MLOps: Five Steps to Guide its Effective Implementation

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ABSTRACT

DevOps practices have increasingly been applied to software development and engineering, as well as the machine learning lifecycle – in a process also known as MLOps. Today, many companies and professionals have been working and writing on this topic. However, in the academic and scientific literature, few results can be found on MLOps and how to implement it efficiently. This paper presents five essential steps to guide the understanding and practice of MLOps, which, based on the authors' research and experience, can assist in its effective implementation. The study aims to serve as a reference guide for all those who wish to learn more about the topic and intend to implement MLOps practices in the development of their systems.

CCS CONCEPTS

• **Software and its engineering** → **Software creation and management**; • **Computing methodologies** → *Machine learning*.

KEYWORDS

MLOps, DevOps, machine learning, model, development

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1 INTRODUCTION

DevOps practices have become increasingly popular in software development and engineering. Although there is no standard definition for the concept of DevOps, we can understand it as a culture of collaboration, which aims to automate the continuous delivery of software, reduce the gap between development and operations teams, and provide more speed, stability, and reliability to the software delivery process – consequently providing more value to end-users [3, 6].

When discussing the development of machine learning (ML) systems, we can also see the growing adoption of DevOps principles, in a practice known as MLOps [1]. Like DevOps, MLOps does not have a formal definition, but can be understood as "an intersection between ML and DevOps practices" [1], or "the standardization and streamlining of ML lifecycle management" [14]. The MLOps lifecycle comprises the **experimentation phase**, with data collection and extraction, and model preparation; the **development phase**, with model training and testing (along with CI/CD practices); and the **operations phase**, which encompasses the continuous delivery of artifacts in production, and monitoring [12, 14].

While MLOps is a topic on the rise [13], research in this area is still emerging since it is a recent concept [5]. In a systematic mapping study on the topic carried out by the authors in the last year [8], we found that even filtering from 2017, we could only find valid results for our search string/research questions from 2019 onwards. Studies mostly focus on specific features or applications of MLOps, rather than the general aspects that compose its lifecycle. The present study aims to bring a more comprehensive and holistic view of implementing MLOps, considering its model preparation, training, validation, deployment, and monitoring phases. We present five steps that we consider essential for those starting to work with MLOps and those who already have experience with machine learning but may be confused by this new concept. These steps reflect the academic and professional experience of the authors with machine learning, DevOps, and MLOps practices, as well as bibliographic research that indicated the need to generate a study with steps aimed at guiding how to implement MLOps, considering the phases of its lifecycle. The following sections outline the five steps we have listed as essential for an effective MLOps implementation.

2 CHANGE THE CULTURE

The first step towards adhering to MLOps practices is related to culture. Teams need to be open to learning and willing to change, which applies to MLOps, DevOps, and any other practice that disrupts the way systems and businesses are traditionally managed. It is also essential to have effective communication and a shared understanding of responsibilities – both by individuals and across entire teams. An ideal scenario would be to implement changes in existing teams without having to modify the entire organizational structure or its *modus operandi*. A good communication plan, top management sponsorship [14], and a clear vision of the business objectives would go a long way towards making the culture transformation process – albeit challenging – as smooth as possible.

3 PREPARE THE MODEL DEVELOPMENT

A critical phase of the MLOps lifecycle is preparing the model to be trained and released. A machine learning model is composed of training data, a performance metric, an ML algorithm, hyperparameters, and an evaluation dataset [14]. When considering each of these components, it is vital to examine the challenges that may arise before starting development – such as those related to the type of algorithm used, data dependencies [11], and continuous

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iteration processes [7]. Each model has characteristics that can affect the MLOps cycle differently. The best way to address these challenges is by analyzing the type of data used and understanding what best suits its purpose. This approach would help reduce dependencies and improve the entire model development process. Also, it is important to consider which tools will be used and have consistent version control, helping keep the model up-to-date, improving maintenance and traceability [14].

4 CHOOSE THE RIGHT TOOLS

A good choice of tools is essential to ensure that the ML model is developed correctly, in the best possible way. Considering that data is constantly changing and that we should avoid manual steps to prevent failures and achieve more productivity, it is crucial to examine some aspects before choosing the tools to be used in the model development process. These aspects are related to the objectives of the work – which can be, for example, maintainability, focus on implementing CI/CD pipelines, containerization, version control, or a robust end-to-end platform to meet all phases of the MLOps lifecycle. Understanding the needs well makes it possible for a practical choice of tools.

5 AUTOMATE THE PIPELINES

Another critical phase of MLOps is effectively getting the ML model running in production. To achieve this goal, the automation of ML pipelines becomes a necessary process, which can be achieved through the DevOps practices of continuous integration (CI) and continuous delivery/deployment (CD) [1, 9]. In MLOps, CI/CD practices are implemented with the aim that all pipelines work in an automated process so that they can be fully tested and validated [1]. From an experimental stage, pipelines are packaged and deployed, initially in a test environment. Being compatible and functional (going through other validation/homologation stages), they are ready to be deployed in production [1]. Such configuration promotes more agility and autonomy, allowing teams to focus on other tasks, such as developing and evaluating other models. It also facilitates the creation of other pipelines when needed, which will be continually created and improved.

6 CONTINUOUSLY MONITOR

Machine learning models and data are continually susceptible to changes, whether planned or unexpected – as in the case of *data drift* [4, 14], where changes in the model's input data lead to the degradation of its performance, causing the model to become stale. A good way to identify and minimize the negative impacts of model staleness is through continuous monitoring [10]. Creating metrics and tracking changes in data makes it possible to identify the root cause of deviation [2], as well as automate and retrain the model with new data, significantly contributing to improving the overall performance of the model in production.

7 CONCLUSIONS

Machine learning and MLOps are constantly evolving and becoming more present in different areas. It brings cultural challenges from the moment when many professionals must reinvent themselves, learn new things and restructure their teams and organizations to apply these new practices. With that comes the challenge of efficiently developing an ML model, considering the characteristics of the data, avoiding biases, training, evaluating, validating, retraining, then deploying and monitoring.

This work presented five steps to guide practitioners and researchers in comprehending and implementing MLOps, considering its entire lifecycle. We understand that no technical change can be made without a cultural shift, which is the recommended first step in this study. Then comes the preparation of the model, which must consider the characteristics of the data and algorithms used and the chosen tools according to the objectives. Automation of ML pipelines is also an essential step for the MLOps lifecycle to be in action, as is continuous monitoring, which allows tracking of ML model's performance, preventing and correcting failures. It is also important to consider the challenges inherent in automating ML pipelines related to their iterative nature and that they can take hours to complete, depending on the amount of data and work running. Aspects such as technical debt [11] and data drifting [4] can also occur, bringing more difficulties when compared to the implementation of standard software. In future studies, the steps presented here can also be deepened, helping to outline a complete structure of best practices to guide the adoption of MLOps.

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