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An Empirical Study of Challenges in Machine Learning Asset Management

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Abstract *Context:* In machine learning (ML) applications, assets include not only the ML models themselves, but also the datasets, algorithms, and deployment tools that are essential in the development, training, and implementation of these models. Efficient management of ML assets is critical to ensure optimal resource utilization, consistent model performance, and a streamlined ML development lifecycle. This practice contributes to faster iterations, adaptability, reduced time from model development to deployment, and the delivery of reliable and timely outputs. *Objective:* Despite research on ML asset management, there is still a significant knowledge gap on operational challenges, such as model versioning, data traceability, and collaboration issues, faced by asset management tool users. These challenges are crucial because they could directly impact the efficiency, reproducibility, and overall success of machine learning projects. Our study aims to bridge this empirical gap by analyzing user experience, feedback, and needs from Q&A posts, shedding light on the real-world challenges they face and the solutions they have found. *Methodology:* We examine $15,065$ Q&A posts from multiple developer discussion platforms, including Stack Overflow, tool-specific forums, and GitHub/GitLab. Using a mixed-method approach, we classify the posts into knowledge inquiries and problem inquiries. We then apply BERTopic to ex-

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tract challenge topics and compare their prevalence. Finally, we use the open card sorting approach to summarize solutions from solved inquiries, then cluster them with BERTopic, and analyze the relationship between challenges and solutions. *Results:* We identify 133 distinct topics in ML asset management-related inquiries, grouped into 16 macro-topics, with software environment and dependency, model deployment and service, and model creation and training emerging as the most discussed. Additionally, we identify 79 distinct solution topics, classified under 18 macro-topics, with software environment and dependency, feature and component development, and file and directory management as the most proposed. *Conclusion:* This study highlights critical areas within ML asset management that need further exploration, particularly around prevalent macro-topics identified as pain points for ML practitioners, emphasizing the need for collaborative efforts between academia, industry, and the broader research community.

Keywords Machine Learning · Asset Management · Mining Software Repositories · Stack Overflow · Topic Modeling

1 Introduction

From personalizing content recommendations on entertainment platforms [73] to enabling predictive diagnostics in healthcare [88], and optimizing traffic flow in urban planning [93], machine learning (ML) has transformed industries and our daily experiences. Despite these advances, the practical implementation of an ML-driven solution in a real-world scenario is fraught with challenges arising from the complexities of dynamic environments, such as changing data distributions, evolving requirements, and the need to constantly update and optimize models to maintain performance and accuracy.

To help address these challenges, an intricate, yet essential task is asset management in ML-driven solutions. Asset management encompasses organizing, tracking, evaluating, and monitoring ML assets such as code, models, data sets, and other artifacts, which are crucial to the effective implementation of ML-driven solutions [60]. Although traditional software management tools, such as Git, are designed to handle software assets such as source code and documentat ion, these tools lack native capabilities to effectively track ML-specific assets, such as model architectures, hyperparameters, and data splits [113]. Therefore, it is imperative to have modern tools specifically designed to manage ML assets throughout the development lifecycle of ML-driven solutions.

In recent years, there has been a significant increase in the development of ML asset management tools. This growth can be attributed to joint efforts from academia and industry. In academia, tools such as CANDLE [134], DLHub [32], MLflow [141], ModelDB [128], Pdmdims [101], and Runway [126] have emerged as prototypes for the management of machine learning experiments. Meanwhile, the industry has introduced tools such as Aim[1], ClearML[2], DVC[3], Kedro[4], and

[1] `https://aimstack.io`
[2] `https://clear.ml`
[3] `https://dvc.org`
[4] `https://kedro.org`

Polyaxon[5], among others. These innovative tools address and mitigate many of the challenges previously associated with traditional software management tools [60].

However, several factors compromise the efficiency of ML asset management tools, leading to a myriad of challenges. For example, Kumar et al. [72] offer an in-depth analysis of the challenges associated with data management in ML workloads. They further explore the primary techniques and systems formulated to address these challenges. Schlegel et al. [112] emphasize the complexities of ensuring the comparability, traceability, and reproducibility of ML artifacts. Idowu et al. [60] further stress that these challenges stem from the absence of tool interoperability and standardized management practices in asset management. While there is some preliminary research in this domain, the literature lacks comprehensive analysis across tools, examination of user challenges, and evaluation of the solutions to these challenges. This underscores the critical need for more extensive empirical studies to gain a holistic understanding from the tool users' perspective, with a focus on cross-tool analysis and solution evaluation.

In this paper, we conduct a comprehensive study of developer discussion forums to identify the main challenges in ML asset management faced by ML practitioners and the strategies they adopt to address these challenges. We start by searching through multiple channels for tools that manage ML assets, then collect Q&A posts about these tools from different developer discussion forums. This includes popular sites, such as Stack Overflow and GitHub, as well as forums set up by tool developers themselves (i.e.,tool-specific forums). Based on the purpose of the inquiries, we sort these Q&A posts into knowledge or problem types. Next, we use a topic modeling technique called BERTopic[6] to extract the common topics in these inquiries. Then we manually group them into macro-topics, which are broad categories encompassing multiple related topics. We study the prevalence of these macro-topics to gain insights into the common challenges faced by ML practitioners. For inquiries marked as solved, we summarize the solutions provided in the content of the posts. We also use BERTopic to cluster these summaries to understand the patterns in the solutions. This analysis helps us to map the strategies that ML practitioners use to tackle the challenges in ML asset management. To our knowledge, this is the first study to use mixed methods to systematically explore user challenges in adopting ML asset management tools.

Our main findings and their implications include the following.

- We identify 133 distinctive challenge topics in ML asset management, which we subsequently group into 16 macro-topics, i.e.,high-level groupings of multiple interconnected topics with similar concerns. The most frequently discussed macro-topics are software environment and dependency (18.89%), model deployment and serving (10.59%), and model creation and training (9%). The high prevalence indicates that these areas are of significant interest and concern for ML practitioners. Also, 55% of the tools predominantly receive inquiries about the software environment and dependency topics. Furthermore, we observe different prevalent topics in each tool of the asset management ecosystem.
- We identify 79 different solution topics in ML asset management, which we subsequently group into 18 macro-topics. Among these, the most commonly

[5] `https://polyaxon.com`

[6] `https://github.com/MaartenGr/BERTopic`

proposed solutions are related to the software environment and dependencies (23.31%), the development of features and components (15.35%), and the file and directory (9.64%). For knowledge inquiries, feature and component development methods are mainly used to solve challenges in source code management. Similarly, issues in experiment management are primarily solved using software environment and dependency-related solutions. On the other hand, for problem inquiries, a significant portion (62.5%) of problems are resolved using software environment and dependency-related solutions. Additionally, feature and component development solutions are often applied to address challenges related to logging and monitoring. Moreover, problem inquiries tend to be solved more effectively using skills or knowledge from different domains, as opposed to knowledge inquiries. This observation highlights the necessity to employ varied approaches when addressing knowledge inquiries compared to problem ones.

- We find that Stack Overflow is the primary forum for practitioners seeking help with asset management, accounting for 48.82% of all such inquiries. Tool-specific forums are next, contributing 34.19%, while repository-specific forums have the fewest, at only 17.16%. Of the tools examined, 25% witness most user inquiries on tool-specific forums, 20% on repository-specific forums, and 35% on Stack Overflow. This trend implies a potential area of exploration for tool maintainers to enhance user engagement on their respective forums. Additionally, inquiries related to software environment and dependency are the most prevalent in both Stack Overflow, GitHub, and tool-specific forums. This suggests that regardless of where practitioners seek help, managing software environments and dependencies remains a top challenge in ML asset management. Furthermore, the frequency distribution of Q&A posts varies significantly between different discussion forums. Developers can leverage these insights to customize content and discussions to align with the distinct characteristics and preferences of the audience in each forum.

2 Background and Related Work

In this section, we provide a comprehensive overview of the role and challenges of asset management in the ML development lifecycle.

2.1 Machine learning development lifecycle

The ML development lifecycle, as shown in Figure 1, is a comprehensive process that encapsulates various stages, each integral to the development and deployment of ML-driven solutions. This lifecycle, as described by Amershi et al. [18], is not a strictly linear progression, but rather a dynamic flow with potential feedback loops. Each stage may require iterative refinement if certain criteria are not met, necessitating a review of previous stages.

- *Problem Understanding* stage is about understanding the problem at hand. It involves identifying potential features, understanding their significance in the context of existing or upcoming ML-driven solutions, and selecting an appropriate model architecture tailored to the problem.

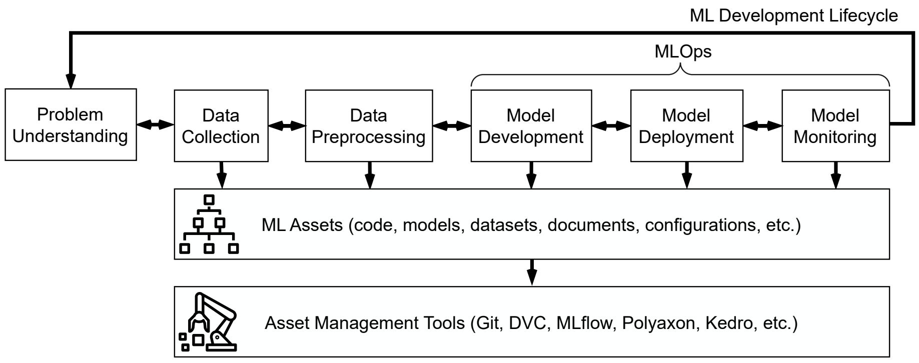


Fig. 1 Machine learning development lifecyle and asset management.

- *Data Collection* stage involves sourcing, integrating, and augmenting datasets, often using generic data for initial model training and specialized data for transfer learning.
- *Data Preprocessing* stage involves cleaning, labeling, and transforming the datasets. It also emphasizes the extraction and selection of the most informative features that serve as input to the ML models.
- *Model Development* stage involves training, evaluating, and testing models on selected features. The performance of these models is typically measured using predefined metrics in validation and test datasets.
- *Model Deployment* stage involves integrating the trained model into real-world applications, allowing it to make inferences based on new data.
- *Model Monitoring* stage is about tracking how the ML model performs over time. If any degradations in performance is observed, the current model might be re-trained with newly collected data.

2.2 Machine learning asset management

In the context of this lifecycle, ML assets emerge as the foundational elements employed throughout each stage. These assets, which encompass datasets, models, hyperparameters, configurations, and more, are significant in ensuring the success of ML operations (MLOps). This pivotal role necessitates the adoption of specialized machine learning asset management tools, such as MLflow. Whether accessed through intuitive web dashboards or command-line interfaces, these tools support the automation of operational tasks such as tracking, exploring, retrieving, collaborating on, archiving, and discarding ML assets [60].

However, managing these assets is fraught with a series of challenges. Schelter et al. [109] categorize the challenges of managing ML models into three core categories: conceptual, data management, and engineering. They highlight issues such as model definition, multiple input handling, metric selection, data quality, and system compatibility in programming languages and hardware. Furthermore, Polyzotis et al. [102] identify three main areas of focus in data lifecycle management for machine learning: understanding, validation/cleaning, and preparation. Some of the most important challenges include dealing with missing or inconsistent data, managing data from heterogeneous sources, ensuring data privacy and security, and keeping up with the latest developments in the ML community. Further expanding on this, Munappy et al. [91] identify 20 data management challenges encountered by deep learning practitioners, categorizing them into four groups based on the presence of solutions. These challenges cover issues ranging from data search, quality, and privacy to data versioning, labeling, and scalability.

In response to these intricate challenges, both research communities and companies have introduced specialized tools for asset management. Academically, tools such as ModelHub [86], DLHub [32], and Pdmdims [101] have been introduced for model management. For experiment management, prototypes include Codalab [99], MLflow [141], Runway [126], and ModelDB [128]. Furthermore, for comprehensive lifecycle management, solutions such as CANDLE [134], Ease.ML [15], VeML [74], Scanflow [30], TITAN [25], Stratum [27], ProvDB [85], and ModelOps [59] have been proposed. In the industrial domain, commercial tools such as Aim[7], ClearML[8], cnvrg.io[9], Comet[10], Domino[11], DVC[12], Kedro[13], Polyaxon[14], and Weights&Biases[15] have been developed to address these challenges.

Despite these advances in tool support, managing ML assets using these tools still faces important challenges. Kumar et al. [72] provide a comprehensive review of the data management-related challenges that arise in ML workloads and analyze the key techniques and systems that have been developed to address these challenges. Moreover, Schlegel et al. [112] highlight the difficulties in ensuring the comparability, traceability, and reproducibility of artifacts, such as models, data, logs, and metadata, throughout the ML development lifecycle, even with specialized tools. Furthermore, Melin [83] underscores the need for end-to-end versioning in the ML development lifecycle, highlights the complexities of lineage tracing due to framework integration issues, and advocates for clear guidelines in managing ML artifacts. In addition, Idowu et al. [60] highlight challenges such as limited interoperability between tools, tight library coupling, and the overhead of the necessary code instrumentation. They also point out the absence of standardized management methods for ML assets, forcing users into ad hoc solutions that hinder efficient model development.

Compared to previous studies, our research explores the experience and feedback of tool users related to machine learning asset management, shedding light on the unexplored challenges and their practical solutions.

3 Methodology

In this section, we first outline our research goals and questions, followed by a detailed explanation of our study design.

[7] `https://aimstack.io`
[8] `https://clear.ml`
[9] `https://cnvrg.io`
[10] `https://comet.com`
[11] `https://domino.ai`
[12] `https://dvc.org`
[13] `https://kedro.org`
[14] `https://polyaxon.com`
[15] `https://wandb.ai`

3.1 Goal and Research Questions

Our study aims to investigate the challenges associated with the management of ML assets. We aim to understand their prevalence and proposed solutions across developer discussion forums. Our research is specifically targeted at a diverse group of stakeholders, including data scientists, ML engineers, infrastructure architects, and other roles in the ML development lifecycle, such as operations managers. Collectively, we describe this group as “ML practitioners”. The rationale behind focusing on these professionals is rooted in their profound engagement and proficiency in the ML development lifecycle. By understanding their perspectives and experiences, our research seeks to illuminate the pathways for more efficient and streamlined management of ML assets.

To achieve our stated goal, we investigate three research questions.

- **RQ$_1$:** *What topics are most frequently discussed related to machine learning asset management?* In RQ1, we identify common (macro-)topics in Q&A posts on ML asset management. We then analyze and compare the frequency of different types of inquiry and macro-topics to determine the most common ones. Our goal is to gain a clear understanding of the key challenges that ML practitioners face in asset management.
- **RQ$_2$**: *What topics of solutions exist for the challenges related to machine learning asset management?* In RQ2, we identify common (macro-)topics found in solutions that address the challenges of ML asset management. We explore the interconnections between challenges and their solutions to uncover discernible trends or correlations in different domains. Our goal is to construct a comprehensive guide for ML practitioners, helping them navigate and overcome these challenges effectively by aligning them with proven solutions.
- **RQ$_3$:** *What are the commonalities and differences between developer forums in their discussion related to machine learning asset management?* In RQ3, we investigate what is consistent and what varies between the different forums in terms of asset management discussion. Our goal is to uncover the unique strengths and patterns of each forum, helping ML practitioners navigate and utilize these forums effectively for their specific needs and interests.

3.2 Study Design

We present the workflow of our study in Figure 2. Our study begins with the collection of Q&A posts from developer discussion forums. Once collected, we classify these posts into two types: problem and knowledge. Following this classification, we preprocess the posts and employ the BERTopic technique to extract their topics. We then manually group them into broader categories, termed “macro-topics”. Furthermore, we evaluate and compare the frequency of these macro-topics based on the type of inquiry and the specific discussion forums from which they are sourced. This evaluation helps to address our research questions, specifically RQ1 and RQ3. To wrap up our study, we manually label the solutions found in the posts and extract the topics associated with these solutions. This step sets the stage for the macro-topic mapping between challenges and solutions in RQ2.

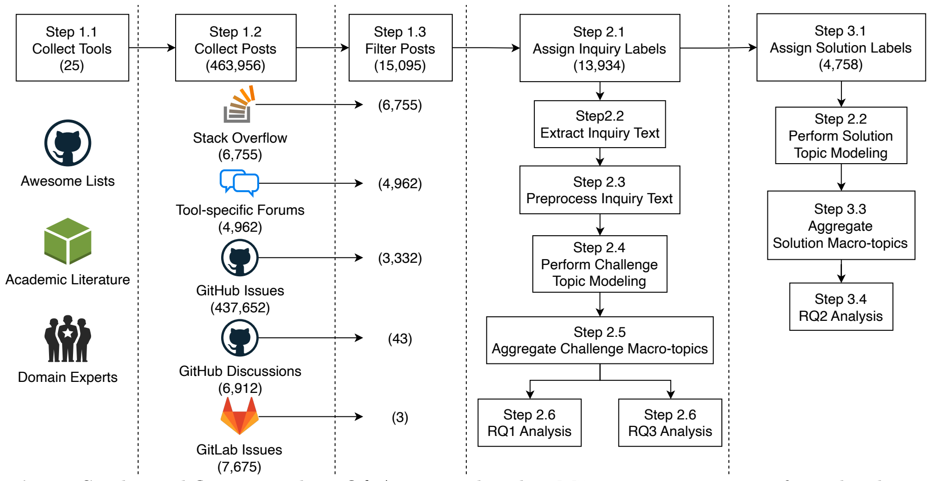


Fig. 2 Study workflow to analyze Q&A posts related to ML asset management from developer discussion forums.

3.2.1 Phase 1: Data collection

In this phase, our goal is to collect Q&A posts related to ML asset management from multiple developer discussion forums. To achieve this, we first start a multivocal literature review, aiming to compile an exhaustive list of tools that are specifically designed to manage ML assets. From this compilation, we derive a curated set of tool-specific keywords. Using these identified keywords, we then extract relevant Q&A posts from multiple developer discussion forums.

Step 1.1: Collect ML asset management-related tools.

We begin by reviewing a range of literature, focusing on references to ML asset management tools. We formulate our initial search queries by refining the strategies used for literature retrieval, as introduced in the foundational work on asset management by Idowu et al. [60]. To expand our search, we include terms such as "MLOps tools" and "machine learning experiment management tools", among others related to asset management. Using these terms, we search Github Awesome Lists[16] and Google Scholar[17] to find relevant literature, with the filtered results listed in Table 9 (Appendix B). We follow a progressive stop method: If we do not find any relevant articles on three consecutive search pages, we conclude our search. Note that we ignore the literature that is similar to any work identified in the previous search. Furthermore, we employ a backward snowballing process [64] to examine the references cited in the literature we review, identifying additional relevant works. This approach ensures that we consider all pertinent information and insights available in the existing body of knowledge.

Then we apply the following exclusion criteria to the tools that are referenced in the collected literature.

- The tool is either restricted for in-house use, such as FBLearner Flow[18], or no longer available, such as Dot Science[19].

[16] `https://github.com/topics/awesome`
[17] `https://scholar.google.com`
[18] `https://venturebeat.com/dev/facebook-details-its-company-wide-machine-learning-platform-fblearner-flow`
[19] `https://www.datanami.com/this-just-in/dotscience-is-shutting-down`

- The tool is hosted in an open-source repository, but it has earned less than 100 stars. Although the number of stars in a repository may not be the only indicator of its quality or utility, it is often seen as a measure of trust and usage in the community [29].
- The tool appears to be poorly maintained or not adequately documented. For example, its open-source repository has not received updates for more than a year. This metric has been used in the previous literature as an indicator to identify dormant open-source projects [37, 63, 68, 84].
- The tool is specifically designed for a particular type of ML asset, such as a dataset or model, such as Dolt[20].
- The tool is a multipurpose asset management tool that is not specifically tailored for ML applications, such as Pachyderm[21].
- The tool is in the research phase and has not yet been discussed in any developer forum or used in open-source repositories, such as VeML [74].

We review more than 500 tools and narrow them down to 25 tools after applying the above exclusion criteria. We present the status (open source or proprietary), launch date, and website address of each tool in Table 10 (Appendix B). In this table, the status indicates whether they are open-source or proprietary tools; the launch date indicates the date when the tool is accessible to the public; and the website shows the links to these tools. We find that 52% of the tools (13 of 25) feature open source repositories, indicating a significant presence of open source options for machine learning asset management.

Step 1.2: Scrape the tool-related posts from the developer discussion forums

Having the list of tools, we scrape Q&A posts from various discussion forums that mention the names of tools. Our focus is on forums predominantly used by developers, specifically those that cater to ML practitioners. In our study, we have chosen to analyze posts from three distinct types of forum: general forums including Stack Overflow, tool-specific forums (officially hosted by the tool providers for discussions related to their tools), such as the MLflow Google Group, and repository-specific forums (dedicated to discussions around specific repositories), such as GitHub Issues. In the following sections, we detail our methodology for collecting posts from each of these forums.

General forums

For general developer discussion forums, we exclusively concentrate on Stack Overflow. Stack Overflow[22] is a renowned platform where people, ranging from beginners to experienced professionals, engage in asking and answering questions about programming and software development. Building on this premise, it is worth noting that, instead of explicitly discussing ML asset management concepts, ML practitioners often allude to these concepts by referencing ML asset management tools in their posts. This can be either through direct mentions of the tool's name or, more commonly, via tags. Specifically, tags play a pivotal role in providing context to discussions about ML asset management tools.

Given their significance, we prioritize tags as our primary filtering criterion for the tools under investigation. Thus, we employ an iterative and heuristic process to

[20] `https://github.com/dolthub/dolt`
[21] `https://github.com/pachyderm/pachyderm`
[22] `https://stackoverflow.com`

curate a relevant set of tags. For example, entering the keyword "[*sagemaker*]" into the Stack Overflow search bar retrieves several tags in the search results, such as `amazon-sagemaker`, `amazon-sagemaker-studio`, and `amazon-sagemaker-neo`, among others. In particular, some retrieved tags may not be directly related to asset management. Therefore, we meticulously review each tag in conjunction with its associated discussions to determine its relevance. Based on this evaluation, we compile a comprehensive list of tags that accurately represent the tools under study, as illustrated in Table 11 (Appendix B). Using these tags, we formulate an SQL query, detailed in our replication package, to extract data from the Stack Exchange Data Explorer[23]. This query enables us to download $6,755$ unique Stack Overflow posts (up to $26^{th} of July, 2023$), ensuring a comprehensive and relevant dataset for our analysis.

Tool-specific forums

In addition to general developer discussion forums, we check the official website of each curated tool for information about any public discussion forum hosted by the tool developers. We provide the website addresses of the tool-specific discussion forums in Table 12 (Appendix B). It is important to note that we have chosen to exclude official chat platforms such as Discord and Slack. This decision is based on the fact that chat data is typically held privately by tool organizations, and their policies prevent us from collecting this data for any public use. Since our primary focus is on Q&A posts in these discussion forums, we have opted to exclude content, such as event announcements[24], which do not align with the objectives of our study. On the other hand, forums such as the MLflow Google Group do not differentiate between Q&A posts and other types of content, such as product announcements. In these scenarios, we employ a manual filtering mechanism during our closed card sorting process, which is elaborated on in Step 2.1. Following this methodology, we have identified $4,962$ unique posts on tool-specific forums (up to $26^{th} July, 2023$).

Repository-specific forums

For repository-specific forums, we consider code collaboration platforms, such as GitHub[25], GitLab[26] and Bitbucket[27]. These platforms offer developers the opportunity to raise inquiries through repository issue channels. Although the discussion within these channels is tailored toward specific projects, they frequently underscore recurring challenges and community-proposed solutions related to ML asset management. Furthermore, GitHub provides an optional feature called "GitHub Discussions" for repositories, specifically catering to broader communication needs, such as Q&A sessions[28]. We leverage these channels to extract insights relevant to our study.

First, we collect all repositories that have a dependency on the curated tools in their codebase. We observe that certain tools, such as DVC, possess GitHub dependency graphs. These graphs are essentially manifests detailing the ecosystems and packages upon which the tool relies. For such tools, we extract the necessary

[23] `https://data.stackexchange.com`
[24] `https://discuss.dvc.org/c/blog-discussions/5`
[25] `https://github.com/features/issues`
[26] `https://docs.gitlab.com/ee/user/project/issues`
[27] `https://support.atlassian.com/bitbucket-cloud/docs/understand-bitbucket-issues`
[28] `https://github.com/features/discussions`

information from dependency repositories using an open source scraping tool[29]. For tools that lack dependency graphs, we rely on "usage patterns" to identify their presence in the repository codebase. A usage pattern is defined as a regular expression that represents a specific code snippet that indicates the use of a curated tool, such as importing a specific library. Our curated usage patterns are found in Table 13 (Appendix B). We derive these patterns by thoroughly examining the official documentation of each curated tool.

Then we resort to Sourcegraph to collect repository information that matches the usage pattern. Sourcegraph[30] is a code search and navigation tool, facilitating developers to search, navigate, and understand their codebases on major code collaboration platforms such as GitHub, GitLab, and BitBucket. From this search, we have identified 37,782 repositories on GitHub and 10 on GitLab. Subsequently, we extracted issue posts from these repositories using the respective platform APIs. During this process, we have encountered some inaccessible repositories that return HTTP error status codes. These errors signify either a policy violation, as indicated by a 451 error, or the nonexistence of the repository, represented by a 404 error. Of the repositories that we can access, we download 437,652 unique issues from GitHub and 7,675 from GitLab (up to $26^{th} of July, 2023$).

To collect posts from the GitHub Discussions, we reuse the GitHub repositories during the aforementioned repository collection. We then narrow our focus to the "Q&A" channels within each discussion forum, such as the one in Apache Airflow[31], since only these channels contain Q&A posts, distinguishing them from feature requests or polls. As a result, our dataset ends up with 6,912 unique GitHub Discussions posts in repository-specific forums.

Step 1.3: *Filter posts that are irrelevant to our study*

In this section, we filter out posts that are not relevant to our research objectives. For posts originating from Stack Overflow and tool-specific forums, we would manually filter them during closed card sorting detailed in Step 2.1.

For GitHub Discussions posts, we systematically curate a list of keywords pertinent to the tools being examined. First, we extract tool-specific keywords from the discussions heuristically. Subsequently, we assess the relevance of these keywords by searching for them within the posts to determine their effectiveness in identifying discussions pertinent to each tool. For example, our analysis of discussions related to Azure Machine Learning revealed that practitioners frequently use terms, such as "aml", "azure machine learning", "azure ml", "azure-ml", and "azureml". Table 14 (Appendix B) provides a comprehensive list of keywords identified for each tool evaluated. We then use these keywords to filter and retain tool-relevant posts, selecting any post whose title contained at least one of these keywords. Using this methodology, we identify 43 relevant posts for further analysis from a total of 6,912.

When analyzing issues on GitHub or GitLab, our initial step involves scrutinizing the 644 unique labels of all collected repositories. From our examination, we find that only four keywords – "bug", "crash", "error" and "invalid" – indicate a user inquiry-related issue. As a result, we exclude issues that do not contain these keywords in their labels, while keeping those with empty labels for additional re-

[29] `https://pypi.org/project/github-dependents-info`
[30] `https://sourcegraph.com`
[31] `https://github.com/apache/airflow/discussions/categories/q-a`

view. Next, we further narrow our selection to issues whose titles contain any of the keywords outlined in Table 14 (Appendix B). After applying these filters, we are left with $3,332$ issues from the initial $437,652$ on GitHub and 3 issues from the $7,675$ on GitLab. Following this, we select a random sample of 385 posts from the refined post collection to achieve a confidence level of 95% with a margin of error of 5%. Upon reviewing the content of these posts, we confirm that they are indeed discussing the specified tools, which validates our choice of keywords.

3.2.2 Phase 2: Inquiry categorization

In this phase, our goal is two-fold in terms of inquiry categorization. First, we analyze the types of inquiry to understand their inherent characteristics. Second, we identify the common topics that emerge from these inquiries. To achieve this, we begin with closed card sorting [133] to categorize the types of inquiry from the collected posts. After categorizing, we preprocess the content of these posts and employ an appropriate topic modeling method. We then fine-tune the models to determine the optimal hyperparameters. Once the topics are identified, we manually group them into macro-topics. To address RQ1, we have evaluated the prevalence of each (macro-)topic, along with the type of inquiry. For RQ3, we similarly analyze prevalence patterns across discussion forums, drawing parallels with the methods used for RQ1.

Step 2.1: *Closed card sorting on inquiries*

In the Q&A context, inquiries primarily fall into two categories based on user intent: “knowledge inquiry” and “problem inquiry”, as illustrated in Figures 3 and Figure 4, respectively. Knowledge inquiry aims to understand concepts such as tool usage, technology comparison, and best practices, while problem inquiry aims to address specific issues such as bugs, errors, and performance degradation. This classification consolidates previous categorizations of “conceptual”, “knowledge-based”, and “howto” inquiries, as proposed by Chen et al. [34] and Treude et al. [125], under the umbrella of knowledge inquiries. For instance, a question such as “What is the correct way to fine-tune a model?” is labeled as a “conceptual” inquiry by Treude et al. [125], whereas “How to fine-tune a model” is considered a “howto” inquiry by Chen et al. [34]. Given the minor difference in verbal semantics, distinguishing between them in our research proves challenging and leads us to combine them into the knowledge inquiry category for clarity. This grouping reduces ambiguity among these types of inquiry, offering a clearer understanding of the common types of inquiry in discussion forums.

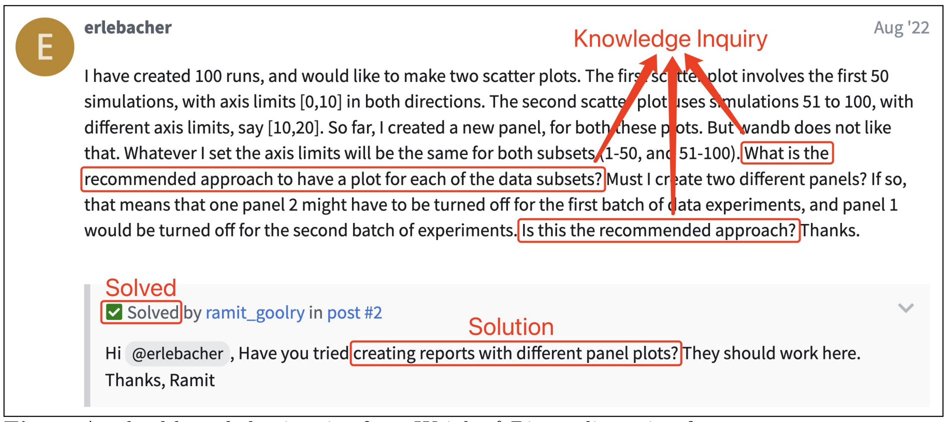
In addition to the problem and knowledge inquiries, posts that are non-inquiries[32], are mistagged[33], or are irrelevant[34] are labeled as “not applicable” (NA). Examples of non-inquiry posts encompass feature requests, event announcements, and user feedback surveys, to name a few.

The first and second authors opt to perform closed card sorting collaboratively, focusing on the three aforementioned types of inquiry. Closed card sorting is a method in which participants sort items into pre-defined categories on the collected posts [133]. From the total of $15,095$ posts, we randomly select 385, providing a

[32] `https://github.com/awslabs/amazon-neptune-tools/issues/38`

[33] `https://stackoverflow.com/questions/63844663`

[34] `https://www.googlecloudcommunity.com/gc/AI-ML/What-you-think-about-CHATGPT/m-p/506958`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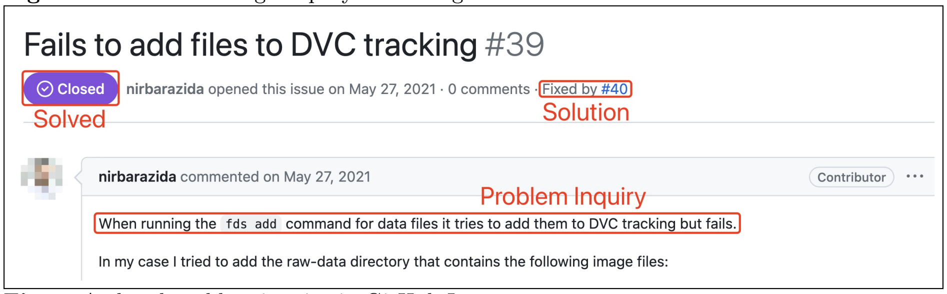
erlebacher
Aug '22
I have created 100 runs, and would like to make two scatter plots. The first scatter plot involves the first 50 simulations, with axis limits [0,10] in both directions. The second scatter plot uses simulations 51 to 100, with different axis limits, say [10,20]. So far, I created a new panel, for both these plots. But wandb does not like that. Whatever I set the axis limits will be the same for both subsets (1-50, and 51-100). What is the recommended approach to have a plot for each of the data subsets? Must I create two different panels? If so, that means that one panel 2 might have to be turned off for the first batch of data experiments, and panel 1 would be turned off for the second batch of experiments. Is this the recommended approach? Thanks.

Solved by ramit_goolry in post #2
Hi @erlebacher , Have you tried creating reports with different panel plots? They should work here.
Thanks, Ramit

Fig. 3 A solved knowledge inquiry from Weights&Biases discussion forum.


Fails to add files to DVC tracking #39
Closed nirbarazida opened this issue on May 27, 2021 · 0 comments · Fixed by #40

nirbarazida commented on May 27, 2021 Contributor
When running the `fds add` command for data files it tries to add them to DVC tracking but fails.
In my case I tried to add the raw-data directory that contains the following image files:

Fig. 4 A closed problem inquiry in GitHub Issues.

confidence level of 95% and a margin of error of 5%. This sample size ensures an adequate representation of the general data [57]. The inter-rater reliability of this process, measured by Cohen's kappa [80], is approximately 0.932. This high value reflects a strong agreement between the authors, underscoring the consistency and reliability of our categorization process. In cases of disagreement, the authors engage in discussions to reconcile their perspectives. After filtering out posts with "NA" labels, the resulting dataset comprises 6,749 Stack Overflow posts, 4,774 tool-specific posts, and 2,403 repository-specific posts.

Step 2.2: *Extract post content for topic modeling*

After categorizing the types of inquiry, we explore the topics of these inquiries using topic modeling, as described in detail in **Step 2.4**. To train a robust topic model, we opt for three distinct ways to extract content from the posts to achieve comprehensive coverage and the most accurate and relevant results.

1. We extract the titles of the posts.
2. We extract the titles of the posts along with their bodies.
3. We generate a refined title for each post using GPT-4[35], a large multimodal language model created by OpenAI. The parameter settings of GPT-4 are detailed in Table 15 (Appendix B). Our methodology involves a rigorous and iterative fine-tuning process of the input prompts, which includes approximately 20 iterations. In every iteration, we meticulously adjust the input prompts to explore possible improvements in the coherence score associated with the identified topics. Subsequently, we conduct a manual assessment of the contextual

[35] `https://platform.openai.com/docs/models/gpt-4`

relevance of each generated title. This iterative fine-tuning continues until we observe no further improvement in coherence scores, signifying the achievement of optimal prompt refinement. Consequently, the final optimized prompt, including the original content of the post, is sent to GPT-4 to generate the most coherent and contextually relevant refinement of the title of a given post.

```
Refine the title of the following post to make it short and clear in simple
English. \n Title: [title text here] \n Body: [body text here] \n Refined
Title:
```

We simplify and edit the content of 153 posts that are too long to fit in GPT-4's 8,000 token limit before feeding it to the model. This process involves removing verbose and non-essential sections, such as execution traces, to ensure that the text remains within the token constraints.

We opt to summarize the posts using GPT-4 due to observed inconsistencies in the quality of the titles and content of the posts. On the one hand, this decision comes from two main observations. First, the titles of the posts[36] can be vague, reducing the efficiency of our topic modeling efforts. This is a significant issue, as unclear titles can obscure the post's main subject, leading to less accurate topic classification. Second, the performance of topic modeling algorithms can suffer from repetition of words within posts [22]. Specifically, excessive use of non-essential repeated words can compromise the algorithm's ability to accurately identify the core topics of discussion. Together, these factors necessitate a more sophisticated approach to post summarization to enhance our topic modeling process. On the other hand, recent research suggests that GPT-4 serves as a reliable and consistent substitute for human labeling in summarization tasks [36,48]. In particular, a recent study shows that GPT-4 achieves a Spearman correlation of 0.514 with human labelers in summarization tasks, surpassing all previous methods by a significant margin [76].

For evaluation purposes, we randomly sample 385 posts from a total of 15,065, with a confidence level of 95% and a margin of error of 5%. After comparing these refined titles with the originals, we agree that the GPT-4 generated versions match or surpass the original titles in brevity, readability, and precision. To illustrate, consider the previous Fastai issue #3085: the refined title, "Broken Documentation Page for Neptune Callback", is notably more descriptive than its original, i.e.,"https://docs.fast.ai/callback.neptune.html broken".

Step 2.3: *Preprocess post content with NLP techniques*

After extracting or generating content using the three aforementioned methods, we preprocess it using basic natural language processing (NLP) techniques. This preprocessing is crucial for topic modeling, as it ensures that the data are clean and ready for accurate and meaningful results. The NLP preprocessing encompasses the following steps:

1. Remove any escape character, punctuation mark, or numeric value.
2. Remove any tool-specific keyword based on Table 14 (Appendix B).
3. Keep nouns and verbs only.
4. Remove any stop word. In our study, we categorize stop words into three distinct types.
   (a) Everyday words in English, e.g.,"you", "like".

[36] `https://github.com/fastai/fastai/issues/3085`

(b) Discussion-specific words. Discussion-specific words are words that frequently occur in Q&A posts, but have minimal relevance to the setting of asset management topics, e.g.,"discuss", "post", "difference". In particular, we exclude error-related terms, such as "error", "bug", and "crash", which occur significantly within problem inquiries in our research, to enhance the clarity and interpretability of generated topics.
(c) Task-specific words. Task-specific words are words that are closely associated with ML tasks, but have limited relevance when it comes to the discussion of asset management. Such terms include "regression", "forecasting", "segmentation" and more. By filtering out task-specific stop words, we improve the relevance and clarity of our topics related to asset management.

We evaluate each stop word by checking the coherence score and reviewing the top 10 keywords for each topic. For a detailed list of each type of stop words, we refer to our replication packages [1].

Following these steps, the preprocessed text is ready for input into BERTopic for hyperparameter tuning.

Step 2.4:*Perform topic modeling*

We use BERTopic[37] to cluster topics from preprocessed content. Previous literature indicates that BERTopic consistently outperforms its competitors in various topic modeling tasks [53] and is frequently used in empirical software engineering research [39, 55, 122]. BERT embeddings are adept at capturing semantic nuances, often outperforming sparse, high-dimensional bag-of-words, or n-gram models. Unlike LDA, which relies on word count, BERTopic captures the semantics of words beyond their frequency. For example, the function "sort" might be referred to as "arrange" or "classify" depending on the programming language or the preference of the developers. Thus, BERTopic has the unique capability to group words that may convey similar meanings but are phrased differently.

Since the default hyperparameters provided by BERTopic might not guarantee optimal performance, our goal is to define a comprehensive hyperparameter space for fine-tuning. This search space is initialized by a review of the official BERTopic documentation and insights from its GitHub issues[38]. As we navigate the search, we pay particular attention to variations in the C_V score, a metric commonly used to measure the quality of topics produced by topic models [120]. If we observe that the most significant improvements occur at the boundaries of the current search range, we expand the hyperparameter search space heuristically. Conversely, if the model's performance begins to deteriorate, we cease expansion to ensure its stability and reliability. When certain hyperparameters do not lead to noticeable changes in performance, we regard them as irrelevant and exclude them from our search.

We show the range of hyperparameters used to fine-tune BERTopic for modeling challenges and solutions, respectively, in Table 16 (Appendix B). The optimal hyperparameters are marked in green. Although coherence C_V is our primary metric, we also consider other metrics when the coherence score of generated topic models is comparable. For instance, we evaluate the number of topics and outliers produced. Outliers refer to posts that do not fall into any of the created topics, suggesting weak semantic connections. Furthermore, we manually assess 5% of the

[37] `https://github.com/MaartenGr/BERTopic`
[38] `https://github.com/MaartenGr/BERTopic/issues`

clustered posts for each topic to ensure their relevance and consistency. If the generated topics are difficult to interpret or have significant overlap, we would review and adjust the hyperparameters or go back to earlier steps. This could involve changing our preprocessing methods, including reviewing the list of stop words.

Upon identifying the most suitable topic model, we assign the most probable topic to each post. For outliers, we integrate them with their closest topic using the HDBSCAN technique. HDBSCAN, as described by McInnes et al. [81], is a soft clustering algorithm that identifies clusters of varying densities in the data without the need to predefine the number of clusters.

Step 2.5:*Aggregate into macro-topics*

Upon reviewing the initial set of 133 topics, we find them too numerous for an effective comparison. In addition, many of these topics exhibit strong interrelations. To streamline our analysis, we aggregate these topics into macro-topics. These macro-topics, which can be thought of as "categories of topics", represent high-level groupings of multiple interconnected topics with similar concerns. Previous studies [16, 19, 35] have employed the term "category" to denote such clusters, but we choose to use the term "macro-topics" for this aggregation. In the qualitative coding phase, we apply the "negotiated agreement" [31] technique to improve the reliability of the coding. This technique involves collaborative coding by the authors to reach a consensus and refine the definitions of the codes, as seen in previous studies such as those by Chen et al. [34]. Our consensus on coding is inspired by key ideas from seminal studies within the MLOps domain. We have been particularly influenced by the works of Idowu et al. [60], Amershi et al. [18], and Schlegel et al. [112].

Step 2.6:*Collect prevalence metrics*

Next, we evaluate the macro-topics based on the "prevalence" metrics, a common practice in previous studies [16, 96, 106, 130, 139]. Prevalence measures the frequency with which a topic emerges in our analyzed posts, expressed as a percentage of the entire dataset.

3.2.3 Phase 3: Solution categorization

In this phase, our objective is to understand and categorize the strategies that ML practitioners use to address inquiries, aiming to find prevalent solutions and explore their interconnection. We start by applying open card sorting to solved posts to summarize the solutions presented in them. With the labels generated from this process, we then use BERTopic for topic modeling to further categorize these solutions. After extracting the topics, we group them into macro-topics for a more holistic view. Then we investigate how frequently each solution macro-topic appears. Lastly, we analyze the correlation between the identified challenges and their corresponding solutions.

Step 3.1: *Open card sorting on solutions*

It is crucial to understand how inquiries are addressed and concluded in different developer discussion forums. Platforms such as Stack Overflow, GitHub Discussions, and many tool-specific forums, such as Microsoft Q&A[39], allow users to mark any answer to an inquiry as "accepted". This acceptance is a clear indication that an inquiry is "solved", which generally encapsulates a "solution" that can

[39] `https://learn.microsoft.com/en-us/answers/`

effectively address the initial concerns. Figure 3 shows a knowledge inquiry[40] in the Weights&Biases discussion forum looking for best practices to visualize datasets. This inquiry is addressed by a suggestion to create reports using different panels.

Unlike traditional Q&A forums, some repository-specific discussion forums, such as GitHub Issues, do not employ an answer acceptance mechanism. Instead, they adopt a "closure" mechanism, indicating that the inquiry is solved, no longer considered active, or requires attention. Figure 4 shows a closed problem inquiry[41] following a merge request.

Following the above criteria, the first and second authors opt to perform open card sorting on the solved posts to categorize the solutions provided for user inquiries. Open card sorting is a method in which participants receive a set of cards, each containing a single piece of content or data, and are asked to group these cards into categories in a way that makes sense for them, without any predefined categories [133]. We choose open card sorting due to its ability to handle the versatility of solutions related to asset management. We randomly sample 385 posts from $4,684$ solved posts, aiming for a 95% confidence level and a 5% margin of error. Our labels show a high level of agreement, confirmed by a Cohen's kappa of approximately 0.852, indicating strong consistency in categorization. In cases of disagreement, the authors engage in discussions to reconcile their perspectives.

To label posts, we use $2-5$ words that start with a verb and end with a noun. Although adjectives are selectively added for clarity, adverbs are used sparingly. This length is chosen to meet both the contextual demands of BERTopic for informative context and to resonate with human labeling practices for consistency. Stop words, punctuation, and non-UTF8 characters are excluded to ensure that only essential information is retained, avoiding any preprocessing that could result in the loss of important data. Following these criteria, the first author independently labels the remaining solved posts. Figure 3 demonstrates a solution labeled "create report".

During open card sorting, we notice that solved posts do not always have a satisfactory solution. We identify three types of abnormally solved inquiries, which we subsequently exclude from our analysis. We give the definition for each type of inquiry below.

- Non-inquiry: This type refers to posts that seem to raise concerns, but upon closer inspection do not contain actual problems[42].
- Intermittent inquiry: In this category, the issues mentioned are inconsistent and cannot be replicated regularly[43].
- Unsolved inquiry: These are inquiries that are marked as accepted or closed but still have unsolved issues[44].

Step 3.2:*Perform topic modeling*

After the open card sorting process, we input our labels into BERTopic for topic modeling. Following a procedure similar to Step 2.4, we identify the optimal hyperparameters by optimizing the coherence score, minimizing the number of outliers, and reducing the overlap of topics.

[40] `https://community.wandb.ai/t/axis-scales/2892`
[41] `https://github.com/DagsHub/fds/issues/39`
[42] `https://stackoverflow.com/questions/56046428`
[43] `https://stackoverflow.com/questions/72641789`
[44] `https://stackoverflow.com/questions/65884046`

If the BERTopic performance falls short of our expectations, we undertake a manual adjustment of our labels. For example, in our initial setup, we labeled solutions related to Docker images with the term "image". However, we later realized that this term also encompassed solutions for "image editing", leading to incorrect grouping. To address this, we revised the label for Docker image solutions to "docker-image", while keeping the label "image" for solutions concerning image editing. Such refinements are essential to prevent future misclustering and ensure accurate categorization.

Similar to Step 2.4, once we identify the optimal topic model, we assign the most probable topic to each solved post using the HDBSCAN technique.

Step 3.3:*Aggregate into macro-topics*

Given the observation that many of these topics (79 in total) share close relationships, the first three authors manually aggregate them into macro-topics using the negotiated agreement technique, similar to Step 2.5. If the generated topics are difficult to interpret or have significant overlap, we would review and adjust the hyperparameters or go back to the earlier steps. This could involve adjusting the open card sorting standard.

Step 3.4:*Collect prevalence metrics*

In our study, we first collect metrics on the prevalence of each macro-topics. Using this data, we then create a heatmap that illustrates the number of posts between challenge and solution macro-topics. This approach not only helps us understand which solutions are commonly associated with specific challenges, but also sheds light on the potential causes leading to those challenges.

4 RQ1 Results: Prevalence of Challenge Topics

In RQ1, we investigate the challenges that ML practitioners face in asset management. To begin with, we categorize the collected posts into two primary types: knowledge and problem inquiries. Subsequently, we extract the topics of these inquiries, aggregate them into macro-topics, and clearly define each of these macro-topics along with illustrative examples. We also evaluate the prevalence of these macro-topics by measuring their frequency in the collected posts. Furthermore, we explore the intricate relationship between macro-topics and curated tools, emphasizing their correlation in the inquiries.

4.1 Prevalence of posts based on type of inquiry

We find that problem inquiries make up 59.42% **of the Q&A posts, whereas knowledge inquiries account for** 40.58%**.** This shows a higher prevalence of problem inquiries compared to knowledge inquiries. This trend aligns with the findings of other studies in different domains, including those related to service mesh systems [34]. However, this trend does not indicate that software engineers are typically more inclined to encounter technical issues than theoretical ones. For example, a study by Treude et al. [125] reports a higher prevalence of knowledge inquiries compared to other types of inquiry on Stack Overflow.

Table 1 Macro-topic list of the identified challenges.

Index	**Name**	**Prevalence (%)**	**Topic List**
$\hat{C}_{01}$	Code Development	2.42	[27, 28, 57]
$\hat{C}_{02}$	Code Management	0.74	[30]
$\hat{C}_{03}$	Computation Management	7.82	[19, 24, 34, 37, 42, 44, 61, 102]
$\hat{C}_{04}$	Data Development	4.12	[10, 13, 22, 29]
$\hat{C}_{05}$	Data Management	8.11	[33, 35, 38, 54, 67, 75, 76, 78, 79, 89, 117, 125, 131]
$\hat{C}_{06}$	Environment Management	18.89	[2, 3, 4, 7, 14, 15, 39, 40, 48, 52, 60, 64, 87, 88, 96, 97, 99, 101, 105, 107, 110, 115, 123]
$\hat{C}_{07}$	Experiment Management	2.52	[18, 116]
$\hat{C}_{08}$	File Management	6.79	[26, 36, 47, 55, 59, 70, 72, 121, 129]
$\hat{C}_{09}$	Model Deployment	10.59	[9, 17, 21, 23, 43, 50, 53, 56, 66, 71, 80, 84, 94, 111, 118, 119, 130, 132]
$\hat{C}_{10}$	Model Development	9.00	[8, 11, 12, 20, 31, 46, 83, 100, 114, 126, 133]
$\hat{C}_{11}$	Model Management	6.13	[32, 62, 69, 77, 82, 103, 106, 108, 109, 112, 127]
$\hat{C}_{12}$	Network Management	3.49	[73, 81, 85, 104, 113, 124, 128]
$\hat{C}_{13}$	Observability Management	6.29	[5, 41, 49, 63, 68, 91, 92, 93, 98]
$\hat{C}_{14}$	Pipeline Management	8.51	[1, 16, 45, 65, 86, 95, 120, 122]
$\hat{C}_{15}$	Security Management	3.20	[25, 51, 58, 74, 90]
$\hat{C}_{16}$	User Interface Management	1.36	[6]

4.2 Macro-topics of the posts

We identify 133 **distinct topics from the collected posts**, using the topic-modeling approach outlined in Step 2.5. Our optimal topic model achieves a coherence score of 0.7478 and identifies $3,584$ posts as outliers. We have listed the names of all identified topics, each accompanied by an index, in Table 17 (Appendix B). For a description of each topic, we refer to our replication package [1]. Then we aggregate the topics into 16 macro-topics, which offer in-depth insights into the challenges of ML asset management, independent of specific frameworks and technologies. This study denotes macro-topics with the prefix $\hat{C}$ and topics with the prefix C. The subscript that follows each prefix indicates the (macro-)topic's index. In Table 1, we illustrate each macro-topic with its index, name, prevalence, and underlying topics.

We compare the distribution of the macro-topics according to the type of inquiry and display the results in Figure 5. In the subsequent sections, we explain each macro-topic by providing its definition, discussing underlying topics, and of-

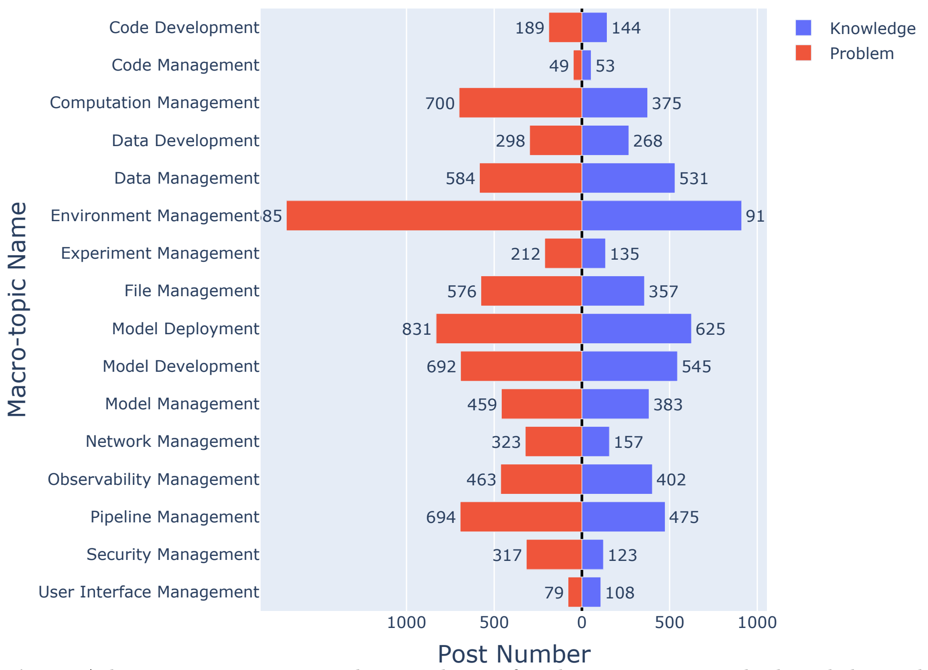


Fig. 5 A histogram representing the prevalence of each macro-topic in the knowledge and problem inquiries.

fering a snapshot of typical content through a sample post. For the sake of clarity in these samples, we abbreviate the verbose content in the posts: long descriptions are denoted by [TEXT], code and logs by [CODE], figures by [IMAGE], and hyperlinks by [URL].

$\hat{C}_{01}$ Code Development

Definition: This macro-topic represents the posts related to creating and optimizing the scripts and code that govern the behavior of a machine learning system. It involves defining the attributes of an object (C_{27}), setting the parameters (C_{28}), and using APIs (C_{57}) to facilitate interoperations between different components of the software. Code development ensures a cohesive and functional codebase that can successfully drive machine learning operations and workflows.
Example: The following example[45] is a problem inquiry from GitHub Issues. The user faces an attribute error when trying to access the *WANDB_PROJECT* attribute from the *params* module in a Weights&Biases run.
E_{01} *When starting a new W&B run, project=params.WANDB_PROJECT returns AttributeError: module 'params' has no attribute WANDB_PROJECT*

$\hat{C}_{02}$ Code Management

[45] https://github.com/wandb/edu/issues/103

Definition: This macro-topic represents the posts related to tracking, documenting, and monitoring changes and versions of codebases [77,105]. It leverages tools such as Git (C_{30}), which serve as version control systems, to ensure consistency, collaboration, and traceability throughout the machine learning development lifecycle.
Example: The following example[46] is a problem inquiry from Stack Overflow. The user encounters an error with DVC Git hooks when running *git push.*
E_{02}: *DVC has Git hooks that are installed with the dvc install. The hooks were working fine, but after an error with dvc push and the DVC remote, I cannot git push because before git push gets executed, dvc push runs and generates an error. This means that I cannot push. How can I disable the DVC Git hooks so that I will no longer face the issue?*

$\hat{C}_{03}$ Computation Management

Definition: This macro-topic represents the posts related to orchestration, allocation, and oversight of computational resources and services to ensure optimal and efficient operations in machine learning workflows [79,92]. This includes monitoring instances (C_{19}), compute infrastructure (C_{24}), servers (C_{37}), compute clusters (C_{42}), system memory (C_{44}), specialized CUDA memory (C_{61}), handling situations where resource limits (C_{34}) or quota requests (C_{102}) are exceeded. Computation management ensures that computational resources are optimally allocated, scalable, and responsive to the demands of machine learning workflows, while maintaining system stability and efficiency.
Example: The following example[47] is a problem inquiry from GitHub Issues. The user faces an error when setting up a Dask cluster following the tutorial.
E_{03}: *When I follow the using-dask tutorial to set up a Dask cluster, I fail to create a new cluster with an odd error that comes up: [Errno 113] No route to the host. I tried searching for it, but the results on Google will come with port and routing issues, which I don't know if are directly related to the problem here.*

$\hat{C}_{04}$ Data Development

Definition: This macro-topic represents the posts related to preparing, processing, and managing data for machine learning operations [62,82,115]. It encompasses tasks such as data annotation for training models (C_{10}), leveraging distributed computing systems such as Spark for large-scale data processing and analytics (C_{13}), manipulating the structure or values of dataframes (C_{22}), and using libraries such as pandas for versatile data manipulation and analysis (C_{29}). Data development ensures that data are properly curated, transformed and ready for subsequent machine learning tasks.
Example: The following example[48] is a problem inquiry from GitHub Issues. The user faces an error related to a mismatch between the number of labels in the multi-label data and the *num_classes* parameter.

[46] `https://stackoverflow.com/questions/75047065`
[47] `https://github.com/Azure/azureml-examples/issues/242`
[48] `https://github.com/aws/amazon-sagemaker-examples/issues/698`

E_{04}: *I am getting an error while running the sagemaker image classification multilabel example: Failed Reason: ClientError: Mismatch between the number of labels in the multilabel data and the num_classes parameter.*

$\hat{C}_{05}$ **Data Management**

Definition: This macro-topic represents the posts related to storing, orchestrating, retrieving, sharing, and connecting various data resources and artifacts throughout the machine learning lifecycle [23, 104]. It encompasses the use of buckets for storage (C_{33}), data factories (C_{35}), managing ML features in feature stores (C_{38}), downloading artifacts (C_{54}), using blob storage for unstructured data (C_{67}), exporting (C_{75}) and importing (C_{117}) data, organizing data in datasets (C_{76}), reading image formats (C_{78}), managing various artifacts produced during ML workflows (C_{79}), utilizing data stores for ML data (C_{89}) and connecting to relational database systems (C_{131}) while benefiting from shared cache storage (C_{125}). Data management ensures efficient storage, retrieval, and flow of data and artifacts, facilitating seamless machine learning operations and workflows.
Example: The following example[49] is a problem inquiry from GitHub Issues. The user faces an invalid bucket name error when running *sm-local* scripts and using the SageMaker defaults from a configuration file.
E_{05}: *Issue: Invalid bucket name "sagemaker.config INFO - Fetched default config from location": The name of the bucket must match the regex. This error message appears when a user executes 'sm-local' scripts and uses SageMaker defaults to set values from the configuration file.*

$\hat{C}_{06}$ **Environment Management**

Definition: This macro-topic represents the posts related to creating, configuring, deploying, and maintaining the various software and infrastructure elements necessary for the development, training, and deployment of machine learning models [24, 42]. It encompasses the management of notebook instances (C_{02}), Docker images (C_{03}), software versions (C_{04}), studios for ML development (C_{07}), RStudio IDE (C_{14}), workspaces (C_{15}), software configurations (C_{39}), initialization processes (C_{40}), Python interpreter (C_{48}), library imports (C_{52}), Terraform infrastructure creation (C_{60}), software configurations (C_{64}), module usage (C_{87}), deployments via Kubernetes (C_{88}), handling missing modules (C_{96}), package installations (C_{97}), notebook imports (C_{99}), software installations (C_{101}), training container configurations (C_{105}), container registries (C_{107}), global YAML configurations (C_{110}), software dependencies (C_{115}), and interactive Jupyter Notebook environments (C_{123}). Environment management ensures the integration and operation of tools, platforms, and configurations in the ML development lifecycle.
Example: The following example[50] is a knowledge inquiry from Stack Overflow. The user inquires about the duties of ensuring consistency and updating software packages in a serverless compute environment such as SageMaker.
E_{06}: *I am learning AWS SageMaker which is supposed to be a serverless computing environment for machine learning. In this type of serverless compute environment, who is supposed to ensure the consistency of the software package and update the versions?*

[49] `https://github.com/aws-samples/sagemaker-ssh-helper/issues/28`
[50] `https://stackoverflow.com/questions/50441181`

$\hat{C}_{07}$ **Experiment Management**

Definition: This macro-topic represents the posts related to designing and executing controlled tests to collect data, evaluate models or hypotheses, and efficiently handle situations where multiple runs or executions overlap or nest in each other [60]. It encompasses the structured process of conducting controlled tests or investigations (C_{18}) and managing conditions where multiple runs or executions are intertwined (C_{116}). Experiment management streamlines the execution and evaluation of controlled tests while handling overlapping or nested runs in the ML development lifecycle.
Example: The following example[51] is a problem inquiry from Stack Overflow. The user faces an error when creating a new experiment after deleting one with the same name.
E_{07}: *[TEXT] I am using Mlflow w/ backend Postgres db. Here is what I have run: [CODE] This deletes the experiment, but when I run a new experiment with the same name as the one I just deleted, it will return this error: [CODE]*

$\hat{C}_{08}$ **File Management**

Definition: This macro-topic represents the posts related to the handling, storage, conversion, and manipulation of files [14, 78]. It encompasses the organization of file directories (C_{26}), the conversion of file formats (C_{36}), the uploading (C_{47}) and downloading (C_{72}) files, the reading of files (C_{55}), the storage solutions (C_{59}), the serialization and deserialization of files (C_{70}), the management of input and output results (C_{121}) and the handling of training files (C_{129}). File management ensures efficient storage, retrieval, and manipulation of data and models throughout the machine learning lifecycle.
Example: The following example[52] is a problem inquiry from Stack Overflow. The user cannot read the files into the DVC control when they are missing from the remote.
E_{08}: *I ran into a problem with DVC when some files are missing on the remote. [TEXT] How can I remove files from the DVC control and add them again?*

$\hat{C}_{09}$ **Model Deployment**

Definition: This macro-topic represents the posts related to integrating a trained machine learning model into an application or system to make real-time predictions or decisions [21, 97]. It encompasses prediction (C_{09}), deploying a model (C_{21}, C_{53}, C_{80}, C_{94}), offering it through web services (C_{17}), setting up inference (C_{23}, C_{130}) and model endpoints (C_{43}), deploying such endpoints (C_{50}, C_{118}), batch prediction (C_{56}), invoking endpoints (C_{66}, C_{119}), leveraging serverless platforms such as Endpoint Lambda (C_{71}) and ACI (C_{111}), and scoring (C_{84}) or serving the model (C_{132}) for production use. Model deployment ensures that trained machine learning models are readily accessible and functional in production environments for real-time or batch predictions.

[51] `https://stackoverflow.com/questions/60088889`
[52] `https://stackoverflow.com/questions/56269391`

Example: The following example[53] is a problem inquiry from GitHub Issues. The user faces an error when trying to deploy it to SageMaker endpoints.
E_{09}: *I have trained and saved a BertForSequenceClassification model to S3. I then used this notebook [URL] to deploy the model to SageMaker Endpoints. I ran: [CODE] I get the following error: [CODE]*

$\hat{C}_{10}$ Model Development

Definition: This macro-topic represents the posts related to training, tuning, and optimizing machine learning models [20,95,131]. It comprises the use of ML frameworks such as scikit-learn (C_{114}), PyTorch (C_{08}), and TensorFlow (C_{12}), paired with optimization methods including fine-tuning (C_{133}), hyperparameter adjustments (C_{11}), and sweeps (C_{20}), while undertaking tasks such as training jobs (C_{31}) and distributed training (C_{46}), and focusing on both general training (C_{83}, C_{100}) and specialized training of YOLO models (C_{126}). Model development ensures the creation of robust and efficient machine learning models that are trained, optimized, and validated using best practices and tools.
Example: The following example[54] is a problem inquiry from GitHub Issues. The user faces a *No such file or directory* error when running a training job for a custom algorithm following the tutorial.
E_{10}: *I am trying to create a custom algorithm following the instructions given in this tutorial [URL]. When I am running the training job, it is failing with the error No such file or directory. As per the documentation, SageMaker should create these documents and copy the data and artifacts during the runtime. But this is not happening.*

$\hat{C}_{11}$ Model Management

Definition: This macro-topic represents the posts related to creating, saving, registering, loading, storing, compiling, and exchanging machine learning models, including their different formats, states, and associated metadata [66, 137]. It encompasses creation (C_{82}), storage (C_{32}), registration (C_{62}), loading (C_{69}), centralized storage in registries (C_{77}), compilation in NEO format (C_{103}), utilization of specialized frameworks such as Huggingface (C_{106}), exchange through formats such as ONNX (C_{108}), general use of trained or pre-trained models (C_{109}), distinction of trained models (C_{112}) and checkpointing of models during training (C_{127}). Model management ensures the systematic development, storage, optimization, and tracking of machine learning models throughout their lifecycle.
Example: The following example[55] is a knowledge inquiry from Stack Overflow. The user asks about retrieving weights from the best performing Keras model in Optuna.
E_{11}: *Is there a way to pull the weights from the Keras model that performs the best and was created using an Optuna study? [TEXT]*

$\hat{C}_{12}$ Network Management

[53] https://github.com/huggingface/transformers/issues/13111
[54] https://github.com/aws/amazon-sagemaker-examples/issues/670
[55] https://stackoverflow.com/questions/74257398

Definition: This macro-topic represents the posts related to the establishment, monitoring, and optimization of communication links and interactions related to the endpoints of the machine learning model [71,135]. It involves addressing broken links (C_{73}), managing endpoint content (C_{81}), conducting endpoint ping tests (C_{85}), establishing connections (C_{104}), utilizing web interfaces (C_{113}), receiving response endpoints (C_{124}), and overseeing endpoint transition (C_{128}). Network management ensures seamless integration, availability, and responsive interactions of the machine learning model endpoints in the ML development lifecycle.
Example: The following example[56] is a knowledge inquiry from GitHub Issues. The user inquires about changing the default API server port in ClearML and updating the system with new credentials.
E_{12}: *I would like to change the default apiserver port from 8008 to 18008. I have changed it to docker-compose.yml. The ClearML app runs without problems. But when I create new credentials, it gives me an old port there. It would be great if I could change this port so it would show up when creating credentials. How to achieve it?*

$\hat{C}_{13}$ **Observability Management**

Definition: This macro-topic represents the posts related to tools, processes, and practices designed to record, monitor, compare, and visualize events, metrics, and performance related to machine learning models throughout their lifecycle [50,70]. It encompasses the recording of events through logs (C_{05}), the usage of custom metrics (C_{41}), visualization with TensorBoard (C_{49}), logging performance metrics (C_{63}), benchmarking model performance (C_{68}), generating training reports (C_{91}), logging model specifics (C_{92}), continuous model monitoring (C_{93}) and integration of logs in Amazon CloudWatch (C_{98}). Observability management ensures continuous, transparent, and efficient monitoring and analysis of machine learning models, fostering improved performance, reliability, and insights.
Example: The following example[57] is a knowledge inquiry from Stack Overflow. The user faces an issue with a binary classification metric evaluation function that leads to inaccurate recall metrics.
E_{13}: *I was trying to assess the metrics for binary classification and got a very strange result. It appears that eval_and_log_metrics will not be able to tell which one is the true positive in the y_test. So it just averages out true positive and true negative, which gave inflated recall metrics. How to pass the true positive value to the eval_and_log_metrics?*

$\hat{C}_{14}$ **Pipeline Management**

[56] `https://github.com/allegroai/clearml-server/issues/201`
[57] `https://stackoverflow.com/questions/71505796`

Definition: This macro-topic represents the posts related to the orchestration and execution of tasks or steps in a machine learning process [112, 136]. It orchestrates the comprehensive progression of a project through defined phases such as individual pipeline steps (C_{01}), handling large data through batch transform (C_{16}), mitigating issues such as Stuck Queue, incorporating inference pipeline strategies (C_{65}), improving efficiency through parallelization jobs (C_{86}), defining pipeline training steps (C_{95}), establishing lifecycle configuration (C_{120}), and integrating custom job tasks (C_{122}) to foster streamlined, effective and robust machine learning operations. Pipeline management ensures a structured and efficient approach to handling machine learning projects from start to finish. **Example**: The following example[58] is a knowledge inquiry from GitHub Issues. The user asks about retrieving information from existing pipelines, including their scheduling and metadata, using the Azure Machine Learning Python SDK.
E_{14}: *I use Azure machine learning services to run an ml-model. When I go to the GUI of AML I can see all the existing pipelines, but I cannot see how they are scheduled. I need to obtain all published pipelines and the associated metadata. How can I get information about an existing pipeline with the Python SDK?*

$\hat{C}_{15}$ Security Management

Definition: This macro-topic represents the posts related to the control and protection of machine learning resources and services [114, 132]. It encompasses the structured utilization and control over user accounts (C_{25}), leveraging authentication processes (C_{51}) for verified access, ensuring secure API interactions through API keys (C_{58}), controlling access through permission authorizations (C_{74}) and handling instances of permission denial (C_{90}) to safeguard resources and services. Security management serves as the guardian in MLOps, orchestrating user account setups, verifying identities, and facilitating secure API accesses while meticulously granting permissions to prevent unauthorized operations and access.
Example: The following example[59] is a problem inquiry from Stack Overflow. The user faces a permission error when deploying a TensorFlow model using Sagemaker.
E_{15}: *I can train my model using the Sagemaker TensorFlow container. Below is the [CODE]. But when I try to deploy the model, I get the following error: UnexpectedStatusException: Error hosting endpoint: Failed. Reason: Make sure that all images included in the model for the production variant AllTraffic exist and that the execution role used to create the model has permission to access them.*

$\hat{C}_{16}$ User Interface Management

Definition: This macro-topic represents the posts related to design, implementation, and maintenance of visual tools and dashboards that enable users to interact with and interpret machine learning systems, models, and data. It encompasses the creation and management of visual representations of data or information, such as plots (C_{06}). User interface management enhances user experience by leveraging visual tools to facilitate effective and intuitive data representation and analysis.

[58] `https://github.com/Azure/MachineLearningNotebooks/issues/1927`
[59] `https://stackoverflow.com/questions/64039980`

Example: The following example[60] illustrates a knowledge inquiry from Weights&Biases discussion forum. The user inquires about the accessibility of the underlying source code for a Vega or Vega-lite visualization in a Weights&Biases panel.

E_{16}: *Is it possible to see the underlying source code of Vega or Vega-lite for a particular panel on wandb?*

4.3 Prevalence of posts based on macro-topics

We find that **Environment Management ($\hat{C}_{06}$) is the most prevalent macro-topic among the collected posts, constituting 18.89% of the total posts.** The high prevalence indicates that ensuring a consistent and controlled environment is challenging for ML practitioners throughout ML asset management. ML models are particularly sensitive to their design, training, and deployment environments[61]. Even minor differences in framework versions, library dependencies, or hardware configurations can result in performance inconsistencies or failures [41].

Moreover, we find that **Model Deployment ($\hat{C}_{11}$) ranks as the second most prevalent macro-topic at 10.59%, with Model Development ($\hat{C}_{09}$) closely following as the third most prevalent macro-topic at 9%.** The prominence of Model Deployment ($\hat{C}_{11}$) indicates that a substantial part of the challenges and focus in ML asset management is on transitioning models from development or testing phases to production. The absence of well-defined routes from development to production exacerbates this issue, and is connected to an alarming AI project failure rate of nearly 50%[62]. Similarly, the notable prevalence of model development emphasizes the importance of core activities in the building of ML models. Activities such as selecting appropriate algorithms, feature engineering, and model training remain pivotal areas of discussion in the ML development lifecycle [21,49].

Lastly, we observe that **Code Management ($\hat{C}_{02}$) remains the least prevalent macro-topic, accounting for only 0.74% of the posts**. This may be due to the perception of source code management as well-established, along with the specialized nature of the forums related to ML asset management, i.e.,discussions about code management are typically found on other platforms. For instance, the tag "Git" on Stack Overflow serves as a lively venue for discussions on this topic, underlining the trend of these dialogues migrating to spaces specifically dedicated to code management.

4.4 Mapping between macro-topics and tools

In Figure 6, we present a heatmap showing the relationship between various tools and challenge macro-topics. Each block in the heatmap represents the percentage of posts associated with a specific tool to each of the challenge macro-topics. One key finding from the heatmap is that the 55% **(11 out of 20) tools are**

[60] `https://community.wandb.ai/t/vega-code/4605`
[61] `https://neptune.ai/blog/ml-model-packaging`
[62] `https://aws.amazon.com/blogs/startups/scaling-ai-ml-and-accelerating-ai-development-with-anyscale-and-aws/`

primarily associated with inquiries related to Environment Management ($\hat{C}_{06}$). This list includes Aim (50.00%), AzureML (22.37%), Comet (30.77%), Guild AI (28.69%), H20 AI Cloud (24.56%), Kedro (33.44%), MLflow (18.77%), Neptune (20.47%), Sacred (43.48%), SageMaker (18.18%) and Vertex AI (16.93%). This trend suggests a strong focus of posts on managing the software environment and dependencies. The diverse ways in which different tools handle environment and dependency management underline the unique integration challenges each encounters.

In contrast, **Domino stands out with a significant** 38.46% **of user inquiries related to Code Development ($\hat{C}_{01}$).** This emphasizes the challenges Domino users face when creating ML-related components or features. Similarly, **Optuna** (32.61%) **and Weights&Biases** (20.27%) **predominantly receive inquiries about Model Development ($\hat{C}_{10}$)**, pointing to the difficulties users face when developing ML models using these tools. An outlier is Determined, which is exclusively related to Computation Management ($\hat{C}_{03}$). However, this association might not be indicative of a broader trend, as only a single post corresponds to this tool in our collected posts. This suggests that challenges related to Determined might be underrepresented in our survey.

Summary of RQ1

- Problem inquiries (59.42%) appear more frequently than knowledge inquiries (40.58%) in Q&A posts related to machine learning asset management.
- Environment Management (18.89%), Model Deployment (10.59%) and Model Development (9%) are the most discussed topics in related posts to machine learning asset management, indicating a strong emphasis on the integration, training, and serving of machine learning models in practical applications.
- 55% of the tools receive the majority of their inquiries related to Environment Management. This pattern indicates a prevalent challenge in the ability of these tools to seamlessly integrate with other software platforms, highlighting an area for improvement and development.

5 RQ2 Results: Prevalence of Solution Topics

In RQ2, we examine the solutions proposed by ML practitioners to address the challenges in ML asset management. We define these topics, offer illustrative examples, and compare their prevalence. In addition, we analyze the distribution of solutions by topic and type of inquiry. Lastly, linking challenges to their respective solution topics, we seek to find the prevailing patterns of solutions in ML asset management.

5.1 Macro-topics of the solutions

We use open card sorting to categorize solved inquiries, as detailed in Step 3.1. The frequency of each type of inquiry is presented in Table 3. In particular, 9.86% (159 in total) GitHub issues are marked as “closed” without any solution found in their posts. This might indicate that these issues may be of low priority or may not have a significant impact on the software project.

We identify 79 **distinct topics from the solutions of normal inquiries** using the topic-modeling approach outlined in Step 3.3. Our optimal topic model

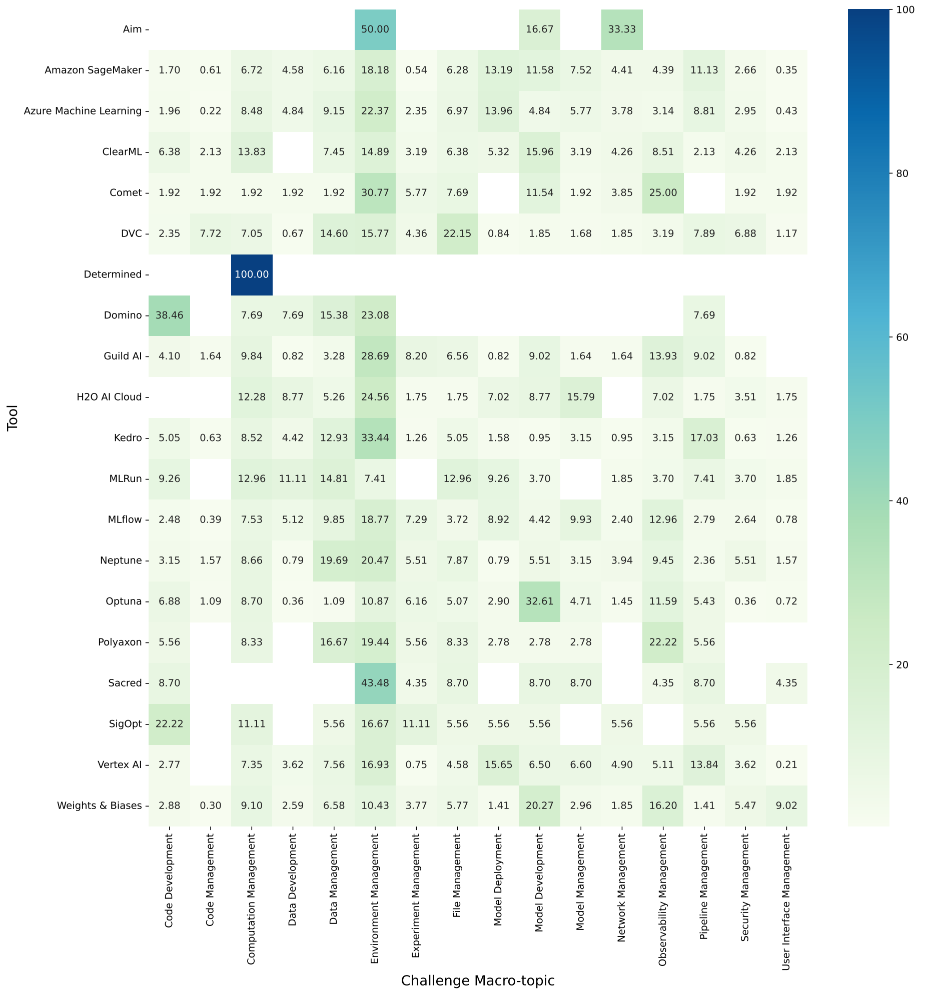


Fig. 6 Mapping between tools and challenge macro-topics based on the number of posts (Normalized across challenge macro-topics).

achieves a coherence score of 0.9085 and identifies 890 posts as outliers. In our study, we use the prefix $\hat{R}$ to represent macro-topics and R to represent regular topics. A detailed list of these topics, along with their indices and names, is provided in Table 18 (Appendix B). For further descriptions of each topic, please refer to our replication packages [1].

Following the practice of RQ1, we formulate 18 macro-topics to encapsulate the original topics. Table 4 shows the macro-topics, their prevalence, and underlying topics. A notable observation is the naming overlap between certain macro-topics associated with solutions and those linked to challenges. This overlap signifies their shared relevance to specific aspects of asset management, underscoring the interconnectedness of challenges and solutions within the same thematic groups.

In this section, we define each solution macro-topic and provide corresponding examples from our dataset of collected posts. Since the first 16 solution macro-topics share identical names with their challenge counterparts, we focus exclusively

Table 3 Types of solved inquiries across discussion forums.

Discussion forum	**Number of normal inquiries**	**Number of non-inquiries**	**Number of intermittent inquiries**	**Number of non-solved inquiries**
Stack Overflow	2187	2	4	5
GitHub Issues	1432	6	15	159
Tool-specific forums	849	1	1	8
GitHub Discussions	17	0	0	0
GitLab Issues	1	0	0	0

Table 4 Macro-topic list of the identified solutions.

Index	**Name**	**Prevalence (%)**	**Topic List**
$\hat{R}_{01}$	Code Development	15.35	[12, 13, 27, 28, 47, 56, 57, 58, 59, 61, 63, 84]
$\hat{R}_{02}$	Code Management	0.80	[43]
$\hat{R}_{03}$	Computation Management	5.25	[19, 30, 35, 53, 60]
$\hat{R}_{04}$	Data Development	3.66	[31, 33, 54]
$\hat{R}_{05}$	Data Management	4.81	[40, 42, 70, 75, 77]
$\hat{R}_{06}$	Environment Management	23.31	[1, 5, 7, 15, 21, 22, 23, 25, 34, 37, 41, 44, 62, 66, 67, 69, 72, 73, 76, 78, 85]
$\hat{R}_{07}$	Experiment Management	4.12	[11, 39, 71, 83]
$\hat{R}_{08}$	File Management	9.64	[16, 20, 29, 36, 49, 55, 64, 65, 68, 86]
$\hat{R}_{09}$	Model Deployment	5.01	[24, 26, 38, 79, 80]
$\hat{R}_{10}$	Model Development	2.10	[3]
$\hat{R}_{11}$	Model Management	4.32	[10, 32, 52]
$\hat{R}_{12}$	Network Management	2.92	[9, 51]
$\hat{R}_{13}$	Observability Management	3.41	[6, 50, 74]
$\hat{R}_{14}$	Pipeline Management	4.08	[14, 18, 45]
$\hat{R}_{15}$	Security Management	4.54	[4, 17, 81]
$\hat{R}_{16}$	User Interface Management	1.04	[48]
$\hat{R}_{17}$	Comparison & Recommendation	2.46	[2, 82]
$\hat{R}_{18}$	Maintenance & Support	3.19	[8, 46]

on the two uniquely named solution macro-topics in this section, directing readers to the Appendix A for the illustrations of the others.

$\hat{R}_{17}$ Comparison & Recommendation

Definition: Comparison & Recommendation represents the posts related to the analytical process in which the efficacy and suitability of various tools, such as SDKs, APIs, databases, platforms, runtimes, versions, tasks, data or pipelines, are examined (R_{82}) and suggested (R_{02}) during the ML development lifecycle. Comparison and recommendation facilitate the selection of the most appropriate tools and resources regarding ML assets, thus promoting efficiency and superior outcomes through well-informed decisions in the production environment.
Example: The following example[63] provides supported runtimes to help the user make an informed decision.
E_{17}: *Accepted Answer: MLRun has several different ways to run a piece of code. At this time, the following runtimes are supported: [TEXT]*

$\hat{R}_{18}$ **Maintenance & Support**

Definition: Maintenance & Support represents the posts related to the continuous process of updating and improving machine learning systems by implementing patches or fixes (R_{08}), and managing operating issues through support tickets (R_{46}) [54, 69]. It ensures the stability, performance, and effective communication of machine learning-based systems.
Example: The following example[64] provides the development plan for the DVC-Hydra integration support.
E_{17}: *Accepted Answer: A DVC-Hydra integration is in development. You can see the proposal in [URL] and the development progress in [URL]. [TEXT]*

5.2 Prevalence of solutions based on macro-topics

Environment Management ($\hat{R}_{06}$) stands out as the most prevalent (23.31%) **solution macro-topic related to ML asset management**, as illustrated in Table 4. This prominent prevalence underscores the intricacies and significance of overseeing environments and dependencies throughout ML asset management. Ensuring adept management of these ML environments and dependencies is paramount for achieving consistent and reproducible model training and deployment across diverse infrastructures.

Following this, Code Development ($\hat{R}_{01}$) constitutes 15.35% and is the second most prevalent solution macro-topic. The prominence of this macro-topic reflects the evolving complexities and nuances of crafting code specifically for ML applications, as opposed to traditional software development. This emphasizes the need for robust development practices, continuous integration, and testing methodologies tailored for ML. File Management ($\hat{R}_{08}$) ranks as the third most prevalent macro-topic with a proportion of 9.64% of Q&A posts. This prominence underscores the essential role of structured file storage, retrieval, and manipulation in the ML development lifecycle.

[63] `https://stackoverflow.com/questions/72408785`
[64] `https://stackoverflow.com/questions/73435172`

5.3 Mapping between challenge and solution macro-topics

Knowledge inquiries are commonly addressed with solutions specific to their respective topics. This correlation can be observed in Figure 7, which shows the mapping between challenges and solution macro-topics in knowledge inquiries. Each cell in the heatmap represents the normalized number of posts corresponding to a specific challenge macro-topic across various solutions. The prominent dark blocks along the diagonal suggest that challenges in a particular domain are frequently solved in the same domain. In our study, we term this phenomenon as "self-resolution". For instance, inquiries related to Environment Management ($\hat{C}_{06}$) are predominantly addressed using environment-specific solutions ($\hat{R}_{06}$). To highlight the prevalence of self-resolution, we set a threshold of 25% to indicate a significant rate of self-resolution. As a result, 56.25% (9 out of 16) macro-topics meet this criterion, implying that the majority of knowledge inquiries rely on domain-specific knowledge from their corresponding macro-topic for solution.

Conversely, we notice a pattern in which specific types of challenge are often addressed by solutions from different areas, a phenomenon we term "counter-self-resolution" in our study. For example, **challenges in Code Management ($\hat{C}_{02}$) are primarily solved by methods in Code Development ($\hat{R}_{01}$).** This connection highlights that effective code management is closely related to the processes and practices in code development. Similarly, **challenges related to Experiment Management ($\hat{C}_{07}$) are primarily tackled with solutions in Environment Management ($\hat{R}_{06}$).** This reveals that the effectiveness of experiment management depends on robust environment management practices.

Lastly, since Environment Management ($\hat{R}06$) emerges as the most prevalent macro-topic in knowledge inquiries, we take a closer examination at the mapping of the underlying topics in this macro-topic. Figure 8 illustrates the relationship between challenge macro-topics and the underlying solution topics in Environment Management ($\hat{R}06$). We observe that **Container Customization (R_{21}) is the most prevalent solution topic (13.46%) for Environment Management ($\hat{R}_{06}$) solutions.** Specifically, it accounts for 50% of the environment-oriented solutions to Network Management ($\hat{C}_{12}$) challenges. Furthermore, this figure highlights that **Package Installation (R_{05}) emerges as the most prevalent solution (100%) for User Interface Management ($\hat{C}_{16}$).** The figure also points out that **for Code Management ($\hat{C}02$) challenges, Package Addition (R_{23}) and Environment Variable Management (R_{34}) are the most prevalent solutions, each accounting for 50%.**

Problem inquiries are less commonly addressed through self-resolution. This observation is evident in Figure 9, where we illustrate the normalized number of posts between challenge and solution macro-topics in problem inquiries. Herein, the diagonal cells in the heatmap are lighter compared to those related to knowledge inquiries. Using a 25% threshold, we observe that only 25% (4 out of 16) of the macro-topics display a high level of self-resolution. This suggests a lower trend for self-resolution in problem inquiries, likely due to their inherent complexity or external, cross-domain factors influencing them.

Conversely, we note that the counter-self-resolution trend is more pronounced in problem inquiries compared to knowledge ones. A case in point is again the resolution of Code Management ($\hat{C}_{02}$) challenges with Code Development ($\hat{R}_{01}$) methods. Furthermore, Environment Management ($\hat{R}_{06}$) emerges as the most prevalent

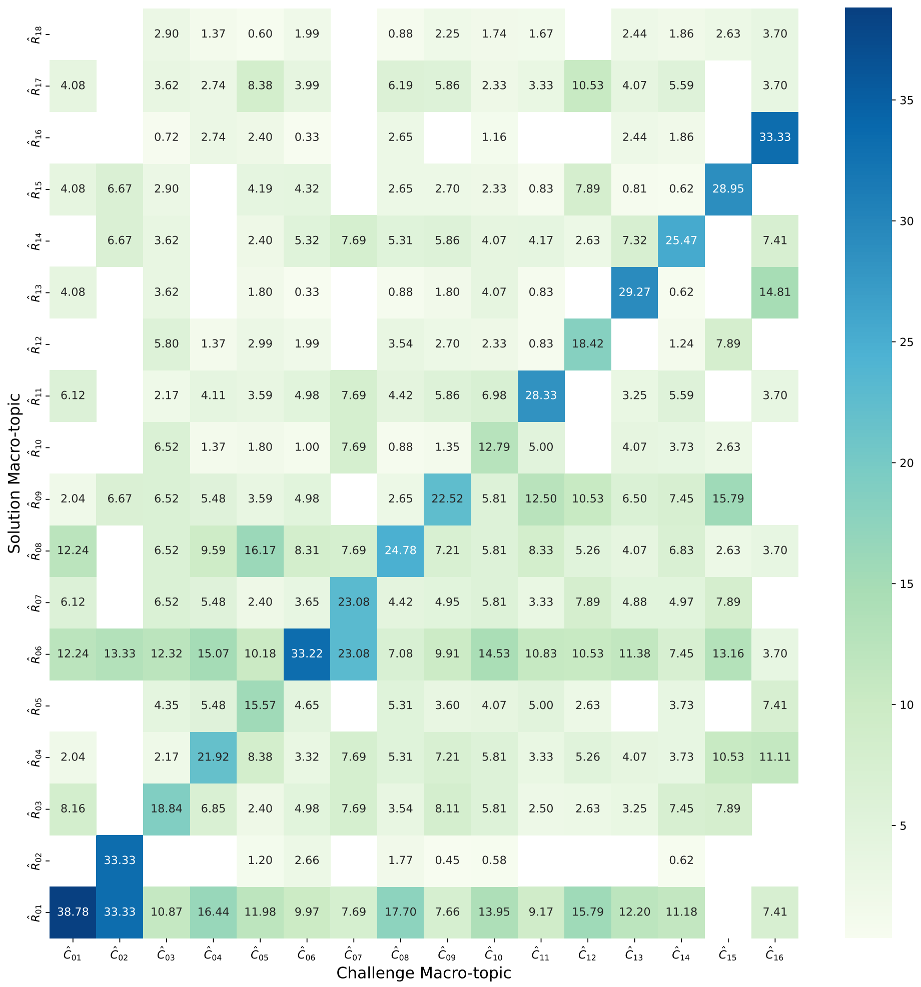


Fig. 7 Mapping of challenge marco-topics (knowledge inquiry) to solution macro-topics, showing the normalized number of posts based on post interactions.

solution macro-topic for 62.5% (10 out of 16) macro-topics, including Computation Management ($\hat{C}_{03}$), Data Development ($\hat{C}_{04}$), Data Management ($\hat{C}_{05}$), Experiment Management ($\hat{C}_{07}$), Model Deployment ($\hat{C}_{09}$), Model Development ($\hat{C}_{10}$), Model Management ($\hat{C}_{11}$), Network Management ($\hat{C}_{12}$), Observability Management ($\hat{C}_{13}$) and User Interface Management ($\hat{C}_{16}$). This pattern implies that software environment and dependency management are a foundational and versatile solution, addressing a wide range of challenges on different topics. Furthermore, challenges in Observability Management ($\hat{C}_{13}$) are commonly addressed with Code Development ($\hat{R}_{01}$) solutions. This implies that the quality and effectiveness of evaluation and monitoring is significantly influenced by the methodologies and practices used in code development.

Lastly, since Environment Management ($\hat{R}06$) emerges as the most prevalent macro-topic in problem inquiries, we also examine the mapping of its underlying topics in Figure 10. In particular, **Package Upgrade (R_{01}), accounting for**

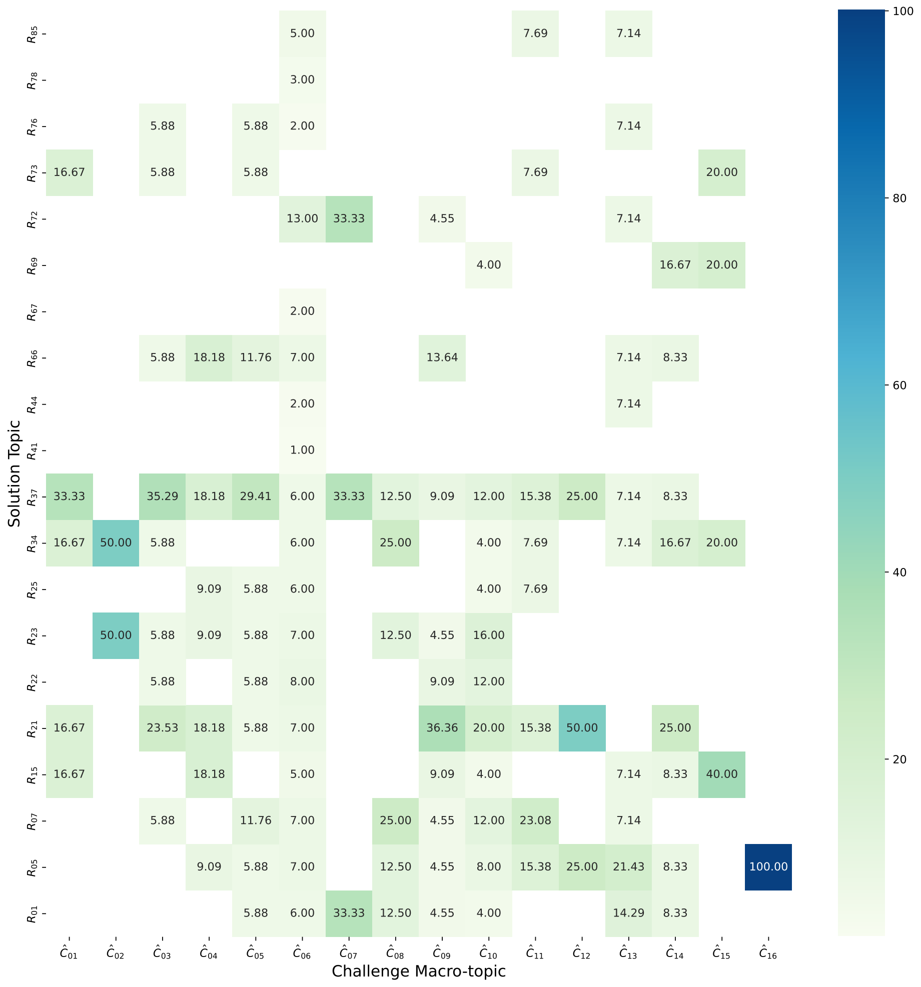


Fig. 8 Zooming down to the level of individual solution topics for Environment Management ($\hat{R}_{06}$) in Figure 7.

20.45% **of the cases, is the most frequently encountered solution topic in the broader category of software dependency and environment, for the majority of challenge macro-topics**, with the exception of Code Management ($\hat{C}_{02}$) and User Interface Management ($\hat{C}_{16}$). This pattern indicates a significant dependence on external packages and libraries in machine learning projects. As these packages undergo updates, they may present new features, optimizations, or necessary bug fixes. Furthermore, **Package Removal** (R_{62}) **stands out as the most prevalent environment-oriented solution** (100%) **to address the challenges related to Code Management** ($\hat{C}_{02}$). It also reveals that **Package Installation** (R_{05}) **is the most prevalent environment-oriented solution** (42.86%) **for User Interface Management** ($\hat{C}_{16}$). This trend further underscores the point that package management is at the heart of environment management, maintenance, and deployment [41]. It allows developers and system administrators to define, reproduce, and share their software environments consistently and predictably.

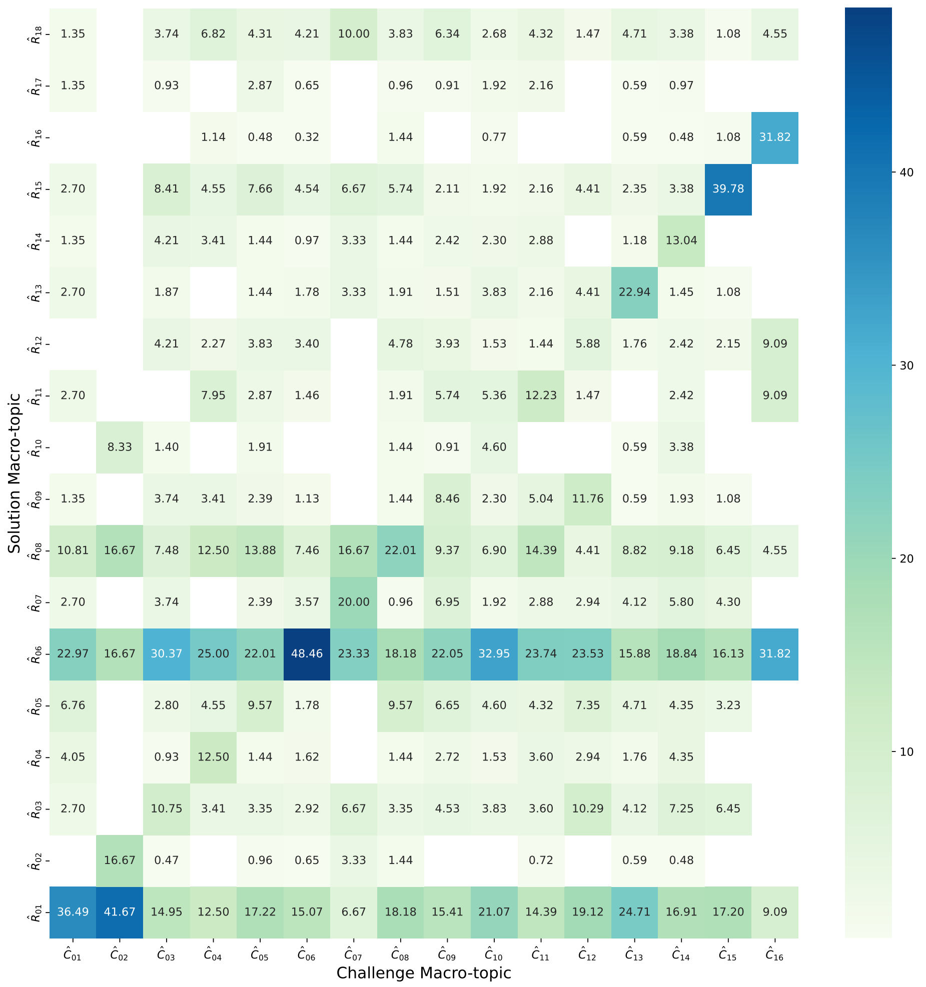


Fig. 9 Mapping of challenge marco-topics (problem inquiry) to solution macro-topics, showing the normalized number of posts based on post interactions.

Summary of RQ2

- Environment Management (23.31%), Code Development (15.35%), and File Management (9.64%) are the most discussed solution topics related to machine learning asset management, indicating that these areas are the most common pain points or areas of interest for machine learning practitioners.
- 56.25% (9 out of 16) of the challenge macro-topics in knowledge inquiries show a high-level self-resolution. In contrast, only 25% (4 out of 16) of the challenge macro-topics in problem inquiries demonstrate a high self-resolution rate. This suggests that a more interconnected and cross-disciplinary approach is needed when addressing specific problems, as opposed to seeking general knowledge.
- The counter-self-resolution trend is more pronounced in problem inquiries than in knowledge inquiries. This may imply that problem inquiries necessitate a broader spectrum of insights, often derived from external or cross-disciplinary domains, to devise viable solutions.

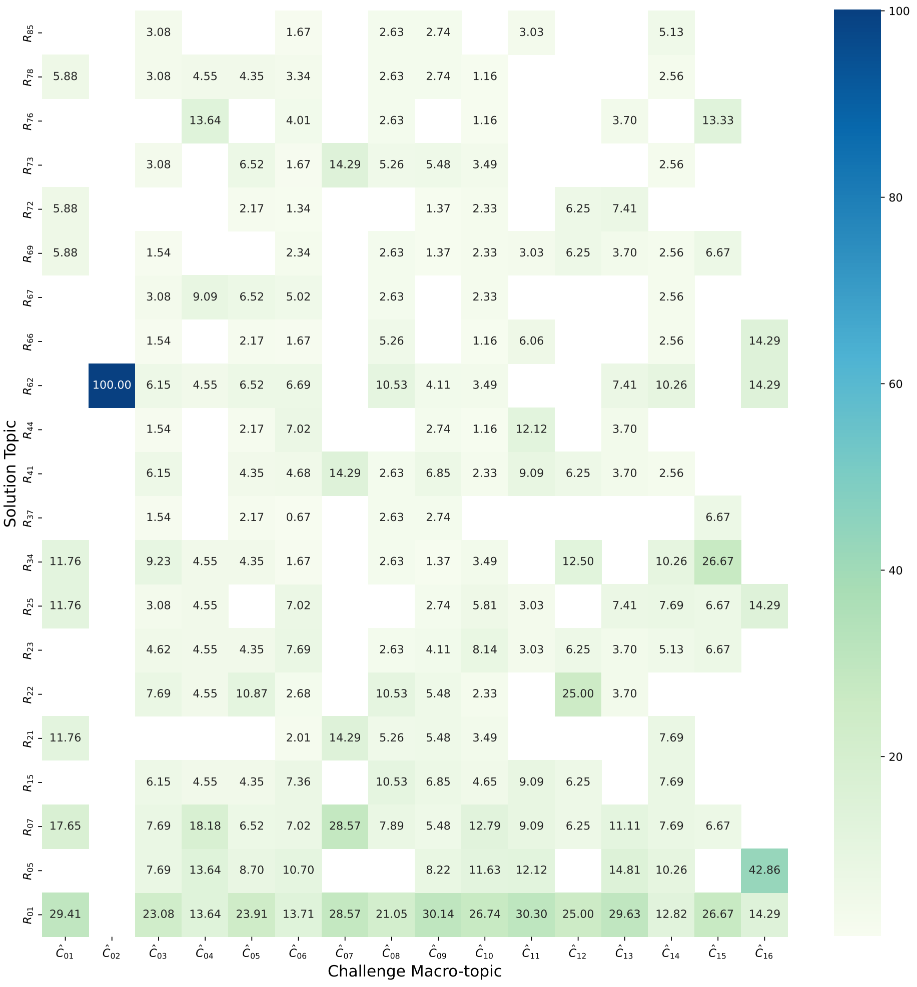


Fig. 10 Zooming down to the level of individual solution topics for Environment Management ($\hat{R}_{06}$) in Figure 9.

6 RQ3 Results: Comparison of Discussion Forums

In RQ3, we explore commonalities and differences in developer discussion forums about ML asset management. Specifically, we compare Stack Overflow, repository-specific forums, and tool-specific forums. We start our analysis by examining the general prevalence metrics on various forums. This initial step gives us a broad overview of the landscape. Next, we narrow our focus to compare these metrics based on different types of inquiry in each forum. This allows us to understand how each forum performs in addressing specific types of inquiry. In the final step, we shift our attention to macro-topics in these forums, comparing the prevalence metrics once more.

6.1 Comparison of discussion forums in general

We find that **Stack Overflow is the main source of inquiries, accounting for** 48.65% **of the total posts. Tool-specific forums are next, contributing** 34.19%**, while repository-specific forums have the fewest, at only** 17.16%**.** The prevalence of Stack Overflow posts is expected due to its popularity for developers worldwide [129]. Its highest number of posts reflects its popularity and wide reach among ML practitioners. However, the low number of posts on repository-specific forums, such as GitHub, could indicate a narrower focus of discussions, often centered on project-specific issues, bugs, or feature requests, rather than the more general questions and broad topics typically found on Stack Overflow [116, 127].

6.2 Comparison of discussion forums based on tools

A distinct distribution emerges in the preferences of the types of discussion forum among users of different tools, as illustrated in Figure 11. The intensity of the color in the heatmap indicates the frequency of posts for each forum-tool pairing. In particular, 25% **(5 out of 20) tools**, namely DVC (65.77%), Domino (100%), Guild AI (100%), Polyaxon (94.44%), and Weights & Biases (69.36%), **have the majority of their discussions originating from tool-specific forums.** This trend could imply a positive user experience on these dedicated forums, which deserves further investigation into the factors contributing to this preference. Conversely, we observe that 20% **(4 out of 20) tools**, including Aim (100%), Comet (80.77%), Determined (100%), and Neptune (90.55%), **predominantly have discussions in repository-specific forums.** This could reflect a tendency among practitioners to discuss the challenges faced in open-source projects where these tools are utilized as dependencies. Furthermore, 35% **of the tools (7 out of 20)**, including Amazon SageMaker (64.89%), H2O AI Cloud (85.96%), Kedro (61.20%), MLRun (100%), MLflow (54.07%), Optuna (67.03%), and Vertex AI (68.48%), **have the most of their discussions on Stack Overflow.** This behavior could highlight a preference to engage with a wider community or a higher popularity of Stack Overflow among developers in general.

6.3 Comparison of discussion forums based on macro-topics

Environmental management ($\hat{C}_{06}$) is the most prevalent macro-topic in all forums, comprising 25.53% **of repository-specific issues,** 18.34% **of Stack Overflow posts, and** 16.34% **of discussions in tool-specific forums.** This trend reinforces the RQ1 finding that software environment and dependency management are the primary macro-topics in ML asset management. In contrast, while **Model Deployment ($\hat{C}$09) is the second most frequent topic on Stack Overflow** (12.49%) **and tool-specific forums** (9.98%)**, it is ranked sixth on repository-specific forums at** 6.45%. Conversely, **Model Development ($\hat{C}$10) is second on repository-specific forums** (9.71%) **but falls to fourth on Stack Overflow** (9.11%) **and tool-specific forums** (8.49%)**.**

Differences in the distribution of posts across macro-topics between any two discussion forums are significant, as evidenced by three pairwise Chi-square goodness of fit tests, conducted at a significance level of 0.05 (Table 6). Chi-square

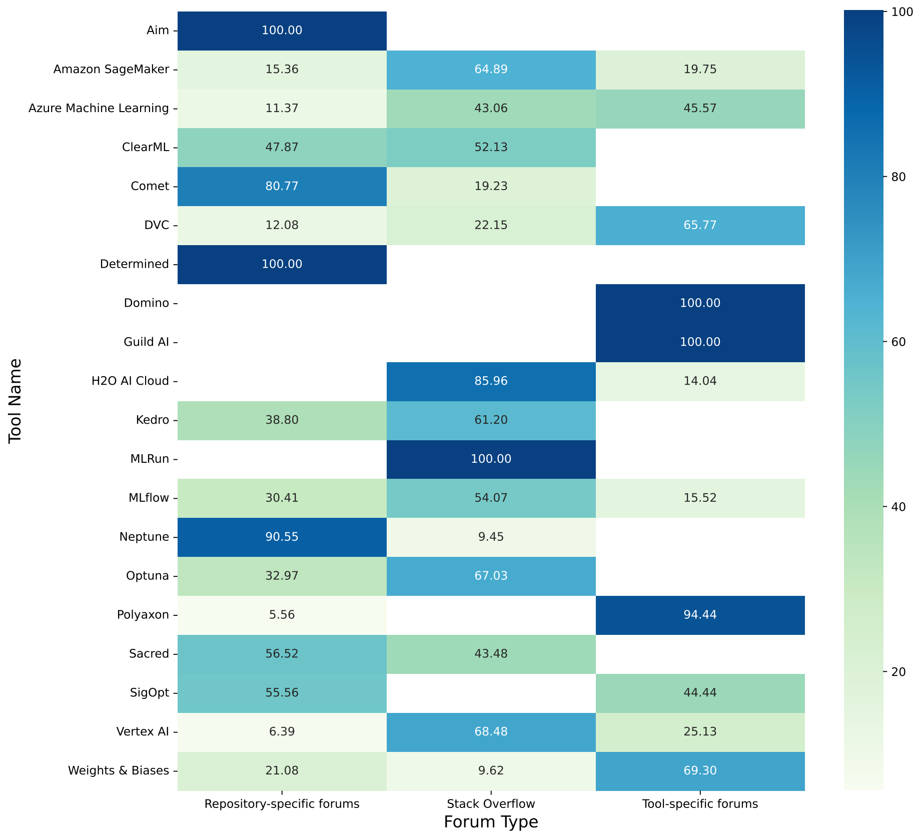


Fig. 11 Normalized distribution of Q&A posts across different types of forum.

tests are commonly used to evaluate the alignment between observed data and a hypothesized distribution [100]. Given the multiple tests conducted, we adjust the p-values to the so-called “q-values” [117] using the Benjamini-Hochberg procedure to account for the False Discovery Rate (FDR) [26]. This adjustment helps mitigate overestimation of significant findings that can arise by chance and is an alternative to related approaches, such as Bonferroni correction [40], which modify the alpha value instead of the p-value.

Table 6 Chi-squared test results between any two different discussion forums across macro-topics.

Forum names	q-value	Cramér's V
Repository-specific forums vs. Stack Overflow	0.000	0.177
Repository-specific forums vs. Tool-specific forums	0.000	0.169
Stack Overflow vs. Tool-specific forums	0.000	0.132

Table 7 Intepretation of Cramér's V estimator

Negligible	Weak	Moderate	Relatively strong	Strong	Very strong
$0 \sim 0.1$	$0.1 \sim 0.2$	$0.2 \sim 0.4$	$0.4 \sim 0.6$	$0.6 \sim 0.8$	$0.8 \sim 1$

Following the Chi-square tests, we also calculate the Cramér's V values, which range from 0.132 to 0.177. Cramér's V is a metric that indicates the strength of association between two variables [38]. As depicted in Table 7, **these values signify weak associations between the distribution of Q&A posts and the associated forums.** Therefore, our statistical analysis implies a significant difference, but its practical implications are not pronounced. Despite this, each forum exhibits a unique pattern of macro-topics discussed. Hence, ML practitioners are still recommended to adapt their discussions to align with the distinct characteristics and preferences of each forum's audience.

Summary of RQ3

- Stack Overflow is the main source of inquiries, accounting for 48.65% of the total posts. Tool-specific forums are next (34.19%), while repository-specific forums have the fewest (17.16%). This pattern might imply that the extensive user base and broad discussion topics make Stack Overflow the go-to platform for inquiries, while repository-specific forums, such as GitHub, are favored for project-oriented discussions.
- A total of 25% of the analyzed tools have majority of user inquiries on tool-specific forums, 20% on repository-specific forums, and 35% on Stack Overflow. This pattern suggests a potential area of exploration for tool maintainers to improve user engagement on their respective forums, fostering a better collaborative community.
- In all types of forums, Environment Management stands out as the most prevalent topic, indicating a critical need for improved tooling, documentation, and best practices in environment setup and dependency management.

7 Implications

Our research provides invaluable insights for a diverse group of ML practitioners, including researchers, educators, and tool/application developers in the software and machine learning domain. Through our findings, we aim to guide their future efforts toward more efficient and cohesive management of ML assets.

7.1 Implications for Researchers

Prevalent Discussion Topics: Our findings show that environment configuration, model training, and deployment are highly prevalent in asset management. Because of this, we see a great opportunity for more research on environment management systems that work well with all stages of ML development and should be flexible enough to work with different ML tools and platforms.

Emerging Foundation Models: To evaluate the prevalence of discussions on foundation models [28] (FM), we perform an analysis based on the frequency of related posts within our dataset. First, we compile a list of keywords associated with FMs from leading GitHub repositories including Awesome-LLM[65], Open LLMs[66], and Awesome-Multimodal-Large-Language-Models[67]. Our systematic search through titles and post bodies, after preprocessing and applying conditional checks to filter out irrelevant content, reveals a modest presence (0.76%) of FM discussions in our

[65] `https://github.com/Hannibal046/Awesome-LLM`
[66] `https://github.com/eugeneyan/open-llms`
[67] `https://github.com/BradyFU/Awesome-Multimodal-Large-Language-Models`

dataset. Although insightful, this figure does not suffice to definitively assess the state of asset management in foundation models. The observed low frequency can be attributed to the nascent stage of local FM system deployment and the associated demand for asset management independent of FM providers, such as OpenAI[68]. This trend began to materialize in the last half of 2023, predominantly after the cut-off date of our data collection, which ended on $26^{th} July, 2023$. In particular, the increase in local FM deployments was significantly influenced by the public release of LLaMA-2 [124] on $18^{th} July, 2023$ and Mistral-7B [65] on $27^{th} Sep, 2023$. Although there may be overlaps in asset management needs between pre-FM and FM models, future research should focus on analyzing FM-related discussion posts that have emerged since the late summer of 2023.

7.2 Implications for Educators

MLOps Curriculum Design: Our research reveals that ML practitioners often face challenges in the software environment and dependency management, model deployment, and model development during asset management. These findings highlight the need to adapt the curriculum design. Educational institutions should prioritize course materials, hands-on experiments, and real-world case studies in the aforementioned areas. MLOps enthusiasts, not limited to computer science students, would greatly benefit from these custom curricula.

7.3 Implications for Application Developers

Holistic ML Development: Our analysis identifies 133 topics, grouped into 16 overarching macro-topics across various domains, suggesting that application developers should adopt a holistic approach to asset management. This approach includes essential steps, such as data preparation, environment setup, and model training. Much like how full-stack developers benefit from understanding every stage of development, ML developers too gain from a similar wide-ranging understanding. Adopting this holistic approach could help application developers uncover and address hidden technical debts [113] in the ML development lifecycle. As a result, they face fewer obstacles and enjoy a smoother development journey.

Tool Selection Bootstrapping: We find a clear pattern of association between certain tools and specific challenge macro-topics. This information is invaluable for application developers, offering a roadmap to anticipate and mitigate potential challenges during the tool selection process. AzureML and SageMaker, for instance, are associated with a broad range of macro-topics, underscoring their versatility. However, developers should also be prepared for the diverse challenges that come with such comprehensive platforms. Furthermore, the strong association of a significant number of tools with software dependency and environment management underscores a common area of challenge. Developers are recommended to pay special attention to this aspect, evaluating how the features and support of each tool can help navigate environment-related issues effectively.

[68] `https://openai.com`

7.4 Implications for Tool Developers

Feature Enhancement Prioritization: Our study shows that ML practitioners face great challenges in solving issues related to user interface, data development, experiment management, and code management. Therefore, we recommend that tool developers prioritize the design of more intuitive interfaces, enhanced data management features, and robust tools to manage experiments and code. For emerging tool developers, tackling these identified challenges not only addresses the core issues faced by ML practitioners but also opens the door to establishing a niche market by providing tailored solutions to these distinct pain points.

User Engagement Analysis: Tool developers, especially those who manage discussion forums, play a crucial role in shaping the experience of users who post their inquiries on these platforms [98]. Tools, such as Amazon SageMaker, H2O AI Cloud, Kedro, MLRun, MLflow, Optuna, and Vertex AI primarily have their discussions hosted on Stack Overflow. This trend may signify a preference among users to engage with a broader community or certain tool-specific forums. This suggests that maintainers of other tools could adopt certain practices from these successful forums to foster more interactions.

8 Threats to Validity

We address the validity threats in our research by examining them from four perspectives: conclusion validity, construct validity, external validity, and internal validity. For each type of threat, we present the specific actions we take to mitigate them.

8.1 Conclusion validity

Open card sorting : We have manually labeled the entire dataset consisting of 4, 687 solved posts, ensuring that we incorporate every available data point for a thorough analysis. By leveraging this comprehensive sample size, we significantly enhance the statistical power of our study. Such an increase not only strengthens the reliability of our findings, but also substantially mitigates the risk of Type II errors. In the context of our study, a Type II error might lead us to inadvertently neglect a recurring category frequently used by practitioners - a misstep that could be attributed to the limitations inherent in analyzing a restricted dataset.

Macro-topic aggregation : To mitigate the inherent risk of individual biases that might lead contributors to different conclusions about topic groupings, we have adopted a rigorous standard to aggregate topics. Initially, the first three authors take on the task independently. Following this, they conduct a collaborative review in which they cross-examine their individual categorizations. This collective approach aimes not only to harmonize their perspectives, but also to minimize any cognitive biases that might skew the results. We refer to established literature if disagreements about the categorization of a specific topic persist. By anchoring our decisions in prior research, we aim to ensure that our categorizations are not only consistent but also justifiably grounded.

Temporal Dynamics : We have collected Q&A posts from multiple developer discussion forums until $26^{th} of July, 2023$. We acknowledge that the content on these forums is dynamic and subject to constant updates and modifications. Consequently, there is a possibility that the information, challenges, and solutions we analyze may become obsolete over time. To mitigate this concern, we employ rigorous analytical methods to validate the relevance and applicability of our findings. We aim to ensure that the insights derived are not constrained by the collection period, but remain valuable and applicable in a longer timeframe.

8.2 Construct validity

Post collection : The absence of posts on certain topics does not necessarily imply the absence of such challenges for a given tool. Instead, this might reflect a potential lack of community support, which is a critical factor in tool adoption and usability. To mitigate this threat, we have broadened our scope of data collection by including data from various discussion channels, such as Stack Overflow, GitHub, and tool-specific websites. This approach aims to provide a more comprehensive understanding of the challenges within the domain.

Closed card sorting : A primary threat to the construct validity of our study stems from the subjectivity inherent in the manual filtering process of tool-specific forum data. Despite implementing a multi-stage review protocol and involving several authors to minimize personal biases, the possibility of subjective interpretation in selecting and categorizing data cannot be eliminated. This subjectivity could impact the reliability and generalizability of our findings.

Post Title refinement : Subtle nuances and the core essence of original posts may not always be accurately manifested in GPT-4 refined titles. To mitigate this, the first two authors work together to review the refined titles by examining a sample of 5% posts. When they find discrepancies, they tweak the prompts to better align the refined titles with the content of the posts. Through this adjustment process, they observe that tweaking the prompts results in topic models with higher coherence (C_V). Our goal is to ensure that the GPT-4 refined titles authentically encapsulate the intent of the original posts. This approach is in line with the recommendations by Sallou et al. [108] that stress the importance of reviewing an LLM's output to ensure its applicability and validity in software engineering research.

Topic model selection : In topic modeling, it is possible to encounter topics with overlapping key terms that may blur the distinctiveness of each topic. To address this, we examine the top-10 topic models, focusing on those with the highest coherence C_V value, to better understand both challenges and solutions. We manually review a sample of 5% of posts for each topic to assess their thematic representation and degree of overlap. Through this comparative approach, we aim to identify the topic model that best fits our study.

Open card sorting : The first and second authors possess over three years of experience in software development. This expertise plays a crucial role in minimizing threats to construct validity during the open card sorting process. Before the categorization process, these contributors engage in extensive discussion to establish a clear consensus on the labeling guideline, as outlined in Step 3.1. This step guarantees that the labels accurately capture the content of the solutions.

Macro-topic aggregation : A specific topic may relate to multiple macro-topics, leading to some uncertainty in our macro-topic aggregation choices. To address this, we conduct a manual review of a 5% sample of posts on each topic. Through this careful examination, we identify the macro-topic that the majority of these topics align with most closely.

8.3 External validity

Tool selection : The operationalization of ML encompasses numerous tools, each relevant to specific aspects of asset management. Overlooking any of these tools potentially compromises the external validity of our findings. To address this, we actively collect information on the most representative tools for ML asset management from various sources, including Google search engine, Google Scholar, GitHub, and insights provided by domain experts. Our tool selection follows the filtering criteria set by previous research [60], as outlined in Step 1.1. This approach ensures that our choices remain systematic and grounded in expert knowledge.

Forum selection : To ensure a comprehensive and representative dataset on ML asset management from the users' perspective, we source data from a diverse spectrum of discussion forums and tools. This strategy addresses potential threats to external validity arising from user preferences. Our dataset incorporates posts from general forums, such as Stack Overflow, repository-specific forums, such as GitHub Issues, and tool-specific forums, such as the MLflow Google Group.

Post translation : In the open card sorting process, we utilize the built-in translator of Microsoft Edge browser[69] to convert non-English text to English text. Although such translations might not encapsulate every nuance or cultural reference inherent in the original language, software engineering inquiry terminologies generally present consistent expressions across languages. Furthermore, considering that non-English posts constitute less than 5% of all entries, any potential influence on external validity remains minimal.

8.4 Internal validity

Closed card sorting : Including unrelated posts can introduce noise that can distort the findings of our study. To mitigate this risk, we employ the closed-open carding approach to exclude any inquiry labeled "NA". This step helps us filter out irrelevant data, allowing for a more precise analysis and, ultimately, more reliable results in our study.

[69] `https://www.microsoft.com/en-us/edge`

GPT-4 prompt tuning : We notice that changing the way we phrase the GPT-4 prompt gives us different results. This shows that it is not always easy to figure out the best way to phrase the prompts. To tackle this issue, we use a heuristic approach to tweak the prompts. Our goal is to find the one that works best for creating refined titles. As we make these adjustments, we see a clear improvement in the coherence (C_V) of the topic models. Most of our new prompts even perform better than our original ones. We then have two team members take a closer look at a random sample of 5% of the posts to make sure that our new titles still match what the original poster meant. We find that for the most part, the improved titles are in line with the original intent and are similar to labels from SE experts. This step guarantees that our analysis and results are solid and takes into account the different ways that prompts can be phrased.

9 Conclusion

In this study, we explore the challenges and their solutions associated with ML asset management tools through an analysis of Q&A posts from various developer discussion forums. We employ a mixed-method approach, using BERTopic to extract and categorize the primary topics of these challenges and the corresponding solutions. Our findings reveal a comprehensive landscape of prevalent challenges and their solutions, offering a granular view of the complexities and needs in managing ML assets. We identify key areas of concern, such as the management of software environments and dependencies, as well as the training and deployment of models. It is important to note that the tools explored in our study accommodate a wide spectrum of ML models, ranging from statistical models to deep neural networks. As a result, our insights are of significant value to a diverse audience in various contexts. These insights facilitate the judicious selection of tools, the development of effective educational resources, and the guidance of future research efforts towards bridging existing gaps.

Our study suggests four promising research directions for further research on ML asset management. Firstly, we underscore the importance of focusing on the specific issues associated with the most prevalent macro-topics identified in our study. These areas, marked by the high frequency of occurrence, represent critical pain points for ML practitioners. Detailed investigations into these macro-topics can reveal underlying issues, potential solutions, and tool and resource development opportunities.

Secondly, a more thorough analysis of the dynamics inherent in problem and knowledge inquiries across various software engineering domains is warranted. Our observations indicate a varied prevalence of inquiry types related to ML asset management. Specifically, problem inquiries are more prevalent than knowledge inquiries regarding ML asset management. This pattern aligns with previous findings in the service mesh domain [34], but diverges from general domain trends, as highlighted by earlier studies [125]. By exploring these patterns, we can gain a clearer understanding of the intricacies surrounding the users' intentions.

Thirdly, our analysis shows an interesting pattern: 16 macro-topics have the same names for both challenges and solutions. This overlap is not mere coincidence, but indicates a significant link between the challenges encountered and the solutions applied in asset management. It reveals the potential for a deeper understanding of how issues are addressed in this area. Future research should incorporate more data points and monitor the evolution of these challenges and solutions over time. Such efforts aim to establish a more comprehensive theory that accurately captures these relationships.

Lastly, exploring the association between various types of FM (e.g.,pre-trained, fine-tuned, instruction-tuned [142], proxy-tuned [75], knowledge-distilled [51]) and identifying challenge topics related to these types presents a promising avenue. In particular, the growing trend toward local deployment, driven by decreased privacy concerns [140], more cost-effective model parameters [111], and the advent of open language models [52], may signal a shift in discussions toward more sophisticated asset management in FMOps. Such research could provide essential insights, fostering innovation in FM deployment strategies.

Given the pivotal role that asset management occupies in the burgeoning field of MLOps, it is essential for ongoing research, dialogue, and collaboration to shape its trajectory, ensuring that it effectively supports the diverse and dynamic needs of ML practitioners.

10 Conflict of Interest

The authors declare that they have no conflict of interest.

11 Data Availability Statement

The datasets generated and analyzed in the course of this study are available from the corresponding author upon reasonable request.

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3. URL `https://github.com/topics/machine-learning-engineering`
4. URL `https://github.com/topics/artifact-management`
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A Appendix

Definition and illustration of solution macro-topics not discussed in section 5.1

$\hat{R}_{01}$ **Code Development**

Definition: Same as $\hat{C}_{01}$. It integrates argument management (R_{12}), code modification (R_{13}), wait time management (R_{27}), command line usage (R_{28}), API integration (R_{47}), parameter update (R_{56}), character removal (R_{57}), troubleshooting guidance (R_{58}), function modification (R_{59}), syntax update (R_{61}), exception handling (R_{63}) and parameter removal (R_{84}) to facilitate a controlled, efficient, and error-resistant MLOps environment.
Example: The following example[70] suggests checking the "Action" field when "Use Action Name" is selected in API methods.
E_{01}: *Accepted Answer: Check in all your API methods that you have not specified "Use Action Name" for any integration request and then leave the "Action" field blank. [TEXT]*

$\hat{R}_{02}$ **Code Management**

[70] https://stackoverflow.com/questions/71255132

Definition: Same as $\hat{C}_{02}$. It encompasses the creation or updating of Git repositories (R_{43}) for optimal version control and collaboration.
Example: The following example[71] illustrates adding the relative path to write to the output folder.
E_{02}: *Accepted Answer: [TEXT] Here is an example of an operation that reads from the relative path where your code exists: [CODE] You can then join the relative path of your git folder before your output. [TEXT]*

$\hat{R}_{03}$ **Computation Management**

Definition: Same as $\hat{C}_{03}$. It includes regulating resource usage through limit adjustments (R_{19}), facilitating functionalities through service provisioning (R_{30}), overseeing the creation and handling of compute instances or clusters for task execution (R_{35}), managing event-driven programming through lambda function management (R_{53}), and improving performance by increasing resource capacities (R_{60}).
Example: The following example[72] suggests increasing GPU memory, decreasing batch size, and changing to a smaller model.
E_{03}: *Accepted Answer: [TEXT] Things that you can try: Provision an instance with more GPU memory; Decrease batch size; Use a different (smaller) model.*

$\hat{R}_{04}$ **Data Development**

Definition: Same as $\hat{C}_{04}$. It covers column manipulation (R_{31}), feature filtering (R_{33}), and data transformation (R_{54}) to enhance and refine data for an effective ML pipeline.
Example: The following example[73] illustrates the usage of a feature store.
E_{04}: *Accepted Answer: [TEXT] Once a feature store is created, you will need to create an entity and then create a feature that has the labels parameter as shown in the below sample Python code. [CODE]*

$\hat{R}_{05}$ **Data Management**

Definition: Same as $\hat{C}_{05}$. It encompasses the conversion of data and datatypes for compatibility and processing (R_{40}, R_{70}), the creation of datasets for model training and validation (R_{42}), facilitating seamless data import/export for access and sharing (R_{75}), and the manipulation of buckets for organized storage in cloud services (R_{77}).
Example: The following example[74] suggests examination of the output location in Amazon S3.
E_{05}: *Accepted Answer: [TEXT] SageMaker places the model artifacts in a bucket that you own, check the S3 output location in the AWS SageMaker console. [TEXT]*

$\hat{R}_{06}$ **Environment Management**

Definition: Same as $\hat{C}_{06}$. It encompasses package upgrades (R_{01}), installation (R_{05}), version management (R_{07}), SDK upgrades (R_{15}), container customization (R_{21}), Docker management (R_{22}), package additions (R_{23}), creation of environments (R_{25}), management of environment variables (R_{34}), SDK usage (R_{37}), package downgrades (R_{41}), reinstallations (R_{44}), removals (R_{62}), notebook usage (R_{66}), Python version management (R_{67}), package imports (R_{69}), workspace creation (R_{72}), region support (R_{73}), kernel restarts (R_{76}), Docker updates (R_{78}) and notebook instance management (R_{85}).
Example: The following example[75] suggests the prohibition of circular dependency.
E_{06}: *Merge Request: Fixes #105 by not allowing circullar dependency on mlflow.*

[71] `https://stackoverflow.com/questions/70335823`
[72] `https://stackoverflow.com/questions/71398882`
[73] `https://stackoverflow.com/questions/72106030`
[74] `https://stackoverflow.com/questions/56024351`
[75] `https://github.com/getindata/kedro-kubeflow/issues/105`

$\hat{R}_{07}$ **Experiment Management**

Definition: Same as $\hat{C}_{07}$. It encapsulates the concepts of specifying run settings (R_{11}), creating or updating ML experiments (R_{39}), providing templates for machine learning tasks (R_{71}) and tailoring sessions for task execution (R_{83}).
Example: The following example[76] suggests adding information from the experiment run.
E_{07}: *Merge Request: Fix #6745: adds additional information about the run, as in the native API. [TEXT]*

$\hat{R}_{08}$ **File Management**

Definition: Same as $\hat{C}_{08}$. It encompasses the processes of storage mounting(R_{16}), directory management(R_{20}), file deletion(R_{29}), file download(R_{36}), filepath update(R_{49}), input management(R_{55}), filepath modification(R_{64}), file load(R_{65}), tracking configuration(R_{68}), and documentation update(R_{86}).
Example: The following example[77] suggests copying files from Amazon S3 to the local drive.
E_{08}: *Accepted Answer: [TEXT] The simplest option is to copy the files from S3 to the local drive (EBS or EFS) of the notebook instance: [CODE]*

$\hat{R}_{09}$ **Model Deployment**

Definition: Same as $\hat{C}_{09}$. It involves endpoint invocation (R_{24}), deployment pipeline creation (R_{26}), model prediction (R_{38}), model deployment (R_{79}) and implementation of the inference pipeline (R_{80}) to efficiently deploy and serve machine learning models in the production environment.
Example: The following example[78] suggests the usage of `undeploy_all` function.
E_{09}: *Accepted Answer: You can undeploy all the models from an endpoint by calling the method undeploy_all() [TEXT]*

$\hat{R}_{10}$ **Model Development**

Definition: Same as $\hat{C}_{10}$. It encompasses the practice of distributed training (R_{03}), which focuses on the implementation and configuration of parallel or continuous training processes for model creation.
Example: The following example[79] suggests creating a custom Docker image and uploading it to Azure Container Registry.
E_{12}: *Solution Comment: Got this working by creating a custom Docker image and putting it to the ACR tied to Azure ML workspace. [TEXT]*

$\hat{R}_{11}$ **Model Management**

Definition: Same as $\hat{C}_{11}$. It integrates the processes of model creation (R_{10}), registration (R_{32}), and file handling (R_{52}) to streamline the lifecycle of machine learning models.
Example: The following example[80] suggests replacing `load_model` with pickle.
E_{11}: *Accepted Answer: [TEXT] In particular, this answer using load_model instead of pickle seemed to work well for me: [CODE]*

$\hat{R}_{12}$ **Network Management**

Definition: Same as $\hat{C}_{12}$. It encompasses both the configuration or alteration of network settings to improve system performance (R_{09}) and the process of updating or configuring hyperlinks for precise navigation (R_{51}).

[76] https://github.com/Lightning-AI/lightning/issues/6745
[77] https://stackoverflow.com/questions/57126765
[78] https://stackoverflow.com/questions/73811793
[79] https://github.com/MicrosoftDocs/pipelines-azureml/issues/12
[80] https://stackoverflow.com/questions/72068059

Example: The following example[81] suggests creating an API gateway to share model as an endpoint.
E_{12}: *Accepted Answer: To share your model as an endpoint, you should use lambda and API gateway to create your API. [TEXT]*

$\hat{R}_{13}$ **Observability Management**

Definition: Same as $\hat{C}_{13}$. It encompasses the setup of logging systems(R_{06}), the updating or scrutiny of performance metrics(R_{50}), and the enhancement of log functions or levels for better debugging(R_{74}).
Example: The following example[82] suggests checking the metrics tab of the current step.
E_{13}: *Accepted Answer: [TEXT] In Studio, if you go to the step's Metrics tab, you will be able to see a chart/table of execution progress, including remaining items, remaining mini batches, failed items, etc. [URL]*

$\hat{R}_{14}$ **Pipeline Management**

Definition: Same as $\hat{C}_{14}$. It encompasses the cohesive administration and orchestration of job processing (R_{14}), where tasks are executed potentially in parallel or on a schedule, combined with pipeline configuration (R_{18}) that involves the creation, updating or modification of pipelines for efficient data and model workflow, and lifecycle configuration (R_{45}), which denotes the management of application states through the implementation or modification of lifecycle scripts.
Example: The following example[83] clarifies the usage of the pipeline construct.
E_{14}: *Accepted Answer: CDK L1 Constructs correspond 1:1 to a CloudFormation resource of the same name. The construct props match the resource properties. Therefore, the go-to source is the CloudFormation documentation.*

$\hat{R}_{15}$ **Security Management**

Definition: Same as $\hat{C}_{15}$. It integrates the processes of establishing, allocating, or altering access permissions (R_{04}), updating authentication credentials (R_{17}), and registering or recreating user accounts (R_{81}) to improve access control.
Example: The following example[84] suggests ungrading the workspace to migrate from V1 to V2.
E_{15}: *Accepted Answer: [TEXT] To migrate from Azure Machine Learning V1 to V2, you need to upgrade the az ml workspace share commands to equivalent az role assignment create commands. [TEXT]*

$\hat{R}_{16}$ **User Interface Management**

Definition: Same as $\hat{C}_{16}$. It includes the creation and modification of data visualizations (R_{48}) for improved data analysis and interpretation.
Example: The following example[85] clarifies the support for the Vega visualization language.
E_{16}: *Accepted Answer: [TEXT] currently Vega only powers custom charts and the underlying code for other panels are created in JavaScript, unfortunately.*

[81] `https://stackoverflow.com/questions/58802366`
[82] `https://stackoverflow.com/questions/67258917`
[83] `https://stackoverflow.com/questions/72203674`
[84] `https://stackoverflow.com/questions/74406041`
[85] `https://community.wandb.ai/t/vega-code/4605`

B Appendix

Table 9 Retrieved literature related to ML asset management tools.

Search String	**Google Scholar**		**GitHub Awesome Lists**	
	Literature	**Snowballing**	**Literature**	**Snowballing**
MLOps tools	[58, 90, 103, 107, 121]		[2, 43, 67, 123]	[3]
machine learning artifact management tools			[4]	
machine learning data management tools	[56, 72]		[5]	
machine learning experiment management tools	[47, 60, 61, 112, 119, 141]	[17, 32, 44, 94, 99, 110]	[6–8]	[9]
machine learning lifecycle management tools	[15, 27, 33, 46, 59, 74, 85–87, 138]		[10]	
machine learning model management tools	[101, 118, 126, 128]		[11]	
machine learning project management tools			[12]	
machine learning workflow management tools	[25, 30, 45, 89, 134]		[13]	

Table 10 Information of ML asset management tools.

Tool Name	**License Status**	**Launch Date**	**Tool Website**
Aim	Open source	May 2019	`https://aimstack.io`
Amazon SageMaker	Proprietary	Nov 2019	`https://aws.amazon.com/sagemaker`
Azure Machine Learning	Proprietary	2015 Feb	`https://azure.microsoft.com/en-us/products/machine-learning`
ClearML	Open source	Jun 2019	`https://github.com/allegroai/clearml`
cnvrg.io	Proprietary	Mar 2020	`https://cnvrg.io`
Codalab	Open source	Nov 2014	`https://github.com/codalab/codalab-worksheets`
Comet	Proprietary	Jan 2017	`https://www.comet.com`
Determined	Open source	Apr 2020	`https://github.com/determined-ai/determined`
Domino	Proprietary	May 2016	`https://domino.ai`
DVC	Open source	Mar 2017	`https://github.com/iterative/dvc`
Guild AI	Open source	Sep 2017	`https://github.com/guildai/guildai`
H2O AI Cloud	Proprietary	Jan 2021	`https://h2o.ai/platform/ai-cloud`
Iterative Studio	Proprietary	May 2021	`https://studio.iterative.ai`
Kedro	Open source	Apr 2019	`https://github.com/kedro-org/kedro`
MLflow	Open source	Jun 2018	`https://github.com/mlflow/mlflow`
MLRun	Open source	Sep 2019	`https://github.com/mlrun/mlrun`
Neptune	Proprietary	Feb 2019	`https://neptune.ai`
Optuna	Open source	Feb 2018	`https://github.com/optuna/optuna`
Polyaxon	Open source	Dec 2016	`https://github.com/polyaxon/polyaxon`
Sacred	Open source	Mar 2014	`https://github.com/IDSIA/sacred`
SigOpt	Proprietary	Nov 2014	`https://sigopt.com`
Valohai	Proprietary	Feb 2017	`https://valohai.com`
Verta	Proprietary	Apr 2018	`https://www.verta.ai`
Vertex AI	Proprietary	Mar 2019	`https://cloud.google.com/vertex-ai`
Weights&Biases	Open source	Mar 2017	`https://github.com/wandb/wandb`

Table 11 Stack Overflow tag list for each curated tool.

Tool Name	Stack Overflow Tags
Amazon SageMaker	amazon-sagemaker, amazon-sagemaker-experiments, amazon-sagemaker-studio, amz-sagemaker-distributed-training, amazon-sagemaker-debugger, amazon-sagemaker-clarify, amazon-sagemaker-compilers, amazon-sagemaker-experiments, amazon-sagemaker-neo
Azure Machine Learning	azureml-python-sdk, azuremlsdk, azure-machine-learning-service, azure-machine-learning-studio, azure-machine-learning-workbench, azure-ml-pipelines
ClearML	clearml
Comet	comet-ml
DVC	dvc
H2O AI Cloud	h2o.ai
Kedro	kedro
MLflow	mlflow
MLRun	mlrun
Neptune	neptune, neptune-python-utils
Optuna	optuna
Sacred	python-sacred
Vertex AI	google-cloud-vertex-ai, vertex-ai-pipeline
Weights&Biases	wandb

Table 12 Information of tool-specific forums.

Tool Name	Forum Website
Amazon SageMaker	`https://repost.aws/tags/TAT80swPyVRPKPcA0rsJYPuA/amazon-sage-maker`
Azure Machine Learning	`https://learn.microsoft.com/en-us/answers/topics/25447/azure-machine-learning`
Domino	`https://tickets.dominodatalab.com/hc/en-us/community/topics`
DVC	`https://discuss.dvc.org/c/questions/9`
Guild AI	`https://my.guild.ai/c/troubleshooting/6`
H2O AI Cloud	`https://community.h2o.ai/categories/general`
MLflow	`https://groups.google.com/g/mlflow-users`
Polyaxon	`https://github.com/orgs/polyaxon/discussions/categories/q-a`
SigOpt	`https://community.sigopt.com/c/general-discussion/9`
Vertex AI	`https://www.googlecloudcommunity.com/gc/AI-ML/bd-p/cloud-ai-ml`
Weights&Biases	`https://community.wandb.ai/c/w-b-support/36`

Table 13 Usage pattern of curated tools.

Tool Name	Usage Pattern
Aim	`import aim|from aim.* import`
Amazon SageMaker	`import sagemaker|from sagemaker.* import |#include <aws\/sagemaker.*\.h>|\"github\.com\/aws\/aws-sdk-go\/service\/sagemaker\"|package com\.amazonaws\.services\.sagemaker.*;|using Amazon\.SageMaker.*;|namespace Aws\\SageMaker\.*;|import .* from (\"@aws-sdk\/client-sagemaker\"|’@aws-sdk\/client-sagemaker’);|require\((\"@aws-sdk\/client-sagemaker\"|’@aws-sdk\/client-sagemaker’)\);|require_relative (’aws-sdk-sagemaker\/.*’|\"aws-sdk-sagemaker\/.*\")`
Azure Machine Learning	`import azureml\.core|from azureml\.core.* import`
ClearML	`file:clearml.conf|import clearml|from clearml.* import`
cnvrg.io	`import cnvrgv2|from cnvrgv2 import`
Codalab	`import codalab|from codalab.* import`
Comet	`import comet_m(l|pm)|from comet_m(l|pm).* import |import ml\.comet\.experiment.*;|library\(cometr\)`
Determined	`import determined|from determined.* import`
Domino	`file:domino\.y(a)?ml|import domino|from domino.* import |library\(domino\)`
DVC	`file:dvc\.y(a)?ml|import dvc|from dvc.* import`
Guild AI	`file:guild\.y(a)?ml|import guild|from guild.* import`
MLflow	`import mlflow|from mlflow.* import |library\(mlflow\)|import org\.mlflow.*;`
Neptune	`import neptune|from neptune.* import |library\(neptune\)`
Optuna	`import optuna|from optuna.* import`
Polyaxon	`import polyaxon|from polyaxon.* import |\"github\.com\/polyaxon\/sdks\/go\/http_client\/v1\/.*\"|require\((’polyaxon-sdk’|\"polyaxon-sdk\")\);|require\((’@polyaxon\/sdk@1\.20\.0’|\"@polyaxon\/sdk@1\.20\.0\")\);|import .* from (’polyaxon-sdk’|\"polyaxon-sdk\");|import .* from (’@polyaxon\/sdk@1\.20\.0’|\"@polyaxon\/sdk@1\.20\.0\");`
Sacred	`import sacred|from sacred.* import`
SigOpt	`import sigopt|from sigopt.* import |library\(SigOptR\)|import com\.sigopt.*;`
Valohai	`file:valohai\.y(a)?ml|import valohai_yaml|from valohai_yaml.* import`
Verta	`import verta|from verta.* import`
Vertex AI	`import google\.cloud\.aiplatform|from google\.cloud import aiplatform|import com\.google\.cloud\.aiplatform.*;|require\((\"@google-cloud\/aiplatform\"|’@google-cloud\/aiplatform’)\);|import .* from (\"@google-cloud\/aiplatform\"|’@google-cloud\/aiplatform’);`
Weights&Biases	`import wandb|from wandb.* import |import com\.wandb.*;`

Table 14 Post title keywords for each curated tool.

Tool Name	Keyword List
Amazon SageMaker	sagemaker
Azure Machine Learning	azure machine learning, azure ml, azure-ml, azureml
ClearML	clearml
cnvrg.io	cnvrg
Codalab	codalab
Comet	comet-ml
Determined	determined
Domino	domino
DVC	dvc
Guild AI	guild ai, guild-ai, guildai
H2O AI Cloud	h2o ai, h2o.ai
Kedro	kedro
MLflow	mlflow
MLRun	mlrun
Neptune	neptune
Optuna	optuna
Polyaxon	polyaxon
Sacred	sacred
SigOpt	sigopt
Valohai	valohai
Verta	modeldb, verta
Vertex AI	vertex ai, vertex-ai, vertexai
Weights&Biases	weights and biases, wandb, Weights&Biases, weights&biases, w & b, w&b

Table 15 Parameters for GPT-4 prompting.

Parameter	Value	Description
`temperature`	0	Temperature controls the randomness of the generated text.
`top_p`	1	Top-p sets the cumulative probability threshold to direct the sampling of words to generate coherent and grammatically correct text.
`frequency_penalty`	0	Frequency penalty controls the use of common words or phrases by the model in the generated text.
`presence_penalty`	0	Presence penalty controls the probability that a specific token is produced next in the generated text.
`max_tokens`	50	Max tokens control the maximum number of tokens to generate in the text.

Table 17: Challenge topic information.

Index	**Topic**	**Index**	**Topic**
C_{01}	Pipeline Step	C_{02}	Notebook Instance
C_{03}	Docker Image	C_{04}	Version
C_{05}	Log	C_{06}	Plots
C_{07}	Studio	C_{08}	PyTorch
C_{09}	Prediction	C_{10}	Labeling Job
C_{11}	Hyperparameter Tuning	C_{12}	TensorFlow
C_{13}	Spark	C_{14}	RStudio
C_{15}	Workspace	C_{16}	Batch Transform
C_{17}	Web Service	C_{18}	Experiment
C_{19}	Instance	C_{20}	Sweep
C_{21}	Deploying Model	C_{22}	Columns Values
C_{23}	Inference Endpoint	C_{24}	Compute
C_{25}	Account	C_{26}	File Directory
C_{27}	Object Attribute	C_{28}	Parameters Parameter
C_{29}	File Pandas	C_{30}	Git Repo
C_{31}	Training Job	C_{32}	Save Model
C_{33}	Bucket	C_{34}	Limit Exceeded
C_{35}	Data Factory	C_{36}	Format Convert
C_{37}	Server	C_{38}	Feature Store
C_{39}	Environment	C_{40}	Initialization Init
C_{41}	Custom Metrics	C_{42}	Compute Cluster
C_{43}	Model Endpoint	C_{44}	Memory
C_{45}	Stuck Queue	C_{46}	Distributed Training
C_{47}	File Upload	C_{48}	Python
C_{49}	TensorBoard	C_{50}	Deploying Endpoint
C_{51}	Authentication	C_{52}	Module Import
C_{53}	Deployment Model	C_{54}	Artifact Download
C_{55}	File Read	C_{56}	Batch Prediction
C_{57}	API	C_{58}	API Key
C_{59}	File Storage	C_{60}	Creating Terraform
C_{61}	CUDA Memory	C_{62}	Register Model
C_{63}	Log Metrics	C_{64}	Config Configuration
C_{65}	Inference Pipeline	C_{66}	Invoke Endpoint
C_{67}	Blob Storage	C_{68}	Comparison Performance
C_{69}	Loading Model	C_{70}	Pickle File
C_{71}	Endpoint Lambda	C_{72}	File Download
C_{73}	Broken Link	C_{74}	Permissions Authorization

C_{75}	Exporting Data	C_{76}	Datasets
C_{77}	Model Registry	C_{78}	Image Read
C_{79}	Artifacts	C_{80}	Deploy Model
C_{81}	Endpoint Content	C_{82}	Creating Model
C_{83}	Train Model	C_{84}	Score Model
C_{85}	Endpoint Ping	C_{86}	Parallelization Job
C_{87}	Module Usage	C_{88}	Deployment Kubernetes
C_{89}	Data Stores	C_{90}	Permission Denied
C_{91}	Training Reports	C_{92}	Log Model
C_{93}	Model Monitoring	C_{94}	Model Deployment
C_{95}	Training Pipeline	C_{96}	Missing Module
C_{97}	Install Package	C_{98}	Logs CloudWatch
C_{99}	Import Notebook	C_{100}	Training Model
C_{101}	Installation	C_{102}	Quota Request
C_{103}	NEO Compiling	C_{104}	Connection
C_{105}	Training Container	C_{106}	Huggingface Model
C_{107}	Container Registry	C_{108}	Model ONNX
C_{109}	Models	C_{110}	Globals YAML
C_{111}	Deployment ACI	C_{112}	Trained Model
C_{113}	Web Interface	C_{114}	scikit-learn
C_{115}	Dependency	C_{116}	Nested Runs
C_{117}	Import Data	C_{118}	Endpoint Deploying
C_{119}	Endpoint Prediction	C_{120}	Lifecycle Configuration
C_{121}	Output Inputs	C_{122}	Custom Job
C_{123}	Jupyter Notebook	C_{124}	Response Endpoint
C_{125}	Shared Cache	C_{126}	Training YOLO
C_{127}	Checkpoints Training	C_{128}	Endpoint Transitioning
C_{129}	Training File	C_{130}	Inference
C_{131}	Connecting RDS	C_{132}	Model Serving
C_{133}	Tuning Model		

Table 18: Solution topic information.

Index	**Topic**	**Index**	**Topic**
R_{01}	Package Upgrade	R_{02}	Recommendation
R_{03}	Distributed Training	R_{04}	Permission
R_{05}	Package Installation	R_{06}	Logging Function
R_{07}	Package Version	R_{08}	Patch and Fix
R_{09}	Network Configuration	R_{10}	Model Creation
R_{11}	Run Configuration	R_{12}	Argument

R_{13}	Code Modification	R_{14}	Job Processing
R_{15}	SDK Upgrade	R_{16}	Storage Mounting
R_{17}	Credential Update	R_{18}	Pipeline Configuration
R_{19}	Resource Limit Adjustment	R_{20}	Directory
R_{21}	Container Customization	R_{22}	Docker
R_{23}	Package Addition	R_{24}	Endpoint Invocation
R_{25}	Environment Creation	R_{26}	Pipeline Deployment
R_{27}	Wait Time	R_{28}	Command Line Usage
R_{29}	File Deletion	R_{30}	Service Provisioning
R_{31}	Column Manipulation	R_{32}	Model Registration
R_{33}	Feature Filtering	R_{34}	Environment Variable
R_{35}	Compute Instance	R_{36}	File Download
R_{37}	SDK Usage	R_{38}	Model Prediction
R_{39}	Experiment Creation	R_{40}	Data Conversion
R_{41}	Package Downgrade	R_{42}	Dataset Creation
R_{43}	Git Repository	R_{44}	Package Reinstallation
R_{45}	Lifecycle Configuration	R_{46}	Support Ticket Creation
R_{47}	API Integration	R_{48}	Data Visualization
R_{49}	Filepath Update	R_{50}	Metrics
R_{51}	Hyperlink Update	R_{52}	Model File Handling
R_{53}	Lambda Function	R_{54}	Data Transformation
R_{55}	Input Schema	R_{56}	Parameter Update
R_{57}	Character Removal	R_{58}	Troubleshooting Guidance
R_{59}	Function Modification	R_{60}	Resource Increase
R_{61}	Syntax Update	R_{62}	Package Removal
R_{63}	Exception Handling	R_{64}	Filepath Modification
R_{65}	File Load	R_{66}	Notebook Usage
R_{67}	Python Version	R_{68}	Tracking Configuration
R_{69}	Package Import	R_{70}	Datatype Conversion
R_{71}	Task Modeling	R_{72}	Workspace Creation
R_{73}	Region Support	R_{74}	Logging Update
R_{75}	Data Import/Export	R_{76}	Kernel Restart
R_{77}	Bucket Manipulation	R_{78}	Docker Update
R_{79}	Model Deployment	R_{80}	Inference Pipeline
R_{81}	Account Creation	R_{82}	Comparison
R_{83}	Session Creation	R_{84}	Parameter Removal
R_{85}	Notebook Instance	R_{86}	Documentation Update

Table 16 Hyperparameter search space for topic modeling of post inquiries.

Hyperparameter Name	**Range for challenge modeling**	**Range for solution modeling**	**Description**
`min_cluster_size`	30,40,. . . ,100	20,30,40	the minimum size of a cluster.
`min_samples`	1,2,. . . ,100	1,2,. . . ,6,. . . ,40	the number of outliers generated.
`n_components`	3,4,5,. . . ,10	3,4,. . . ,8	the dimensionality of the embeddings after reduction.
`ngram_range`	1,2,3	1,2,3	the number of words in the topic representation.
`embedding_model`	all-mpnet-base-v2	all-mpnet-base-v2	the transformation of input documents into numerical representations.
`metrics`	cosine	cosine	similarity measure between two data points in the embedding space.
`random_state`	42	42	the algorithmic randomness for reproducibility.