Bloat beneath Python's Scales: A Fine-Grained Inter-Project Dependency Analysis

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Modern programming languages promote software reuse via package managers that facilitate the integration of inter-dependent software libraries. Software reuse comes with the challenge of *dependency bloat*, which refers to unneeded and excessive code that is incorporated into a project through reused libraries. The presence of bloated dependency code exhibits security risks and maintenance costs, increases storage requirements, and slows down application load times. In this work, we conduct a large-scale, fine-grained analysis for understanding bloated dependency code in the PyPI ecosystem. Our analysis is the first to focus on different granularity levels, including bloated dependencies, bloated files, and bloated methods. This allows us to identify the specific parts of a library that contribute to the bloat. To do so, we analyze the source code of 1,302 popular Python projects and their 3,232 transitive dependencies. For each project, we employ a state-of-the-art static analyzer and incrementally construct the *fine-grained project dependency graph (FPDG)*, a representation that captures all inter-project dependencies at method-level.

Our reachability analysis on the FPDG enables the assessment of bloated dependency code in terms of several aspects, including its prevalence in the PyPI ecosystem, its relation to software vulnerabilities, its root causes, and developer perception. Our key finding suggests that PyPI exhibits significant resource underutilization: more than 50% of dependencies are bloated. This rate gets worse when considering bloated dependency code at a more subtle level, such as bloated files and bloated methods. Our fine-grained analysis also indicates that there are numerous vulnerabilities that reside in bloated areas of utilized packages (15% of the defects existing in PyPI). Other major observations suggest that bloated code primarily stems from omissions during code refactoring processes and that developers are willing to debloat their code: Out of the 36 submitted pull requests, developers accepted and merged 28, removing a total of 33 bloated dependencies. We believe that our findings can help researchers and practitioners come up with new debloating techniques and development practices to detect and avoid bloated code, ensuring that dependency resources are utilized efficiently.

1 INTRODUCTION

Over the past decade, software reuse [Krueger 1992; Mohagheghi and Conradi 2007; Naur and Randell 1969] has experienced a significant rise. This trend is driven by the growing popularity of of open-source software and the extensive use of package managers. Open-source software libraries are hosted in centralized repositories and are made accessible through package managers, such as Python's `pip`, Java's Maven, or JavaScript's `npm` [Cox 2019; Spinellis 2012]. Developers specify project dependencies in a textual file, allowing package managers to automate the process of fetching the required library versions from the repositories [Boldi and Gousios 2020]. While software reuse offers the benefits of reduced development and maintenance costs [Mohagheghi and Conradi 2007], it also introduces security and reliability risks [Cox 2019; Gkortzis et al. 2019], or license compatibility issues among dependencies [German et al. 2010; van der Burg et al. 2014].

This study focuses on an emerging challenge originating from code reuse, that is, the presence of *bloated dependency code*. Introduced in 2021 by Soto-Valero et al. [2021b], this concept refers to the incorporation of unused code into a software project via dependencies (reused libraries). Research indicates that bloated dependencies (1) introduce dependency conflicts [Patra et al. 2018; Wang et al. 2020] and increased maintenance effort [Jafari et al. 2022; Soto-Valero et al. 2021b], (2) are related to vulnerable code [Azad et al. 2023, 2019]. To illustrate the negative effects of bloated dependency code, consider the case of a Python project named zopefoundation/Zope. This project declares an unused dependency, which breaks the corresponding build process due to incompatibility issues with other declared dependencies. To fix this issue, the developers of `Zope` simply remove the bloated dependency from their codebase [Gmach 2021].

In spite of its importance, bloated dependency code has only been touched by a few studies. A handful of them have addressed bloated dependencies in various software ecosystems such as Maven [Ponta et al. 2021; Soto-Valero et al. 2021a] and Rust's Cargo [Hejderup et al. 2022], with others exploring dependency-related issues, including bloated dependencies in Python [Cao et al. 2023] and JavaScript [Jafari et al. 2022]. Surprisingly, all those studies quantify the prevalence of bloat *only* at package level (e.g., number of bloated dependencies). This can result in false estimations regarding bloated dependency code, as the actual code reuse occurs at the level of methods or functions [Boldi and Gousios 2020]. For example, a programmer might import a certain dependency, but not actually invoke any of its code. This consideration demands a more fine-grained analysis for quantifying bloated dependency code.

In this work, we perform the first *fine-grained inter-project dependency analysis* of bloated dependency code in Python projects. Python, being one of the most popular programming languages [Cosentino et al. 2017; GitHub 2023], has experienced a 24% growth in 2023 according to GitHub's annual statistics [GitHub 2023]. Additionally, Python Package Index (PyPI) facilitates one of the largest software ecosystems, hosting more than 450k projects and their 9M Python releases. The extensive software reuse in PyPI emphasizes the importance of studying and addressing dependency bloat in this ecosystem. Our study seeks answers to the following research questions.

RQ1 (Prevalence) How prevalent is bloated dependency code in the PyPI ecosystem? What are the qualitative characteristics of bloated dependency code at different granularities (i.e., package, file, method)? (Section 3.1)

RQ2 (Security) What is the relation between bloated dependency code and software vulnerabilities? Do vulnerabilities reside in bloated code regions? (Section 3.2)

RQ3 (Causes) What are the main causes of bloated PyPI dependencies? What is the frequency of these causes? (Section 3.3)

RQ4 (Developer perception) To what extent are developers willing to remove bloated PyPI dependencies? Does the cause of bloated code affect developer decision and responsiveness? (Section 3.4)

To answer these questions, we design and implement a large scale, fine-grained analysis on popular Python projects. We select 1,302 GitHub Python projects from a well-established dataset [Alfadel M 2020]. For each project in our dataset, we build the *fine-grained project dependency graph (FPDG)*, which captures the *entire* dependency network of a project at the level of methods. To do so, we fetch the source code of every project along with the source code of its dependencies (including direct and transitive ones). Following the approach of Keshani [2021] for practical and large-scale analyses, we then employ PyCG [Salis et al. 2021], the state-of-the-art static analyzer for Python, to construct the (partial) call graph of every Python project and dependency. Through a process called *stitching*, we merge all partial call graphs and derive the final FPDG. Stitching essentially connects an external method in a partial call graph (client code) with its counterpart found in the dependent call graph (library code).

Running standard reachability analyses on the resulting FPDGs allows the assessment of bloated dependency code. We evaluate the identified bloated code in terms of several aspects, including its prevalence, its relation to software vulnerabilities, its main causes, and developer perception.

Contributions: Our work makes the following contributions.

- We conduct the first large-scale analysis for constructing fine-grained dependency networks in the PyPI ecosystem. We provide a corresponding reference dataset containing dependency networks that come from 1,302 Python projects and 3,232 PyPI releases (Section 2).
- We quantify bloat in the PyPI ecosystem, and provide a thorough assessment of its prevalence, its security impact, its main causes, and developer perception (Section 3).

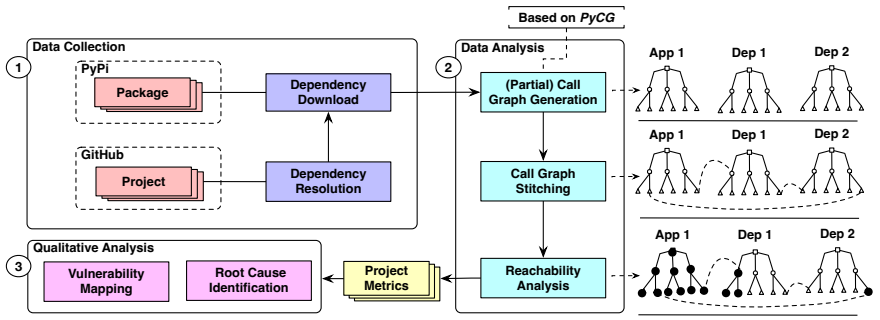


Fig. 1. The overview of our approach for studying bloated code in PyPI ecosystem.

- We enumerate the implications of our findings, and discuss potential future directions in software dependency management (Section 4).

Summary of findings: We find that the PyPI ecosystem exhibits severe dependency under-utilization (RQ1). On average, a Python project consists of ten bloated dependencies. Bloated dependency code becomes more prevalent when measuring bloat at the level of files or methods. In particular, 87% of the dependency source files and 95% of the external methods in a Python project are bloated. Further, our fine-grained analysis highlights the security concerns related to bloated dependency code (RQ2): We identify several vulnerabilities in bloated areas of utilized packages (15% of the total defects in PyPI). Currently there are no attack techniques to directly exploit such defects (i.e., application vulnerabilities have to reside in reachable parts of the code to be exploited [Azad et al. 2023]). However, vulnerabilities that exist in bloated code can act as "time-bombs" which in turn can get activated after a slight code change. Furthermore, bloated dependencies are mainly introduced by pervasive changes in developers' code base (e.g., feature removals) (RQ3). Finally, developers are willing to remove bloated dependencies, especially when they are aware of their main causes (RQ4).

Implications: Through our analysis, we directly addressed bloated dependencies by submitting pull requests, targeting 42 cases across 36 Python projects. Our efforts have already led to the successful debloating of 33 dependencies in 28 projects, underlining the impact of our work. We believe that our study can help researchers and practitioners to build appropriate linters and automated refactoring tools to detect and eliminate bloated dependency code in Python projects.

2 METHODOLOGY

Figure 1 summarizes our approach for studying bloated code within the PyPI ecosystem. As a starting point (①), we select a set of popular and well-established Python projects based on a specific criteria (Section 2.2). Then, for each selected project, we resolve its direct and transitive dependencies (Section 2.2), and download the source code of each dependency for further analysis.

The *data analysis* step (②) begins with the construction of the partial (stand-alone) call graph of every individual project and dependency using the state-of-the-art static analysis tool PyCG [Salis et al. 2021]. Next, we merge all partial call graphs through a process we call stitching (Section 2.3.2). Stitching connects the external calls of each partial call graph with the corresponding nodes that appear in the call graphs of the callee dependencies. We call the resulting (stitched) call graph, the *fine-grained project dependency graph (FPDG)* of a project. The FPDG captures the caller-callee relationships within a project's entire dependency tree. Following the construction of the FPDG, we perform a reachability analysis to identify the packages, files, or methods that are accessible within each application. All unreachable methods are marked as *bloated*, and serve the basis for detecting bloated files and bloated dependencies according to a set of formal definitions (Section 2.1).

In addition to the quantitative analysis, we also perform a qualitative analysis (③) on our bloated code results. The goal of our qualitative analysis is twofold. First, we identify the root causes of code bloat. Second, we map previously-reported Python vulnerabilities taken from GitHub's advisory database [gad 2023] to the individual methods these vulnerabilities come from. This allows us to determine whether these vulnerabilities are associated with bloated dependency code.

2.1 Definition of Bloated Dependency Code

Before we describe in detail each step of our approach, we define (1) our representation for capturing inter-project dependencies, and (2) bloated dependency code.

Fine-Grained Project Dependency Graph: A fine-grained project dependency graph (FPDG) captures the method-level relationships of a Python project across its different dependencies. Formally, we define an FPDG as $FPDG = (V, E)$, where a node $v \in V = Method$ corresponds to a method defined in a project or a dependent PyPI release (external dependency). Each method $\langle m, n \rangle \in Method$ is described by a tuple, where m is the method name and n is the namespace where the method is defined. For example, consider a Python module file named `mymodule.py`, as illustrated in Listing 1: The namespace of method `m1` is `mymodule.A`, while the namespace of method `m2` is `mymodule.A.m1`. Since Python does not support method overloading (i.e., having multiple methods of the same name within the same scope), the combination of namespaces and method names is sufficient to uniquely identify each method.

```
1  class A:
2    def m1(x):
3      def m2(y):
4        pass
5        pass
```

Listing 1. A Python program.

Finally, an edge $e \in E \subseteq V \times V$ in an FPDG represents a caller-callee relationship. For example, the edge (m_1, m_2) indicates that there is a direct method call from method m_1 to method m_2. A complete example of a Python project, and its corresponding FPDG is shown in Figure 2.

Bloated dependency code: We focus on *unused* code originating from third-party libraries integrated into a Python's application ecosystem. This unused code stems from two major sources: (1) *direct* dependencies, explicitly declared by the developers, or (2) *transitive* dependencies, automatically resolved by the package manager (e.g., `pip`). We now formalize the notion of software bloat in project dependencies at different granularity levels.

In our setting, we represent each project as a triple of the form $\langle n, F, D \rangle \in Project = ProjectName \times \mathcal{P}(File) \times \mathcal{P}(Project)$. Essentially, a project consists of its name, a set of source files, and another set of its direct dependencies. Each file is a pair $\langle f, M \rangle \in File = FileName \times \mathcal{P}(Method)$. The first element of the pair corresponds to the file name, while the second element stands for the set of methods defined in the source file. For what follows, the function $Paths(g, s, t)$ returns the set of paths between the source node s and the target node t in graph g. Function $Methods : Project \longrightarrow \mathcal{P}(Methods)$ gives the set of all methods defined in a project $p \in Project$ as follows:

$$Methods(\langle n, F, D \rangle) = \bigcup_{(f,M) \in F} M$$

Function $Deps : Project \longrightarrow (Project)$ gives all direct and transitive dependencies of a project:

$$Deps(\langle n, F, D \rangle) = D \cup (\bigcup_{d \in D} Deps(d))$$

Definition 2.1 (Bloated Method). Consider a project $p = (n, F, D) \in Project$, an FPDG g, and a project dependency $d \in Deps(p)$. A method $m \in Methods(d)$ is considered a *bloated method (BM)*, if $\forall\, m' \in Methods(p).\ Paths(g, m', m) = \emptyset$.

This definition says that a method m of a dependency is marked as bloated, when m is *not* reachable by any method defined in the current project.

Definition 2.2 (Bloated File). Consider a project $p = (n, F, D) \in Project$, an FPDG g, and a project dependency $(n', F', D') \in Deps(p)$. A file $(f, M) \in F'$ is considered a *bloated file (BF)*, when $\forall m \in M.\ m$ is a bloated method.

In essence, a source file f of a dependency is considered bloated when none of the methods defined in f are used by the current project.

Definition 2.3 (Bloated Dependency). Consider a project $p = (n, F, D) \in Project$ and an FPDG g. A dependency $(n', F', D') \in Deps(p)$ is considered a *bloated dependency (BD)*, when $\forall f \in F'.\ f$ is a bloated file.

According to the above definition, a dependency d is marked as bloated, when the current project does not invoke any code included in the source files of d.

Relation of bloated dependency code with Python's import statements: Python employs two different styles of importing code, summarized as follows.

- `import x`: Imports module `x` entirely, allowing access to its elements (e.g., functions) as `x.f`.
- `from x import a, b`: Imports specific elements (e.g., `a` and `b`) from module `x`, making only those elements directly accessible.

Both of these styles can introduce the following instances of dependency underutilisation: (1) unloaded dependency code, which is part of a dependency package (existing in the file system), but never imported or loaded at runtime, and (2) unused imports which correspond to code that is imported and loaded into the application but remains unused. According to our formal definitions, a piece of dependency code is considered bloated when it is *not* necessary for the correct execution of an application that depends on it. Our formal definitions essentially treat the two instances as *indistinguishable*, as we focus on *unused* parts of *both* loaded and unloaded dependency code. Notably, our definition on bloated dependency code is consistent with other empirical studies [Soto-Valero et al. 2021a,b].

Other dependency-related issues: In addition to bloated dependency code, there are other kinds of dependency-related issues, such as circular dependencies [Melton and Tempero 2007; Oyetoyan et al. 2015; Suryanarayana et al. 2014]. Although our FPDG can capture cycles among caller-callee relationships, indicating mutually recursive functions, it cannot effectively determine whether there are cycles corresponding to mutually dependent modules and dependencies. This is mainly because of the complexity introduced by higher-order functions, where functions are passed as arguments to external code, and subsequently invoked by the external code. In this context, a caller module is not necessarily the one that has imported the callee function. Circular dependencies fall outside the scope of our study as they represent a different category of issues. Their detection would require additional metadata in the FPDG to distinguish whether a callee method is directly imported by the caller module or injected by an external module.

2.2 Project Selection and Dependency Resolution

Selecting Python projects: Our study focuses on the impact of bloated dependency code from the perspective of an *end-user*. Thus, our dataset contains actual user applications. We chose to use a dataset of Python GitHub projects provided by the work of Alfadel et al. [2023]. The dataset [Alfadel M 2020] includes 2,224 Python projects, all of which use PyPI for their dependency management. Each project in the dataset has at least ten stars, indicating community interest [Dabic et al. 2021]. In addition, all projects (1) have a minimum of 100 commits, (2) involve at least two contributors, (3) are original (e.g not forked), and (4) demonstrate recent activity, with the latest commit pushed after June 1, 2021. Notably, our selection criteria are consistent with standards utilized in other studies [Abdalkareem et al. 2020; Kalliamvakou et al. 2014].

Table 1. The evolution of our initial dataset [Alfadel M 2020] after applying each step of our data collection and data analysis approach. The final dataset consists of 1,302 Python GitHub projects. We have resolved 21,787 dependencies in total corresponding to 3,232 unique PyPI releases. Each GitHub project contains 17 dependencies on average.

Step	Operation	Total GitHub projects	Resolved deps	PyPI releases	Avg. deps
Data Collection	Initial dataset of Python GitHub projects	2,224	-	-	-
	Filtering inaccessible projects	2,215	-	-	-
	Dependency resolution	1,644	34,821	5,611	21
Data Analysis	Partial call graph construction	1,302	21,787	3,232	17
	Call graph stitching	1,302	21,787	3,232	17
	Reachability analysis	1,302	21,787	3,232	17

We have been able to successfully download the source code of all GitHub projects, with the exception of nine projects that have been either deleted or (potentially) set to private on GitHub. Consequently, we have access to the source code of 2,215 GitHub projects (Table 1).

Resolving project dependencies: For each downloaded project, we look for standardized configuration files [Cannon et al. 2016; Python Packaging Authority 2023] that control the installation of Python dependencies. This includes the traditional setup scripts (`setup.py`), the `pyproject.toml` files, or the `requirements.txt` file. When we detect at least one of the three files, we employ `pip`, which is the official package installer for Python, to install dependencies in a fresh and isolated environment. To do so, for every individual GitHub project, we run `pip install` in a new virtual environment created through the `virtualenv` utility.

Based on the aforementioned steps, we successfully resolve a set of dependencies and obtain their corresponding releases (uniquely identified by the `package_name:package_version` pattern) for 1,644 out of the 2,215 projects. The failed scenarios (571 in total) can be attributed to two main factors. First, some projects do not contain any configuration files for dependency resolution. Therefore, we are unable to accurately determine the corresponding dependencies. Second, during the installation process, we have encountered some unexpected errors due to either dependency conflicts or missing dependencies that are not explicitly specified. Projects without resolved dependencies, are excluded from our analysis. As a final step, we download the source code of these releases using the `pip download` command.

2.3 Construction of Fine-Grained Project Dependency Graph

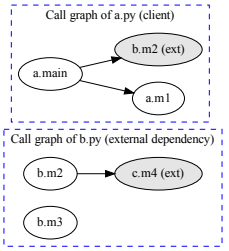
Our dependency graph generation method is inspired by the practical approach proposed by Keshani [2021]. This method addresses the scalability challenges of ecosystem-wide analyses by generating call graphs in an incremental manner. Specifically, unlike other traditional methods that employ whole-program analyses, the method of Keshani [2021] involves the construction of partial call graphs for individual projects or dependencies (Section 2.3.1). Through a stitching process (Section 2.3.2), these partial call graphs are combined together to derive a universal call graph, that is, FPDG. (Section 2.1). We now present the technical details behind the construction of the FPDG.

2.3.1 Partial Call Graph Construction. The process of constructing an FPDG begins with the generation of partial call graphs for every Python project and its dependencies. To do so, we use PyCG [Salis et al. 2021], the state-of-the-art static analyzer for Python. The input of PyCG is a set of Python source files, while its output is a call graph represented in a JSON format. Given a Python project $p = \langle n, F, D \rangle \in \mathit{Project}$, we feed the set of source files F to PyCG and store the resulting call graph. Then, we do the same for the source code of every individual dependency of p, that is $d \in D$.

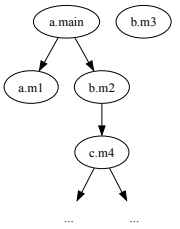
PyCG has succeeded in generating the partial call graph for 1,502 out of the 1,644 GitHub projects included in our dataset. The remaining 142 projects are excluded from our analysis because they are written in Python 2, which PyCG does not support. The 1,502 projects processed by PyCG include

```python
# a.py (client)
from b import m2

def main():
  m1()
  m2()
def m1():
  pass

# b.py (external dependency)
from c import m4

def m2():
  m4()
def m3():
  pass
```

(a) Python program



(b) Partial call graphs



(c) FPDG graph

Fig. 2. An example demonstrating a Python program with its direct and transitive dependencies (a), the corresponding partial call graphs (b), the resulting fine-grained project dependency graph (c). A gray node in a partial call graph represents an external method whose definition can be found in the dependency.

Algorithm 1: Stitching

```
1  fun stitch(callGraphs)=
2      g ← ∅
3      for cg ∈ callGraphs do
4          for v ∈ nodes(cg) do
5              addNode(g, v)
6          for (s, t) ∈ edges(cg) do
7              if isExternal(t) then
8                  t ← resolveExternalNode(t)
9              if t ≠ nil then addEdge(g, s, t)
10     return g
```

Algorithm 2: Method resolution

```
1  fun resolveExternalNode(t)=
2      (d, cg) ← getDependencyAndCallGraph(t)
3      if t ∈ cg then return t
4      Install dep d in a fresh environment
5      obj ← getFunctionObject(t)
6      if obj = None then continue
7      mod_name ← inspect.getModule(obj)
8      (n, m) ← obj.__qualname__.rsplit(".", 1)
9      n ← mod_name + "." + n
10     return (n, m)
```

a total of 4,968 unique PyPI releases as dependencies. PyCG managed to generate the partial call graph for 4,789 releases, while the remaining 175 releases are written in Python 2.

Based on the PyCG results, we perform an extra filtering step to identify all projects and releases that depend on at least one release for which PyCG produces no results. This leads to the exclusion of 196 additional Python projects from our dataset. This filtering procedure is an important step, as it filters out projects with incomplete analysis results. Incomplete analysis results can introduce a substantial number of false positives and false negatives in the corresponding call graphs. Overall, we were able to build the partial call graph for 1,302 projects and 3,232 PyPI releases. On average, each project contains 17 resolved dependencies (see Table 1).

Example: Figure 2a shows an example Python module named a that invokes a number of methods that are both internal and external. Figure 2b demonstrates the partial call graphs of module a and its dependency. External methods are denoted with gray nodes. External methods have *no* outgoing edges, because the source code of these methods is not available to PyCG.

2.3.2 Stitching of Call Graphs. Having generated the partial call graph of every project and dependency, we develop a method, which we call *stitching*, for combining individual partial call graphs into an FPDG. The key idea behind our method is to merge a list of call graphs by connecting an external node (method) with its counterpart found in the partial call graph of the dependency.

Our stitching procedure accepts a list of partial call graphs as input and follows the steps outlined in Algorithm 1. Initially, the algorithm adds every orphan node (i.e., a node with no incoming or

```
1  # a.py (client code)
2  from ext import B
3  def main():
4    obj = B()
5    obj.m()
6  ...
7  # ext/module.py
8  class B:
9    def m():
10     pass
11 class C:
12   def m():
13     pass
14 # ext/__init__.py
15 from ext.module import *
```

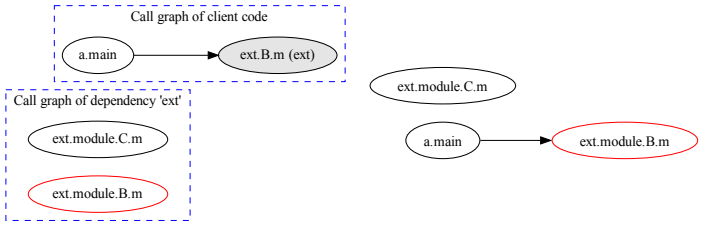


Fig. 3. An example Python program where the access path of an external method is different from its definition namespace (see external method `ext.module.B.m`). Our stitching process matches the access path at the call site (`ext.B.m`) with the corresponding definition node in the dependent call graph (`ext.module.B.m`).

outgoing edges) of a partial call graph into the FPDG (lines 4, 5). Next, for every edge (s, t) in a given call graph, the algorithm checks whether the edge reaches an external node (method). If this is the case, the algorithm resolves the target method t based on the call graph of the dependency where method t is defined (see method resolveExternalNode, line 8). When this resolution process ends, the algorithm creates a new edge in the FPDG consisting of source node s and the resolved method t. Once the algorithm iterates over all the given call graphs, it returns graph g (line 10), which stands for the fine-grained project dependency graph of the project.

Example: An example of the stitching procedure is shown on Figure 2b and Figure 2c. Notice how the internal method `b.m2` of the first call graph (dependency `b`) is matched against the external method `b.m2 (ext)` of the second call graph (project `a`). The algorithm merges these nodes and adds all the incoming edges of `b.m2 (ext)` to node `b.m2` (see Figure 2c).

Resolving external nodes: External calls represent interactions between a node in the current graph and a node in another partial call graph. However, our stitching procedure faces two major challenges associated with the resolution of external calls. First, the official distribution name of a package might be different from its import name (Challenge 1). For example, the PyPI package `beautifulsoup4` is imported as `bs4` in the code. The second challenge (Challenge 2) lies in correctly associating method identifiers with their corresponding internal nodes in the dependent partial call graphs. This is because of the Python's import system, where an external callable can be imported and accessed in multiple ways, depending on the contents of Python `__init__.py` files. Notably, an `__init__.py` file contains code that is executed once a specific module is imported.

To illustrate this, consider the code fragment in Figure 3. The code imports a class `B` from an external dependency named `ext`. In turn, it creates an object of `B` and calls the instance method `m` (lines 4, 5). At use site, the method `m` is accessed through the namespace (`ext.B.m`), which is different from the namespace where the method is defined in the external dependency (i.e., `ext.module.B.m`, line 9). This is because of the contents of file `__init__.py`, which imports all contents of module `ext.module.py` beforehand (line 15). Since PyCG does not have access to the source code of the dependency `ext`, it becomes impossible for us to determine the namespace where method `m` is actually defined.

To address the aforementioned challenges, the function resolveExternalNode (Algorithm 2) takes a method node t and works as follows. First, the function retrieves the dependency and the call graph associated with the external call to t. To do so, the function consults the `top_level.txt` file that accompanies every downloaded PyPI package [Python Packaging Authority 2024]. This file outlines the top-level directories or modules included in every PyPI package. Based on this

Table 2. Statistics on the resolved and unresolved external calls during our stitching process.

External Calls	Aggregate count	Proportion of total	Average (per project)	Median (per project)
Resolved	7,799,929	96.7%	5,990	144.5
Unresolved	260,249	3.2%	199	11.5

information, we maintain a dictionary that maps every module to the package it belongs to, thus addressing Challenge 1. For example, when the algorithm encounters an external call of the form `bs4.parse_html`, the algorithm is able to map the module `bs4` to the dependency `beautifulsoup4`, and retrieve its corresponding partial call graph *cg* (Algorithm 2, line 1).

After retrieving the dependency *d* and the call graph *cg* associated with node *t*, the algorithm tries to match *t* with a corresponding internal node found in the dependent call graph *cg* (Challenge 2). We illustrate this process using the example of Figure 3. In this example, we want to resolve node `ext.B.m` found in the call graph of the client module `a.py`. The algorithm first checks whether this node appears in the call graph of the dependency (Algorithm 2, line 2). Since this is not the case, the algorithm employs a dynamic method to precisely identify the namespace where the callee method `m` is defined based on its access path.

The dynamic approach first installs the dependency *d* in a clean environment. Then, it leverages Python's metaprogramming features to analyze elements within the module or its class objects. For example, consider the access path `ext.B.m`. The algorithm first dynamically imports the module `ext` via the `__import__` functionality. Then, it recursively retrieves the object of every element included in the access path until it reaches the object *obj* that corresponds to the target method `m` (Algorithm 2, line 5). Upon retrieving the method object *obj*, our method uses Python's `inspect` module (Algorithm 2, lines 7, 8), which offers an API for getting (1) the module name where this method is defined (i.e., `ext.module`), and (2) the fully qualified name of the method (i.e., `B.m`). Combining the two leads to the resolved node as found in the dependent call graph (i.e., `ext.module.B.m`). When resolveExternalNode returns, our stitching procedure finally proceeds with the creation of the FPDG as explained in Algorithm 1.

Discussion on external call resolution: In the stitching process, we use a dynamic method to resolve external calls, which by construction, does not yield false positives. It *precisely* identifies the namespace where a callee method is defined in a certain dependency, using Python's metaprogramming features. However, there are cases where our resolution method fails to resolve a specific call. This is because of callee methods defined in non-Python source files. For example, many methods included in the `numpy` package (e.g., `np.asarray`) are written in C. To address such scenarios, a cross-language analysis is required to build both the partial call graphs and the FPDG.

Table 2 presents statistics from our method resolution process. Roughly 3% of the unique external calls remain unresolved. Upon examining a random sample of 100 unresolved cases, we find that all these instances are due to callee functions defined in languages other than Python.

As a final note, to avoid polluting the namespace with dynamic imports, Algorithm 2 runs on a separate system process.

2.3.3 Reachability Analysis. Once we generate the FPDG for every project, we perform a standard reachability analysis through a Breadth-First Search (BFS) algorithm to compute the set of reachable methods in every project dependency. These reachable methods are directly or transitively called by the project. Based on the results of our reachability analysis, we identify the set of bloated methods, bloated files, and bloated dependencies according to definitions 2.1, 2.2, and 2.1 respectively.

2.4 Analyzing Reachability Results

We now explain how we analyze our reachability results to answer each of our research questions.

RQ1: Prevalence of software bloat: To quantify the prevalence of code bloat (RQ1), we measure the number and the size (in terms of lines of code — LoC) of bloated methods, bloated files, and bloated dependencies respectively. For each analyzed source file and method, PyCG provides metadata, such as their code size. We use this information to measure the code size of each identified bloated method and file. Note that our method-level assessment only examines code within the scope of methods, whereas file-level analysis includes all lines in a file, including the ones outside the scope of methods (e.g., global variables). Finally, for bloated dependencies, we aggregate the size of every enclosing bloated file.

RQ2: Relation between software bloat and software vulnerbilities: We examine the GitHub Advisory Database [gad 2023] and collect all reviewed vulnerabilities reported on PyPI packages. We exclude all vulnerabilities marked with the *"withdrawn"* label, which indicates that the vulnerability is duplicate or invalid. Through this process, we have collected 1,930 unique PyPI vulnerabilities. Next, for each of the GitHub advisories we extract the version constraints of the affected PyPI packages and match them against the package versions of our dataset. Specifically, we mark a package version as vulnerable if it falls within an advisory's affected range. In this manner, we identify 76 vulnerable PyPI releases in our dataset. We then leverage our reachability analysis findings to detect how many GitHub projects within our dataset depend on at least one of these vulnerable releases. To make our analysis more fine-grained, we take a step further and perform a vulnerability mapping. That is, for each vulnerable dependency, we manually identify which method contains the vulnerability described in the corresponding CVE. To do so, we extract the affected functions or classes from the CVE descriptions and then we look for their implementation. If the CVE description does not include such information, we take one more step and examine the patching commits to pinpoint the affected functions or classes. By using our reachability analysis we are able to check if a vulnerability resides in a bloated method (Definition 2.1).

RQ3: Root cause analysis: In this question, we aim to study the main causes of bloated dependencies. Since the manual analysis of each bloated dependency is costly and challenging (see below), it is infeasible for us to study each bloated dependency in the population. Therefore, we take a random sample of 50 bloated dependencies that stem from the outcome of our reachability analysis. All the selected dependencies are *direct* dependencies, meaning the they are explicitly declared in the configuration files (e.g., `setup.py`) of a project. We chose to study the root cause of bloated direct dependencies because developers have typically a better control over direct dependencies. Therefore, it is easier for us to explain the causes of bloated code.

For each bloated dependency, we proceed as follows. We use the `git blame` command to identify the commit where this dependency was introduced in the config files (e.g., `setup.py`, requirements.txt). We then examine the message of this introductory commit, and if the commit is linked with a pull request (PR), we also inspect the corresponding PR comments. Examining commit messages and developers' discussion helps us uncover the reasons why the dependency is introduced. In the same manner, we employ `git` to find the commit where developers stopped using the dependency, and examine possible reasons for this decision.

Note that a bloated dependency might have been already used and removed for different purposes. This can be relevant to the root cause. To investigate the full history of the dependency, we extend our analysis beyond the configuration files. Specifically, we conduct GitHub searches to identify corresponding imports and examine relevant code sections in the project's source files throughout its history. For each identified reference, we repeat our `git`-based analysis to track both the introduction and removal of the bloated dependency. In the context of our root cause analysis, one author independently assigns every bloated dependency to a root cause category. The final categorization has been validated by an additional researcher.

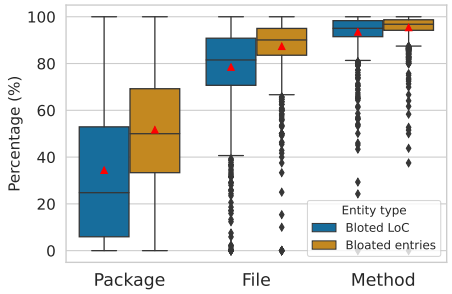


Fig. 5. The distribution of bloat metrics per granularity. Each entry indicates the percentage of bloated entities (e.g., files, methods), and the size of bloated dependency code compared to the overall LoC.

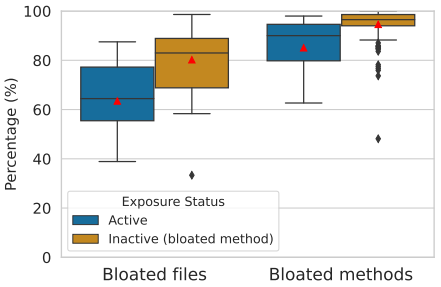


Fig. 6. The distribution of bloat metrics per vulnerability exposure. Each entry indicates the relationship between a vulnerable release, and a project that uses it. For example, 82% of the files in an inactive vulnerable release are bloated.

RQ4: Developer perception on software bloat: We have provided fixes for 42 out of the 50 bloated dependencies for which we have performed root cause analysis (see RQ3). We did not submit any pull request for eight out of the 50 bloated dependencies, because although they are unused, these dependencies constrain the resolved versions of some other transitive dependencies included in the project. Developers employ this pattern to ensure compatibility with an older library version, or avoid a vulnerable version (see Section 3.3 for more details). Based on the insights from our root cause analysis (RQ3), we design PRs containing the following elements: (1) a *summary* section, (2) a *rationale* section, (3) a *list of changes* in the project's source files, and (4) the *impact and expected outcome* of removing bloated dependencies. Notably, the *rationale* section of each PR is crucial, as it details the historical context and specific reasons behind the introduction and removal of the bloated dependency. This context is backed by data from our RQ3 analysis.

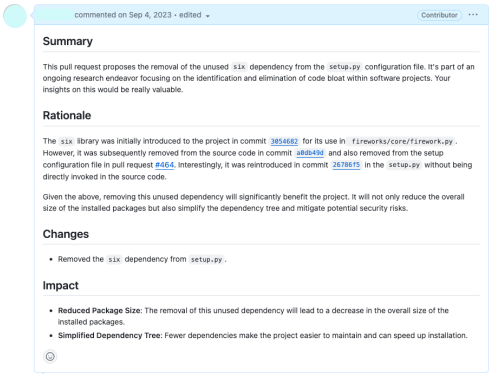


Fig. 4. Example of a pull request body sent to the GitHub project materialsproject/fireworks.

Figure 4 shows an example PR of removing the bloated dependency to package `six` on project materialsproject/fireworks. The PR demonstrates how our root cause analysis informs and enriches the PR content. For example, the *rationale* section cites three specific commits and one PR, each of those affect the bloated dependency `six`. As we will see in Section 3.4, our detailed PRs significantly enhance the likelihood of developer acceptance and action. Based on our provided fixes and cause insights, developers respond to our pull requests. We then examine their feedback.

3 RESULTS

3.1 RQ1: How prevalent is bloated dependency code in the PyPI ecosystem?

Our reachability analysis leverages our definitions on bloated dependency code (Section 2.1) and identifies the set of bloated: dependencies, files, and methods. At each granularity level, we compute

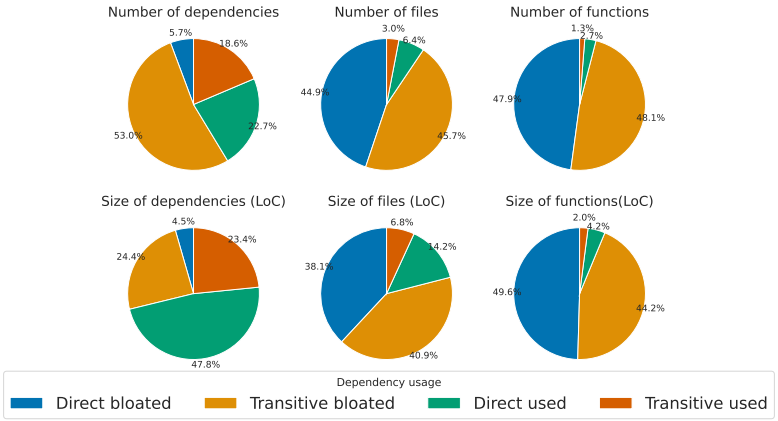


Fig. 7. The distribution of the usage status of dependencies, dependency files, and dependency methods, along with their size in LoC, as aggregated from our dataset.

(1) the number of bloated entities (e.g., files, methods), and (2) the size of bloated entities in terms of LoC. Figure 5 presents the quantitative characteristics of bloated dependency code. The red marker in each box plot represents the mean of the distribution.

Package level: We observe that more than half of the dependencies (51%) in a typical PyPI project are bloated. On average, a Python project contains ten bloated dependencies. Furthermore, we see varied dependency usage practices: for 25% of the examined projects, at most 33% of project dependencies are bloated. However, for another 25% of the studied projects, this ratio exceeds 69%. Such a high ratio could be attributed to several factors including: (1) developers declaring unused direct dependencies, or (2) projects using only a subset of a direct dependency's functionalities, leading to bloated transitive dependencies.

Regarding lines of code, 34% of the dependency code is bloated, on average. This suggests that while many dependencies might be unused, their code contribution is not as extensive. However, in sheer volume, an average project in our dataset still carries a significant number of bloated lines of code, that is, 98,097 LoC, on average. However, there are still projects in our dataset that diverge from the aforementioned trend. Specifically, approximately 10% (142 projects) have optimally managed dependencies with no bloat. On the other hand, 109 projects (~8%) do not use any of their declared dependencies, indicating potential areas for better dependency management.

File level: Moving to bloated files (Figure 5), on average, 87% of the dependency source files are bloated. A Python project contains on average 688 bloated files. Regarding the size of these bloated files, the bloated code consists of 243,156 LoC, on average. Worse, Figure 5 suggests that more than half of the projects have their dependency code as bloated, implying that less than 20% of the source files from dependencies are actively used. This emphasizes that even within seemingly used dependencies, a substantial amount of code is unused. This uncovers an additional layer of software bloat that goes beyond bloated packages. Therefore, debloating techniques that are less granular than method-level removal, such as file-level removal, can still effectively reduce bloat.

Method level: At the method level, our measurements exhibit an even more significant increase of dependency code bloat. Specifically, within a Python project, 95% of its external methods (i.e., 10,618 methods) are bloated, on average. Considering the size of these external methods, we find a similar picture: 93% of the dependency code within an application is bloated. This translates to 185,052 lines of bloated code per project.

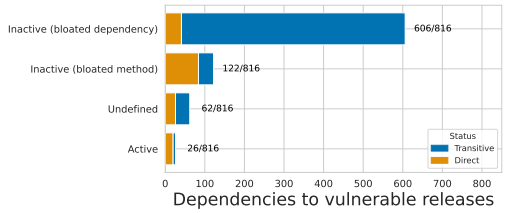


Fig. 8. Number of different usage statuses of vulnerable PyPI dependencies in Github projects.

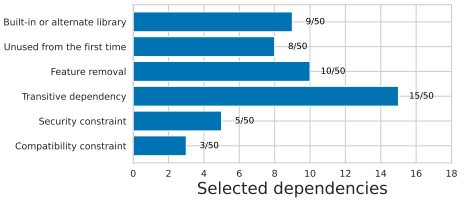


Fig. 9. The distribution of causes leading to bloated-direct PyPI dependencies.

Direct vs. transitive dependencies: For completeness, we have also examined the degree to which direct dependencies contribute to the bloat compared to transitive dependencies. Figure 7 presents the distribution of dependency usage statuses across different granularities. In particular, at the package level, it seems that the bloated dependency code mainly stems from transitive dependencies, as more than half of the project dependencies (53%) are transitive and unused. However, when examining LoC, we see that only one quarter (24.4%) of the overall project size is bloated because of unused transitive dependencies. As granularity refines to file and method levels, an overwhelming majority of dependency code is unused. Interestingly, direct and transitive dependencies contribute almost equally to this software bloat.

Overall, as we make our analysis more fine-grained (i.e., from dependencies to files and then to methods), we observe that bloat becomes more prevalent: nearly half of the dependencies in a typical Python project are bloated. The amount of bloated code gets worse at the file and method levels. Our fine-grained analysis helps us uncover which specific code parts contribute to the bloat, and allows for targeted improvements. For example, understanding which specific dependency code is bloated enables developers to refactor or rewrite their code more efficiently.

3.2 RQ2: What is the relation between bloated dependency code and software vulnerabilities?

In this research question, we explore the relation between bloated dependency code and software vulnerabilities shipped through PyPI releases. Our dataset includes 76 package releases that contain known vulnerabilities. Our reachability analysis results indicate that out of the 1,302 Python projects of our dataset, 595 projects depend on *at least one* vulnerable release. In total, we have 816 unique pairs consisting of a project and a vulnerable package release.

Usage patterns: Figure 8 shows the usage patterns of the vulnerable packages across the 595 projects. In nearly three quarters of the cases (606/816), a project depends on a vulnerable package that it does not actually use. Therefore, package-level debloating alone, although less granular, could still effectively eliminate the number of dependencies to vulnerable code.

Furthermore, we discover a significant number of instances where a project imports and invokes a vulnerable package, but the specific vulnerable function or class within the release remains unused. This accounts for the 15% (122 out of 816) of cases (see "bloated method in used release"). Notably, among these 122 inactive exposures, 29 of them (23%) appear in *non-bloated* files. Developers should stay alert for such "time-bombs", because a seemingly innocuous code change (e.g., replacing a method call with another one) in the project could trigger the execution of vulnerable code. Automatically removing those critical vulnerabilities from a project's code base demands a more fine-grained debloating approach.

Vulnerabilities located within non-Python dependency files appear in 7.5% (62/816) of our project-vulnerable release pairs. Given our Python-centric methodology, the invocation status of such

defects remains uncertain. Yet, their prevalence within the PyPI ecosystem suggests the necessity for broader security evaluations that consider multiple languages and file types. Finally, when examining active security threats, we find that in 26 out of 816 instances a project invokes a vulnerable function. This means that there is still a non-negligible number of urgent situations, where a Python project is exposed to vulnerabilities that are directly exploitable.

Furthermore, our distinction between direct and transitive dependencies in Figure 8 shows that the majority of vulnerabilities reside in bloated dependencies that are transitive. However, direct dependencies are mainly responsible for vulnerabilities that appear in (1) invoked methods (i.e., active exposure status) or (2) bloated methods found in used releases. This can be attributed to direct dependencies exhibiting a higher usage status, as previously demonstrated on RQ1 (Figure 7).

Software bloat: To examine the prevalence of bloated methods and files in vulnerable releases, we need to take into account that several projects may depend upon the same vulnerable release. To address this challenge we consider all relationships between a vulnerable release and a dependent project, and measure the corresponding bloat. The results are illustrated in Figure 6 where we present the distribution of bloated code in terms of files and functions. We focus on two categories, (1) releases that include vulnerable code invoked by the projects (active exposure status), and (2) used releases with unused vulnerable code (inactive exposure status). On average, 63% of the files in an active vulnerable release are bloated, increasing to 85% in the case of methods. In contrast, for inactive vulnerable dependencies, an average of 80% of files and 94% of methods are bloated.

Overall, our results show that a significant number (89%) of vulnerabilities in PyPI dependencies are found within bloated code sections, with a noteworthy 15% existing in used dependencies.

3.3 RQ3: What are the main causes of bloated PyPI dependencies?

To delve into the root causes of bloated dependency code, we manually inspected 50 bloated dependencies picked at random as explained in Section 2.4. Our manual analysis has resulted in six categories as shown in Figure 9.

Replacement with built-in or alternate library: This root cause arises when developers shift from a third-party library to a built-in or a different library, but neglect to remove the former from their declared dependencies. For example, the `ewels/MultiQC` project replaced `simplejson` library with the Python's internal module `json`, but failed to remove `simplejson` from its dependency list. Such cases account for nine instances in our study.

Feature removal: As software evolves, certain features or code sections may be deprecated or removed. Such removals could render some dependencies redundant. Our investigation identifies ten instances, where some dependencies become bloated, after developers remove certain implementation features from their code base. For example, the `HadrienG/InSilicoSeq` project uses the `future` library to bridge compatibility between Python 2 and Python 3. However, at a later stage, the project decides to drop support for Python 2, removing the corresponding source code and making the dependency to package `future` redundant.

Unused from the first time: We have discovered instances where dependencies are introduced in a project dependency list without any corresponding usage in the source code. The reasons for these introductions often remain unclear. For example, in one case the developers of `PSLmodels/Cost-of-Capital-Calculator` project may have added the `psutil` library for potential benchmarking, but was never used in the code base. We have identified eight bloated dependencies that lie in this category. This highlights that some developers tend to introduce extraneous dependencies, possibly during exploratory development phases. Caution during code reviews and cleanup routines can help prune such inclusions.

Table 3. The status of our pull requests, proposing the removal of bloated dependencies (BD)

PR status	# of PRs	# of BD removed
Merged	28	33
Approved	2	2
Rejected	1	1
Pending	5	6
Total	**36**	**42**

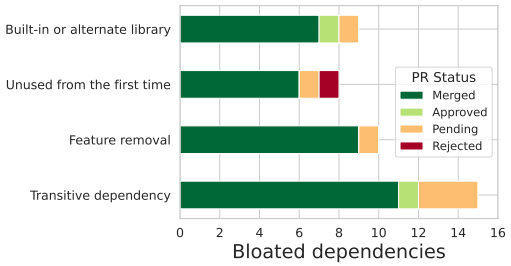


Fig. 10. The distribution of PR statuses per root cause.

Redundant declaration of a transitive dependency: When installing a Python project, `pip` resolves all transitive dependencies without requiring them to be declared in the project's dependency list. We have observed that 15 projects redundantly list their transitive dependencies as direct. Such a practice possesses risks: for example, consider a package p_1 that stops relying on package p_2. All projects that redundantly depend on both p_1 and p_2 will still retain a dependency to p_2. This can make projects maintain redundant transitive dependencies, and worse, face version conflicts due to discrepancies between directly and transitively included dependencies. By eliminating such redundancies, projects have exclusive control over the dependencies they directly invoke. These redundancies can be attributed to misunderstandings about how the dependency resolution process of `pip` works. Specifically, through our interaction with developers (RQ4), we have observed that some development teams are unaware that `pip` also retrieves transitive dependencies.

Security constraint: This category contains cases where developers intentionally constrain the versions of transitive dependencies for security reasons, e.g., to avoid resolving a transitive dependency to a package release with a known vulnerability. We have run into five such instances. This phenomenon occurs when a library upon which the application relies, fails to timely update its direct dependencies and mitigate the security risk, thereby indirectly exposing end-user applications to vulnerabilities that are mitigated through this preventive measure.

Compatibility constraint: Developers occasionally enforce version constraints on transitive dependencies to ensure compatibility and avoid potential conflicts with certain functionalities or components [Patra et al. 2018; Wang et al. 2020]. In our study, we have detected three such instances. As an example, the `20c/vaping` project constrains the version of package `Werkzeug` between 2.0.0 and 2.1.0. This declaration is accompanied by the following comment: *"FIXME: werkzeug >2.1.0 breaks static file serving"*. This comment is a sign of a compatibility issue: versions of `Werkzeug` greater than 2.1.0 would break a specific functionality in the project.

Overall, the primary factor contributing to bloated-direct PyPI dependencies is mistakes and omissions during code refactoring (34%). Additionally, another 30% of the bloated dependencies arise from unnecessary listing of transitive dependencies, while 16% comes from dependencies that are introduced without ever being used. Our results uncover several key areas for consideration, including (1) the significance of maintaining updated configuration files after code refactoring, and (2) better control over transitive dependencies avoiding the declaration of redundant dependencies.

3.4 RQ4: To what extent are developers willing to remove bloated PyPI dependencies?

We aim to investigate how developers react to bloated PyPI dependencies. To do so, we have opened 36 pull requests that fix 42 bloated dependencies detected by our reachability analysis (Section 2.4). Table 3 presents the outcomes of these pull requests. Note that a single pull request can propose

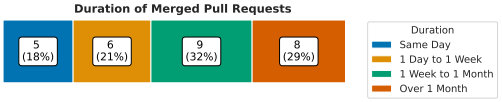


Fig. 11. Duration of merged pull requests.

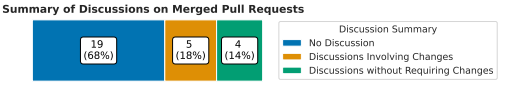


Fig. 12. Summary of discussions on merged pull requests.

the removal of multiple dependencies. At the time of writing, we have received responses for 31 out of 36 pull requests submitted. For the five pending PRs, the involved repositories have collectively seen a mere total of 10 commits over the three-month period we awaited feedback. This suggests that the absence of feedback on our PRs is likely due to project inactivity. Among the PRs that received feedback, 90% (28/31) have been accepted and integrated into developers' code base, resulting in the removal of 33 bloated direct dependencies. In total, this process led to the removal of 285,322 lines of Python code from projects' code base. In two cases, developers have approved our fixes, but they have not merged the corresponding pull requests yet. In a notable instance, a PR was declined because the developer prioritized the potential future utility of a dependency over code simplification. Developers often expressed gratitude for our pull requests, with many highlighting the value of the proposed changes. Specifically, in 22 out of the 28 merged cases, developers conveyed their appreciation (e.g., *"Huh, great spot - thanks!"*, *"Thanks for the detailed explanation!"*, or *"thanks for catching that."*). This positive feedback indicates that developers understand the risks of bloated dependencies, and the importance of removing them. Below, we discuss some interesting cases that come from the our interaction with developers.

Example 1: In the project `EasyPost/easypost-python`, we encountered diverse feedback from the development team. A developer initially rejected our PR, commenting: *"If the dependency is unused, that is a mistake as we want to implement typing in this library. Recommend to reject."*. However, the lead developer answered with *"This dependency is unused at this time and has been since its introduction over a year and a half ago. I'm down to remove it. If we ever need it in the future we can easily reintroduce it."* Subsequently, the opposing developer approved and merged our fix.

Example 2: In the project `maurosoria/dirsearch`, we submitted a PR proposing the removal of five bloated transitive dependencies. Initially, the developers were hesitant with removing those dependencies: *"Hi, thanks for your PR, I remember there were reasons in the past that made us keep those dependencies in requirements.txt, I'm not sure if it's safe or not to remove them..."*. However, after three months, the lead developer proceeded to merge the pull request commenting: *"Thanks for the detailed explanation!"*. This interaction reveals that developers are sometimes hesitant to remove explicitly declared transitive dependencies without a clear rationale for their initial inclusion.

Qualitative analysis on our PRs: To gain further insights, we also performed a qualitative analysis on our PRs in terms of their (1) lifespan, (2) accompanying developer discussions, and (3) relation to the underlying root causes of the bloated dependencies they fix. Figure 11 shows the lifespan of our accepted PRs, measuring the duration from when the PR is opened to when it is merged. The distribution of merge times ranges from same-day merges to those extending over a month. While some PRs are quickly integrated, others require more extensive consideration. This might be attributed to the resources and the PR prioritization of each project development team.

Figure 12 shows the classes of the discussions that took place before merging our accepted fixes. The majority of PRs (68%) were accepted without the need of further discussions, indicating that many changes were straightforward and immediately recognized as valuable. However, discussions arose in nine cases. For example, five PRs involved changes to meet contributing guidelines, and fix failing tests unrelated to our PR. In other instances, developer requested reverting changes in certain files where a dependency, though redundant for the package itself, was required for specific

operational contexts, such as continuous integration processes. Finally, four merged PRs led to discussions about our fixes without requiring changes, as seen in Example 1.

Figure 10 also shows how the underlying root cause of a bloated dependency affects the status of our PRs. 22 accepted fixes are linked to direct dependencies that fall into two categories: (1) mistakenly declared dependencies, and (2) dependencies that are no longer used due to code refactoring, such as feature removal. Interestingly, there are 11 accepted fixes related to redundant transitive dependencies. This pattern of responses could be attributed to the clarity of root causes. For example, removing unnecessary dependencies is often part of a code cleanup process following pervasive code changes. Unfortunately, developers sometimes overlook this cleanup, which makes them quickly address and resolve issues that stem from such omissions.

4 KEY TAKEAWAYS AND SUGGESTIONS

We now discuss several implications of our work, and how our findings can serve as a basis for future research endeavors in debloating the PyPI ecoysystem.

The PyPI ecosystem exhibits considerable resource underutilization. We have shown that a substantial portion of Python dependency code is bloated (Section 3.1). This indicates a need for tailored solutions within the Python domain. Researchers and practitioners should consider the development of Python-specific debloating techniques that effectively address the widespread bloat in the PyPI ecosystem.

Dependency code bloat becomes more prevalent via fine-grained analysis. Figure 5 reveals that the majority of the dependency code bloat can only be identified only when examining inter-project dependencies at file- or method-level. Removing unused packages will contribute to reducing bloat to some extent [Soto-Valero et al. 2021b], however a significant amount of bloat hidden within used dependencies will continue to exist. Hence, effective debloating techniques should consider file and method bloat within dependencies that are partially used by the developers.

"Time-bombs" in bloated dependency code. Our results reveal a relationship between code bloat and security vulnerabilities in the PyPI ecosystem. A significant 89% of these vulnerabilities are identified within bloated code regions (Figure 8). Interestingly, 15% of them are marked as "time-bombs", i.e., the corresponding code is not used at the moment, but this may change in the future and trigger the vulnerability. Another layer of complexity is added by a non-trivial number of vulnerabilities (7.5%) found in non-Python files. This is consistent with the findings of a recent study on the security risks posed by native extensions in ecosystems like PyPI [Staicu et al. 2023]. Addressing the identified cross-language vulnerabilities (e.g., via a technique that goes beyond Python source files) could further reduce the attack surface of Python projects.

Given the absence of detailed localization information for vulnerabilities in CVEs, devising a fully automated debloating process for defect removal is technically challenging. In response, we advocate for a method akin to our study's approach (Section 2.4). This involves an automated tool, scanning patching commits linked to CVEs to identify potentially vulnerable methods or classes. Such a strategy might introduce false positives by over-approximating vulnerable functions or classes, as not all of the functions modified in the commit might be vulnerable. To address this, we propose a semi-automatic solution where a tool (e.g., a linter) alerts developers about bloated dependency code (i.e., classes or methods) appearing in patching commits, suggesting careful examination and possible removal.

Code refactoring introduces bloated dependencies. Figure 9 shows that bloated dependencies are introduced after extensive modifications in the developers' code base, such as feature removal, replacement of algorithms, etc. This suggests that developers might be less careful when tidying up post-feature deprecations or refactoring. To mitigate this issue, existing linters and automated refactoring tools, such as `pylint` or `flake8`, could be extended with additional functionalities.

Such functionalities should check and update (if necessary) the configuration files of a project so that the declared list of dependencies contains only used ones.

Developers are willing to remove bloated dependency code especially when they are aware of its major causes. Our interaction with development teams indicates that developers are willing to debloat their code (Section 3.4). This finding contradicts with the findings of a previous study on bloated dependencies [Cao et al. 2023], where the authors found that the majority of Python developers are not willing to remove bloated dependencies. This discrepancy in findings could be attributed to our methodology, which not only identifies issues, but also offers immediate and well-justified action steps via our PRs (see Figure 4). Based on this observation, future linters and debloating tools should clearly enumerate and document the reasons why a certain bloated dependency code should be removed and, importantly, offer actionable steps akin to our pull requests to guide developers in making these changes effectively. Finally, our findings suggest that future tools should prioritize warnings based on the causes of bloated code. For example, developers are more likely to accept debloating code that stems from code refactoring processes.

5 THREATS TO VALIDITY

Internal validity: One threat to the internal validity of our work is related to the resulting FPDG. Because of the dynamic nature of Python, our static FPDG might contain false negatives and false positives. This is unavoidable even when dealing with statically-typed programming languages, such as Java [Soto-Valero et al. 2021a,b]. We build FPDG using PyCG [Salis et al. 2021], the de-facto static analyzer of Python, which has been employed in other empirical studies [Simon et al. 2023; Venkatesh et al. 2023]. Another threat is the representativeness of the selected Python projects. Using established selection criteria [Abdalkareem et al. 2020; Kalliamvakou et al. 2014], we chose a carefully crafted dataset [Alfadel et al. 2023; Alfadel M 2020], that contains real-world Python applications from various domains, ranging from web technologies to biomedical tools amd high-performance computing. Finally, another internal threat to validity relates to our stitching process and the resolution of external calls (Section 2.2). First, we consulted the `top_level.txt` file to associate every external module with its package distribution. This is the standard practice employed by other studies [Cao et al. 2023]. Second, we leveraged Python's metaprogramming features (e.g., `inspect`) to reliably identify the definition namespace of every external method.

External validity: The generalizability of our findings to other software ecosystems is one threat to external validity. Our findings are restricted to the scope of Python and the PyPI ecosystem: Generalising them requires further research. Notably, some of our findings (e.g., RQ1—prevalence) are also consistent with the findings of other studies targeting Maven [Soto-Valero et al. 2021b].

The representativeness of the bloated dependencies selected for answering RQ3 and RQ4 is another threat to the external validity. Since the number of bloated dependencies found by our analysis is large, it is not feasible to manually analyze all of them for RQ3 and RQ4. We picked a random sample of 50 bloated dependencies, which is in line with other studies on bloated dependencies. For example, Cao et al. [2023] have manually analyzed the causes of 127 bloated dependencies. Following the reasoning outlined in the work of Mastrangelo et al. [2019], when working with a random sample of 50 bloated dependencies, there is an approximately 8% chance of missing a cause category with a relative frequency of at least 5%. These probabilities are computed by the following formula described in the work of Mastrangelo et al. [2019]: $(1 - \mathit{relative\_frequency})^{\mathit{sample\_size}} = (1 - 5\%)^{50} \approx 8\%$.

Finally, our manual cause analysis might be subjective. To mitigate this threat, the proposed categorization has been validated by an additional researcher, following the best practices in manual qualitative analyses [Brereton et al. 2007; Chaliasos et al. 2021; Kotti et al. 2023].

6 RELATED WORK

Software bloat: Research has focused on reducing the code size of source programs by adopting program transformation and syntax-aware techniques [Regehr et al. 2012; Sun et al. 2018], or reinforcement learning [Heo et al. 2018]. Other debloating techniques operate on C/C++ binaries to reduce their attack surface [Qian et al. 2019; Quach et al. 2018; Sharif et al. 2018]. In recent years, there has been a growing interest in debloating Java applications [Bruce et al. 2020; Jiang et al. 2016; Macias et al. 2020; Soto-Valero et al. 2023, 2021b]. The proposed tools employ static and dynamic analysis that works on Java bytecode. Another important body of work has targeted debloating JavaScript and PHP web applications. For JavaScript, approaches range from static [Koishybayev and Kapravelos 2020] and dynamic analysis [Vázquez et al. 2019] to hybrid approaches [Turcotte et al. 2022]. For PHP, techniques range from semi-automated static debloating schemes [Jahanshahi et al. 2023] to dynamic analysis [Azad et al. 2019], and concolic execution [Azad et al. 2023]. Software debloating has also been applied to domain-specific programs, including the Chromium browser [Qian et al. 2020], Android applications [Jiang et al. 2018], Docker containers [Rastogi et al. 2017] and shared binary libraries [Agadakos et al. 2020]. Surprisingly, despite its popularity, there has not yet been any developments in debloating techniques for Python. Our work provides insights that could guide the design of effective debloating methods tailored to the Python ecosystem.

Bloated dependencies: The concept of "bloated dependencies" was first introduced by Soto-Valero et al. [2021b] in their study that focuses on the Maven ecosystem. By statically analyzing Java bytecode, they identify and remove unused dependencies from Maven POM files. Their study reveals a significant 75% bloat rate in dependency relationships, primarily stemming from transitive dependencies. In comparison, our findings indicate a bloated dependency rate of only 51%, probably indicating a better dependency utilization in the PyPI ecosystem. In a subsequent study [Soto-Valero et al. 2021a], the authors find that the addition of new and unused dependencies is the main root cause of bloated direct dependencies. In contrast, we identify omissions during code refactoring processes as the main root cause of bloat (RQ3). In another study, Hejderup et al. [2022] leverage call graphs to build the dependency network of the Rust ecosystem. They discover that ~60% of the package dependencies are bloated. Jafari et al. [2022] identifies a similar trend in the `npm` ecosystem.

The closest study to our work is the one of Cao et al. [2023], who investigate *"dependency smells"* across 132 Python projects. The term "dependency smells" describes a set of dependency-related issues, including bloated dependencies. To identify bloated dependencies, the authors parse configuration files and analyze import statements in the source code. The authors characterize each bloated dependency by its prevalence, evolution, causes, and developer perceptions. The main findings of this study show that bloated direct dependencies appear in 86% of projects, with 75% of these dependencies coming from new dependency declarations without subsequent source code use. Contrary to this study, our approach is more fine-grained: we quantify bloat at both the file- and method-level. Additionally, our analysis is able to distinguish transitive dependencies from direct ones. This is particularly evident in our root cause analysis. For instance, our fine-grained analysis allows us to know whether a dependency declaration corresponds to a transitive dependency. Without this knowledge, we would have misclassified such cases as *"unused from the first time"*.

Furthermore, Cao et al. [2023] pinpoint that developers tend to be hesitant when it comes to removing bloated dependencies (0/10 reported issues fixed, 4/10 rejected). In contrast, we show that developers are willing to remove unused direct dependencies, even in cases where the dependencies are used transitively. As described in Section 4, this difference could be explained by our well-justified pull requests that incorporate the results of our root cause analysis.

Access path reasoning: Wang et al. [2021] focus on restoring the execution environments of Jupyter notebooks by identifying the PyPI packages required for executing the notebooks. To achieve

this, they statically analyze the source code and map library APIs to their source code definitions using an import flow analysis. In contrast, we use dynamic analysis to tackle the same issue. Moreover, recent work on program analysis of JavaScript code involve grammar-based access path reasoning for call graph construction [Nielsen et al. 2021], extraction of taint specifications [Staicu et al. 2020], or detection of breaking library changes [Mezzetti et al. 2018; Møller et al. 2020].

Software ecosystem analysis: Hejderup et al. [2018] introduce the idea of using call graphs to represent actual calling relationships within software ecosystems. Building on this method, Mir et al. [2023] design a fine-grained analysis for the Maven ecosystem, and reveal that while one third of the packages are vulnerable due to transitive dependencies, only 1% of them has a reachable call to a vulnerable dependency method. This is in line with our RQ2 results.

In recent years, there has been a growing interest in software supply-chain security and particularly within scripting languages ecosystems. Duan et al. [2020] perform an in-depth study on the indicators of malicious packages in the ecosystems of PyPI, RubyGems and npm, and construct a program analysis pipeline to detect malicious packages in those ecosystems. Focusing on JavaScript, Zahan et al. [2022] analyze the metadata of 1.6 million packages and propose specific metrics that can act as warning signs for supply chain vulnerabilities. Staicu et al. [2018] reveal the high prevalence of injection attacks in the npm ecosystem, while Rack and Staicu [2023] conduct an empirical study on JavaScript bundles and reveal that they are prevalent and often ship vulnerable dependency code. Similarly, Shcherbakov et al. [2023] study prototype pollutions in Node.js and find out that they can lead to remote code execution attacks. Focusing on the npm ecosystem, Zimmermann et al. [2019] indicate that the lack of project maintenance leads to dependency on vulnerable artifacts. Focusing on the PyPI Ecosystem, Neupane et al. [2023] study more than 1200 typosquatting attacks and define 13 distinct categories of confusion mechanisms. Vu et al. [2020] propose a source code repositoriy analysis for detecting malicious code in PyPI packages. Alfadel et al. [2023] find that the average number of vulnerabilities affecting a PyPI package increases over time, with each vulnerability taking three years to be discovered. Our work provides methods, impetus, and guidance for counter-regressive software changes involving dependencies.

7 CONCLUSION

We have presented the first fine-grained study of bloated dependency code in the PyPI ecosystem. We have constructed large, inter-project dependency graphs that capture the relationship between 1,032 Python projects and 3,232 PyPI releases at the method level. Using standard graph reachability algorithms, we study bloated dependency code at different granularities. We find that the PyPI ecosystem is full of bloat: more than half of the dependencies in a typical Python project are entirely unused. Worse, the bloat considerably increases when considering the granularity of files and methods. Further, through our fine-grained analysis, we have identified a number of "time-bombs"(15%), i.e., vulnerable code that is not invoked by the different projects, yet it exists in packages that the projects use. Moreover, bloated dependency code mainly originates from pervasive code changes (e.g., feature removals). Finally, developers are willing to remove their bloated dependencies: 28 out of 36 pull requests we submitted have already been merged by developers, removing a total of 33 direct dependencies. We believe our work can guide the design of future bloat detection and prevention tools for Python. Such tools should effectively address bloat at granularities that go beyond the package level, thereby significantly reducing maintenance risks of Python applications. Finally, bloat prevention tools need to provide informative and actionable messages to developers, and prioritize warnings based on the root cause of bloat.

8 DATA AVAILABILITY

We have incorporated the data supporting our results within our submission.

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