An LLM-based Agent for Reliable Docker Environment Configuration

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Abstract

Environment configuration is a critical yet time-consuming step in software development, especially when dealing with unfamiliar code repositories. While Large Language Models (LLMs) demonstrate the potential to accomplish software engineering tasks, existing methods for environment configuration often rely on manual efforts or fragile scripts, leading to inefficiencies and unreliable outcomes. We introduce Repo2Run, the first LLM-based agent designed to fully automate environment configuration and generate executable Dockerfiles for arbitrary Python repositories. We address two major challenges: (1) enabling the LLM agent to configure environments within isolated Docker containers, and (2) ensuring the successful configuration process is recorded and accurately transferred to a Dockerfile without error. To achieve this, we propose atomic configuration synthesis, featuring a **dual-environment architecture** (internal and external environment) with a rollback mechanism to prevent environment "pollution" from failed commands, guaranteeing atomic execution (execute fully or not at all) and a **Dockerfile generator** to transfer successful configuration steps into runnable Dockerfiles. We evaluate Repo2Run on our proposed benchmark of 420 recent Python repositories with unit tests, where it achieves an 86.0% success rate, outperforming the best baseline by 63.9%. Repo2Run is available at `https://github.com/bytedance/Repo2Run`.

1 Introduction

Configuring the environment is typically the first step for developers to run and test the code. Meanwhile, Large Language Models (LLMs) are increasingly being integrated into tools such as chatbots and coding assistants, showcasing their potential to accomplish various software engineering tasks [32, 12, 4]. As a result, the research community explores how LLMs can be leveraged to assist with more complex real-world tasks in software development. Furthermore, LLM-based agents [13, 5, 1] are also increasingly being utilized in software engineering. With the advancement of LLM-based agents and their applications in automated programming, many techniques now require running tests in the runtime environment to acquire more comprehensive information. However, previous approaches often rely on manually configuring environments [14], and writing individual configuration scripts for each task, which is both time-consuming and labor-intensive.

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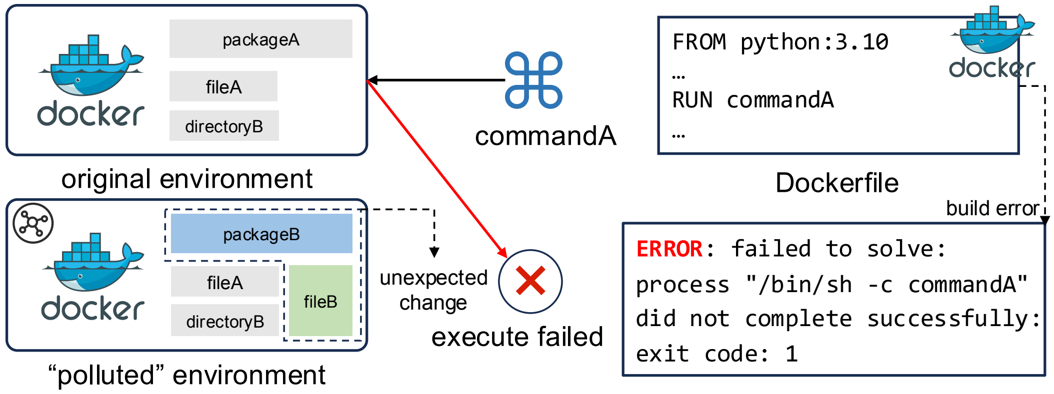
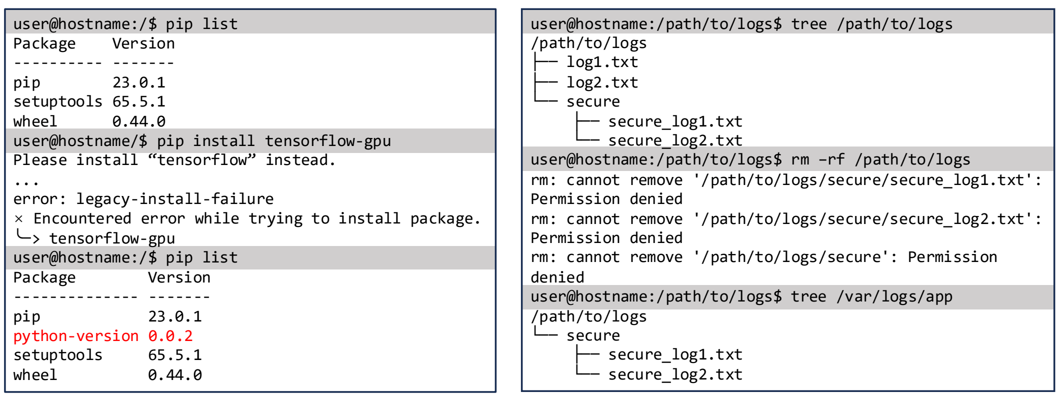


Figure 1: The illustration of a command executing failed and "polluting" the environment.



(a) Failed "pip install" example. (b) Failed "rm -rf" example.

Figure 2: Examples of the failed command causing "polluted" environment.

We conduct an empirical study with eight professional developers from Internet companies, all with an average of seven years of development experience. The results indicate that when dealing with unfamiliar code repositories, five out of eight developers spend a great amount of time configuring the environment. Moreover, there is a strong willingness among them to use automated tools to alleviate the burden of environment setup. Details of the empirical study are presented in Appendix A.

In response to the growing complexity and time required for manual environment configuration, containerization tools like Docker have become a good solution. Docker allows developers to create isolated and consistent environments across different systems, thus eliminating the common "it works on my machine" problem [23]. Dockerfiles are commonly used to configure Docker environments, which include two parts: the base image and the configuration process. The base image is a pre-packaged environment (e.g., python:3.10) that provides a standardized, isolated environment for development without the need for local deployment. The configuration process involves additional steps performed on top of the base image.

Inspired by the idea of the Docker container, we design our LLM agent for environment configuration, Repo2Run, with a fundamental concept: utilize an LLM agent to configure the environment within an isolated Docker container. If the LLM successfully configures the environment, we only need to record the configuration steps and transfer them into a Dockerfile. During the environment configuration process, we mainly face the following two major challenges:

Ensure the LLM agent configures the environment within a Docker container. One major challenge is ensuring that the LLM agent can accurately configure the environment inside the Docker container. This involves selecting an appropriate base image, installing dependencies, resolving conflicts, and running tests, etc. If we do not provide the LLM agent with effective tools, the LLM agent will find it difficult to handle the various complex issues encountered during configuration.

Ensure the successful configuration process is recorded and accurately transferred to a runnable Dockerfile. Another major challenge is maintaining an accurate and comprehensive record of the environment configuration process. As illustrated in Figure 1, a failed executed command "`commandA`" may cause irreversible "pollution". Although "`commandA`" fails to run, it still causes "pollution" to the original environment, potentially leading to unexpected changes to packages, files, or directories in the system. To accurately reproduce such system changes, we need to add the "`RUN commandA`" statement in the Dockerfile. However, this will cause the Dockerfile to build fail.

Figure 2 shows two practical examples. As shown in Figure 2 (a), when we run "`pip install tensorflow-gpu`", the command fails to execute because the package `tensorflow-gpu` has been deprecated. However, it still introduces the "`python-version`" package which is not present in the original environment. In Figure 2 (b), when we run the "`rm -rf /path/to/logs`" command to delete the directory, some files fail to be deleted due to a lack of permission. However, the files that have already been deleted (e.g., `log1.txt` and `log2.txt`) are not restored. Such "pollution" caused by failed commands may make the environment enter an **uncertain state**. This state cannot be reached by directly adding commands to the Dockerfile, as doing so would cause the Dockerfile build process to fail.

To address the aforementioned two challenges, we propose **Repo2Run** based on **atomic configuration synthesis**, which consists of a dual-environment architecture and a Dockerfile generator. To the best of our knowledge, this is the first work that leverages the LLM agent for automated Dockerfile generation and environment configuration in a completely automated manner.

The dual-environment architecture comprises both an **internal** and an **external** environment. The internal environment serves as a Docker container sandbox, allowing the LLM agent to execute various commands. The external environment assists in configuring the environment in the internal environment. It facilitates the action-observation interactions of the LLM agent and supports operations such as changing the base image of the internal environment. In addition, we design a rollback mechanism that performs a rollback when a command fails, preventing the system from entering an uncertain state. This ensures that we can execute commands "atomically", meaning each command either executes fully or not at all.

The Dockerfile generator designs a set of rules to transfer the successfully executed commands in the internal environment into statements in the Dockerfile without errors. Combined with the rollback mechanism, we finally ensure that all generated Dockerfiles are successfully built.

In summary, the contributions of this paper are as follows:

• We propose Repo2Run, the first LLM-based agent designed to automate environment configuration and generate Dockerfiles for arbitrary Python repositories, enabling the execution of tests within these repositories.

• We propose atomic configuration synthesis, which includes a dual-environment architecture and a Dockerfile generator, ensuring that all Dockerfiles generated by Repo2Run are runnable.

• We create a benchmark to evaluate the performance of Repo2Run by crawling 420 popular Python repositories with unit tests from GitHub released within 2024. Repo2Run successfully configures the environment for 361 of these repositories, achieving a success rate of 86.0%, which is 63.9% higher than the best baseline.

2 Environment configuration

In this part, we formulate the task of the environment configuration. It involves identifying an appropriate **base image** (B) and a **configuration process** (Γ). The objective is to ensure that the final system state (S_f) successfully runs all the unit tests in the repository.

2.1 State Transition

Environment State (S): The environmental state (S) represents the current state of the computer system, which encompasses all variables, files, cache, etc. Any state $S \in \mathcal{S}$, where ($\mathcal{S}$) denotes the set of all possible environment states.

Command (C): The command C represents an individual instruction or action that can be executed in the environment through interfaces such as `bash`, thus directly changing the system state.
State Transition Function (δ): The state transition function (δ) defines the process through which the system transitions from one state to another state upon execution of a given command, i.e.,

$$\delta : \mathcal{S} \times \mathcal{C} \rightarrow \mathcal{S}, \quad \delta(S, C) = S' \tag{1}$$

Here, S' is the new state after execution of command C.

2.2 Base image

Empty initial state ($S_\emptyset$): The empty initial state ($S_\emptyset$) represents a completely unconfigured, bare operating system or a purely hypothetical state without applications and configurations. This state is used for theoretical purposes to define the starting point of a system's configuration. $S_\emptyset \in \mathcal{S}$.
Base image (B): From the empty initial state ($S_\emptyset$), we can construct the base image B by applying a series of actions. The base image B is essentially the final state achieved by applying a sequence of instructions starting from $S_\emptyset$:

$$B = \delta^m(S_\emptyset, C_1^B, C_2^B, \ldots, C_m^B) \tag{2}$$

Here, $C_1^B, C_2^B, \ldots, C_m^B$ are the individual commands that constitute the base image.

2.3 Configuration process and target state

Configuration Process (Γ): The configuration process, denoted as Γ, involves transforming the environment starting from the base image B by applying a series of actions. The result of this process is a state S_f, which we refer to as the resultant state. Formally, the configuration process can be represented as:

$$S_f = \delta^n \left(B, C_1, C_2, \ldots, C_n\right) \tag{3}$$

Following this transformation, it is crucial to verify whether S_f meets all the required conditions to be considered the target state. This verification is performed using the state verification function.

State verification (ϵ): The state verification function (ϵ) determines whether the resultant state (S_f) successfully runs all tests within the repository after executing the configuration process (Γ). It maps a given state (S) to a binary value indicating whether all tests could be run in the resultant configuration: $\epsilon(S)$ returns 0 if all tests are successfully run, and 1 otherwise. If $\epsilon(S_f) = 0$, it indicates that the configuration process has finished and the resultant state S_f is considered the **target state**. Otherwise, it means that S_f does not meet the necessary conditions.

3 Repo2Run

In this part, we introduce the design of Repo2Run and atomic configuration synthesis. As shown in Repo2Run Workflow in Figure 3, the dual-environment architecture consists of an external environment and an internal environment. The internal environment is a Docker container where the actual environment configuration is executed, while the external environment assists the internal environment in setting up the configuration. After successfully configuring the environment, the Dockerfile generator will create the Dockerfile.

3.1 External environment

• **Action-observation interaction**: In each turn of the environment-agent interaction, the event history $E_t = (a_1, o_1), (a_2, o_2), \ldots, (a_{t-1}, o_{t-1})$ records the historical actions and observations up to time step t. Additionally, the sequence of successfully executed commands $C_1, C_2, \ldots, C_n$ helps remind the LLM agent of the current system state.

At time step t, given the event history E_t and the sequence of successfully executed commands $C_1, C_2, \ldots, C_n$, the LLM agent generates a response including an action a_t:

$$a_t = \pi(E_t, C_1, C_2, \ldots, C_n) \tag{4}$$

where π is the function of the LLM agent's decision. The environment state then transitions based on the action a_t:

$$S_{t+1} = \delta(S_t, a_t) \tag{5}$$

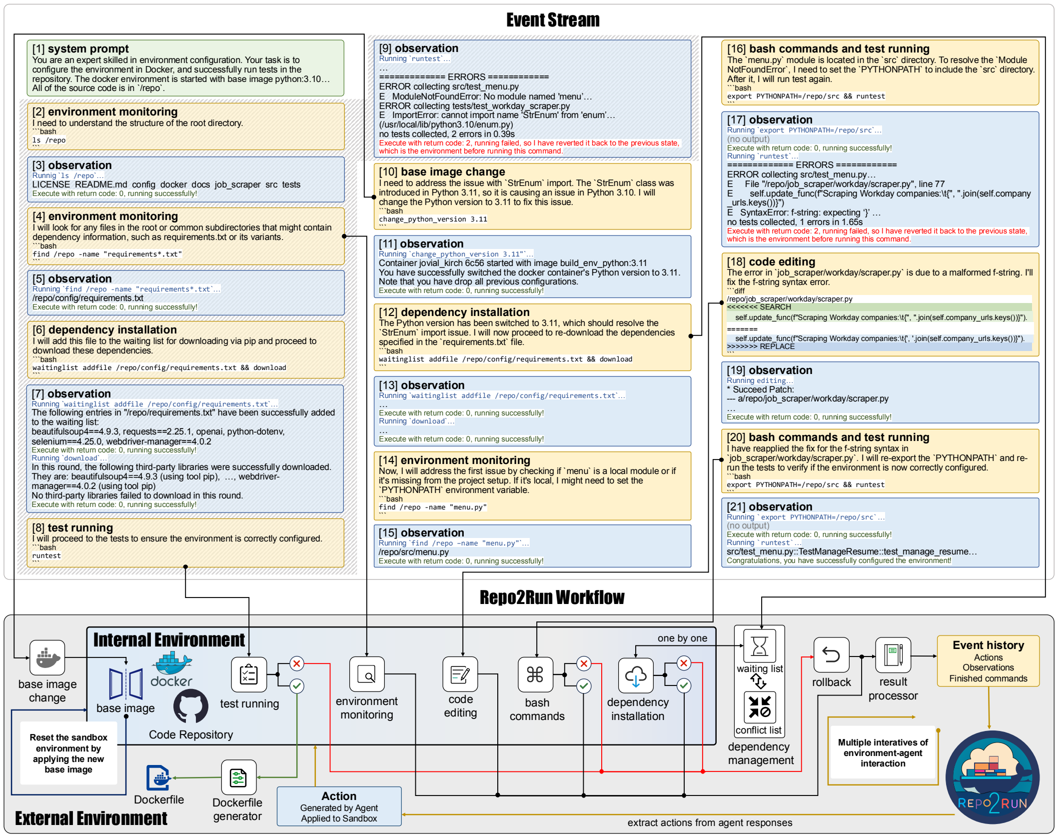


Figure 3: An example process of **Repo2Run**, which illustrates two main parts: **Event Stream** and **Repo2Run Workflow**. The Event Stream tracks the entire action-observation process, where green boxes represent system prompts, yellow boxes represent responses from the LLM agent including the actions, and blue boxes represent observations from the Runtime Environment. The shaded actions indicate configurations abandoned after **base image change**. In the Event Stream, the blue text indicates that the command starts running, the green text indicates that the command runs successfully, and the red text indicates that the command fails. The **Repo2Run Workflow** consists of the **internal environment** and the **external environment**. The internal environment serves as the actual configuration Docker-based sandbox, which builds an actual testing runtime environment. The external environment executes the action-observation process and assists in the configuration process within the internal environment.

This iterative process ensures that the LLM agent remains informed of the system's current state and makes decisions accordingly, facilitating effective multi-turn interaction within the environment.

• **Rollback** (ρ): As illustrated in Figure 1, commands C_{fail} may lead to an **uncertain state** (S_u) if not successfully executed. When a command executes failed (i.e., the command returns a non-zero return code), the system transitions into an uncertain state as defined by:

$$S_u = \delta(S_{k-1}, C_{fail}) \tag{6}$$

Here, C_{fail} is the failed executed command. If a command fails, the system will transition to the uncertain state S_u. To avoid such uncertainty, we introduce **rollback** (ρ). In the event of a failure at any step, the rollback mechanism restores the environment to the last certain state:

$$\rho : \mathcal{S} \times \mathcal{C} \to \mathcal{S}, \quad \rho(S_u, C_1, C_2, \ldots, C_k) = S_{k-1} \tag{7}$$

Specifically, each time an instruction (C) is executed, we utilize the "`docker commit`" command to take a snapshot of the current state. Once the instruction is completed, we check its return code. If the return code is not 0, it indicates a failure in executing the instruction, and we replace the image with the most recently committed one. Besides, some instructions, such as "`cat`", generally do not

(default base image: python:3.10)

	internal command	return code	dir
1	ls /repo	0	/
2	cat /repo/README.md	0	/
3	pip install A	0	/
4	pip install -e /repo	1	/
5	change_python_version 3.11	0	/
6	cd /repo	0	/
7	cat setup.py	0	/repo
8	pip install -e .	0	/repo
9	python code_edit.py 0.patch	0	/repo
10	poetry install	1	/repo
11	pip install B>=1.0, <2.0	0	/
12	runtest	1	/
13	export TOKEN=123	0	/
14	runtest	0	/
15	pipdeptree –json-tree	0	/

(a) Commands running in the internal environment.

(b) The process of generating the Dockerfile by Dockerfile generator.

Figure 4: An example of the Dockerfile generator to transfer the commands into a runnable Dockerfile.

change the state of the environment, and thus, we do not apply the rollback mechanism to them. The complete list of these actions is shown in Appendix B.

• **Base image change**: If the LLM agent identifies that the currently selected base image is incorrect or unsuitable during the environment configuration process, it can reselect the base image. Once a new image is chosen, all previous configurations become invalid, and the executed commands are cleared, necessitating a restart of the configuration process. For instance, as shown in Figure 3, when the LLM agent discovers that the "`StrEnum`" class cannot be imported through testing, which is only available in the Python standard library starting from version 3.11, it decides to reselect the base image to python:3.11.

• **Result processor**: In each turn of the interaction, executing commands may generate extensive output (e.g., logs), which can greatly increase the burden of the LLM agent. Therefore, whenever such information is added to the event history, we truncate excessively long text, retaining only the initial and final sections up to a specific length.

• **Dockerfile generator**: If the LLM agent successfully runs all tests in the repository in the internal environment, the configuration process needs to be recorded in a Dockerfile. Figure 4 illustrates the Dockerfile generator's operation. 4 (a) lists the internal commands actually executed in the internal environment, their return codes (e.g., `0` indicates success, otherwise failure), and the current directory (`dir`). 4 (b) shows the process of generating the Dockerfile.

The principles for the conversion process include the following steps, scanning all internal commands sequentially, and the line numbers mentioned below match the line number of Figure 4 (a):

1. By default, use `python:3.10` as the base image.
2. For commands that run successfully (i.e., have a return code of `0`), prepend the command with "`RUN`" to form a Dockerfile statement (e.g., line 3). Commands that fail (i.e., have a return code other than `0`, such as line 4) are rolled back and not included in the Dockerfile. An exception is some commands typically do not change the current state (such as "`cat`" on line 2). These commands are not added to the Dockerfile. We show the details in Appendix B.
3. If `dir` is not the root directory, use `cd` to change to that directory before running the command, as each Dockerfile statement runs in its own directory session.
4. If a base image change statement is encountered (e.g., line 5), discard all previous configurations and switch to the new base image.
5. If a code editing command is encountered (e.g., line 9), copy the patch and editing script into the Docker container before executing the editing command.
6. If an export statement for adding environment variables is encountered (e.g., line 13), convert it to a persistent `ENV` statement.
7. After all statements have been scanned, check for dependency installation commands and replace any unspecified versions (e.g., "`B>=1.0,<2.0`" in line 11) with the actual versions

downloaded in the Docker container (e.g., "`B==1.5.1`" in the final Dockerfile of Figure 4 (b)).

3.2 Internal environment

As shown in the Repo2Run workflow of Figure 3, the internal environment consists of a Docker container with a base image B and the code repository to be configured. According to the latest data[3] from 2025, we select Python 3.10 as our default Docker base image due to its increasing usage and wide application among all Python 3 versions. Additionally, we categorize the executable actions within the internal environment into five types: environment monitoring, dependency installation, bash commands, code editing, and test running.

• **Environment monitoring**: It serves as the eyes of the LLM agent in the internal environment, allowing it to observe the current state of the environment. These commands usually do not change the state of the environment. For instance, commands like "`ls`" and "`cat`" are employed to inspect directories and files. Additionally, commands like "`pip list`" and "`pipdeptree`"[4] are utilized to get the installed version of third-party libraries in the current environment. For example, in the fourth part of Event Stream in Figure 3, the LLM agent calls the "`find`" command to search for `requirements.txt` within the environment to determine which dependencies need to be installed.

• **Dependency installation**: It is primarily used to install the third-party libraries necessary for running tests, including libraries managed by both "`pip`" and "`apt-get`". To avoid dependency conflicts that may arise when downloading multiple packages, we implement a dependency management system in the external environment. Initially, the third-party libraries to be downloaded are added to a waiting list. If there are different constraints for the same library (e.g., "`A>=1.0`" and "`A<1.0`"), they will be moved to a conflict list, and the LLM agent will determine the appropriate version to download.

We design a set of tools for the LLM agent to manage the installations. For instance, as shown in Figure 3, the action "`waitinglist addfile`" adds all elements from `requirements.txt` to the waiting list, while executing the "`download`" command, third-party libraries are taken one by one from the waiting list and installed in the internal environment. The installation commands (e.g., "`pip install`" and "`apt-get install`") are executed. If the installation succeeds, the state of the environment is updated; if it fails, a rollback is performed. We show all our designed tools in Appendix C.

• **Test running**: It detects whether the current environment is successfully configured by running "`pytest`" unit tests. If the state (S_f) of the current environment passes the tests, it indicates that the LLM agent has successfully configured the environment within the Docker container, and the internal environment's process concludes. Conversely, if some tests fail, the error information is communicated back to the LLM agent, allowing it to perform further configurations and adjustments based on the errors.

• **Code editing**: It allows the LLM agent to modify the code within the internal environment, including codes inside and outside the repository. Besides, to prevent the LLM agent from spuriously running the tests by directly modifying or deleting the test files, we do not permit the LLM agent to modify or delete the original test files within the repository. For instance, Figure 3 demonstrates code editing to correct a syntax error resulting from the improper use of double quotes in a Python f-string.

• **Bash commands**: Aside from the commands above, we also enable the LLM agent to directly invoke bash commands to interact with the internal environment. As shown in Figure 3, the LLM agent uses the command "`export PYTHONPATH=/repo/src`".

4 Experiment

We evaluate the effectiveness of Repo2Run on 420 Python code repositories. As the popular option, we select `gpt-4o-2024-05-13` for subsequent experiments, with the temperature uniformly set to 0.2.

[3]https://w3techs.com/technologies/history_details/pl-python/3

[4]https://github.com/tox-dev/pipdeptree

Table 1: The results of different baselines.

Metric	DGSR	ECSR
pipreqs	29.8% (125)	6.0% (25)
LLM generator	47.6% (200)	22.1% (93)
SWE-agent	26.9% (113)	9.0% (38)
Repo2Run	100% (420)	86.0% (361)

4.1 Benchmark

To the best of our knowledge, there is no prior work similar to Repo2Run that constructs an environment for arbitrary Python repositories. To validate the capability of Repo2Run in environment configuration, we create our new benchmark consisting of selected Python repositories from GitHub based on the following criteria:

• **Creation date**: To minimize the impact of data contamination, we carefully selected repositories created in 2024, ensuring they are not part of the training data for mainstream large language models.

• **Star count**: To ensure the quality of the repositories, we only select those with a star count greater than 100.

• **Test directory**: `Pytest` is a leading Python testing framework that is compatible with many other Python testing tools, such as `unittest`. It identifies and runs test files and test functions that are named with a "`test_`" prefix or a "`_test`" suffix. Python repositories usually place their test files in the "`test`" or "`tests`" directory. To effectively filter repositories with unit tests, we keep repositories with the "`test`" or "`tests`" directory in their root directory to filter the repositories that most probably have unit tests.

Through the selection process, we crawl all 449 repositories that meet all the above requirements[5]. Then, we filter 420 repositories containing at least one unit test. These repositories constitute our benchmark for subsequent experiments. The details of the benchmark are presented in Appendix D.

4.2 Evaluation metrics

• **Dockerfile Generation Success Rate (DGSR)**: It indicates the percentage of attempts where the method successfully generates a **runnable** Dockerfile. To be considered successful, the generated Dockerfile must be able to build without errors. If the Dockerfile for a code repository successfully builds, it is regarded as a successful generation. Generating runnable Dockerfile is fundamental for successfully configuring the environment.

• **Environment Configuration Success Rate (ECSR)**: It represents the percentage of attempts where the method successfully configures environments. For a successful configuration, the generated Dockerfile must not only build successfully but also allow tests to run by "`pytest`" in the Docker container. We are only concerned with whether tests can be executed, regardless of whether they pass or fail, as outcomes of tests may inherently vary within the repository.

4.3 Baselines

• **pipreqs**[6]: It is an automated tool that generates a "`requirements.txt`" file by analyzing the import statements in the Python scripts and identifying the necessary dependencies without LLM. Using the `requirements.txt` file generated by pipreqs, we create a Dockerfile. The detail is provided in Appendix E.

• **LLM generator**: The "`README`" file in a code repository usually contains environment configuration instructions. Therefore, we directly drive the LLM to read the "`README`" file and generate an executable Dockerfile accordingly.

• **SWE-agent** [26]: SWE-agent establishes a custom agent-computer interface (ACI) that facilitates the LLM agent's interaction with the repository environment by allowing actions such as reading

[5] The crawling was performed in December 2024.

[6] `https://github.com/bndr/pipreqs`

Table 2: The results of ablation experiments.

Metric	DGSR	ECSR
w/o dual-environment	92.4% (388)	41.7% (175)
w/o Dockerfile generator	19.5% (82)	13.8% (58)
Repo2Run	100% (420)	86.0% (361)

files, editing files, and executing bash commands. Initially intended as an LLM agent for bug fixing, we preserve its framework and default settings, adjust its prompts, and use it as a baseline.

4.4 Experimental Results

The results of different baselines are presented in Table 1. We observe that Repo2Run consistently outperforms other baselines on both DGSR and ECSR. Repo2Run ultimately completed environment configuration for 361 code repositories, achieving an ECSR of 86.0%. It is 63.9% higher than the highest rate achieved by other methods, demonstrating great advantages. Due to the design of atomic configuration synthesis, Repo2Run successfully generates Dockerfiles that can be built successfully for all 420 code repositories, which other tools cannot guarantee.

For pipreqs, the main failures come from two reasons. First, generating the requirements.txt fails when there are issues within the repository, such as encoding errors or syntax errors in the files. This happens in 30 repositories (7.1%). Second, even when requirements.txt is generated, it might not download properly due to package version conflicts. This occurs in 265 repositories (63.1%). Besides, both the LLM generator and SWE-agent fail to ensure that the generated Dockerfile can be successfully built due to the lack of an ensuring mechanism. Surprisingly, the ability of SWE-agent, a general agent framework, to generate Dockerfiles is even weaker than simply letting the LLM read the "`README`" file. This indicates that a general agent framework cannot guarantee the generation of runnable Dockerfiles. Ensuring mechanisms like atomic configuration synthesis are necessary to effectively use the interactive information from the agent to generate runnable Dockerfiles.

4.5 Ablabtion of Repo2Run

To investigate the impacts of the dual-environment architecture and Dockerfile generator separately, as two parts of atomic configuration synthesis, we separately remove each component of them. For the experiment without the dual-environment architecture, we retain only the internal environment's bash commands as the most basic interface and remove all other tools. For the experiment without the Dockerfile generator, we directly instruct the LLM to generate a runnable Dockerfile.

Experimental result of the ablation study is shown in Table 2. We observe that removing the dual-environment architecture and retaining only bash commands results in a 7.6% decrease in DGSR. The main reason for this drop is the removal of rollback and other designs, making the system more prone to entering uncertain states and subsequently failing to reproduce. In addition, ECSR shows a 44.3% decrease, primarily because the simplification of design makes it more difficult for the LLM agent to complete configuration in the internal environment. Besides, removing the Dockerfile generator directly leads to an 80.5% drop in DGSR. This indicates that having the LLM directly generate Dockerfiles is unlikely to fully follow the event history, resulting in Dockerfiles that fail to build successfully. This also directly causes a sharp decline in ECSR.

It is also observed that Repo2Run without the Dockerfile generator is outperformed by the LLM generator. This is because the LLM generator leverages the "`README`" file, which provides a clear, simple and high-level overview of the environment configuration, allowing for more accurate Dockerfile generation. In contrast, the event history-based approach lacks this context, making it harder for the LLM to fully understand the configuration goals. However, the Dockerfile generator effectively utilizes the detailed event history, highlighting the complementary roles of both components of Repo2Run in generating a reliable Dockerfile.

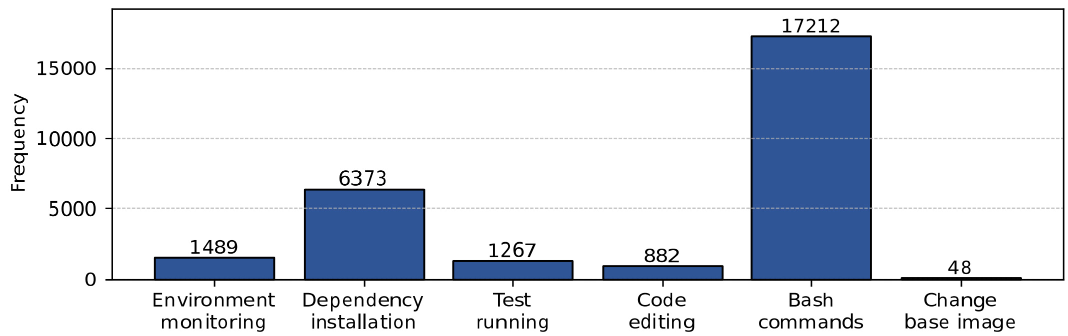


Figure 5: Tool usage frequency of the success configuration.

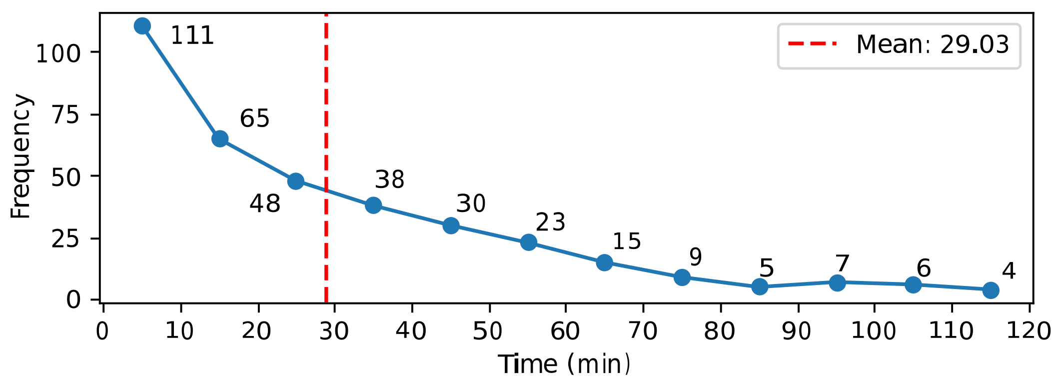


Figure 6: The time distribution of each successful configuration.

5 Discussion

5.1 Tool usage frequency

As shown in Figure 5, we analyze the invocation times of various action types in 361 successfully configured projects, including the five actions within the internal environment and the action of changing the base image. Bash commands are the most frequently used action, as they encompass the majority of instructions. Additionally, we observe that the LLM agent tends to call dependency installation quite frequently, averaging about 18 times per configuration, which means roughly 18 dependencies are installed per configuration on average. Moreover, the LLM agent calls test running approximately 3.5 times per configuration on average, which typically helps the agent better identify issues. Among successful configurations, we see 48 instances of changing the base image, accounting for 13.3% of success cases, indicating that the initial selection of the base image is often incorrect and requires subsequent adjustments.

5.2 Time consumption

Figure 6 shows the distribution of time spent successfully configuring 361 code repositories. The average time for successful configuration using Repo2Run is 29.03 minutes. 111 (30.7%) of the repositories are successfully configured in less than 10 minutes. Additionally, our empirical study through sampling indicates an average manual configuration time of 21.33 minutes (Appendix A). Considering network differences and randomness, Repo2Run achieves a time consumption comparable to manual configuration. Additionally, for complex issues, Repo2Run shows greater advantages over manual configuration. Repo2Run successfully configures all the cases that were manually successful in our empirical study. Moreover, the cases where Repo2Run fails are also not successfully configured manually.

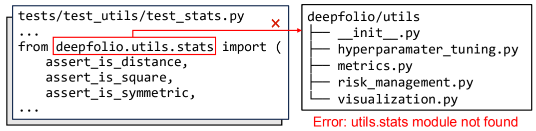


Figure 7: An example of "`module not found`" error due to the absence of updating the unit tests in the repository.

5.3 Case study

For the code repositories that fail to configure, we manually inspect the reasons for failures and find that most are due to issues within the repositories themselves. Figure 7 illustrates a "module not found" error when configuring the repository "`jialuechen/deepfolio`". In this case, the issue arises from the absence of updating the unit tests. The test file "`test_stats.py`" attempts to import modules from "`deepfolio.stats`", but "`stats`" does not exist in "`deepfolio`". Consequently, no matter how the LLM agent operates, it cannot directly run this test. This highlights the importance for developers to continuously update existing unit tests as the code repository evolves.

6 Related Work

6.1 Environment configuration and Dockerfile generation

Oss-Fuzz-Gen [17] relies on predefined build instructions (such as "`./bootstrap.sh`", "`./configure`", "`make`") to build projects for fuzzing but lacks of flexibility for diverse projects when specified files are absent.

Existing solutions that help developers write Dockerfiles broadly fall into three categories: (1) Template-based generators that create Dockerfiles based on project context [2, 18], (2) Task-specific tools such as DockerizeMe which supports environment dependency inference for Python projects [11] and DockerGen [27] for dependency recommendations based on knowledge graphs built from existing Dockerfiles, and (3) Code completion tools including GitHub Copilot [7] and HumpBack [8] that generate suggestions for developers while writing Dockerfiles. The use of deep learning models to generate Dockerfiles based on natural language specifications of software requirements is also investigated [21]. While these approaches provide valuable assistance, they either require significant manual input from developers or are limited to specific use cases.

6.2 LLM-based agent

LLM-based agents typically consist of four key components: planning, memory, perception, and action [25]. Planning is crucial for agent systems, as it schedules agents to ensure a smooth process. LLM-based agents employ various planning strategies, including single [3] or multiple planners [15], single [29] or multi-turn planning [33], and single [9] or multi-path planning [31]. The memory component in LLM-based agents stores historical data to support coherent reasoning and complex tasks. Implementations vary in terms of memory duration (short-term [6] or long-term memory [28]), memory ownership (specific [20] or shared memory [10]). For perception, LLM-based agents primarily utilize textual input [19, 28] (natural language and programming language) and visual input [24, 22] (images and diagrams) to perceive and process information. To extend capabilities beyond interactive dialogue, the action component employs various external tools [30, 16], such as searching tools, file operations, and GUI operations. Nowadays, LLM-based agents have demonstrated superior performance compared to standalone LLMs in various software engineering tasks [13, 5, 1]. However, no LLM-based agents are specifically designed for environment configuration currently. To fill this gap, this paper employs a novel approach for automated coding environment configuration and Dockerfile generation.

7 Conclusion

In this paper, we propose Repo2Run, the first LLM-based agent for automated coding environment configuration and Dockerfile generation for Python repositories based on atomic configuration synthesis. With a dual-environment architecture and a Dockerfile generator, Repo2Run is able to select and change the base image, manage and install dependencies based on action observation and rollback mechanism, and utilize bash commands and existing test suites. Our evaluation of 420 popular Python repositories hosted on GitHub demonstrates the effectiveness of Repo2Run with an 86.0% success rate.

Impact Statement

Repo2Run demonstrates the potential and impact that LLM-based agents can have towards automating coding environment configuration and docker file generation. We are hopeful that Repo2Run may inspire more works that advance broader aspects of automated software engineering. There might be more potential societal consequences of our work, none of which which we feel must be specifically highlighted here.

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Appendix

A Manual experiment

A.1 Settings

To ensure a fair comparison among participants, we conducted training and demonstrated examples before the experiment to ensure everyone understood the procedure. Additionally, to minimize discrepancies in time consumption due to network factors, all participants conducted the experiment in the same network environment.

A.2 Survey

We selected eight technical staff from internet companies to participate in the experiment and conducted a survey regarding their backgrounds prior to the experiment. Their development experience ranges from 4 to 11 years, with an average of 7 years in software development and 3.8 years in Python development. Seven participants have experience in complex development projects, while one has experience in multiple small-scale projects.

Regarding environment configuration, three participants indicated that they spend a significant amount of time configuring the environment when faced with an unfamiliar code repository; another three stated that, although they spend a long time, it is generally manageable; two participants reported spending minimal time.

In terms of successful environment configuration in their regular work, three participants mentioned they only fail with extremely complex environments, while five indicated they can build environments for most medium-scale repositories. As for their confidence in successfully configuring unfamiliar environments, six participants expressed that they are usually successful, and two said they are sometimes successful.

When it comes to the amount of time they are willing to wait to configure an unfamiliar repository, four participants are willing to wait for over 90 minutes, two are willing to wait 40-60 minutes, one is willing to wait 20-40 minutes, and one is only willing to wait 10-20 minutes.

Participants' overall evaluation of configuring code running environments is diverse: one finds it very troublesome with many issues, four find it somewhat troublesome, two indicate moderate difficulty, and one finds it relatively simple.

Additionally, all participants expressed a high or very high willingness to use a tool that could automatically configure the environment for an unfamiliar repository.

A.3 Experiment guideline

We request all participants to conduct the experiment following the guidelines below:

1. Environment Setup

Configure the Docker environment. Verify the installation is successful: If installed correctly, you should be able to use the following command (python:3.10 is just an example; select the base image according to your requirements):

```
docker run -it python:3.10 bash
```

2. Overall Procedure

Our objective is to install the given package in a Docker container, configure its environment, and be able to run its internal tests. During the process, record the time developers spend configuring the environment and eventually save the logs using docker logs.

2.1 Review the Repository to be Configured (Optional)

Review the GitHub repository that needs to be configured.

2.2 Determine the Docker Base Image (Generally start with python:3.10)

Select the Docker base image based on the repository (all repositories use Python as the main language). Common base images include: Note, in this experiment, it is generally sufficient to use the official Python series images. The main concern is the version; if uncertain, you can start with newer versions like 3.10, 3.11, 3.12, or select the recommended Python version based on the repository's README.

Python series (the number after python indicates the version): python:3.10, python:3.12, python:3.9, python:3.6, python:3.9... PyTorch series: pytorch/pytorch, pytorch/pytorch:1.9.0-cuda10.2-cudnn7-runtime... Anaconda series: continuumio/anaconda3... Note: If you find the selected version is incorrect later, you can exit and reselect.

2.3 Create and Enter the Container

Using the determined base image name (e.g., python:3.10), enter the container with the following command:

```
docker run -it --name mytest python:3.10 bash
```

Here, mytest is the container name, recorded for log export later. It can be freely named, just keep track of it to avoid losing it later. Note: If any issues arise here, check if Docker is correctly installed and if the image name is valid, and troubleshoot accordingly.

2.4 Install Relevant Tools

APT tool downloads:

```
apt-get update && apt-get install -y curl
```

Download pytest:

```
pip install pytest
```

2.5 Download the Repository

Select the repository to be configured and download its GitHub repository to a location (generally directly in the root directory):

```
git clone https://github.com/{full_name}.git
```

2.6 Configure the Environment

Now, use your skills to configure: First, enter the downloaded file directory, for example:

```
cd wddbfs
```

Switch to the specified branch SHA (refer to the corresponding SHA of the repository), for example:

```
git checkout 5c68aa
```

Our goal is to successfully run pytest (not necessarily to pass all tests, just to run them). A simple criterion is to successfully run:

```
pytest --collect-only -q
```

At this point, you can use your experience and information from the repository documentation and debugging error messages to configure. However, there are a few restrictions:

Do not directly edit the test files! (Files starting with test_ or ending with _test.py). Do not directly delete test files! Editing the original repository files is not recommended.

During this process, you may perform various operations, including but not limited to pip, apt-get, and other tool downloads, as well as searching online or using GPT for debugging help.

Additionally, if there are long download times requiring waiting, you may decide according to your situation whether to leave this running and do other things (just don't forget about this task).

2.7 Completion and Logging

A task can conclude in two scenarios:

Scenario One: If "`pytest --collect-only -q`" runs without issues, you can then execute pytest. If pytest completes successfully, the task is done. Scenario Two: If you feel the package is extremely difficult to configure, for example exceeding your patience threshold (refer to your usual development habits), you may also terminate.

Once finished, input exit to exit. Make sure to save your output logs with the following command (replace container_name with the container name you recorded earlier, if you forget, you can use docker ps to check):

```
docker logs container_name -t > wddbfs.log
```

2.8 Fill Out the Form and Record Information

You need to fill out the form according to your feelings.

Question	**Description**
Is it successful?	Yes or No - whether the task successfully passed "`pytest --collect-only -q`" without errors and eventually ran "`pytest`".
Final base image used	E.g., python:3.10
Reason for failure	Summarize the main reasons for failure (if failed), including: • Long download time • Difficulty handling repository dependencies • Unresolvable bug • Errors in repository tests • Lengthy test durations • Other reasons (please specify)
Waiting time	Approximate value, indicating the time spent waiting for dependencies to download. Does not include time spent on decision-making and research. Provide an approximate range: • ¡3 minutes • 3-5 minutes • 6-10 minutes • 11-20 minutes • 20-40 minutes • 40-60 minutes • 60-90 minutes • 90+ minutes
Longest time-consuming process	Describe the most time-consuming configuration process, such as: • Downloading a specific dependency • Resolving a specific error • Incorrect Python version selection
Tolerance level	Based on your subjective feeling and development experience. Rate the process (1-5): • 1: Extremely unbearable • 2: Somewhat unbearable, but manageable • 3: Neutral, tolerable • 4: Comfortable, no significant discomfort • 5: Very comfortable, highly satisfactory configuration experience

Configuration difficulty	Based on the complexity of the configuration process (ignoring time spent): Rate the process (1-5): • 1: Very simple, completed with intuition and experience, no reference materials needed • 2: Fairly simple, referred to basic materials (e.g., README), simple overall steps • 3: Moderate difficulty, encountered some issues, but manageable • 4: Difficult, required extensive debugging and configuration • 5: Very difficult, needed numerous references and encountered unresolved or time-consuming issues
Materials referenced	List the materials used for reference (e.g., README, internal configuration files, online searches, GPT). If none, mention “Directory”.
Biggest challenge during the process	Describe the most troublesome aspect of the configuration process, such as long wait times, unclear error messages, dependency version conflicts, inability to find required software versions, etc.

Example 1:

Question	**Answer**
Is it successful?	Yes
Final base image used	python:3.10
Reason for failure	Successful
Waiting time	3-5 minutes
Longest time-consuming process	Downloading poetry
Tolerance level	5
Configuration difficulty	1
Materials referenced	Directory
Biggest challenge during the process	Waiting for configuration and installation

Example 2:

Question	**Answer**
Is it successful?	No
Final base image used	python:3.11
Reason for failure	Unresolvable bug, provide bug image
Waiting time	40-60 minutes
Longest time-consuming process	Resolving FileNotFoundError, ImportError, incorrect Python version selection
Tolerance level	2
Configuration difficulty	5
Materials referenced	README, GPT, StackOverflow
Biggest challenge during the process	Dependency version conflicts, long wait times

A.4 Repository assignment

We randomly assigned each participant four unique code repositories that were successfully configured by Repo2Run. Additionally, each participant was assigned two code repositories that Repo2Run failed to configure. To avoid chance occurrences, each failed repository was assigned to two different participants. Below is the list of selections:

Successfully configured:

[alexwlchan/safari-webarchiver, ManiMozaffar/aioclock, mixedbread-ai/batched, mobiusml/gemlite, circlemind-ai/fast-graphrag, knowsuchagency/promptic, mbodiai/embodied-agents, modelscope/agentscope, Adibvafa/CodonTransformer, kennethreitz/simplemind, lmstudio-ai/venvstacks, mlecauchois/micrograd-cuda, IST-DASLab/PanzaMail, MetaGLM/zhipuai-sdk-python-v4, openai/mle-bench, RealOrangeOne/django-tasks, basf/MolPipeline, dai-motoki/zoltraak, lucidrains/alphafold3-pytorch, mistralai/mistral-common, BMPixel/moffee, DataformerAI/dataformer, jahwag/ClaudeSync, volfpeter/htmy, Genentech/gReLU, OpenNLPLab/lightning-attention, paradigmxyz/spice, reagento/dishka, arcee-ai/fastmlx, KyanChen/RSMamba, neuralmagic/guidellm, simonw/files-to-prompt]

Failed to configure:

[zhuqinfeng1999/Samba, dongxuyue/Open-ReplaceAnything, LazyAGI/LazyLLM, jialuechen/deepfolio, KOSASIH/pi-nexus-autonomous-banking-network, AARG-FAN/Yolo_for_Wukong, plinder-org/plinder, expectedparrot/edsl]

A.5 Results

Based on the times shown in the logs, we calculated that the average configuration time for each repository is 21.33 minutes. Furthermore, none of the repositories that Repo2Run failed to configure were successfully configured manually. Additionally, in the manual experiment, five environments that were successfully configured by Repo2Run were not successfully configured, representing 15.6% of the total successfully configured assignments.

B Safe commands

If Repo2Run executes the following commands without using ">" or ">>" for output redirection, they are regarded to be safe commands that typically do not affect the system. Therefore, rollback is not necessary, and they are not added to the generated Dockerfile.

["`cd`", "`ls`", "`cat`", "`echo`", "`pwd`", "`whoami`", "`who`", "`date`", "`cal`", "`df`", "`du`", "`free`", "`uname`", "`uptime`", "`w`", "`ps`", "`pgrep`", "`top`", "`dmesg`", "`tail`", "`head`", "`grep`", "`find`", "`locate`", "`which`", "`file`", "`stat`", "`cmp`", "`diff`", "`xz`", "`unxz`", "`sort`", "`wc`", "`tr`", "`cut`", "`paste`", "`tee`", "`awk`", "`env`", "`printenv`", "`hostname`", "`ping`", "`traceroute`", "`ssh`"]

C Repo2Run tools

Showing in Table 6, we design the following actions for Repo2Run to facilitate its invocation.

Table 6: Command list and their functions

Command	Function
`waitinglist add -p package_name [-v version_constraints] -t tool`	Add item into waiting list. If no "version_constraints" are specified, the latest version will be downloaded by default.
`waitinglist addfile file_path`	Add all entries from a file similar to requirements.txt format to the waiting list. Format should be package_name [version_constraints].
`waitinglist clear`	Clear all items in the waiting list.
`conflictlist solve -v "[version_constraints]"`	Resolve the conflict for the first element in the conflict list, and update the version constraints for the corresponding package_name and tool to version_constraints. If no "version_constraints" are specified, the latest version will be downloaded by default. The package_name and tool in the original waiting list must match one of the elements in the conflictlist. Here, the version_constraints are specified.
`conflictlist solve -u`	Keep the original version constraint that exists in the waiting list, and discard the other version constraints with the same name and tool in the conflict list.
`conflictlist clear`	Clear all items in the conflict list.
`conflictlist show`	Show all items in the conflict list.
`waitinglist show`	Show all items in the waiting list.
`download`	Download all pending items in the waiting list at once, and the conflict list must be empty before executing.
`runtest`	Check if the configured environment is correct using "`pytest`".
`poetryruntest`	Check if the configured environment is correct in the poetry environment. If you want to run tests in the poetry environment, run it.
`runpipreqs`	Generate `requirements_pipreqs.txt` and `pipreqs_output.txt` and `pipreqs_error.txt`.
`change_python_version python_version`	Switching the Python version in the Docker container will forgo any installations made prior to the switch. The Python version number should be represented directly with numbers and dots, without any quotation marks.
`clear_configuration`	Reset all the configuration to the initial setting of `python:3.10`.

D Benchmark

Table 7: Success status of each package in the benchmark.

full_name	sha	success	full_name	sha	success
271374667/VideoFusion	9ba7b8	Yes	6abd/horus	c1d093	Yes
a-r-r-o-w/cogvideox-factory	80d115	Yes	a-s-g93/neo4j-runway	16b441	Yes
Aaditya-Prasad/consistency-policy	eed0c4	No	AARG-FAN/Yolo_for_Wukong	07f61a	No
adamobeng/wddbfs	5c68aa	Yes	Adibvafa/CodonTransformer	2842ef	Yes
AdityaNG/kan-gpt	0c6e4c	Yes	Admyral-Security/admyral	de332e	Yes
AgentOps-AI/AgentStack	ff9c6a	Yes	aidatatools/ollama-benchmark	c6a5fd	Yes
AIR-Bench/AIR-Bench	4b27b8	Yes	airbytehq/PyAirbyte	7e65ab	Yes
airtai/fastagency	1ff503	Yes	Akkudoktor-EOS/EOS	fff685	Yes
alexmolas/microsearch	632ff2	Yes	alexwlchan/safari-webarchiver	0e4974	Yes
AlibabaPAI/llumnix	b319b2	Yes	All-Hands-AI/OpenHands	246107	Yes
alvin-r/databonsai	3f2b7c	Yes	amchii/tg-signer	926dbb	Yes
andrewyng/aisuite	763996	Yes	andrewyng/translation-agent	e0fc60	Yes
AnswerDotAI/byaldi	4583c0	Yes	AnswerDotAI/rerankers	ecd1f6	Yes
antgroup/agentUniverse	ed8f55	Yes	apapiu/transformer_latent_diffusion	84a75e	Yes
apify/crawlee-python	267063	Yes	apple/ToolSandbox	1a1dc8	Yes
apple/ml-cross-entropy	1f3ebd	Yes	apple/ml-mdm	9a5632	Yes
arcee-ai/fastmlx	fd37bc	Yes	argmaxinc/whisperkittools	03898f	Yes
arvindrajan92/DTrOCR	a10aa0	Yes	astramind-ai/Auralis	c357a1	Yes
atonderski/neuro-ncap	ecdcf2	Yes	aurelio-labs/semantic-chunkers	04acc2	Yes
AuvaLab/itext2kg	941a1d	Yes	awslabs/agent-evaluation	3df695	Yes
Azure/co-op-translator	a4709e	Yes	Azure-Samples/rag-postgres-openai-python	61bde7	Yes
bananaml/fructose	5f24ec	Yes	basf/MolPipeline	2f9bae	Yes
basf/mamba-tabular	af1ea0	Yes	beatzxbt/mm-toolbox	728e35	Yes
bellingcat/ShadowFinder	578d5a	Yes	Benexl/FastAnime	677f46	Yes
betaacid/FastAPI-Reference-App	8caeca	Yes	bhavnicksm/chonkie	990493	Yes
bigcode-project/bigcodebench	aa634d	Yes	Bl3f/yato	4906b0	Yes
Blealtan/efficient-kan	7b6ce1	Yes	block/goose	c497a5	Yes
BMPixel/moffee	0e643d	Yes	boheumd/MA-LMM	ffe9fa	Yes
bytewiz3/TravelGPT	b19b43	Yes	CausalLearning/ReAct	7d3665	No
cfahlgren1/observers	d46fdb	Yes	chaidiscovery/chai-lab	b6e7fa	Yes
character-ai/prompt-poet	466432	Yes	cheahjs/palworld-save-tools	7dc2c7	Yes
chernyadev/bigym	72d305	Yes	chrschy/fact-finder	ca57d1	Yes
circlemind-ai/fast-graphrag	447511	Yes	cloudflare/cloudflare-python	228479	Yes
codefuse-ai/CodeFuse-muAgent	e93924	No	codeintegrity-ai/mutahunter	f88922	Yes
codematrixer/hmdriver2	c0d075	Yes	codeskyblue/tidevice3	d83c34	Yes
codeskyblue/uiautodev	eb8577	Yes	Codium-ai/AlphaCodium	eb7577	Yes
Codium-ai/cover-agent	5c4b88	Yes	COLA-Laboratory/TransOPT	de8bf3	No
Comfy-Org/comfy-cli	7711db	Yes	CompEpigen/figeno	14b904	Yes
computer-agents/agent-studio	d7f6cb	Yes	cosmic-cortex/mlfz	5bf8d2	Yes
cremebrule/digital-cousins	49400b	Yes	crewAIInc/crewAI-tools	873935	Yes
cvg/nerf-on-the-go	3659e7	Yes	D-Star-AI/dsRAG	2d5431	Yes
D4Vinci/Scrapling	012820	Yes	DAGWorks-Inc/burr	79137e	Yes
dai-motoki/zoltraak	4dce44	Yes	darrenburns/posting	94feab	Yes
DataformerAI/dataformer	0cf88c	Yes	daxa-ai/pebblo	e67b01	Yes
daya0576/beaverhabits	c01257	Yes	dbos-inc/dbos-transact-py	d6c6ac	Yes
deepsense-ai/db-ally	26033f	Yes	dendrite-systems/dendrite-python-sdk	27c9da	Yes
denser-org/denser-retriever	76256e	No	dingo-actual/infini-transformer	08d0a1	Yes
discord/access	19e9b1	Yes	dleemiller/WordLlama	e38d47	Yes
dongxuyue/Open-ReplaceAnything	83f0ae	No	dottxt-ai/outlines-core	31ab9f	Yes
dottxt-ai/prompts	3d2689	Yes	dreadnode/rigging	82ac80	Yes
droid-dataset/droid_policy_learning	205ff6	Yes	DS4SD/docling	aee9c0	Yes
dynamiq-ai/dynamiq	6cca1c	Yes	eakmanrq/sqlframe	61fda5	Yes
EleutherAI/sae	0483b5	Yes	emcf/thepipe	02e397	Yes
Emerging-AI/ENOVA	b3661d	Yes	EnhancedJax/Bagels	d72d7f	Yes
enoch3712/ExtractThinker	4872a7	No	epic-open-source/seismometer	b3e812	Yes
epistoteles/TensorHue	1564fa	Yes	epogrebnyak/justpath	0aca51	Yes

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Table 7 – continued from previous page

full_name	sha	success	full_name	sha	success
erezsh/reladiff	d8683b	Yes	etianen/logot	54e5ef	Yes
expectedparrot/edsl	aa7a2d	No	explosion/spacy-layout	64c6f4	Yes
facebookresearch/audioseal	ea10f5	Yes	facebookresearch/lightplane	34fe6c	Yes
facebookresearch/spiritlm	52fb2f	Yes	FalkorDB/GraphRAG-SDK	250ebe	Yes
Fanqi-Lin/Data-Scaling-Laws	bd6941	No	fastapi/fastapi-cli	bc0840	Yes
fedirz/faster-whisper-server	cbb6c9	Yes	felafax/felafax	34a475	Yes
filipstrand/mflux	627398	Yes	FlagOpen/FlagGems	ca13b7	No
fmind/cookiecutter-mlops-package	00fef7	Yes	foundation-model-stack/fms-fsdp	408c75	Yes
fpgmaas/cookiecutter-uv	90de47	Yes	frdel/agent-zero	3cefa1	Yes
frostming/tetos	106ea5	Yes	Fugaku-LLM/DeepSpeedFugaku	74753f	No
gauge-sh/bridge	8b3430	Yes	Genentech/gReLU	efd308	Yes
genomoncology/FuzzTypes	d96243	Yes	getludic/ludic	a6db96	Yes
getzep/graphiti	9f3dd5	Yes	GigaxGames/gigax	c3c209	Yes
gojasper/flash-diffusion	48e3bc	Yes	gomate-community/TrustRAG	1334c4	Yes
gomate-community/rageval	01e258	Yes	google-deepmind/nanodo	10aefd	Yes
google-deepmind/penzai	fda6cd	Yes	google-deepmind/treescope	dac18b	Yes
google-research/timesfm	02bc2f	Yes	goombalab/hydra	b6b9b7	Yes
gpustack/gpustack	4f0c67	Yes	gregpr07/browser-use	5e545d	Yes
groq/groq-python	fa2e13	Yes	gusye1234/nano-graphrag	18fa3a	Yes
hailo-ai/hailo-rpi5-examples	82cfc8	Yes	Haiyang-W/GiT	ef2b64	No
HanaokaYuzu/Gemini-API	e8a2d2	Yes	HATTER-LONG/Verbiverse	82f988	Yes
hinthornw/trustcall	eaaaad	Yes	HKUDS/HiGPT	2b0793	No
HKUDS/UrbanGPT	be3515	No	hngprojects/hng_boilerplate_python_fastapi_web	bc9740	Yes
hpcaitech/Open-Sora	38de63	Yes	hpcaitech/SwiftInfer	239fd3	No
hrnoh24/stream-vc	faa629	Yes	huchenlei/ComfyUI_omost	7ef00d	Yes
huggingface/lerobot	4c41f6	Yes	huggingface/lighteval	6ad727	Yes
HZAI-ZJNU/Mamba-YOLO	ea97fc	No	IAAR-Shanghai/Grimoire	3fe89d	Yes
ib-api-reloaded/ib_async	38cf54	Yes	IBM/fastfit	396611	Yes
IBM/terratorch	16e5af	Yes	IEIT-Yuan/Yuan2.0-M32	b403a2	No
igorbenav/SQLModel-boilerplate	2ead04	Yes	igorbenav/fastcrud	dc831b	Yes
igrek51/wat	0d6079	Yes	illuin-tech/colpali	e45c4c	Yes
illuin-tech/vidore-benchmark	469665	Yes	Indoxer/LKAN	16c48e	No
Infini-AI-Lab/Sequoia	688079	No	instanseg/instanseg	0df8b2	Yes
instructlab/instructlab	c978b2	Yes	Integuru-AI/Integuru	928e82	Yes
InternLM/InternEvo	5ad2eb	Yes	invariantlabs-ai/invariant	81547a	Yes
IST-DASLab/PanzaMail	b1807c	Yes	iterative/datachain	b67d59	Yes
IvanDrokin/torch-conv-kan	7a0e83	Yes	jahwag/ClaudeSync	000633	Yes
jgravelle/pocketgroq	e995c4	Yes	jhj0517/AdvancedLivePortrait-WebUI	a7975c	Yes
jialuechen/deepfolio	15d247	No	jina-ai/late-chunking	db558c	Yes
jlowin/fastmcp	baa300	Yes	jmschrei/tangermeme	a96897	Yes
jonbarron/camp_zipnerf	8e6d57	Yes	JosephBARBIERDARNAL/pypalettes	826930	Yes
JoshuaC215/agent-service-toolkit	c72f48	Yes	jshuadvd/LongRoPE	eb9aba	Yes
jxnl/n-levels-of-rag	2ce110	Yes	karpathy/minbpe	1acefe	Yes
kennethreitz/simplemind	39b5a5	Yes	kevinzakka/mink	cf1a30	Yes
knowsuchagency/promptic	a1930c	Yes	koaning/uvtrick	2d7f27	Yes
kohjingyu/search-agents	7c35ac	No	KOSASIH/pi-nexus-autonomous-banking-network	7fcff4	No
kotaro-kinoshita/yomitoku	71c85b	Yes	KruxAI/ragbuilder	db3d3d	No
kujirahand/tkeasygui-python	b1f293	No	KyanChen/RSMamba	3fa305	Yes
kyegomez/MultiModalMamba	58db40	No	landing-ai/vision-agent	63eab8	Yes
langchain-ai/langchain-postgres	064e5b	Yes	lavague-ai/LaVague	b3557f	Yes
LazyAGI/LazyLLM	e0dd38	No	lenML/Speech-AI-Forge	0b31b2	Yes
leopiney/neuralnoise	c0313f	Yes	lichao-sun/Mora	7a030e	No
Lightning-AI/litdata	0a97de	Yes	lightonai/pylate	8de184	No
LilianHollard/LeYOLO	872841	Yes	line/lighthouse	ba9da7	Yes
LlmKira/fast-langdetect	5728ba	Yes	LMCache/LMCache	7d3443	Yes
lmstudio-ai/mlx-engine	daeb7a	Yes	lmstudio-ai/venvstacks	235ce3	Yes
lucasdelimanogueira/PyNorch	ed391e	Yes	LucasFaudman/apkscan	3b3e62	Yes
lucidrains/alphafold3-pytorch	49f7c9	Yes	lucidrains/infini-transformer-pytorch	5774bb	Yes
lucidrains/pi-zero-pytorch	8ad66f	Yes	lucidrains/titok-pytorch	2f9525	Yes
lucidrains/transfusion-pytorch	16f73e	Yes	MadcowD/ell	36ca5e	Yes

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full_name	sha	success	full_name	sha	success
ManiMozaffar/aioclock	3d196b	Yes	MaoXiaoYuZ/Long-Novel-GPT	e952ac	No
Marker-Inc-Korea/AutoRAG	aa0bfb	Yes	martius-lab/hitchhiking-rotations	45b49f	Yes
mbodiai/embodied-agents	8715f6	Yes	McGill-NLP/weblinx	6f2014	Yes
McGill-NLP/webllama	696a7c	Yes	Menghuan1918/pdfdeal	e08199	Yes
meta-llama/llama-stack-apps	f14a73	Yes	MetaGLM/zhipuai-sdk-python-v4	7ff4de	Yes
metavoiceio/metavoice-src	de3fa2	Yes	microsoft/MInference	7a3e5a	No
microsoft/TinyTroupe	9b8d4e	Yes	microsoft/Trace	826cf5	Yes
microsoft/aurora	8b1165	Yes	microsoft/graphrag	de1252	Yes
microsoft/semantic-link-labs	8e37ef	Yes	mikekelly/AgentK	e9ec89	Yes
Mindinventory/MindSQL	3d0ff0	Yes	MinishLab/model2vec	4e3fba	Yes
miquido/draive	270f0c	Yes	mistralai/mistral-common	5cac5e	Yes
mistralai/mistral-finetune	656df1	Yes	mixedbread-ai/baguetter	a6e915	Yes
mixedbread-ai/batched	1a1797	Yes	mkjt2/lockbox	58430d	Yes
mlecauchois/micrograd-cuda	ab1ca0	Yes	MLT-OSS/open-assistant-api	44eeaf	Yes
mlx-graphs/mlx-graphs	4619d9	No	mobiusml/gemlite	5ebcca	Yes
ModelCloud/GPTQModel	a5aefc	No	modelcontextprotocol/python-sdk	aaf32b	Yes
modelscope/MemoryScope	330b76	Yes	modelscope/agentscope	ceaf89	Yes
modern-python/that-depends	65e656	Yes	muchdogesec/history4feed	614182	Yes
muditbhargava66/PyxLSTM	f3c9bb	Yes	narwhals-dev/narwhals	a2088f	Yes
nasa-jpl/rosa	5471dc	Yes	neo4j/neo4j-graphrag-python	0ac06b	Yes
neuralmagic/AutoFP8	e94461	Yes	neuralmagic/guidellm	ecf298	Yes
NewT123-WM/tnlearn	50ee75	Yes	NexaAI/nexa-sdk	33f6ba	No
nicobrenner/commandjobs	4c7264	Yes	Nike-Inc/koheesio	9bd29e	Yes
nlmatics/nlm-ingestor	c72542	Yes	NLPJCL/RAG-Retrieval	d73057	No
nomic-ai/contrastors	496a05	No	NousResearch/finetuning-subnet	e2f5eb	Yes
NUS-HPC-AI-Lab/VideoSys	6c92ae	No	NVIDIA/Megatron-Energon	28aa3b	Yes
NVIDIA/NeMo-Skills	5591f3	Yes	NVIDIA/kvpress	715f8a	Yes
NVIDIA/logits-processor-zoo	db179a	Yes	NVIDIA/nv-ingest	eec9fa	No
NVlabs/Sana	41dcbe	Yes	NVlabs/VILA	ec7fb2	No
NVlabs/nvTorchCam	cc27be	Yes	ogkalu2/comic-translate	1933d1	Yes
Open-Wine-Components/umu-launcher	b0c0d4	Yes	openai/mle-bench	51ec2b	Yes
openai/swarm	9db581	Yes	opendatalab/MinerU	391a99	Yes
openfoundry-ai/model_manager	34f9ff	Yes	opengeos/HyperCoast	c1604c	Yes
OpenInterpreter/aifs	3f74c6	Yes	OpenNLPLab/lightning-attention	d74395	Yes
openpsi-project/ReaLHF	62d9cd	Yes	openrecall/openrecall	225a27	Yes
OpenSPG/KAG	68b2c6	No	orbital-materials/orb-models	251573	Yes
outspeed-ai/outspeed	049b40	Yes	OwlAIProject/Owl	919226	Yes
PacktPublishing/LLM-Engineers-Handbook	ec6717	Yes	paradigmxyz/spice	e962a9	Yes
patched-codes/patchwork	c9b02b	Yes	paulrobello/parllama	421238	Yes
PeiJieSun/NESCL	365d20	Yes	plinder-org/plinder	9658cc	No
pomonam/kronfluence	884255	Yes	PrefectHQ/ControlFlow	f259fa	Yes
PrimeIntellect-ai/OpenDiloco	71f5c2	Yes	PrimeIntellect-ai/prime	a974cf	Yes
princeton-nlp/SWE-agent	8b3571	Yes	proger/accelerated-scan	db7145	Yes
pydantic/logfire	3d7924	Yes	pymupdf/RAG	b25718	No
pytorch-labs/LeanRL	a416e6	Yes	raphaelmansuy/code2prompt	3b377b	No
RapidAI/RapidDoc	5e5fef	Yes	RapidAI/RapidLayout	8e9677	Yes
reagento/dishka	2ed985	Yes	real-stanford/universal_manipulation_interface	298776	No
Realiserad/fish-ai	f32c7f	Yes	RealOrangeOne/django-tasks	e6d26c	Yes
reidjs/text-scheduler	8bb7d6	Yes	reka-ai/reka-vibe-eval	93ecd9	Yes
remigenet/TKAN	8a1de0	Yes	rio-labs/rio	eda40a	Yes
robocasa/robocasa	27f992	Yes	RobotecAI/rai	d15910	No
robusta-dev/holmesgpt	c4743a	Yes	royreznik/rexi	f1dca8	Yes
run-llama/llama_deploy	47efff	Yes	run-llama/llama_extract	89438f	Yes
run-llama/llama_parse	f78186	Yes	SamKhoze/ComfyUI-DeepFuze	edd7fe	No
ScrapeGraphAI/Scrapegraph-ai	bae92b	Yes	seanchatmangpt/dspygen	69f305	No
serverless-ca/terraform-aws-ca	2da837	No	ServerlessLLM/ServerlessLLM	8f1e6b	Yes
ServiceNow/BrowserGym	12aa5e	Yes	ServiceNow/TapeAgents	3eca5c	Yes
ServiceNow/WorkArena	0ab9cb	No	ShaShekhar/aaiela	4e8d6a	No
shawntan/scattermoe	63b76a	Yes	ShoggothAI/motleycrew	19837e	Yes
showlab/computer_use_ootb	419d9d	Yes	shun-liang/yt2doc	201ec2	Yes

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full_name	sha	success	full_name	sha	success
siliconflow/BizyAir	cdb3bb	Yes	simonw/files-to-prompt	f9a4d8	Yes
simonw/llm-claude-3	c62bf2	Yes	simonw/llm-cmd	74fb98	Yes
simonw/llm-jq	beaada	Yes	simular-ai/Agent-S	ca83be	Yes
sirocco-ventures/raggenie	99dfe5	Yes	souzatharsis/podcastfy	804a61	Yes
SpecterOps/cred1py	432f91	Yes	StacklokLabs/promptwright	42f69b	Yes
steinathan/reelsmaker	75369c	Yes	stephengpope/no-code-architects-toolkit	ffc1a8	Yes
StonyBrookNLP/appworld	bc9c47	Yes	Storia-AI/sage	f47fa4	No
superlinear-ai/raglite	b02c5a	Yes	swarmzero/swarmzero	6fcd7a	Yes
tahnok/colmi_r02_client	84d3a6	Yes	taketwo/llm-ollama	dd616e	Yes
taobojlen/django-zeal	232987	Yes	TencentARC/BrushNet	101dc3	No
TheAiSingularity/graphrag-local-ollama	bcb98d	Yes	thousandbrainsproject/tbp.monty	a39a26	Yes
THU-MIG/yolov10	6fbaf4	Yes	thu-nics/MoA	da034c	No
tjmlabs/AgentRun	1997dd	Yes	tobiasfshr/map4d	0b8bcd	Yes
Toloka/dbt-af	e7f436	Yes	TorchJD/torchjd	1eaafe	Yes
tox-dev/tox-uv	d7405a	Yes	TuragaLab/flybody	2e1088	Yes
turbo-llm/turbo-alignment	009574	Yes	TY-Cheng/torchvinecopulib	c3a477	Yes
ucbepic/docetl	00a761	Yes	ultrasev/llmproxy	1a1100	Yes
uname-n/deltabase	5eafb9	Yes	unifyai/unify	ea2088	No
Vashkatsi/deply	6d6875	Yes	VideoVerses/VideoTuna	ffc6df	Yes
vintasoftware/django-ai-assistant	5b26c7	Yes	virattt/financial-datasets	985664	Yes
vllm-project/llm-compressor	606aab	Yes	volcengine/verl	ed2eaf	Yes
volfpeter/fasthx	e850b9	Yes	volfpeter/htmy	0322a3	Yes
vysakh0/dravid	25b03b	Yes	warmshao/FasterLivePortrait	6aa810	Yes
weareprestatech/hotpdf	55ab97	Yes	web-arena-x/visualwebarena	89f5af	No
Weixiang-Sun/Bora	c08bb6	Yes	whyhow-ai/knowledge-graph-studio	c41043	Yes
whyhow-ai/rule-based-retrieval	91701f	Yes	whyhow-ai/whyhow	63a3c6	Yes
WongKinYiu/YOLO	b96c8e	Yes	WU-CVGL/BAD-Gaussians	bdd8b3	Yes
wy-z/container-vm	07d402	Yes	xdit-project/xDiT	a7bd51	Yes
xhluca/bm25s	c4fef2	Yes	yihong0618/klingCreator	e567c6	Yes
yihong1120/Construction-Hazard-Detection	f5e1ca	Yes	yinjunbo/IS-Fusion	86c882	No
YUCHEN005/GenTranslate	62e59d	No	YUCHEN005/RobustGER	ad4e37	No
yurujaja/pangaea-bench	e1d12e	Yes	ZenGuard-AI/fast-llm-security-guardrails	6a867c	Yes
zeroasiccorp/logik	ca4bb1	Yes	zhuqinfeng1999/Samba	229687	No
zipnn/zipnn	007319	Yes	zou-group/textgrad	b2dc68	Yes

E pipreqs baseline settings

Figure 8 shows the template of a Dockerfile generated using "requirements_pipreqs.txt" created by pipreqs.

```
FROM python:3.10
WORKDIR /
RUN apt-get update && apt-get install -y curl && \\
curl -sSL https://install.python-poetry.org | python -
ENV PATH="/root/.local/bin:$PATH"
RUN pip install pytest pytest-xdist && \\
    pip install pipdeptree && \\
    git clone https://github.com/{author_name}/{package_name}.git && \\
    mkdir /repo && \\
    git config --global --add safe.directory /repo && \\
    cp -r {package_name}/. /repo && rm -rf {package_name}/ && \\
    rm -rf {package_name}
COPY requirements_pipreqs.txt /requirements_pipreqs.txt
RUN pip install -r /requirements_pipreqs.txt
RUN cd /repo && pytest --collect-only -q
```

Figure 8: Dockerfile prompt using the "requirements_pipreqs.txt" generated by pipreqs.