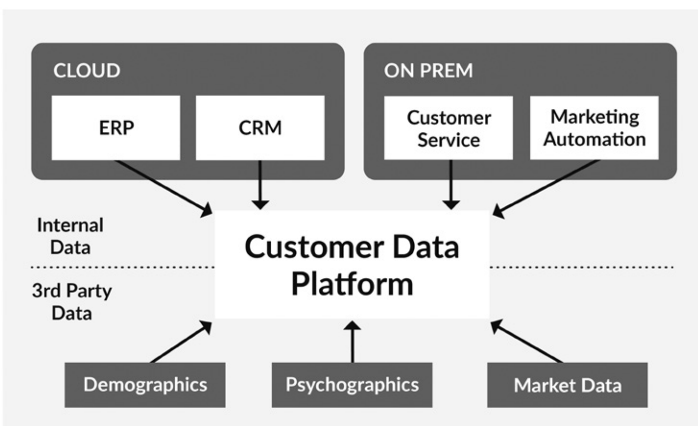


Figure 56: The Customer Data Platform consolidates data from operational systems to provide a unified customer view for sales and marketing.

DATAOPS

A CDP is a step in the right direction, but it won't provide much improvement in team productivity if the team relies on cumbersome processes and procedures to create analytics. DataOps is a set of methodologies and tools that will help you optimize the processes by which you create analytics, manage the data-analytics pipeline and automatically deploy new analytics and data. DataOps rests on three foundational principles:

Agile Development – DataOps utilizes a methodology called Agile Development to minimize the cycle time for new data analytics. Studies show that software development projects using Agile complete significantly faster and with far fewer defects.

DevOps – In DataOps, new analytics production is automated and monitored. Automated tests verify new analytics before publishing them to sales and marketing users. This allows the analysts to focus less on the mechanics of deploying analytics and more on the creation of new insights that address sales and marketing requests. In the software development domain, the automated deployment of code is called DevOps. Prominent software industry leaders use DevOps to publish software updates many times per second while assuring quality. DataOps incorporates DevOps methods and principles to publish new analytics and data in an automated fashion.

Statistical Process Control – DataOps employs a methodology called Statistical Process Control (SPC) to assure data quality using end-to-end data pipeline automation and quality controls. SPC is a lean manufacturing method that institutes continuous testing on data flowing from sources to users, ensuring that data stays within statistical limits and remains consistent with business logic. SPC monitors data and verifies it 24x7. If an anomaly occurs, SPC notifies the data-analytics team via an automated alert. This reduces the operational burden on team members while improving data quality and reliability. Also, the quantity of data and the number of data sources can more easily scale independently of the size of the data engineering team.

When implemented in concert, Agile, DevOps and SPC take the productivity of data-analytics professionals to a whole new level. DataOps will help you get the most out of your data, human resources and integrated CDP database.

Achieving Growth Targets by Implementing a DataOps-Powered Customer Data Platform

As the leader of a data-analytics organization, your mission is to utilize data from operational systems and other sources to create insights that help the organization achieve its growth targets. Figure 57 provides a conceptual view of this flow. The dark boxes show the domain that is under the control of the analytics leader. It includes people, tools, technologies and processes that together comprise the DataOps-powered CDP.

The Eight Challenges of Data Analytics

1. The Goalposts Keep Moving
2. Data Lives in Silos
3. Data Formats are not Optimized
4. Data Errors
5. Bad Data Ruins Good Reports
6. Data Pipeline Maintenance Never Ends
7. Manual Process Fatigue
8. The Trap of Hope and Heroism

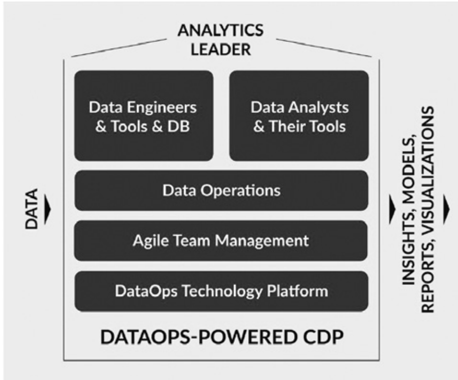


Figure 57: The resources under data-analytics control that leverage data to meet business objectives

DATA ANALYSTS AND THEIR TOOLS

The Data Analyst works to satisfy the needs of the sales and marketing department by continually delivering insights. The data analyst creates visual representations of data to communicate information in a way that leads to insights either on an ongoing basis or by responding to ad-hoc questions. With a DataOps-powered CDP, data analysts work with autonomy and speed, drawing analytics from CDP data. Analysts use tools like Tableau and Alteryx to create these insights and independently promote their investigative work into production deliverables as needed.

Every resource, technology and tool in the data-analytics organization exists to support the data analyst's ability to serve Sales and Marketing. This also applies to Data Scientists who also deliver insights directly to Sales and Marketing colleagues.

DATA ENGINEERS AND THEIR TOOLS AND DATABASES

The Data Engineer works with the IT department and all data source providers to institute automated processes that move data from various data sources into a trusted, integrated CDP database under the complete control of the data-analytics team. The CDP database may include a data lake, which provides revision history, easy access, control and error recovery.

The engineer writes transforms that operate on the data lake, creating data warehouses and data marts used by data analysts and scientists. The data engineer also implements tests that monitor data at every point along the data-analytics pipeline assuring a high level of quality.

The data engineer lays the groundwork for other members of the team to perform analytics without having to be operations experts. With a dedicated data engineering function, DataOps provides a high level of service and responsiveness to the data-analytics team.

DATA OPERATIONS

The DataOps-powered CDP provides automated support for the creation, monitoring and management of the end-to-end data pipeline. This includes stewardship of every aspect of the journey from data sources to reporting. Statistical Process Control (SPC) data-quality tests monitor each stage of the automated pipeline, alerting data engineering when data fails to meet statistical controls or match business logic.

With tests monitoring each stage of the automated data pipeline, DataOps can produce a dashboard showing the status of the pipeline. The DataOps dashboard provides a high-level overview of the end-to-end data pipeline. Is any data failing quality tests? What are the error rates? Which are the troublesome data sources? With this information at his or her fingertips, the Data Engineer can proactively improve the data pipeline to increase robustness. In the event of a high-severity data anomaly, an alert is sent to the Data Engineer who can take steps to protect production analytics and work to resolve the error. If the anomaly relates to a data supplier, data engineering can work with the vendor to drive the issue to resolution. Workarounds and data patches can be implemented as needed with information in release notes for users. In many cases, errors are resolved without the users (or the organization's management) ever being aware of any problem.

AGILE TEAM MANAGEMENT

The Agile methodology governs the creation of new analytics, producing a steady stream of valuable innovations and improvements to analytic insights in short increments of time. Agile is particularly effective in environments where requirements are quickly evolving — a situation all too familiar to data-analytics professionals. Agile development is not only a method; it is also a philosophy and a mindset. Developers collaborate with sales/marketing customers, respond to change, measure progress through "delivered analytics," release frequently, seek feedback on releases, and adjust behavior to become more effective.

DATAOPS PLATFORM

The various methodologies, processes, people (and their tools) and the CDP analytics database are tied together cohesively using a technical environment called a DataOps Platform. The DataOps Platform includes support for:

- Agile project management
- Deployment of new analytics
- Execution of the data pipeline (orchestration)
- Integration of all tools and platforms
- Management of development and production environments
- Source-code version control
- Testing and monitoring of data quality
- Data Operations reporting and dashboards

The high degree of automation offered by DataOps eliminates a great deal of work that has traditionally been done manually. This frees up the team to create new analytics requested by stakeholder partners.

A DataOps Platform is not a one-size-fits-all tool. It is the central application that coordinates the various tools that drive your orchestration, testing, deployment, model deployment, development-environment management, change management, and data integration. You can create your own DataOps Platform from scratch, although partnering with a supplier can reduce time to market. Working with a partner also gives you the option of treating the entire CDP and data pipeline as a managed service, which can be initially outsourced and then partly or entirely taken over by internal resources at a later time.

DATAKITCHEN DATAOPS-CDP SOLUTION

An enterprise can outsource data engineering, databases, data operations, Agile team management and the DataOps Technology Platform to gain efficiencies. DataKitchen offers a DataOps Technology Platform as well as managed services for each of the gray boxes in Figure 58. In essence, DataKitchen offers all aspects of the DataOps-powered CDP except for data analysis and data science, which rely upon vertical market expertise and close collaboration with sales and marketing.

The enterprise can also outsource the functions shown initially but insource them at a later date. Once set-up, the DataOps Platform can be easily and seamlessly transitioned to an internal team.

Customer Data Platforms promise to drive sales and improve the customer experience by unifying customer data from numerous disjointed operational systems. As a leader of the analytics team, you can take control of sales and marketing data by implementing efficient analytics-creation and deployment processes using a DataOps-powered CDP. A DataOps platform makes analytics responsive and robust. This enables your data analysts and scientists to rise above the bits and bytes of data operations and focus on new analytics that help the organization achieve its goals.

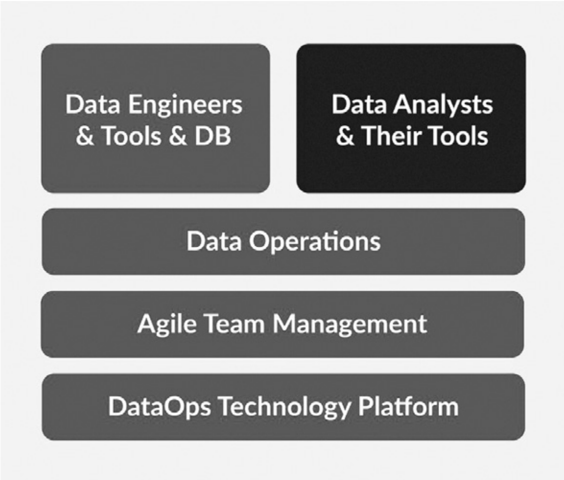


Figure 58: DataKitchen DataOps-Powered CDP and Managed Services

How a Mixed Martial Arts Fighter Would Approach Data Analytics

By James Royster, Director, Commercial Analytics, Celgene

Mixed Martial Arts (MMA) combines striking, wrestling and other fighting techniques into a unified sport. Every martial art and fighting technique has its strengths and strategic advantages. Boxing is known for punching but also provides footwork, guard position and head movement. Wrestling relies upon takedowns. Karate features striking techniques such as kicking. MMA is a hybrid of all of these (and many more) drawing upon each mode of combat as needed for a given competitive situation. If an MMA athlete competed against a boxer or karate expert, the mixed martial artist would clearly have an unfair advantage. MMA's real strength is its versatility and its ability to absorb new methods.

DataOps is the mixed martial arts of data analytics. It is a hybrid of Agile Development, DevOps and the statistical process controls drawn from lean manufacturing. Like MMA, the strength of DataOps is its readiness to evolve and incorporate new techniques that improve the quality, reliability, and flexibility of the data analytics pipeline. DataOps gives data analytics professionals an unfair advantage over those who are doing things the old way — using hope, heroism or just going slowly in order to cope with the rapidly changing requirements of the competitive marketplace.

Agile development has revolutionized the speed of software development over the past twenty years. Before Agile, development teams spent long periods of time developing specifications that would be obsolete long before deployment. Agile breaks down software development into small increments, which are defined and implemented quickly. This allows a development team to become much more responsive to customer requirements and ultimately accelerates time to market.

Data analytics shares much in common with software development. Conceptually, the data analytics pipeline takes raw data, passes it through a series of steps and turns it into actionable information. Files, such as scripts, code, algorithms, configuration files, and many others, drive each processing stage. These files, taken as a whole, are essentially just code. As a coding endeavor, data analytics has the opportunity to improve implementation speeds by an order of magnitude using techniques like Agile development. DevOps offers an additional opportunity for improvement.

The difficulty of procuring and provisioning physical IT resources has often hampered data analytics. In the software development domain, leading-edge companies are turning to DevOps, which utilizes cloud resources instead of on-site servers and storage. This allows developers to procure and provision IT resources nearly instantly and with much greater control over the run-time environment. This improves flexibility and yields another order of magnitude improvement in the speed of deploying features to the user base.

DataOps also incorporates lean manufacturing techniques into data analytics through the use of statistical process controls. In manufacturing, tests are used to monitor and improve the quality of factory-floor processes. In DataOps, tests are used to verify the inputs, business logic, and outputs at each stage of the data analytics pipeline. The data analytics professional adds a test each time a change is made. The suite of tests grows over time until it eventually becomes quite substantial. The tests validate the quality and integrity of a new release when a feature set is released to the user base. Tests allow the data analytics professional to quickly verify a release, substantially reducing the amount of time spent on deploying updates.

Statistical process control also monitors data, alerting the data team to an unexpected variance. This may require updates to the business logic built into the tests, or it might lead data scientists down new paths of inquiry or experimentation. The test alerts can be a starting point for creative discovery.

The combination of Agile development, DevOps, and statistical process controls gives DataOps the strategic tools to reduce time to insight, improve the quality of analytics, promote reuse and refactoring and lower the marginal cost of asking the next business question. Like mixed martial arts, DataOps draws its effectiveness from an eclectic mix of tools and techniques drawn from other fields and domains. Individually, each of these techniques is valuable, but together they form an effective new approach, which can take your data analytics to the next level.

Reinvent Marketing Automation with the DataKitchen DataOps Platform

A global pharmaceutical giant sought to drive top-line growth by modernizing its marketing operations. The project included a migration to Salesforce Marketing Cloud, integrations with numerous internal and third-party data sources, and a continuous flow of data. The plan initially required eighteen months for implementation. Using the DataKitchen DataOps Platform, which automates deployment, controls quality and supports Agile development of analytics, the company was able to start delivering value in six weeks and completed the migration in about one third the time.

THE CHALLENGE OF MARKETING AUTOMATION AT SCALE

The company faced numerous difficulties when implementing marketing automation for multiple global business units:

- **Distributed Data –** The company's marketing analytics and customer data were distributed in many specialized systems that do not easily talk to each other. This made it challenging to link customer data from one system with another. Customers engage through emails, partner websites, advertisements, campaigns and across product lines. Each of these touchpoints produces a continuous stream of fine-grained opt-in/opt-out requests which all must be consolidated and synchronized. Cross-referencing customer data with third-party databases also provides valuable segmentation information.
- **Supporting Agile –** The company lacked the technical infrastructure to implement Agile development of data flows and analytics. Using a slow and inflexible development process prevented them from keeping up with the fast-paced requirements of the sales and marketing teams.
- **Iterating on Data Quality –** Analysts had trouble specifying data quality rules until they saw the data. In a non-agile environment, this caused requirements to keep changing, causing delays.
- **Continuous Change Requests –** Once a system is operational, users are inspired to request additional data sources, segmentations and other enhancements. With long development cycles, it was difficult for the team to keep up with the users' continuous demands.

AUTOMATED EFFICIENCY AND QUALITY WITH DATAKITCHEN

The company utilized the DataKitchen Platform to oversee and monitor the end-to-end data pipeline. With the DataKitchen solution, the company is now able to:

- **Automate and monitor data pipelines –** Data flows from sources to user analytics in a continuous pipeline.
- **Implement continuous deployment –** New analytics are tested and deployed to users with speed and confidence using automation.

- **Control quality –** Data is continuously monitored for anomalies with alerts and dashboards that provide real-time information about data quality and operations.
- **Manage sandboxes –** Development environments are created as needed to prevent enhancements from disrupting operations.

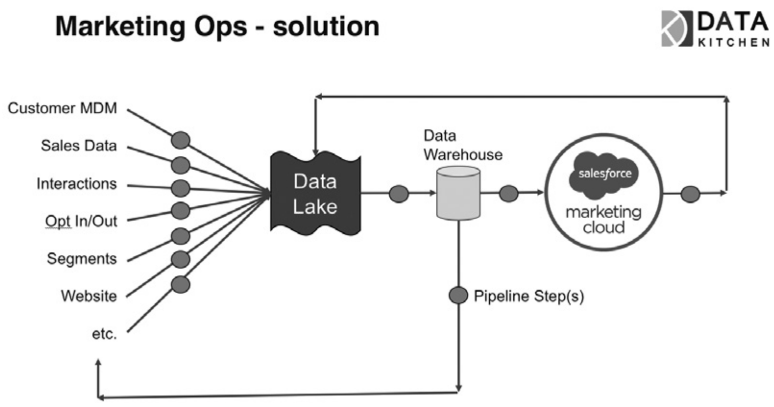


Figure 59: With DataKitchen, marketing automation data flows continuously from numerous sources through the analytics pipeline with efficiency and quality.

BUSINESS IMPACT

With the DataKitchen Platform, the company was able to break the long 18-month project into sprints and began to deliver value in six weeks. The agility of the DataKitchen DataOps approach enabled the analytics team to rapidly respond to changing user requirements with a continuous series of enhancements. Users no longer waited months to add new data sources or make other changes. The team can now deploy new data sources, update schemas and produce new analytics quickly and efficiently without fear of disrupting the existing data pipelines.

DataKitchen's lean manufacturing control helped the team be more proactive addressing data quality issues. With monitoring and alerts, the team is now able to provide immediate feedback to data suppliers about issues and can prevent bad data from reaching user analytics.

All this has led to improved insight into customers and markets and higher impact marketing campaigns that drive revenue growth.

DataKitchen's DataOps Platform helped this pharmaceutical company achieve its strategic goals by improving analytics quality, responsiveness, and efficiency. DataKitchen software provides support for improved processes, automation of tools, and agile development of new analytics. With DataKitchen, the analytics team was able to deliver value to users in 1/10th the time, accelerating and magnifying their impact on top line growth.

Meeting the Product Launch Challenge with DataOps

Celgene is a $12B biopharmaceutical company committed to delivering innovative treatments for patients worldwide. Celgene relies upon DataKitchen to enable rapid-response, high-quality data analytics that help the company maximize product lifetime revenue.

> *"So much of what we do involves business questions that are fire drills. Executives want answers as quickly as possible. The infrastructure that we've set-up with DataKitchen allows us to mix and match data in new ways so that we can quickly get the answer to a question."*
>
> *—Manager, Data Analyst, Celgene*

It costs between $2-3B to bring a new pharmaceutical to market. When a new drug is introduced, it is already halfway through its patent life. This makes the first 6-12 months of a pharmaceutical launch critical to a product's lifetime revenue. The vendor needs up-to-date information to allocate samples, plan marketing events, and monitor progress vs. goals. With so much at stake, pharmaceutical companies like Celgene make strategic investments to maximize product adoption and adherence during the initial phase of a drug product's life cycle.

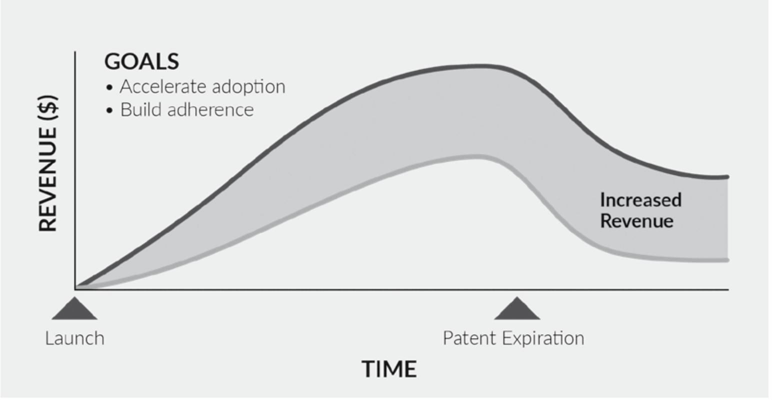


Figure 61: The first year is critical to a pharmaceutical product's lifetime revenue.

THE ROLE OF DATA IN LAUNCH SUCCESS

Celgene has found that using analytics to understand customers and markets can significantly improve product launch success. The analytics produced range from weekly, standardized reports to ad-hoc analyses. In the first months of a product's lifecycle, the sales and marketing teams can't wait weeks or months for new analytics. Every new data source, question, and innovative idea demands an immediate and accurate response.

THE OBSTACLES TO RESPONSIVE, HIGH-QUALITY ANALYTICS

The Celgene data engineering and analytics teams faced many obstacles that prevented analytics responsiveness and quality. Data was organized in silos—using a variety of technologies and isolated platforms. Without the right processes and tools in place, the data engineering and analytics teams can spend a majority of their time on data engineering and pipeline maintenance. This distracts them from their main mission — producing analytic insights that help the business attain its objectives.

THE DATAKITCHEN PLATFORM

Celgene chose DataKitchen to enable data engineering that streamlines development and data operations processes, helping the data analysts and scientists to remain focused on creating value — at the speed of business. With the DataKitchen Platform, Celgene has been able to:

- **Automate orchestration –** DataKitchen automates the deployment of new analytics and performs data pipeline orchestration, freeing up the team from manual processes and enabling them to focus on extracting value from data.
- **Monitor data quality –** Statistical process control and dashboards help monitor and control the quality of the end-to-end data pipeline, and real-time alerts provide high-level visibility into incidents and provide critical information.
- **Automate deployment –** Once new features pass all their tests, just a push of a button is required to deploy into production, with confidence.

DATA SOURCES & INTEGRATIONS
IQVIA (IMS)
Symphony
Veeva (salesforce.com)
Specialty Pharmacies
Email & Web Interactions
Sales Alignments Targets and Prospects
Product Hierarchies
Customer Segments

Table 7

ANALYTICS AT SUPER SPEED

With help from DataKitchen, Celgene was able to improve the productivity of the data engineering function by an order of magnitude. With automation of their data pipeline, they were able to update 30X more visualizations per week. They were able to compress the cycle time required to produce new analytics from weeks (or months) to one day. This enabled the data analytics team to successfully address the volume of questions from sales and marketing, helping them maximize product adoption during the critical first phase of their product launch. Instead of just fighting fires, the data team felt like they had acquired *superpowers*.

METRIC	BEFORE	WITH DATAKITCHEN
Data analysts supported by one data engineer	0.5	12
Schema changes per week by one data engineer	1	12
Sales people supported by one data analyst	50	250
Cycle time to publish new visualizations	weeks/ months	next day
Visualizations updated/wk	50	1500

Table 8

MOVING FORWARD WITH DATAKITCHEN

> *"DataKitchen has enabled us to become nimble and agile when it comes to data. We are now a self-service data organization — from the marketing department to the sales reps."*
>
> *—Director, Market Insights, Celgene*

Use of DataKitchen fostered a tight collaboration between data analytics and the business unit, unlocking creativity made possible by DataOps agility and quality. Impressed by the performance of the data-analytics team using DataKitchen, Celgene decided to expand their use of DataKitchen throughout the company.

Additional Recipes

DataOps Vegan Corn Chowder

by Eran Strod

INGREDIENTS AND TOOLS

Cashew Cream

- 1 cup cashews soaked in water for at least 2 hours
- 2 cups veg stock
- 4 teaspoons cornstarch (can sub tapioca starch if desired)
- Drain the cashews. In a blender, combine all the ingredients and work for 2 to 5 minutes or until smooth, scraping down the sides with a rubber spatula several times. Set aside.

Soup

- 1 Tablespoon olive oil
- 1 large onion coarsely chopped
- 2 celery ribs, chopped
- 3 cups veg broth
- 1 large carrot chopped
- 1 red pepper diced (could sub 1 bag Frozen mixed-vegetables, thawed in a pinch)
- 1 potato, diced
- 3 ears of fresh corn (cut the kernels off and scrape the corn cobs for corn milk to add to the soup)
- Can of corn

INSTRUCTIONS

1. Heat the oil in 4-quart pot
2. When hot add onion and celery with a pinch of salt, cook until start to soften.
3. Add carrots and potatoes
4. Add corn and red pepper and stir-fry for 10 minutes
5. Add 3 cups veg stock and the corn milk
6. Bring to a boil, lower the head and cover — simmer 10 min or until veg tender but not overcooked.
7. Stir in Cashew Cream and stir gently for 7 minutes until nicely thickened.
8. Blend up to half the soup to make more liquid and add it back in
9. Add salt & pepper to taste, depending on the type of veg stock you used.

My own adaptation of a vegan New England Clam Chowder recipe from the Boston Globe from Isa-does-it by Isa Chandra Moskowitz

DataOps Classic Baked Macaroni and Cheese

by Joanne Ferrari

INGREDIENTS AND TOOLS

- 2 Cups Milk
- 2 Tablespoons Butter
- 2 Tablespoons All-Purpose Flour
- ½ Teaspoon Salt
- ¼ Teaspoon Freshly Ground Black Pepper
- 1 (10 oz.) Block Extra Sharp Cheddar Cheese, Shredded
- ¼ Teaspoon Ground Red Pepper (Optional)
- ½ (16 oz.) Package Elbow Macaroni, Cooked

INSTRUCTIONS

1. Preheat oven to 400◦. Microwave milk at HIGH for 1 ½ minutes. Melt butter in a large skillet or Dutch oven over medium-low heat; whisk in flour until smooth. Cook, whisking constantly for 1 minute.
2. Gradually whisk in warm milk and cook, whisking constantly 5 minutes or until thickened.
3. Whisk in salt, black pepper, 1 cup shredded cheese, and if desired, red pepper until smooth; stir in pasta. Spoon pasta mixture into a lightly greased 2-qt. baking dish; top with remaining cheese. Bake at 400◦ for 20 minutes or until golden and bubbly.

NOTES

For this recipe, it is recommended that you grate the block(s) of cheese. I combine Sharp Cheddar and Swiss cheeses — my favorite. Pre-shredded varieties won't give you the same sharp bite or melt into creamy goodness over your macaroni as smoothly as block cheese that you grate yourself. You can go reduced-fat (but then it's even more important to prep your own). Grating won't take long, and the rest of this recipe is super simple. Use a pasta that has plenty of nooks to capture the cheese—like elbows, shells, or cavatappi. Try it just once, and I guarantee that Classic Baked Macaroni and Cheese will become your go-to comfort food.

DataOps Resources

The Agile Manifesto	http://agilemanifesto.org/
DatOps Blog	http://bit.ly/2Ef2Hto
The DataOps Manifesto	http://dataopsmanifesto.org
DataOps News	http://bit.ly/2ORDlUr
DataOps SlideShare	http://bit.ly/2PygnSb
DataOps Videos	http://bit.ly/2UFcKO8
Scrum Guides	http://www.scrumguides.org
Statistical Process Control	https://en.wikipedia.org/wiki/Statistical_process_control
W. Edwards Deming	https://en.wikipedia.org/wiki/W._Edwards_Deming
Wikipedia DataOps	http://bit.ly/2DnlqR1
Wikipedia DevOps	https://en.wikipedia.org/wiki/DevOps

About the Authors

Christopher Bergh is a Founder and Head Chef at DataKitchen where, among other activities, he is leading DataKitchen's DataOps initiative. Chris has more than 25 years of research, engineering, analytics, and executive management experience.

Previously, Chris was Regional Vice President in the Revenue Management Intelligence group in Model N. Before Model N, Chris was COO of LeapFrogRx, a descriptive and predictive analytics software and service provider. Chris led the acquisition of LeapFrogRx by Model N in January 2012. Prior to LeapFrogRx Chris was CTO and VP of Product Management of MarketSoft (now part of IBM) an innovative Enterprise Marketing Management software. Prior to that, Chris developed Microsoft Passport, the predecessor to Windows Live ID, a distributed authentication system used by 100s of Millions of users today. He was awarded a US Patent for his work on that project. Before joining Microsoft, he led the technical architecture and implementation of Firefly Passport, an early leader in Internet Personalization and Privacy. Microsoft subsequently acquired Firefly. Chris led the development of the first travel-related e-commerce web site at NetMarket. Chris began his career at the Massachusetts Institute of Technology's (MIT) Lincoln Laboratory and NASA Ames Research Center. There he created software and algorithms that provided aircraft arrival optimization assistance to Air Traffic Controllers at several major airports in the United States.

Chris served as a Peace Corps Volunteer Math Teacher in Botswana, Africa. Chris has an M.S. from Columbia University and a B.S. from the University of Wisconsin-Madison. He is an avid cyclist, hiker, reader, and father of two college age children.

Gil Benghiat is a Founder and VP of Products at DataKitchen where he is focusing on DataKitchen users and the Agile data practices.

Gil has held various technical and leadership roles at Solid Oak Consulting, HealthEdge, Phreesia, LeapFrogRx (purchased by Model N), Relicore (purchased by Symantec), Phase Forward (IPO and then purchased by Oracle), Netcentric, Sybase (purchased by SAP), and AT&T Bell Laboratories (now Nokia Bell Labs).

Gil's career has been data oriented starting with collecting and displaying network data at AT&T Bell Labs, managing data at Sybase, collecting and cleaning clinical trial data at PhaseForward, integrating pharmaceutical sales data at LeapFrogRx, protecting patient and financial data at Phreesia, processing claims data at HealthEdge, and liberating data at Solid Oak Consulting.

Gil holds an M.S. in Computer Science from Stanford University and a Sc.B. in Applied Mathematics/Biology from Brown University. He completed hiking all 48 of New Hampshire's, 4,000 peaks and is now working on the New England 67, and is the father of one high school and two college age boys.

Eran Strod works in marketing at DataKitchen where he writes white papers, case studies and the DataOps blog. Eran was previously Director of Marketing for Atrenne Integrated Solutions (now Celestica) and has held product marketing and systems engineering roles at Curtiss-Wright, Black Duck Software (now Synopsys), Mercury Systems, Motorola Computer Group (now Artesyn), and Freescale Semiconductor (now NXP), where he was a contributing author to the book "Network Processor Design, Issues and Practices."

Eran began his career as a software developer at CSPi working in the field of embedded computing.

Eran holds a B.A. in Computer Science and Psychology from the University of California at Santa Cruz and an M.B.A. from Northeastern University. He is father to two children and enjoys hiking, travel and watching the New England Patriots.

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