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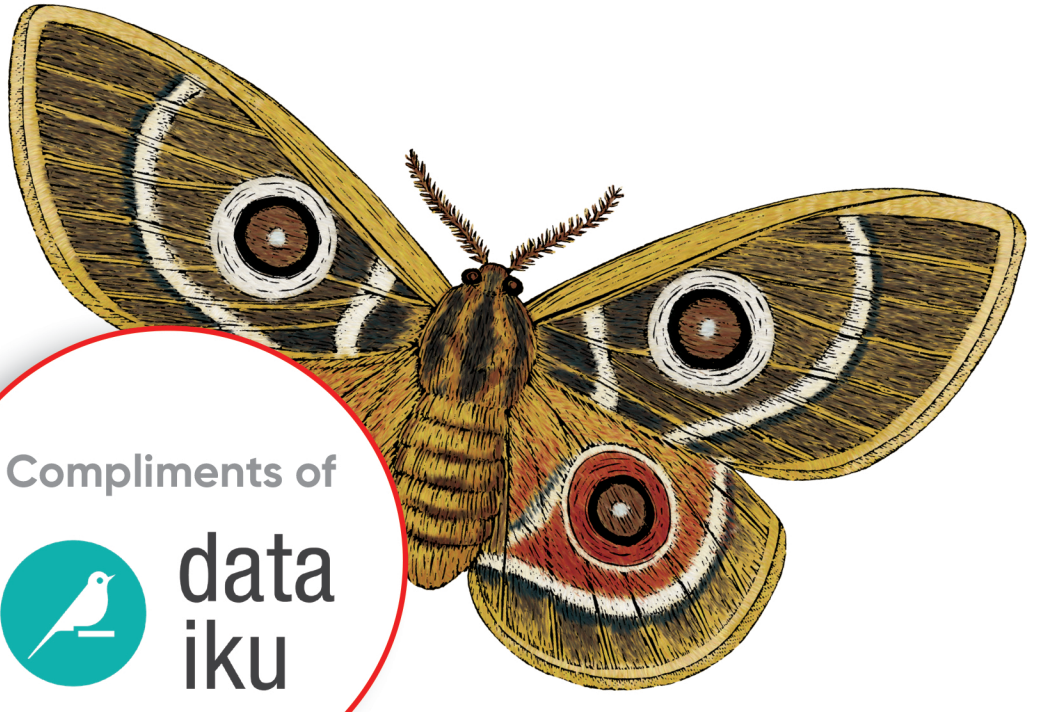
Introducing MLOps

How to Scale Machine Learning in the Enterprise



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Mark Treveil
& the Dataiku Team

Mastering MLops

with Dataiku

Dataiku is the only platform that provides one simple, consistent UI for data connection, wrangling, mining, visualization, machine learning, deployment, and model monitoring, all at enterprise scale.

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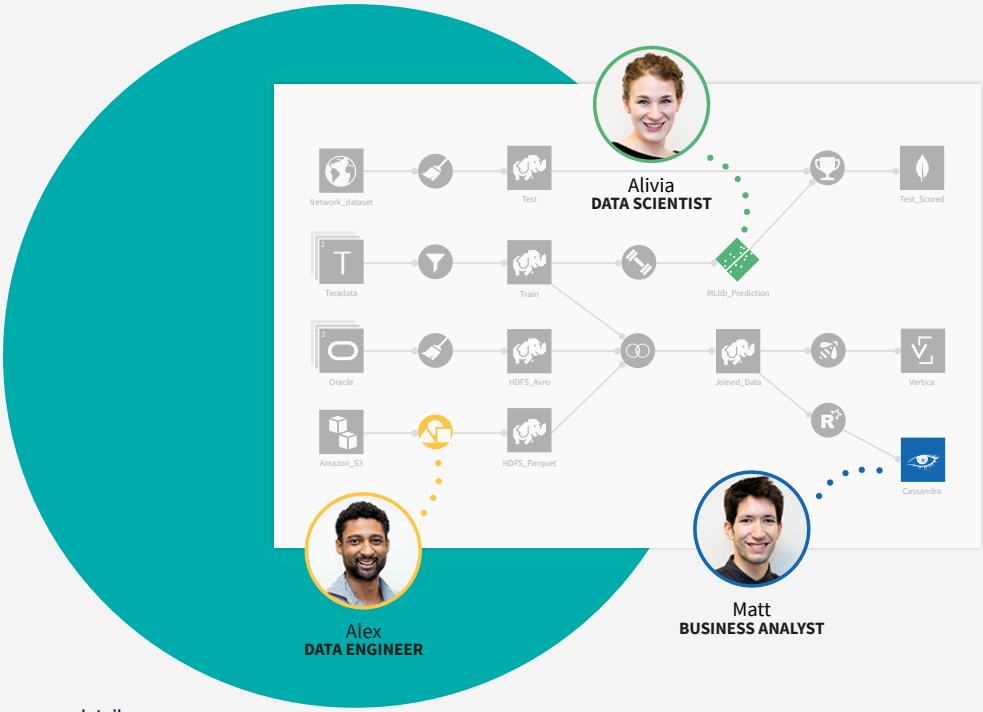

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Mark Treveil and the Dataiku Team

Beijing • Boston • Farnham • Sebastopol • Tokyo

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Table of Contents

Preface

We've reached a turning point in the story of machine learning where the technology has moved from the realm of theory and academics and into the "real world"—that is, businesses providing all kinds of services and products to people across the globe. While this shift is exciting, it's also challenging, as it combines the complexities of machine learning models with the complexities of the modern organization.

One difficulty, as organizations move from experimenting with machine learning to scaling it in production environments, is maintenance. How can companies go from managing just one model to managing tens, hundreds, or even thousands? This is not only where MLOps comes into play, but it's also where the aforementioned complexities, both on the technical and business sides, appear. This book will introduce readers to the challenges at hand, while also offering practical insights and solutions for developing MLOps capabilities.

Who This Book Is For

We wrote this book specifically for analytics and IT operations team managers, that is, the people directly facing the task of scaling machine learning (ML) in production. Given that MLOps is a new field, we developed this book as a guide for creating a successful MLOps environment, from the organizational to the technical challenges involved.

How This Book Is Organized

This book is divided into three parts. The first is an introduction to the topic of MLOps, diving into how (and why) it has developed as a discipline, who needs to be involved to execute MLOps successfully, and what components are required.

The second part roughly follows the machine learning model life cycle, with chapters on developing models, preparing for production, deploying to production, monitoring, and governance. These chapters cover not only general considerations, but

MLOps considerations at each stage of the life cycle, providing more detail on the topics touched on in Chapter 3.

The final part provides tangible examples of how MLOps looks in companies today, so that readers can understand the setup and implications in practice. Though the company names are fictitious, the stories are based on real-life companies' experience with MLOps and model management at scale.

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.

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Thanks to those who supported our vision from the beginning of writing this book with O'Reilly. Thanks to those who stepped in to help with writing and editing. Thanks to those who provided honest feedback (even when it meant more writing and rewriting and re-rewriting). Thanks to those who were internal cheerleaders and, of course, those who helped us promote the finished product to the world.

PART I

MLOps: What and Why

CHAPTER 1
Why Now and Challenges

Machine learning operations (MLOps) is quickly becoming a critical component of successful data science project deployment in the enterprise (Figure 1-1). It's a process that helps organizations and business leaders generate long-term value and reduce risk associated with data science, machine learning, and AI initiatives. Yet it's a relatively new concept; so why has it seemingly skyrocketed into the data science lexicon overnight? This introductory chapter delves into what MLOps is at a high level, its challenges, why it has become essential to a successful data science strategy in the enterprise, and, critically, why it is coming to the forefront now.

MLOps Versus ModelOps Versus AIOps

MLOps (or ModelOps) is a relatively new discipline, emerging under these names particularly in late 2018 and 2019. The two—MLOps and ModelOps—are, at the time this book is being written, largely being used interchangeably. However, some argue that ModelOps is more general than MLOps, as it's not only about machine learning models but any kind of model (e.g., rule-based models). For the purpose of this book, we'll be specifically discussing the machine learning model life cycle and will thus use the term "MLOps."

AIOps, though sometimes confused with MLOps, is another topic entirely and refers to the process of solving operational challenges through the use of artificial intelligence (i.e., AI for DevOps). An example would be a form of predictive maintenance for network failures, alerting DevOps teams to possible problems before they arise. While important and interesting in its own right, AIOps is outside the scope of this book.

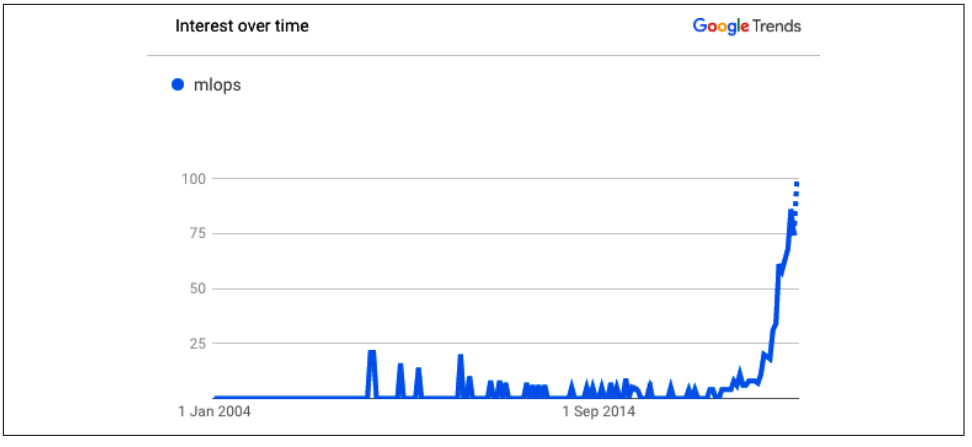

Figure 1-1. Representation of the exponential growth of MLOps (not the parallel growth of the term "ModelOps")

Defining MLOps and Its Challenges

At its core, MLOps is the standardization and streamlining of machine learning life cycle management (Figure 1-2). But taking a step back, why does the machine learning life cycle need to be streamlined? On the surface, just looking at the steps to go from business problem to a machine learning model at a very high level, it seems straightforward.

For most traditional organizations, the development of multiple machine learning models and their deployment in a production environment are relatively new. Until recently, the number of models may have been manageable at a small scale, or there was simply less interest in understanding these models and their dependencies at a company-wide level. With decision automation (that is, an increasing prevalence of decision making that happens without human intervention), models become more critical, and, in parallel, managing model risks becomes more important at the top level.

The reality of the machine learning life cycle in an enterprise setting is much more complex, in terms of needs and tooling (Figure 1-3).

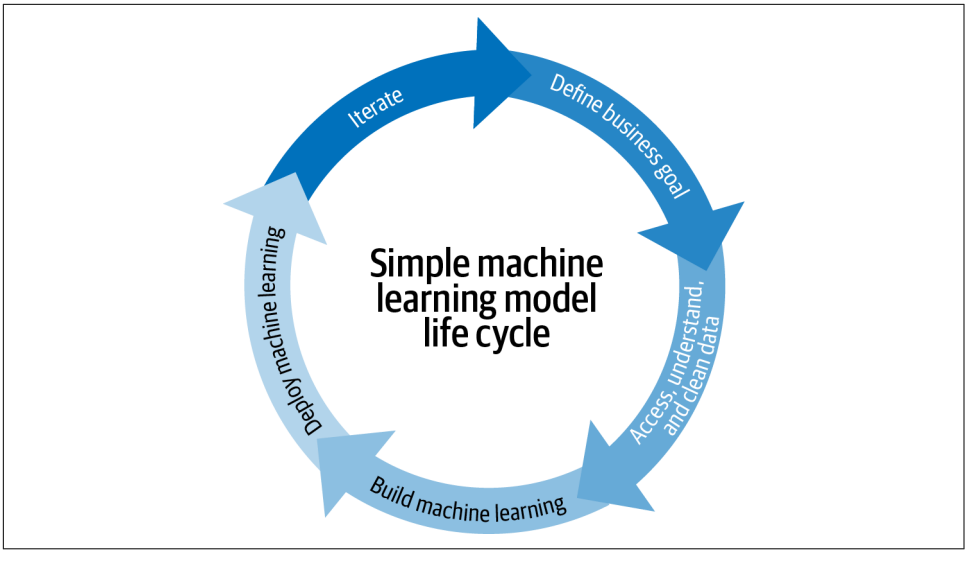

Figure 1-2. A simple representation of the machine learning model life cycle, which often underplays the need for MLOps, compared to Figure 1-3

There are three key reasons that managing machine learning life cycles at scale is challenging:

- There are many dependencies. Not only is data constantly changing, but business needs shift as well. Results need to be continually relayed back to the business to ensure that the reality of the model in production and on production data aligns with expectations and, critically, addresses the original problem or meets the original goal.
- Not everyone speaks the same language. Even though the machine learning life cycle involves people from the business, data science, and IT teams, none of these groups are using the same tools or even, in many cases, share the same fundamental skills to serve as a baseline of communication.
- Data scientists are not software engineers. Most are specialized in model building and assessment, and they are not necessarily experts in writing applications. Though this may start to shift over time as some data scientists become specialists more on the deployment or operational side, for now many data scientists find themselves having to juggle many roles, making it challenging to do any of them thoroughly. Data scientists being stretched too thin becomes especially problematic at scale with increasingly more models to manage. The complexity becomes exponential when considering the turnover of staff on data teams and, suddenly, data scientists have to manage models they did not create.

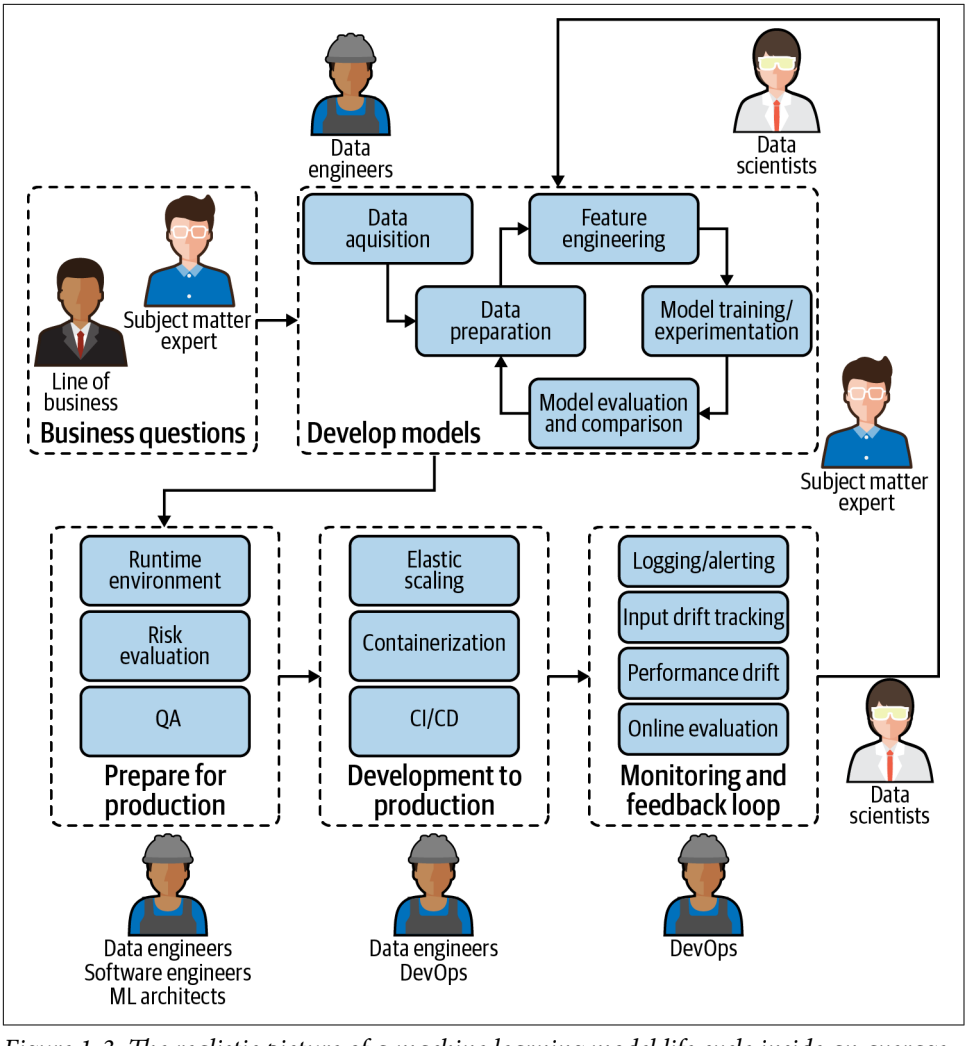

Figure 1-3. The realistic picture of a machine learning model life cycle inside an average organization today, which involves many different people with completely different skill sets and who are often using entirely different tools.

If the definition (or even the name MLOps) sounds familiar, that's because it pulls heavily from the concept of DevOps, which streamlines the practice of software changes and updates. Indeed, the two have quite a bit in common. For example, they both center around:

- Robust automation and trust between teams
- The idea of collaboration and increased communication between teams