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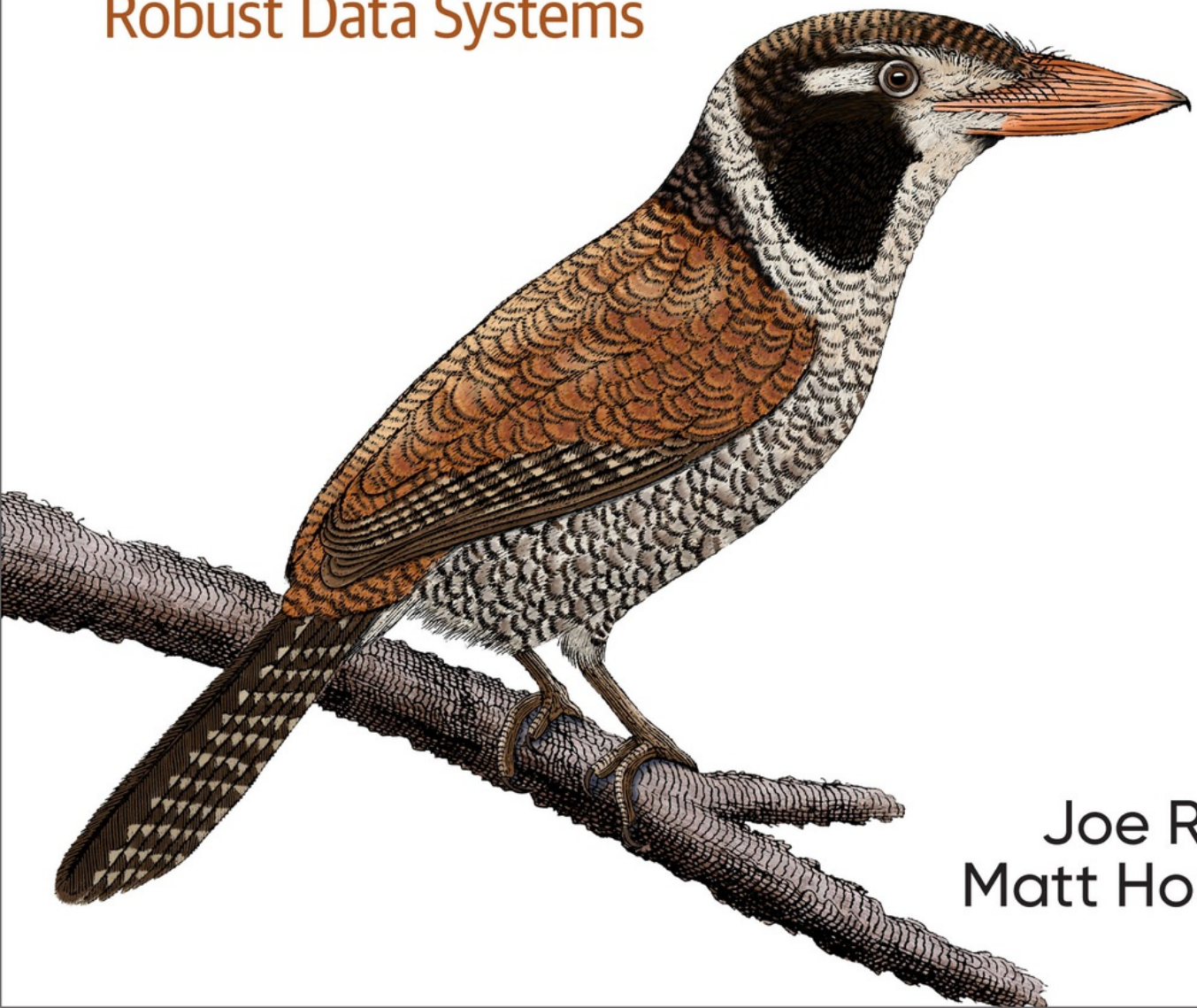
Fundamentals of Data Engineering

Plan and Build Robust Data Systems



Joe Reis &
Matt Housley

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by Joe Reis and Matt Housley

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Preface

How did this book come about? The origin is deeply rooted in our journey from data science into data engineering. We often jokingly refer to ourselves as *recovering data scientists*. We both had the experience of being assigned to data science projects, then struggling to execute these projects due to a lack of proper foundations. Our journey into data engineering began when we undertook data engineering tasks to build foundations and infrastructure.

With the rise of data science, companies splashed out lavishly on data science talent, hoping to reap rich rewards. Very often, data scientists struggled with basic problems that their background and training did not address—data collection, data cleansing, data access, data transformation, and data infrastructure. These are problems that data engineering aims to solve.

What This Book Isn’t

Before we cover what this book is about and what you’ll get out of it, let’s quickly cover what this book *isn’t*. This book isn’t about data engineering using a particular tool, technology, or platform. While many excellent books approach data engineering technologies from this perspective, these books have a short shelf life. Instead, we try to focus on the fundamental concepts behind data engineering.

What This Book Is About

This book aims to fill a gap in current data engineering content and materials. While there's no shortage of technical resources that address specific data engineering tools and technologies, people struggle to understand how to assemble these components into a coherent whole that applies in the real world. This book connects the dots of the end-to-end data lifecycle. It shows you how to stitch together various technologies to serve the needs of downstream data consumers such as analysts, data scientists, and machine learning engineers. This book works as a complement to O'Reilly books that cover the details of particular technologies, platforms and programming languages.

The big idea of this book is the *data engineering lifecycle*: data generation, storage, ingestion, transformation, and serving Since the dawn of data, we've seen the rise and fall of innumerable specific technologies and vendor products, but the data engineering life cycle stages have remained essentially unchanged. With this framework, the reader will come away with a sound understanding for applying technologies to real-world business problems.

Our goal here is to map out principles that reach across two axes. First, we wish to distill data engineering into principles that can encompass *any relevant technology*. Second, we wish to present principles that will stand the test of *time*. We hope that these ideas reflect lessons learned across the data technology upheaval of the last twenty years and that our mental framework will remain useful for a decade or more into the future.

One thing to note: we unapologetically take a cloud-first approach. We view the cloud as a fundamentally transformative development that will endure for decades; most on-premises data systems and workloads will eventually move to cloud hosting. We assume that infrastructure and systems are *ephemeral* and *scalable*, and that data engineers will lean toward deploying managed services in the cloud. That said, most concepts in this book will translate to non-cloud environments.

Who Should Read This Book

Our primary intended audience for this book consists of technical practitioners, mid- to senior-level software engineers, data scientists, or analysts interested in moving into data engineering; or data engineers working in the guts of specific technologies, but wanting to develop a more comprehensive perspective. Our secondary target audience consists of data stakeholders who work adjacent to technical practitioners—e.g., a data team lead with a technical background overseeing a team of data engineers, or a director of data warehousing wanting to migrate from on-premises technology to a cloud-based solution.

Ideally, you're curious and want to learn—why else would you be reading this book? You stay current with data technologies and trends by reading books and articles on data warehousing/data lakes, batch and streaming systems, orchestration, modeling, management, analysis, developments in cloud technologies, etc. This book will help you weave what you've read into a complete picture of data engineering across technologies and paradigms.

Prerequisites

We assume a good deal of familiarity with the types of data systems found in a corporate setting. In addition, we assume that readers have some familiarity with SQL and Python (or some other programming language), and experience with cloud services.

Numerous resources are available for aspiring data engineers to practice Python and SQL. Free online resources abound (blog posts, tutorial sites, YouTube videos), and many new Python books are published every year.

The cloud provides unprecedented opportunities to get hands-on experience with data tools. We suggest that aspiring data engineers set up accounts with cloud services such as AWS, Azure, Google Cloud Platform, Snowflake, Databricks, etc. Note that many of these platforms have *free tier*

options, but readers should keep a close eye on costs, and work with small quantities of data and single node clusters as they study.

Developing familiarity with corporate data systems outside of a corporate environment remains difficult and this creates certain barriers for aspiring data engineers who have yet to land their first data job. This book can help. We suggest that data novices read for high level ideas, and then look at materials in the *additional resources* section at the end of each chapter. On a second read through, note any unfamiliar terms and technologies. You can utilize Google, Wikipedia, blog posts, YouTube videos, and vendor sites to become familiar with new terms and fill gaps in your understanding.

What You'll Learn and How It Will Improve Your Abilities

This book aims to help you build a solid foundation for solving real world data engineering problems.

By the end of this book you will understand:

- How data engineering impacts your current role (data scientist, software engineer, or data team lead).
- How to cut through the marketing hype and choose the right technologies, data architecture, and processes.
- How to use the data engineering lifecycle to design and build a robust architecture.
- Best practices for each stage of the data lifecycle.

And you will be able to:

- Incorporate data engineering principles in your current role (data scientist, analyst, software engineer, data team lead, etc.)
- Stitch together a variety of cloud technologies to serve the needs of downstream data consumers.

- Assess data engineering problems with an end-to-end framework of best practices
- Incorporate data governance and security across the data engineering lifecycle.

The Book Outline

This book is composed of four parts:

- Part I, "Foundation and Building Blocks"
- Part II, "The Data Engineering Lifecycle in Depth"
- Part III, "Security, Privacy, and the Future of Data Engineering"
- Appendices A and B: cloud networking, serialization and compression

In Part I, we begin by defining data engineering in Chapter 1, then map out the data engineering lifecycle in Chapter 2. In Chapter 3, we discuss *good architecture*. In Chapter 4, we introduce a framework for choosing the right technology—while we frequently see technology and architecture conflated, these are in fact very different topics.

Part II builds on Chapter 2 to cover the data engineering lifecycle in depth; each lifecycle stage—data generation, storage, ingestion, transformation and serving—is covered in its own chapter. Part II is arguably the heart of the book, and the other chapters exist to support the core ideas covered here.

Part III covers additional topics. In Chapter 10, we discuss *security and privacy*. While security has always been an important part of the data engineering profession, it has only become more critical with the rise of for profit hacking and state sponsored cyber attacks. And what can we say of privacy? The era of corporate privacy nihilism is over—no company wants to see its name appear in the headline of an article on sloppy privacy practices. Reckless handling of personal data can also have significant legal ramifications with the advent of GDPR, CCPA and other regulations. In short, security and privacy must be top priorities in any data engineering work.

In the course of working in data engineering, doing research for this book and interviewing numerous experts, we thought a good deal about where the field is going in the near and long term. Chapter 11 outlines our highly

speculative ideas on the future of data engineering. By its nature, the future is a slippery thing. Time will tell if some of our ideas are correct. We would love to hear from our readers on how their visions of the future agree with or differ from our own.

In the appendix, we cover a handful of technical topics that are extremely relevant to the day to day practice of data engineering, but didn't fit into the main body of the text. Specifically, cloud networking is a critical topic as data engineering shifts into the cloud, and engineers need to understand serialization and compression both to work directly with data files, and to assess performance considerations in data systems.

Conventions Used in This Book

The following typographical conventions are used in this book:

Italic

Indicates new terms, URLs, email addresses, filenames, and file extensions.

`Constant width`

Used for program listings, as well as within paragraphs to refer to program elements such as variable or function names, databases, data types, environment variables, statements, and keywords.

`Constant width bold`

Shows commands or other text that should be typed literally by the user.

`Constant width italic`

Shows text that should be replaced with user-supplied values or by values determined by context.

> **TIP**
>
> This element signifies a tip or suggestion.

> **NOTE**
>
> This element signifies a general note.

> **WARNING**
>
> This element indicates a warning or caution.

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Acknowledgments

When we started writing this book, we were warned by many people that we faced a hard task. A book like this has a lot of moving parts, and due to its comprehensive view of the field of data engineering, it required a ton of research, interviews, discussions, and deep thinking. We won't claim to have captured every nuance of data engineering, but we hope that the results resonate with you. Numerous individuals contributed to our efforts, and we're grateful for the support we received from many experts.

First, thanks to our amazing crew of technical reviewers. They slogged through many readings, and gave invaluable (and often ruthlessly blunt) feedback. This book would be a fraction of itself without their efforts. In no particular order, we give endless thanks to Bill Inmon, Andy Petrella, Matt Sharp, Tod Hanseman, Chris Tabb, Danny Lebzyon, Martin Kleppman, Scott Lorimor, Nick Schrock, Lisa Steckman, and Alex Woolford.

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Todd Beauchene, Tudor Girba, Scott Taylor, Ori Rafael, Lee Edwards, Bryan Offutt, Ollie Hughes, Gilbert Eijkelenboom, Chris Bergh, Fabiana Clemente, Andreas Kretz, Ori Reshef, Nick Singh, Mark Balkenende, Kenten Danas, Brian Olsen, Lior Gavish, Rhaghu Murthy, Greg Coquillo, David Aponte, Demetrios Brinkmann, Sarah Catanzaro, Michel Tricot, Levi Davis, Ted Walker, Carlos Kemeny, Josh Benamram, Chanin Nantasenamat, George Firican, Jordan Goldmeir, Minhaaj Rehmam, Luigi Patruno, Vin Vashista, Danny Ma, Jesse Anderson, Alessya Visnjic, Vishal Singh, Dave Langer, Roy Hasson, Todd Odess, Che Sharma, Scott Breitenother, Ben Taylor, Thom Ives, John Thompson, Brent Dykes, Josh Tobin, Mark Kosiba, Tyler Pugliese, Douwe Maan, Martin Traverso, Curtis Kowalski, Bob Davis, Koo Ping Shung, Ed Chenard, Matt Sciorma, Tyler Folkman, Jeff Baird, Tejas Manohar, Paul Singman, Kevin Stumpf, Willem Pineaar, and Michael Del Balso from Tecton, Emma Dahl, Harpreet Sahota, Ken Jee, Scott Taylor, Kate Strachnyi, Kristen Kehrer, Taylor Miller, Abe Gong, Ben Castleton, Ben Rogojan, David Mertz, Emmanuel Raj, Andrew Jones, Avery Smith, Brock Cooper, Jeff Larson, Jon King, Holden Ackerman, Miriah Peterson, Felipe Hoffa, David Gonzalez, Richard Wellman, Susan Walsh, Ravit Jain, Lauren Balik, Mikiko Bazeley, Mark Freeman, Mike Wimmer, Alexey Shchedrin, Mary Clair Thompson, Julie Burroughs, Jason Pedley, Freddy Drennan, Jake Carter, Jason Pedley, Kelly and Matt Phillipps, Brian Campbell, Faris Chebib, Dylan Gregerson, Ken Myers, and many others.

If you're not mentioned specifically, don't take it personally. You know who you are. Let us know and we'll get you on the next edition.

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Working with the O'Reilly crew was amazing! Special thanks to Jess Haberman for having confidence in us during the book proposal process, our amazing and extremely patient development editors Nicole Taché and Michele Cronin for invaluable editing, feedback and support. Thank you also to the superb production crew at O'Reilly (Greg and crew).

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Matt would like to thank his friends and family for their enduring patience and support. He’s still hopeful that Seneca will deign to give a five star review after a good deal of toil and missed family time around the holidays.

Part I. Foundation and Building Blocks

Chapter 1. Data Engineering Described

If you work in data or software, you may have noticed data engineering emerging from the shadows and now sharing the stage with data science. Data engineering is one of the hottest fields in data and technology, and for a good reason. It builds the foundation for data science and analytics in production. This chapter explores what data engineering is, how the field was born and its evolution, the skills of data engineers, and with whom they work.

What Is Data Engineering?

Despite the current popularity of data engineering, there's a lot of confusion about what data engineering means and what data engineers do. Data engineering has existed in some form since companies started doing things with data—such as predictive analysis, descriptive analytics, and reports—and came into sharp focus alongside the rise of data science in the 2010s. For the purpose of this book, it's critical to define what *data engineering* and *data engineer* mean.

First, let's look at the landscape of how data engineering is described and develop some terminology we can use throughout this book. Endless definitions of *data engineering* exist. In early 2022, a Google exact-match search for "what is data engineering?" returns over 91,000 unique results. Before we give our definition, here are a few examples of how some experts in the field define data engineering:

Data engineering is a set of operations aimed at creating interfaces and mechanisms for the flow and access of information. It takes dedicated specialists—data engineers—to maintain data so that it remains available and usable by others. In short, data engineers set up and operate the organization's data infrastructure, preparing it for further analysis by data analysts and scientists.

—From "Data Engineering and Its Main Concepts" by AlexSoft[1]

The first type of data engineering is SQL-focused. The work and primary storage of the data is in relational databases. All of the data processing is done with SQL or a SQL-based language. Sometimes, this data processing is done with an ETL tool.[2] The second type of data engineering is Big Data–focused. The work and primary storage of the data is in Big Data technologies like Hadoop, Cassandra, and HBase. All of the data processing is done in Big Data frameworks like MapReduce, Spark, and Flink. While SQL is used, the primary processing is done with programming languages like Java, Scala, and Python.

—Jesse Anderson[3]

In relation to previously existing roles, the data engineering field could be thought of as a superset of business intelligence and data warehousing that brings more elements from software engineering. This discipline also integrates specialization around the operation of so-called "big data" distributed systems, along with concepts around the extended Hadoop ecosystem, stream processing, and in computation at scale.

—Maxime Beauchemin[4]

Data engineering is all about the movement, manipulation, and management of data.

—Lewis Gavin[5]

Wow! It's entirely understandable if you've been confused about data engineering. That's only a handful of definitions, and they contain an enormous range of opinions about the meaning of *data engineering*.

Data Engineering Defined

When we unpack the common threads of how various people define data engineering, an obvious pattern emerges: a data engineer gets data, stores it, and prepares it for consumption by data scientists, analysts, and others. We define *data engineering* and *data engineer* as follows:

> *Data engineering is the development, implementation, and maintenance of systems and processes that take in raw data and produce high-quality, consistent information that supports downstream use cases, such as analysis and machine learning. Data engineering is the intersection of security, data management, DataOps, data architecture, orchestration, and software engineering. A data engineer manages the data engineering lifecycle, beginning with getting data from source systems and ending with serving data for use cases, such as analysis or machine learning.*

The Data Engineering Lifecycle

It is all too easy to fixate on technology and miss the bigger picture myopically. This book centers around a big idea called the *data engineering lifecycle* (Figure 1-1), which we believe gives data engineers the holistic context to view their role.

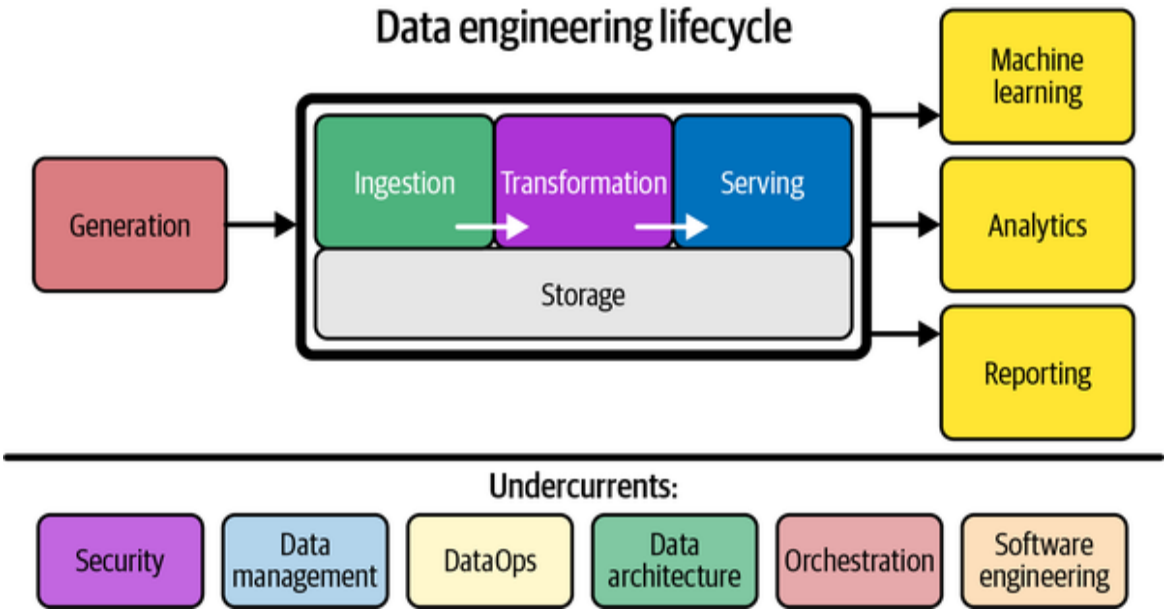

Figure 1-1. The data engineering lifecycle

The data engineering lifecycle shifts the conversation away from technology and toward the data itself and the end goals that it must serve. The stages of the data engineering lifecycle are as follows:

- Generation
- Storage
- Ingestion
- Transformation
- Serving

The data engineering lifecycle also has a notion of *undercurrents*—critical ideas across the entire lifecycle. These include security, data management, DataOps, data architecture, orchestration, and software engineering. We cover the data engineering lifecycle and its undercurrents more extensively in Chapter 2. Still, we introduce it here because it is essential to our definition of data engineering and the discussion that follows in this chapter.

Now that you have a working definition of data engineering and an introduction to its lifecycle, let's take a step back and look at a bit of history.

Evolution of the Data Engineer

> *History doesn't repeat itself, but it rhymes.*
>
> —A famous adage often attributed to Mark Twain

Understanding data engineering today and tomorrow requires a context of how the field evolved. This section is not a history lesson, but looking at the past is invaluable in understanding where we are today and where things are going. A common theme constantly reappears: what's old is new again.

The early days: 1980 to 2000, from data warehousing to the web

The birth of the data engineer arguably has its roots in data warehousing, dating as far back as the 1970s, with the *business data warehouse* taking shape in the 1980s and Bill Inmon officially coining the term *data warehouse* in 1990. After engineers at IBM developed the relational database and Structured Query Language (SQL), Oracle popularized the technology. As nascent data systems grew, businesses needed dedicated tools and data pipelines for reporting and business intelligence (BI). To help people correctly model their business logic in the data warehouse, Ralph Kimball and Inmon developed their respective eponymous data-modeling techniques and approaches, which are still widely used today.

Data warehousing ushered in the first age of scalable analytics, with new massively parallel processing (MPP) databases that use multiple processors to crunch large amounts of data coming on the market and supporting unprecedented volumes of data. Roles such as BI engineer, ETL developer, and data warehouse engineer addressed the various needs of the data warehouse. Data warehouse and BI engineering were a precursor to today's data engineering and still play a central role in the discipline.

The internet went mainstream around the mid-1990s, creating a whole new generation of web-first companies such as AOL, Yahoo, and Amazon. The dot-com boom spawned a ton of activity in web applications and the backend systems to support them—servers, databases, and storage. Much of the infrastructure was expensive, monolithic, and heavily licensed. The vendors selling these backend systems likely didn't foresee the sheer scale of the data that web applications would produce.

The early 2000s: The birth of contemporary data engineering

Fast-forward to the early 2000s, when the dot-com boom of the late '90s went bust, leaving behind a tiny cluster of survivors. Some of these companies, such as Yahoo, Google, and Amazon, would grow into powerhouse tech companies. Initially, these companies continued to rely on the traditional monolithic, relational databases and data warehouses of the 1990s, pushing these systems to the limit. As these systems buckled, updated approaches were needed to handle data growth. The new

generation of the systems must be cost-effective, scalable, available, and reliable.

Coinciding with the explosion of data, commodity hardware—such as servers, RAM, disks, and flash drives—also became cheap and ubiquitous. Several innovations allowed distributed computation and storage on massive computing clusters at a vast scale. These innovations started decentralizing and breaking apart traditionally monolithic services. The "big data" era had begun.

The *Oxford English Dictionary* defines big data as "extremely large data sets that may be analyzed computationally to reveal patterns, trends, and associations, especially relating to human behavior and interactions." Another famous and succinct description of big data is the three *V*'s of data: velocity, variety, and volume.

In 2003, Google published a paper on the Google File System, and shortly after that, in 2004, a paper on MapReduce, an ultra-scalable data-processing paradigm. In truth, big data has earlier antecedents in MPP data warehouses and data management for experimental physics projects, but Google's publications constituted a "big bang" for data technologies and the cultural roots of data engineering as we know it today. You'll learn more about MPP systems and MapReduce in Chapters 3 and 8, respectively.

The Google papers inspired engineers at Yahoo to develop and later open source Apache Hadoop in 2006.[6] It's hard to overstate the impact of Hadoop. Software engineers interested in large-scale data problems were drawn to the possibilities of this new open source technology ecosystem. As companies of all sizes and types saw their data grow into many terabytes and even petabytes, the era of the big data engineer was born.

Around the same time, Amazon had to keep up with its own exploding data needs and created elastic computing environments (Amazon Elastic Compute Cloud, or EC2), infinitely scalable storage systems (Amazon Simple Storage Service, or S3), highly scalable NoSQL databases (Amazon DynamoDB), and many other core data building blocks.[7] Amazon elected to offer these services for internal and external consumption through

Amazon Web Services (AWS), becoming the first popular public cloud. AWS created an ultra-flexible pay-as-you-go resource marketplace by virtualizing and reselling vast pools of commodity hardware. Instead of purchasing hardware for a data center, developers could simply rent compute and storage from AWS.

As AWS became a highly profitable growth engine for Amazon, other public clouds would soon follow, such as Google Cloud, Microsoft Azure, and DigitalOcean. The public cloud is arguably one of the most significant innovations of the 21st century and spawned a revolution in the way software and data applications are developed and deployed.

The early big data tools and public cloud laid the foundation for today's data ecosystem. The modern data landscape—and data engineering as we know it now—would not exist without these innovations.

The 2000s and 2010s: Big data engineering

Open source big data tools in the Hadoop ecosystem rapidly matured and spread from Silicon Valley to tech-savvy companies worldwide. For the first time, any business had access to the same bleeding-edge data tools used by the top tech companies. Another revolution occurred with the transition from batch computing to event streaming, ushering in a new era of big "real-time" data. You'll learn about batch and event streaming throughout this book.

Engineers could choose the latest and greatest—Hadoop, Apache Pig, Apache Hive, Dremel, Apache HBase, Apache Storm, Apache Cassandra, Apache Spark, Presto, and numerous other new technologies that came on the scene. Traditional enterprise-oriented and GUI-based data tools suddenly felt outmoded, and code-first engineering was in vogue with the ascendance of MapReduce. We (the authors) were around during this time, and it felt like old dogmas died a sudden death upon the altar of big data.

The explosion of data tools in the late 2000s and 2010s ushered in the *big data engineer*. To effectively use these tools and techniques—namely, the Hadoop ecosystem including Hadoop, YARN, Hadoop Distributed File

System (HDFS), and MapReduce—big data engineers had to be proficient in software development and low-level infrastructure hacking, but with a shifted emphasis. Big data engineers typically maintained massive clusters of commodity hardware to deliver data at scale. While they might occasionally submit pull requests to Hadoop core code, they shifted their focus from core technology development to data delivery.

Big data quickly became a victim of its own success. As a buzzword, *big data* gained popularity during the early 2000s through the mid-2010s. Big data captured the imagination of companies trying to make sense of the ever-growing volumes of data and the endless barrage of shameless marketing from companies selling big data tools and services. Because of the immense hype, it was common to see companies using big data tools for small data problems, sometimes standing up a Hadoop cluster to process just a few gigabytes. It seemed like everyone wanted in on the big data action. Dan Ariely tweeted, "Big data is like teenage sex: everyone talks about it, nobody really knows how to do it, everyone thinks everyone else is doing it, so everyone claims they are doing it."

Figure 1-2 shows a snapshot of Google Trends for the search term "big data" to get an idea of the rise and fall of big data.

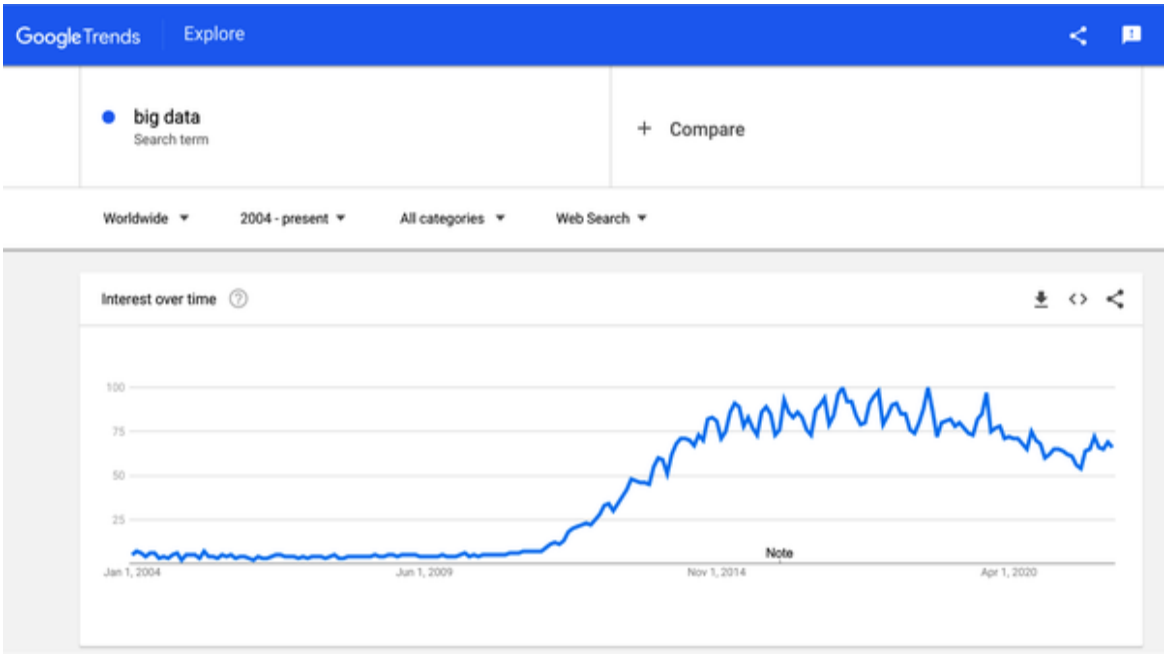

Figure 1-2. Google Trends for "big data" (March 2022)

Despite the term's popularity, big data has lost steam. What happened? One word: simplification. Despite the power and sophistication of open source big data tools, managing them was a lot of work and required constant attention. Often, companies employed entire teams of big data engineers, costing millions of dollars a year, to babysit these platforms. Big data engineers often spent excessive time maintaining complicated tooling and arguably not as much time delivering the business's insights and value.

Open source developers, clouds, and third parties started looking for ways to abstract, simplify, and make big data available without the high administrative overhead and cost of managing their clusters, and installing, configuring, and upgrading their open source code. The term *big data* is essentially a relic to describe a particular time and approach to handling large amounts of data.

Today, data is moving faster than ever and growing ever larger, but big data processing has become so accessible that it no longer merits a separate term; every company aims to solve its data problems, regardless of actual data size. Big data engineers are now simply *data engineers*.

The 2020s: Engineering for the data lifecycle

At the time of this writing, the data engineering role is evolving rapidly. We expect this evolution to continue at a rapid clip for the foreseeable future. Whereas data engineers historically tended to the low-level details of monolithic frameworks such as Hadoop, Spark, or Informatica, the trend is moving toward decentralized, modularized, managed, and highly abstracted tools.

Indeed, data tools have proliferated at an astonishing rate (see Figure 1-3). Popular trends in the early 2020s include the *modern data stack*, representing a collection of off-the-shelf open source and third-party products assembled to make analysts' lives easier. At the same time, data sources and data formats are growing both in variety and size. Data engineering is increasingly a discipline of interoperation, and connecting various technologies like LEGO bricks, to serve ultimate business goals.

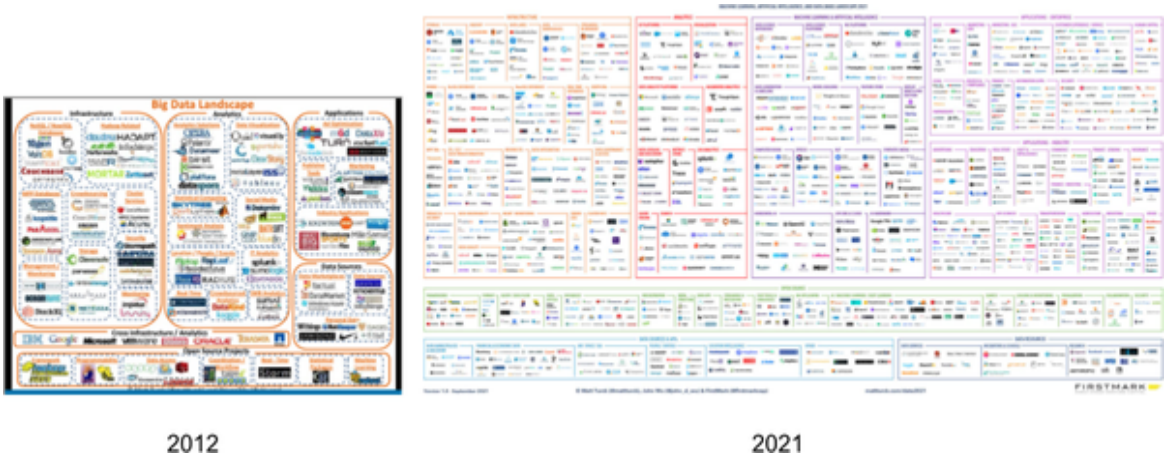

Figure 1-3. Matt Turck's Data Landscape in 2012 versus 2021

The data engineer we discuss in this book can be described more precisely as a *data lifecycle engineer*. With greater abstraction and simplification, a data lifecycle engineer is no longer encumbered by the gory details of yesterday's big data frameworks. While data engineers maintain skills in low-level data programming and use these as required, they increasingly find their role focused on things higher in the value chain: security, data management, DataOps, data architecture, orchestration, and general data lifecycle management.[8]

As tools and workflows simplify, we've seen a noticeable shift in the attitudes of data engineers. Instead of focusing on who has the "biggest data," open source projects and services are increasingly concerned with managing and governing data, making it easier to use and discover, and improving its quality. Data engineers are now conversant in acronyms such as *CCPA* and *GDPR*;[9] as they engineer pipelines, they concern themselves with privacy, anonymization, data garbage collection, and compliance with regulations.

What's old is new again. While "enterprisey" stuff like data management (including data quality and governance) was common for large enterprises in the pre-big-data era, it wasn't widely adopted in smaller companies. Now that many of the challenging problems of yesterday's data systems are solved, neatly productized, and packaged, technologists and entrepreneurs have shifted focus back to the "enterprisey" stuff, but with an emphasis on

decentralization and agility, that contrasts with the traditional enterprise command-and-control approach.

We view the present as a golden age of data lifecycle management. Data engineers managing the data engineering lifecycle have better tools and techniques than ever before. We discuss the data engineering lifecycle and its undercurrents in greater detail in the next chapter.

Data Engineering and Data Science

Where does data engineering fit in with data science? There's some debate, with some arguing data engineering is a subdiscipline of data science. We believe data engineering is *separate* from data science and analytics. They complement each other, but they are distinctly different. Data engineering sits upstream from data science (Figure 1-4), meaning data engineers provide the inputs used by data scientists (downstream from data engineering), who convert these inputs into something useful.

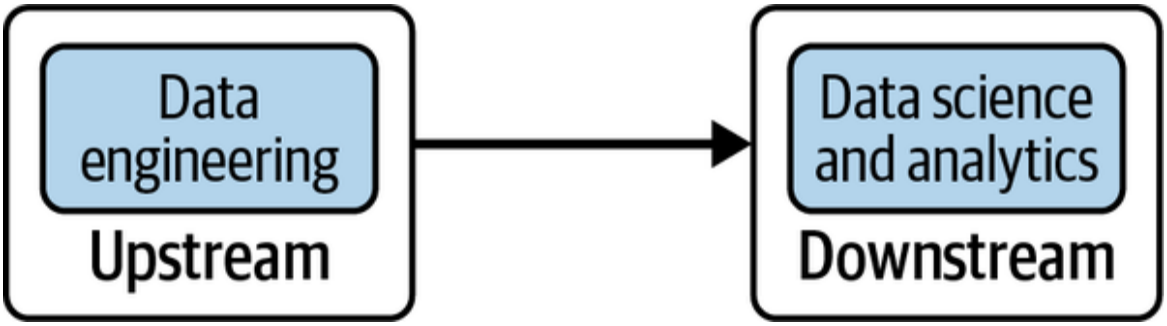

Figure 1-4. Data engineering sits upstream from data science

Consider the Data Science Hierarchy of Needs (Figure 1-5). In 2017, Monica Rogati published this hierarchy in an article that showed where AI and machine learning (ML) sat in proximity to more "mundane" areas such as data movement/storage, collection, and infrastructure.

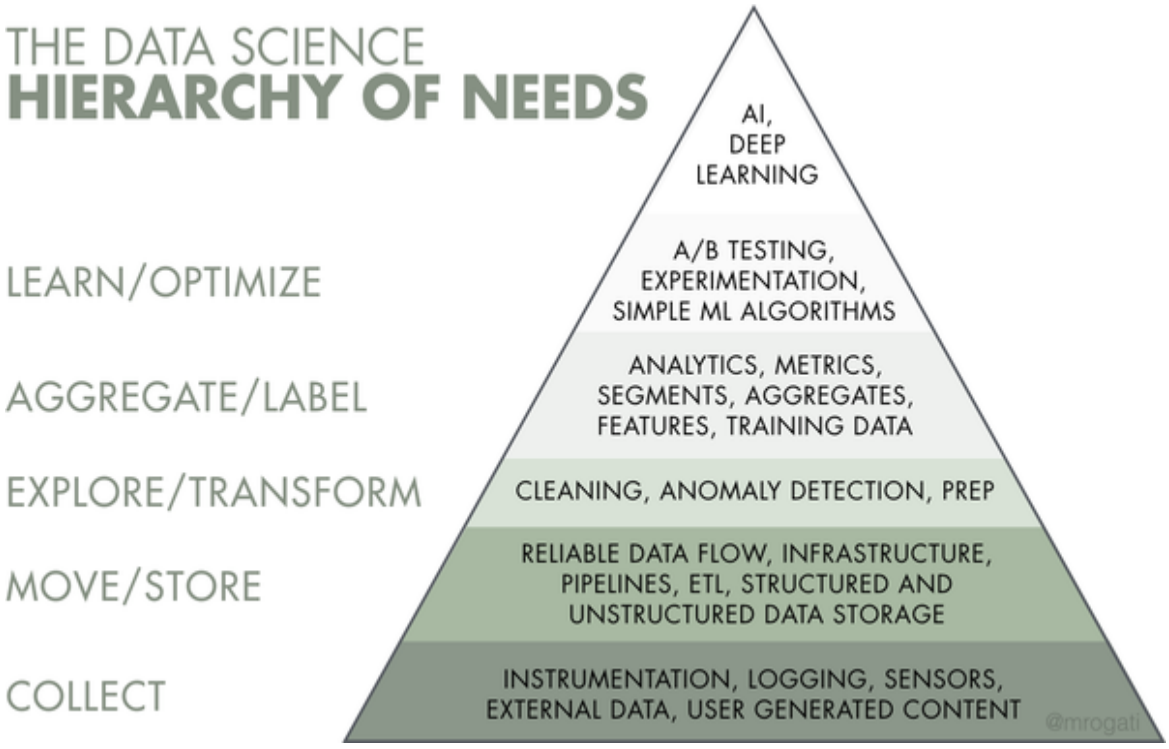

Figure 1-5. The Data Science Hierarchy of Needs

Although many data scientists are eager to build and tune ML models, the reality is an estimated 70% to 80% of their time is spent toiling in the bottom three parts of the hierarchy—gathering data, cleaning data, processing data—and only a tiny slice of their time on analysis and ML. Rogati argues that companies need to build a solid data foundation (the bottom three levels of the hierarchy) before tackling areas such as AI and ML.

Data scientists aren't typically trained to engineer production-grade data systems, and they end up doing this work haphazardly because they lack the support and resources of a data engineer. In an ideal world, data scientists should spend more than 90% of their time focused on the top layers of the pyramid: analytics, experimentation, and ML. When data engineers focus on these bottom parts of the hierarchy, they build a solid foundation for data scientists to succeed.

With data science driving advanced analytics and ML, data engineering straddles the divide between getting data and getting value from data (see Figure 1-6). We believe data engineering is of equal importance and

visibility to data science, with data engineers playing a vital role in making data science successful in production.

Figure 1-6. A data engineer gets data and provides value from the data

Data Engineering Skills and Activities

The skill set of a data engineer encompasses the "undercurrents" of data engineering: security, data management, DataOps, data architecture, and software engineering. This skill set requires an understanding of how to evaluate data tools and how they fit together across the data engineering lifecycle. It's also critical to know how data is produced in source systems and how analysts and data scientists will consume and create value after processing and curating data. Finally, a data engineer juggles a lot of complex moving parts and must constantly optimize along the axes of cost, agility, scalability, simplicity, reuse, and interoperability (Figure 1-7). We cover these topics in more detail in upcoming chapters.

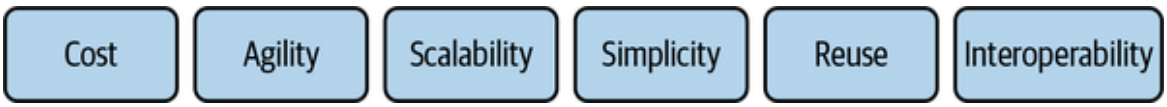

Figure 1-7. The balancing act of data engineering

As we discussed, in the recent past, a data engineer was expected to know and understand how to use a small handful of powerful and monolithic technologies (Hadoop, Spark, Teradata, Hive, and many others) to create a data solution. Utilizing these technologies often requires a sophisticated understanding of software engineering, networking, distributed computing, storage, or other low-level details. Their work would be devoted to cluster administration and maintenance, managing overhead, and writing pipeline and transformation jobs, among other tasks.

Nowadays, the data-tooling landscape is dramatically less complicated to manage and deploy. Modern data tools considerably abstract and simplify

workflows. As a result, data engineers are now focused on balancing the simplest and most cost-effective, best-of-breed services that deliver value to the business. The data engineer is also expected to create agile data architectures that evolve as new trends emerge.

What are some things a data engineer does *not* do? A data engineer typically does not directly build ML models, create reports or dashboards, perform data analysis, build key performance indicators (KPIs), or develop software applications. A data engineer should have a good functioning understanding of these areas to serve stakeholders best.

Data Maturity and the Data Engineer

The level of data engineering complexity within a company depends a great deal on the company's data maturity. This significantly impacts a data engineer's day-to-day job responsibilities and career progression. What is data maturity, exactly?

Data maturity is the progression toward higher data utilization, capabilities, and integration across the organization, but data maturity does not simply depend on the age or revenue of a company. An early-stage startup can have greater data maturity than a 100-year-old company with annual revenues in the billions. What matters is the way data is leveraged as a competitive advantage.

Data maturity models have many versions, such as Data Management Maturity (DMM) and others, and it's hard to pick one that is both simple and useful for data engineering. So, we'll create our own simplified data maturity model. Our data maturity model (Figure 1-8) has three stages: starting with data, scaling with data, and leading with data. Let's look at each of these stages and at what a data engineer typically does at each stage.

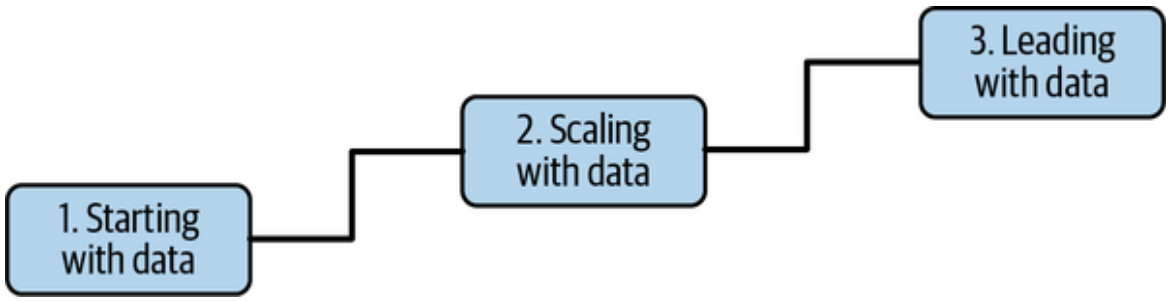

Figure 1-8. Our simplified data maturity model for a company

Stage 1: Starting with data

A company getting started with data is, by definition, in the very early stages of its data maturity. The company may have fuzzy, loosely defined goals or no goals. Data architecture and infrastructure are in the very early stages of planning and development. Adoption and utilization are likely low or nonexistent. The data team is small, often with a headcount in the single digits. At this stage, a data engineer is usually a generalist and will typically play several other roles, such as data scientist or software engineer. A data engineer's goal is to move fast, get traction, and add value.

The practicalities of getting value from data are typically poorly understood, but the desire exists. Reports or analyses lack formal structure, and most requests for data are ad hoc. While it's tempting to jump headfirst into ML at this stage, we don't recommend it. We've seen countless data teams get stuck and fall short when they try to jump to ML without building a solid data foundation.

That's not to say you can't get wins from ML at this stage—it is rare but possible. Without a solid data foundation, you likely won't have the data to train reliable ML models nor the means to deploy these models to production in a scalable and repeatable way. We half-jokingly call ourselves "recovering data scientists", mainly from personal experience with being involved in premature data science projects without adequate data maturity or data engineering support.

A data engineer should focus on the following in organizations getting started with data:

- Get buy-in from key stakeholders, including executive management. Ideally, the data engineer should have a sponsor for critical initiatives to design and build a data architecture to support the company's goals.
- Define the right data architecture (usually solo, since a data architect likely isn't available). This means determining business goals and the competitive advantage you're aiming to achieve with your data initiative. Work toward a data architecture that supports these goals. See Chapter 3 for our advice on "good" data architecture.
- Identify and audit data that will support key initiatives and operate within the data architecture you designed.
- Build a solid data foundation for future data analysts and data scientists to generate reports and models that provide competitive value. In the meantime, you may also have to generate these reports and models until this team is hired.

This is a delicate stage with lots of pitfalls. Here are some tips for this stage:

- Organizational willpower may wane if a lot of visible successes don't occur with data. Getting quick wins will establish the importance of data within the organization. Just keep in mind that quick wins will likely create technical debt. Have a plan to reduce this debt, as it will otherwise add friction for future delivery.
- Get out and talk to people, and avoid working in silos. We often see the data team working in a bubble, not communicating with people outside their departments and getting perspectives and feedback from business stakeholders. The danger is you'll spend a lot of time working on things of little use to people.
- Avoid undifferentiated heavy lifting. Don't box yourself in with unnecessary technical complexity. Use off-the-shelf, turnkey solutions wherever possible.

- Build custom solutions and code only where this creates a competitive advantage.

Stage 2: Scaling with data

At this point, a company has moved away from ad hoc data requests and has formal data practices. Now the challenge is creating scalable data architectures and planning for a future where the company is genuinely data-driven. Data engineering roles move from generalists to specialists, with people focusing on particular aspects of the data engineering lifecycle.

In organizations that are in stage 2 of data maturity, a data engineer's goals are to do the following:

- Establish formal data practices
- Create scalable and robust data architectures
- Adopt DevOps and DataOps practices
- Build systems that support ML
- Continue to avoid undifferentiated heavy lifting and customize only when a competitive advantage results

We return to each of these goals later in the book.

Issues to watch out for include the following:

- As we grow more sophisticated with data, there's a temptation to adopt bleeding-edge technologies based on social proof from Silicon Valley companies. This is rarely a good use of your time and energy. Any technology decisions should be driven by the value they'll deliver to your customers.
- The main bottleneck for scaling is not cluster nodes, storage, or technology but the data engineering team. Focus on solutions that are simple to deploy and manage to expand your team's throughput.

- You'll be tempted to frame yourself as a technologist, a data genius who can deliver magical products. Shift your focus instead to pragmatic leadership and begin transitioning to the next maturity stage; communicate with other teams about the practical utility of data. Teach the organization how to consume and leverage data.

Stage 3: Leading with data

At this stage, the company is data-driven. The automated pipelines and systems created by data engineers allow people within the company to do self-service analytics and ML. Introducing new data sources is seamless, and tangible value is derived. Data engineers implement proper controls and practices to ensure that data is always available to the people and systems. Data engineering roles continue to specialize more deeply than in stage 2.

In organizations in stage 3 of data maturity, a data engineer will continue building on prior stages, plus they will do the following:

- Create automation for the seamless introduction and usage of new data
- Focus on building custom tools and systems that leverage data as a competitive advantage
- Focus on the "enterprisey" aspects of data, such as data management (including data governance and quality) and DataOps
- Deploy tools that expose and disseminate data throughout the organization, including data catalogs, data lineage tools, and metadata management systems
- Collaborate efficiently with software engineers, ML engineers, analysts, and others
- Create a community and environment where people can collaborate and speak openly, no matter their role or position

Issues to watch out for include the following:

- At this stage, complacency is a significant danger. Once organizations reach stage 3, they must constantly focus on maintenance and improvement or risk falling back to a lower stage.
- Technology distractions are a more significant danger here than in the other stages. There's a temptation to pursue expensive hobby projects that don't deliver value to the business. Utilize custom-built technology only where it provides a competitive advantage.

The Background and Skills of a Data Engineer

Data engineering is a fast-growing field, and a lot of questions remain about how to become a data engineer. Because data engineering is a relatively new discipline, little formal training is available to enter the field. Universities don't have a standard data engineering path. Although a handful of data engineering boot camps and online tutorials cover random topics, a common curriculum for the subject doesn't yet exist.

People entering data engineering arrive with varying backgrounds in education, career, and skill set. Everyone entering the field should expect to invest a significant amount of time in self-study. Reading this book is a good starting point; one of the primary goals of this book is to give you a foundation for the knowledge and skills we think are necessary to succeed as a data engineer.

If you're pivoting your career into data engineering, we've found that the transition is easiest when moving from an adjacent field, such as software engineering, ETL development, database administration, data science, or data analysis. These disciplines tend to be "data aware" and provide good context for data roles in an organization. They also equip folks with the relevant technical skills and context to solve data engineering problems.

Despite the lack of a formalized path, a requisite body of knowledge exists that we believe a data engineer should know to be successful. By definition, a data engineer must understand both data and technology. With respect to data, this entails knowing about various best practices around data management. On the technology end, a data engineer must be aware of

various options for tools, their interplay, and their trade-offs. This requires a good understanding of software engineering, DataOps, and data architecture.

Zooming out, a data engineer must also understand the requirements of data consumers (data analysts and data scientists) and the broader implications of data across the organization. Data engineering is a holistic practice; the best data engineers view their responsibilities through business and technical lenses.

Business Responsibilities

The macro responsibilities we list in this section aren't exclusive to data engineers, but are crucial for anyone working in a data or technology field. Because a simple Google search will yield tons of resources to learn about these areas, we will simply list them for brevity:

Know how to communicate with nontechnical and technical people.

> Communication is key, and you need to be able to establish rapport and trust with people across the organization. We suggest paying close attention to organizational hierarchies, who reports to whom, how people interact, and which silos exist. These observations will be invaluable to your success.

Understand how to scope and gather business and product requirements.

> You need to know what to build and ensure that your stakeholders agree with your assessment. In addition, develop a sense of how data and technology decisions impact the business.

Understand the cultural foundations of Agile, DevOps, and DataOps.

> Many technologists mistakenly believe these practices are solved through technology. We feel this is dangerously wrong. Agile, DevOps,

and DataOps are fundamentally cultural, requiring buy-in across the organization.

Control costs.

You'll be successful when you can keep costs low while providing outsized value. Know how to optimize for time to value, the total cost of ownership, and opportunity cost. Learn to monitor costs to avoid surprises.

Learn continuously.

The data field feels like it's changing at light speed. People who succeed in it are great at picking up new things while sharpening their fundamental knowledge. They're also good at filtering, determining which new developments are most relevant to their work, which are still immature, and which are just fads. Stay abreast of the field and learn how to learn.

A successful data engineer always zooms out to understand the big picture and how to achieve outsized value for the business. Communication is vital, both for technical and nontechnical people. We often see data teams succeed based on their communication with other stakeholders; success or failure is rarely a technology issue. Knowing how to navigate an organization, scope and gather requirements, control costs, and continuously learn will set you apart from the data engineers who rely solely on their technical abilities to carry their career.

Technical Responsibilities

You must understand how to build architectures that optimize performance and cost at a high level, using prepackaged or homegrown components.

Ultimately, architectures and constituent technologies are building blocks to serve the data engineering lifecycle. Recall the stages of the data engineering lifecycle:

- Generation
- Storage
- Ingestion
- Transformation
- Serving

The undercurrents of the data engineering lifecycle are the following:

- Security
- Data management
- DataOps
- Data architecture
- Software engineering

Zooming in a bit, we discuss some of the tactical data and technology skills you'll need as a data engineer in this section; we discuss these in more detail in subsequent chapters.

People often ask, should a data engineer know how to code? Short answer: yes. A data engineer should have production-grade software engineering chops. We note that the nature of software development projects undertaken by data engineers has changed fundamentally in the last few years. Fully managed services now replace a great deal of low-level programming effort previously expected of engineers, who now use managed open source, and simple plug-and-play software-as-a-service (SaaS) offerings. For example, data engineers now focus on high-level abstractions or writing pipelines as code within an orchestration framework.

Even in a more abstract world, software engineering best practices provide a competitive advantage, and data engineers who can dive into the deep architectural details of a codebase give their companies an edge when specific technical needs arise. In short, a data engineer who can't write production-grade code will be severely hindered, and we don't see this changing anytime soon. Data engineers remain software engineers, in addition to their many other roles.

What languages should a data engineer know? We divide data engineering programming languages into primary and secondary categories. At the time of this writing, the primary languages of data engineering are SQL, Python, a Java Virtual Machine (JVM) language (usually Java or Scala), and bash:

SQL

: The most common interface for databases and data lakes. After briefly being sidelined by the need to write custom MapReduce code for big data processing, SQL (in various forms) has reemerged as the lingua franca of data.

Python

: The bridge language between data engineering and data science. A growing number of data engineering tools are written in Python or have Python APIs. It's known as "the second-best language at everything." Python underlies popular data tools such as pandas, NumPy, Airflow, sci-kit learn, TensorFlow, PyTorch, and PySpark. Python is the glue between underlying components and is frequently a first-class API language for interfacing with a framework.

JVM languages such as Java and Scala

: Prevalent for Apache open source projects such as Spark, Hive, and Druid. The JVM is generally more performant than Python and may

provide access to lower-level features than a Python API (for example, this is the case for Apache Spark and Beam). Understanding Java or Scala will be beneficial if you're using a popular open source data framework.

bash

The command-line interface for Linux operating systems. Knowing bash commands and being comfortable using CLIs will significantly improve your productivity and workflow when you need to script or perform OS operations. Even today, data engineers frequently use command-line tools like awk or sed to process files in a data pipeline or call bash commands from orchestration frameworks. If you're using Windows, feel free to substitute PowerShell for bash.

THE UNREASONABLE EFFECTIVENESS OF SQL

The advent of MapReduce and the big data era relegated SQL to passé status. Since then, various developments have dramatically enhanced the utility of SQL in the data engineering lifecycle. Spark SQL, Google BigQuery, Snowflake, Hive, and many other data tools can process massive amounts of data by using declarative, set-theoretic SQL semantics. SQL is also supported by many streaming frameworks, such as Apache Flink, Beam, and Kafka. We believe that competent data engineers should be highly proficient in SQL.

Are we saying that SQL is a be-all and end-all language? Not at all. SQL is a powerful tool that can quickly solve complex analytics and data transformation problems. Given that time is a primary constraint for data engineering team throughput, engineers should embrace tools that combine simplicity and high productivity. Data engineers also do well to develop expertise in composing SQL with other operations, either within frameworks such as Spark and Flink or by using orchestration to combine multiple tools. Data engineers should also learn modern SQL semantics for dealing with JavaScript Object Notation (JSON) parsing and nested data and consider leveraging a SQL management framework such as dbt (Data Build Tool).

A proficient data engineer also recognizes when SQL is not the right tool for the job and can choose and code in a suitable alternative. A SQL expert could likely write a query to stem and tokenize raw text in a natural language processing (NLP) pipeline but would also recognize that coding in native Spark is a far superior alternative to this masochistic exercise.

Data engineers may also need to develop proficiency in secondary programming languages, including R, JavaScript, Go, Rust, C/C++, C#, and Julia. Developing in these languages is often necessary when popular across the company or used with domain-specific data tools. For instance, JavaScript has proven popular as a language for user-defined functions in

cloud data warehouses. At the same time, C# and PowerShell are essential in companies that leverage Azure and the Microsoft ecosystem.

KEEPING PACE IN A FAST-MOVING FIELD

Once a new technology rolls over you, if you're not part of the steamroller, you're part of the road.

—Stewart Brand

How do you keep your skills sharp in a rapidly changing field like data engineering? Should you focus on the latest tools or deep dive into fundamentals? Here's our advice: focus on the fundamentals to understand what's not going to change; pay attention to ongoing developments to know where the field is going. New paradigms and practices are introduced all the time, and it's incumbent on you to stay current. Strive to understand how new technologies will be helpful in the lifecycle.

The Continuum of Data Engineering Roles, from A to B

Although job descriptions paint a data engineer as a "unicorn" who must possess every data skill imaginable, data engineers don't all do the same type of work or have the same skill set. Data maturity is a helpful guide to understanding the types of data challenges a company will face as it grows its data capability. It's beneficial to look at some critical distinctions in the kinds of work data engineers do. Though these distinctions are simplistic, they clarify what data scientists and data engineers do and avoid lumping either role into the unicorn bucket.

In data science, there's the notion of type A and type B data scientists.[10] *Type A data scientists*—where *A* stands for *analysis*—focus on understanding and deriving insight from data. *Type B data scientists*—where *B* stands for *building*—share similar backgrounds as type A data scientists and possess strong programming skills. The type B data scientist builds systems that make data science work in production. Borrowing from

this data scientist continuum, we'll create a similar distinction for two types of data engineers:

Type A data engineers

> *A* stands for *abstraction*. In this case, the data engineer avoids undifferentiated heavy lifting, keeping data architecture as abstract and straightforward as possible and not reinventing the wheel. Type A data engineers manage the data engineering lifecycle mainly by using entirely off-the-shelf products, managed services, and tools. Type A data engineers work at companies across industries and at all levels of data maturity.

Type B data engineers

> *B* stands for *build*. Type B data engineers build data tools and systems that scale and leverage a company's core competency and competitive advantage. In the data maturity range, a type B data engineer is more commonly found at companies in stage 2 and 3 (scaling and leading with data), or when an initial data use case is so unique and mission-critical that custom data tools are required to get started.

Type A and type B data engineers may work in the same company and may even be the same person! More commonly, a type A data engineer is first hired to set the foundation, with type B data engineer skill sets either learned or hired as the need arises within a company.

Data Engineers Inside an Organization

Data engineers don't work in a vacuum. Depending on what they're working on, they will interact with technical and nontechnical people and

face different directions (internal and external). Let's explore what data engineers do inside an organization and with whom they interact.

Internal-Facing Versus External-Facing Data Engineers

A data engineer serves several end users and faces many internal and external directions (Figure 1-9). Since not all data engineering workloads and responsibilities are the same, it's essential to understand whom the data engineer serves. Depending on the end-use cases, a data engineer's primary responsibilities are external facing, internal facing, or a blend of the two.

Figure 1-9. The directions a data engineer faces

An *external-facing* data engineer typically aligns with the users of external-facing applications, such as social media apps, Internet of Things (IoT) devices, and ecommerce platforms. This data engineer architects, builds, and manages the systems that collect, store, and process transactional and event data from these applications. The systems built by these data engineers have a feedback loop from the application to the data pipeline, and then back to the application (Figure 1-10).

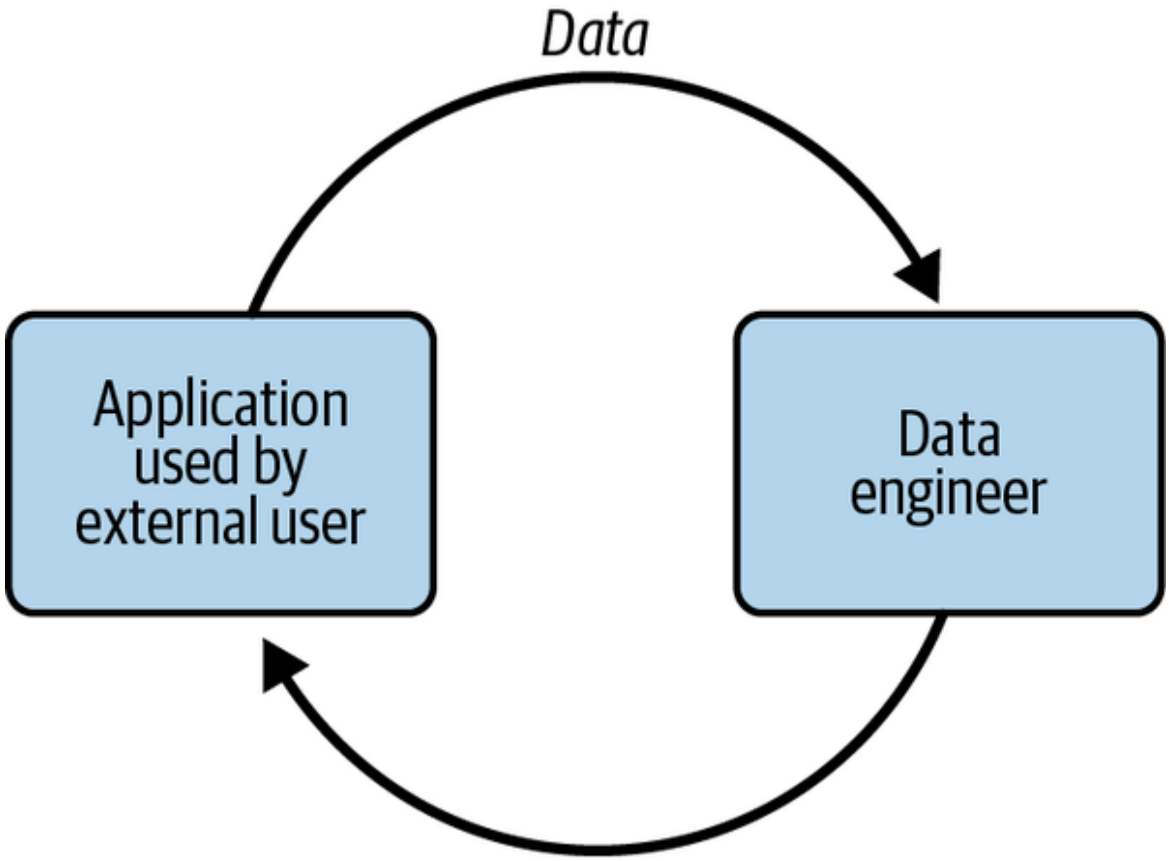

Figure 1-10. External-facing data engineer systems

External-facing data engineering comes with a unique set of problems. External-facing query engines often handle much larger concurrency loads than internal-facing systems. Engineers also need to consider putting tight limits on queries that users can run to limit the infrastructure impact of any single user. In addition, security is a much more complex and sensitive problem for external queries, especially if the data being queried is multitenant (data from many customers and housed in a single table).

An *internal-facing data engineer* typically focuses on activities crucial to the needs of the business and internal stakeholders (Figure 1-11). Examples include creating and maintaining data pipelines and data warehouses for BI dashboards, reports, business processes, data science, and ML models.

Figure 1-11. Internal-facing data engineer