
World of Code: Enabling a Research Workflow for Mining and Analyzing the Universe of Open Source VCS data

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Abstract Open source software (OSS) is essential for modern society and, while substantial research has been done on individual (typically central) projects, only a limited understanding of the periphery of the entire OSS ecosystem exists. For example, how are the tens of millions of projects in the periphery interconnected through technical dependencies, code sharing, or knowledge flow? To answer such questions we: a) create a very large and frequently updated collection of version control data in the entire FLOSS ecosystems named World of Code (WoC), that can completely cross-reference authors, projects, commits, blobs, dependencies, and history of the FLOSS ecosystems and b) provide capabilities to efficiently correct, augment, query, and analyze that data. Our current WoC implementation is capable of being updated on a monthly basis and contains over 18B Git objects. To evaluate its research potential and to create vignettes for its usage, we employ WoC in conducting several research tasks. In particular, we find that it is capable of supporting trend evaluation, ecosystem measurement, and the determination of package usage. We expect WoC to spur investigation into global properties of OSS development leading to increased resiliency of the entire OSS ecosystem. Our infrastructure facilitates the discovery of key technical dependencies, code flow, and social networks that provide the basis to determine the structure and evolution of the relationships that drive FLOSS activities and innovation.

Keywords Software mining · Software supply chain · Software ecosystem

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1 Introduction

Tens of millions of software projects hosted on GitHub and other forges attest to the rapid growth and popularity of Free/Libre Open Source Software (FLOSS). These online repositories include a variety of software projects ranging from classroom assignments to components, libraries, and frameworks used by millions of other projects. Such large collections of projects are currently archived in public version control systems, and, if made available for analysis, would represent a unique opportunity to study FLOSS at large and answer both theoretical and practical questions that rely on the availability of the entirety of FLOSS data. In particular, our infrastructure, referred to as World of Code (WoC) and described below, supports a number of research and practical tasks that would not be possible without it. For example, a census of open source software with types and prevalence of projects, technologies, and practices and could serve as a guide to setting policies or creating innovative services. Also, the ability to discover complete chains of technical dependencies, code flow, and global social networks of developers to provide the basis to understand the structure and evolution of the relationships that drive FLOSS activities and innovation. A sampling capabilities of WoC provide a basis for “natural experiments” that evaluate the effectiveness of different software development approaches.

WoC focuses on global reach and effective cross-referencing of public version control data. The primary aim is to support research and industry that studies/relies on open source ecosystems. Specifically, it provides capabilities a) for stratified sampling in order to improve external generalizability of empirical studies; b) to measure critical properties of code, dependencies, and developer behaviour that are beyond reach of project-centric approaches that can reach only data within a limited set of projects; c) to study global networks of developers, code dependencies, and code copying behaviours; d) for building tools that increase the transparency and efficiency of open source in general and help mitigate risks, thus allowing more use and contributions from industry.

Given the tremendous benefits from the collection of FLOSS development data, an infrastructure for mining FLOSS repositories and serving potential analysis and studies in software domain is in high demand. A number of other platforms have been built by researchers (see the Related Work section for details) to leverage this data for various ends. None of them, however, provide cross-referencing needed to measure code, developers, or dependencies in the context of the entire FLOSS.

We propose the following question:

RQ: How to design an infrastructure to cross-reference source code change data over the entire FLOSS community in order to enable sampling, measurement, and analysis within and across software ecosystems?

Our contribution is to describe a prototype of such an infrastructure that can store the huge and growing amount of data in the entire FLOSS ecosystem and can provide basic capabilities to efficiently cross-reference, sample, and analyze it at that scale. The primary focus is on the types of analyses that require global reach across FLOSS projects. A good example is a software supply chain [4] where software developers correspond to the nodes or producers, relationships among software projects or packages represent the “chain”, and changes to the source code represent products or information (that flow along the chain) with corporate

backers representing “financing.” It would be impossible to measure properties and relationships of the producers without first having data from a complete collection of software projects, since it is impossible to know which projects each developer has contributed to. Similarly, it is difficult to determine downstream dependencies, i.e., discovering all projects that depend on a specific project is not trivial. WoC is intended to make such measurements straightforward.

Several formidable obstacles obstruct progress towards this vision. The traditional approaches for obtaining the repository of a project or a small ecosystem does not scale well and may require too many resources and too much effort for individual researchers or smaller research groups. Thus, the community needs a way to scale and share the data and analytic capabilities. The underlying data are also lacking in context necessary for meaningful analysis and are often incorrect or missing critical attributes [56]. Keeping such large datasets up-to-date poses another formidable challenge.

In a nutshell, our approach is a software analysis pipeline starting from discovery and retrieval of data, storage and updates, and transformations and data augmentation necessary for analytic tasks downstream. Our engineering principles are focused on using the simplest possible techniques and components for each specific task ranging from project discovery to fitting large-scale models. The result is a prototype that appears to approximate the entirety of the publicly available source code in version control systems and the latency of updates on the existing hardware platform does not exceed one calendar month, which is relatively fast given the size of the dataset and the complexity of the task (See Sections 3.1 and 3.2 for more details). Furthermore, we built a tool on top of the infrastructure and provided two types of API to enable wide data access for users.

We begin with an overview of related work in Section 2. The architecture of the prototype implementation of the infrastructure is discussed in Section 3. We facilitate wide access to the large data collection by developing a tool on top of our infrastructure, which is described in Section 4, along with an evaluation of query performance. We present a couple of applications in Section 5, demonstrating the tremendous value of this infrastructure to numerous software analytic tasks. We also provide a tutorial about how to use the WoC infrastructure, using an example on Java language trend analysis in Section 6. We present a comparison between WoC and platforms offering similar functionality, viz. GHTorrent, Software Heritage, BOA, GH Archive, in Section 7. Details of a Hackathon event organized around the WoC infrastructure and projects undertaken in the event are described in Section 8, which demonstrates the communities’ interest in WoC and some possible applications of the WoC infrastructure. We discuss various ways of improving the existing infrastructure in Section 9, discuss a few existing limitations in Section 10, and conclude our paper in Section 11.

2 Related Work

While we are not aware of a complete census of FLOSS with an analysis engine, several large-scale software mining efforts exist and may be roughly subdivided into attempts at preservation, data sharing for research purposes, and construction of decision support tools.

As described above, the aims of WoC is not to replace or replicate any of these efforts, but to provide the cross-referencing needed to analyze global properties of the entire FLOSS. Some of the design decisions, for example, the use of Git object IDs, are intended to make linking to and leveraging the information in other systems easier or to simplify the provisioning of cross-referencing services to enhance the capabilities of the other collections.

Software development is a novel cultural activity that warrants preservation as a cultural heritage. The software source code, the only representation of software that contains human readable knowledge, needs to be preserved to avoid permanent loss of knowledge [27]. Software Heritage [27] is a distributed system involved in collecting and storing large amount of open source development data from various open source platforms and package hosts. It currently has software from GitHub, GitLab, Debian, PyPI, etc., and contains 73M projects, 1.7B commits, and 15.6B source files. This effort does not presently focus on enabling applications to software analytics. The provided APIs allows for quick query of every historical particle in a software project and meets the preservation need, however, it does not grant the access to the full relationships (e.g., the set of projects containing a given commit) among these particles across entire collection of software. Quick access to these relationships is crucial in conducting software analytics such as identification of dependencies among artifacts and authors as well as code spread in the open source community.

One potential value of archiving software lies in the reuse of software artifacts. For example, Nexus [1] repository manager, allows developers to share software artifacts in a standard way and provides support for building and provisioning tools (e.g. Maven) to access necessary components such as libraries, frameworks and containers.

Commercial efforts, such as BlackDuck or FOSSID¹ have proprietary collections they use to determine if their clients have included open source software within their proprietary software code. It is generally not clear how complete these collections are nor if the companies involved might consider opening them for research purposes.

In addition to source code and binaries, large scale collection of other software development resources could be integrated with the source code data. For example, GHTorrent [38, 39, 41–43] attempts to record every event for each repository hosted on GitHub and provides multiple approaches (SQL request and MongoDB data dump) for data access. The primary limitation is that the collected metadata is specific to GitHub and it does not include the underlying source code as well. Therefore, obtaining dependencies encoded within the source code cannot be accomplished. A similar platform, named GH Archive², is also focused on the collection of GitHub events. It provides new events dump per hour since 2011, and cloud service to meet the SQL based BigQuery. FLOSSmole [45] collects open source metadata from various forges as a base for academic research but only focuses on software project metadata.

Another platform is Candoia [68–71] which provides software development data collections abstraction for building and sharing Mining Software Repository (MSR) applications. In particular, Candoia contains many tools for artifact extraction

¹ blackducksoftware.com, fossid.com

² <https://www.gharchive.org/>

from different VCSs and bug databases and it also support projects written in different languages. On top of these artifacts, Candoia created its general data abstraction for researchers to implement ideas and build tools upon. This design increased portability and applicability for MSR tools by enabling application on software repositories across hosting platforms, VCSs and bug recording tools. The approach is focused on the design and benefits of creating a specialized software repository mining language. While it abstracts a number of repository acquisition tasks, it also makes it more difficult to handle operational data problems that tend to occur at much lower levels of abstraction and tend to be too idiosyncratic for generalized abstraction. The main drawbacks of Candoia are that it only supports limited programming language (JS and Java) based projects, and ecosystem-wide research might be difficult to implement since Candoia relies on users to provide software related data (e.g., targeted software repository URL) and eco-system wide compliance is generally low.

Other platforms are aimed at improving reproducibility by providing a repository of datasets for researchers to share their data. These include PROMISE Repository [66] and SourcererDB [59]. PROMISE Repository is a collection of donated software engineering data. It was created to facilitate generations of repeatable and verifiable results as well as to provide an opportunity for researchers to extend their ideas to a variety of software systems. Black Duck OpenHub is a platform that discovers open source projects, tracks the development and provides the functionality of comparison between softwares. Currently, it is tracking 1.1M repositories, connecting 4.2M developers and indexing 0.4M projects. SourcererDB is an aggregated repository of 3K open source Java projects that are statically analyzed and cross-linked through code sharing and dependency. On top of providing datasets, it also provides a framework for users to create custom datasets using their projects.

Apart from providing datasets (repository) for potential users, platforms such as Moose [28], RepoGrams [64], Kenyon [8], Sourcerer [7], and Alitheia Core [40] are more focused on facilitating building and sharing MSR tools. Moose is a platform that eases reusing and combining data mining tools. RepoGrams is a tool for comparing and contrasting of source code repositories over a set of software metrics and assists researchers in filtering candidate software projects. Kenyon is a data platform for software evolution tools. It is restricted to supporting only software evolution analysis. Sourcerer is an infrastructure for large scale collection of open source code where both meta data and source code are stored in a relational database. It provides data through SQL query to researchers and tool builders but is only focused on Java projects. Alitheia Core is a platform with a highly extensible framework and various plug-ins for analyzing software on a large database of open source projects' source code, bug records, and mailing lists.

Furthermore, there were efforts to standardize software mining data description for enhanced reproducibility [48]. None of the listed platforms focus on both collection and analysis of the dependencies of the entirety of FLOSS source code version control data. Further, they contain either limited collections (e.g. only GitHub, no source code, have only donated data, or do not contain an analysis engine). For example, it is not possible to answer simple questions such as "In which projects has a file been used?", "What projects/codes depend on a specific module?", "What changes has a specific author made?" etc.

Some large companies have devoted substantial effort to develop software analysis platforms for the entire enterprise, aiming to improve the quality of software they build and to help the enterprise achieve its business goals by providing recommendations to software development organizations/teams, monitoring software development trends, and prioritizing research areas. For example, Avaya, a telecommunications company, built a platform [44], which collects software development related data from most of its software development teams and third parties and enabled systematic measurements and assessments of the state of software. CodeMine [14], is a software platform developed by Microsoft that collects a variety of source code related artifacts for each software repository inside Microsoft. It is designed to support developer decisions and provide data for empirical research. We hope that similar benefits can be realized with the WoC platform targeted to the entire FLOSS community.

Large scale software mining efforts also include domain specific languages. Robert Dyer et al. developed Boa [29–33, 62], both as a domain specific language and as an infrastructure, to ease open source-related research over large scale software repositories. The approach is focused on the design and benefits of an infrastructure and language combination. However, the lack of explicit tools to deal with operational data problems make it of limited use to achieve our aims. Their collection procedures -discovery, retrieval, storage, update, and completeness issues (for example, only certain languages are supported)- are not the primary focus of this effort. The tools to deal with operational data problems common in version control data are also lacking in Boa.

The system described in this paper is loosely modeled after a system described a decade ago [54, 55]. In comparison, at that time, Git was just beginning to emerge as a popular version control system, but now it dominates the FLOSS project landscape. The number of software forges and individually hosted projects was much larger then in contrast to the consolidation of forges and the overwhelming dominance of GitHub. Furthermore, the scale of the FLOSS ecosystem is more than an order of magnitude larger now and it continues to experience very rapid growth. WoC could not, therefore, reproduce that design closely and, instead, is focused on preserving the original Git objects and on creating a design that enables both efficient updating of this huge database and ways to cross-reference it so that the complete network of relationships among code and people is readily available.

3 Building the WoC Infrastructure

The process of mining individual Git repositories is complex to begin with [10], but becomes even more difficult on a large scale [37]. Specifically, using operational data from software repositories requires resolution to three major problems [56]: the lack of context, missing attributes or observations, and incorrect data.

The lack of context: Operational data originates from traces collected and integrated from a variety of operational support tools. Each event recovered from such traces has a specific context of what may have been on the actor’s conscious and subconscious mind, the purpose of that action, the tools and practices used, and the project or the ecosystem involved. Each event, therefore, may have a unique meaning. Some actions, such as verbal communication, may be missing if conducted without tool support. Mining software traces in VCSs has the limitation

of losing information that was not recorded by VCS. We, therefore, focus on revealing as much context as possible by providing related development components to each key property/object in the software repository through easy query on the map architecture described in Sec. 3.6.2

Missing attributes or observations, and incorrect data: Data filtering or tampering may be done by the actors, operating tools, or data processing and integration at the time of action or later. Determining how to properly segment, filter, augment, and model such data to ensure that they contain a representative sample of relevant activities, is the fundamental challenge of engineering operational data solutions and it will be essential to develop methods to draw valid conclusions from such disparate and low-veracity data. In WoC implementation, we strictly followed the usage of the related VCS(Git) APIs for the extraction of development data to make sure we do not miss any attributes or observations. A common data quality issue with VCS is developer name disambiguation, and we detailed the correction of developer ID errors in Sec. 5.2

Moreover, to cope with these big data challenges we employed both vertical and horizontal prototyping [3, 11, 51, 63] before building the complete infrastructure.

In this section, we present a prototype WoC implementation. It has three stages: project discovery, data retrieval, and reorganization as shown in Figure 1, which is typical of most big data systems, that use the layered data approach where the initial layers accumulate and process raw data and the later layers produce cleaned/augmented data. We also perform data augmentation on the collected data, focusing on tasks like fork resolution [67] and author identity resolution [6, 35].

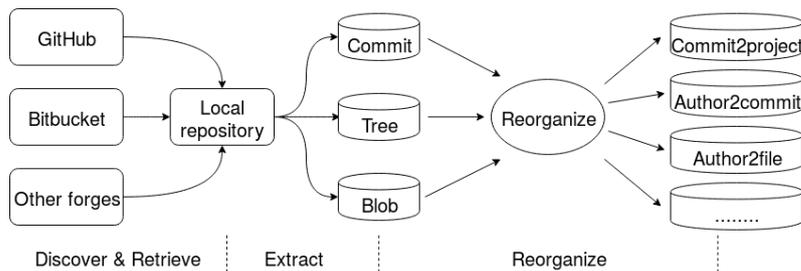


Fig. 1 Overarching data flow

The paper describes a rapidly evolving WoC prototype with some aspects of the system evolving over time. While an attempt was made to focus on aspects that should persist, the need to provide specific examples almost ensures that the actual system will differ in some ways from the description provided here.

3.1 Project Discovery

Millions of projects are developed publicly on popular collaborative platforms/-forges such as GitHub, Bitbucket, GitLab, and SourceForge. Some of the FLOSS projects can be identified from the registries maintained by various package managers (e.g. CRAN, NPM) and Linux distributions (e.g. Debian, Fedora). Most

other project repositories, however, are hosted in personal or project-specific sites. A complete list of FLOSS repositories is, therefore, difficult to compile and maintain since new projects and forges are constantly being created and many older forges disappear continually. There is also a tendency for the FLOSS repositories to migrate to (or be mirrored on) several very large forges [52]. A number of older forges provide convenient approaches to migrate repositories to other viable forges before being shut down. This consolidation has alleviated some of the challenge of discovering all FLOSS projects [55], though the task remains nontrivial. We discuss several approaches to project discovery below. To package our project discovery procedure we have created a “docker” container³ that has the necessary scripts.

Using Search API: Some APIs may be used to discover the complete collection of public code repositories within a forge. The APIs are specific to each forge and come with different caveats. Most APIs tend to be rate limited (for user or IP address) and the retrieval can be sped up by pooling the IDs of multiple users.

Using Search Engine: Search engines (e.g. Google or Bing) can supplement the discovery of FLOSS project repositories on collaborative forges when the forge does not provide an API, or when the API is broken. The primary drawback is the incompleteness of the repositories discovered.

Keyword Search: Some forges provide keyword based search of public repositories, which is a complementary approach when a forge does not provide APIs for the enumeration of repositories and the results returned from search engines are lacking.

Using these and other opportunistic approaches help ensure that they complement each other in approximating the publicly available set of repositories though it does not guarantee the completeness. We expected that various ways of crowdsourcing the discovery (with incentives to share a project’s Git URL) would help increase the coverage in the future.

3.2 Project Retrieval

This data retrieval task can be done in parallel on a very large number of servers but requires a substantial amount of network bandwidth and storage. The simplest approach is to create a local copy of the remote repositories via “git clone” command. As of May 2019, we estimate over 73M unique repositories (excluding GitHub repositories marked as forks, repositories with no content, and private repositories). A single thread shell process on a typical server CPU (we used Intel E5-2670) with no limitations on network bandwidth clones between 20K and 50K repositories (the time varies dramatically with the size of a repository and the forge) in 24 hours. To clone 73M repositories in one week would, therefore, require between two and five hundred servers. However, we do not possess dedicated resources of that size and, therefore, optimize the retrieval by running multiple threads per server and retrieving a small subset of the repositories that have changed since the last retrieval. Specifically, we use five Data Transfer Nodes of a cluster computing platform which provides 300 nodes in total with a bandwidth up to 56 Gb/s.

³ <https://github.com/ssc-oscar/gather>

3.3 Data Extraction

Code changes are organized into commits that typically change one or more source code files within the project. Once the repository is cloned as described above, we extract the Git objects [12] from each repository.

3.3.1 Data Model

Git [12] is a content-addressable filesystem containing four types of objects. The reference to these objects is a SHA1 [34,61,72] calculated based on the content of that object. A few typical Git objects are described below.

commit: A commit is a string including the SHA1's of commit parent(s) (if any), the folder (tree object), author ID and timestamp, committer ID and timestamp, and the commit message.

tree: A tree object is a list that contains SHA1's of files (blobs) and subfolders (other trees) contained in that folder with their associated mode, type, and name.

blob: A blob is the compressed version of the file content (the source code) of a file.

tag: A tag is the string (tag) used to associate readable names with specific versions of the repository.

Figure 2 illustrates the relationships among the Git objects described above. The snapshot at any entry point (commit) is constructed by following the arrows from left side to right side. Each commit points to a tree(folder), and each tree points to blobs(files in this folder) inside it and its subtrees(subfolders).

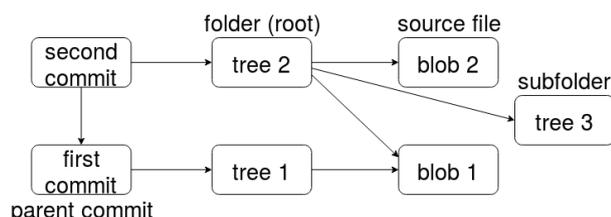


Fig. 2 Git objects

3.3.2 Object Extraction

While a standard Git client allows extraction of raw Git objects, it displays them for manual inspection. For bulk extraction of the Git objects, first we list all objects within the Git database, categorize them, and then create a bulk extractor based on a portable pure C implementation of *libgit2*.⁴ (*libgit2* is a portable, pure C implementation of the Git core methods provided as a re-entrant linkable library with a solid API, allowing you to write native speed custom Git applications in any language which supports C bindings) We run listing and extraction using 16 threads on each of the 16-CPU node on a cluster.⁵ The process takes approximately two hours for a single node to process 50K repositories.

⁴ <https://libgit2.org/>

⁵ CPU: E5-2670, No. node: 36, No. core: 16, Mem size: 256 GB

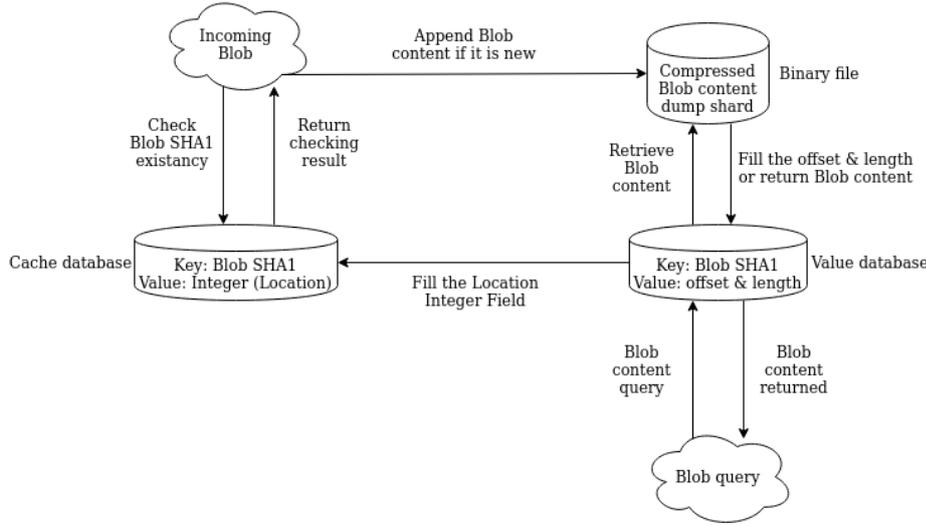


Fig. 3 The workflow of storing Git Blob into WoC

3.4 Data Storage

Table 1 Storage Abstraction

Abstraction	Schema	Technology	# records (Billion)	size
Cache/Location Index	Key-Value pair Key: Git object SHA1 Value: Packed Integer	Tokyo Cabinet	Commit: 2.0 Tree: 8.3 Blob: 7.9	Commit: 121 GB Tree: 487 GB Blob: 487 GB
Value/Content Index	Key-Value pair Key: Git object SHA1 Value: offset & length	Tokyo Cabinet	Same as above	Commit: 107 GB Tree: 388 GB Blob: 370 GB
Physical Storage	Concatenated compressed Git object in binary file	Binary Compression	Same as above	Commit: 542 GB Tree: 8.6 TB Blob: 102 TB

The collection of public Git repositories as a whole replicates many of the same Git objects hundreds of times [55]. Without removing this redundancy, the required storage for the entire collection exceeds 1.5PB, and it also makes analytics tasks virtually impossible without extremely powerful hardware. Many reasons for this redundancy exist, such as pull-based development, usage of identical tools or libraries, and copying of code.

To avoid storing identical Git objects, we store all Git objects into a single database. The database is organized into four parts corresponding to each type of Git object. Each part is further separated into a cache and content. The cache is used to rapidly determine if the specific object is already stored in our database and is necessary for data extraction described above. Furthermore, the cache helps determine if a specific repository needs to be cloned or if an object needs to be extracted from the cloned repository. If the heads (the latest commits in each branch in `.git/refs/heads`) of a repository are already in our database, there is no need to clone the repository altogether.

Cache database is a key-valued database, with the twenty byte Git object SHA1 being the key and the packed integer (indexing the location of the object in the corresponding value database) being the value. The value database consists of an offset lookup table that provides the offset and the size of the compressed Git object in a binary file (containing concatenated compressed Git objects). The workflow of storing a Git object (e.g. blob) is described in Figure3. An incoming blob sha1 is checked against the Cache database to see if our system already contains it. If not, then we append it to a binary file, then generate a new record in the Value database with key being the blob SHA1 and value being the offset of the blob in the binary file and the length of the blob. A new record is also generated in the Cache database with the key being the blob SHA1 and the value being a packed Integer pointing out the order of the record (in Value database dumped text index file).

While this storage allows for a fast sweep over the entire database, it is not optimal for random lookups needed, for example, when calculating diffs associated with each commit. For commits and trees, therefore, we also create a key value database where a key is SHA1 of the Git object and a value is the compressed content of the said object. Cache performance is relatively fast: a single thread on Intel E5-2623 is capable of querying of 1M Git objects in under 6 seconds, or over 170K Git objects per second per thread. This can be multi-threaded and run on multiple hosts, thus reaching any desired speeds with expanded hardware.

Needless to say, with 18B objects occupying over 120TB we need to use parallel processing to do virtually anything. Thankfully, we can use SHA1 itself to split the database into pieces of similar size. We, therefore, split each of the database into 128 slices based on the first seven bits of Git object SHA1. This results in 128 key-offset cache databases for all four types of objects, 128 content databases as flat files for the four types of objects, and 128 key value databases for commits and trees: $128*(4+4+2)$ databases with each capable of being placed on a separate server to speed up parallel tasks. The individual databases containing content range from 20MB for tags up to over 0.5TB for blobs. The largest individual cache databases are over 2Gb for tree object SHA1s.

Databases are fragile and may get corrupted due to hardware malfunction, internet attack, pollution/loss by unrecoverable operation, etc. To enhance the robustness and reliability and to avoid permanent data loss, we maintain three copies of the databases: two copies on two separate running servers and one copy on a workstation that is not permanently connected to Internet. In the future, we will consider keeping a copy using a commercial cloud service.

Furthermore, due to the size of the data and complexity of the pipeline, some of the objects may have been missed or have been retrieved but are not identical to originals. Techniques to validate the integrity of the data at every stage of the process are necessary. We therefore, include numerous tests to ensure that only valid data gets propagated to the next stage.

In particular, the errors when listing and extracting objects are captured and the operation is repeated in case a problem occurs. The extracted objects are validated to ensure that they are not corrupt and also to ensure that they are not going to damage the database or the analytics layer. To validate correctness, the object is extracted per Git specifications and recreated from scratch. The SHA1 signature is compared to ensure it matches that of the original object. A substantial number of historic objects have issues due to a bug in Git that has since

been fixed. Furthermore, a much smaller number of objects also had issues that we assume are either caused by problematic implementations of Git or problems in operation (zero-size objects that may be occasionally created when Git runs out of disk space during a transaction).

Despite the scrubbing and validation efforts, some of the data may still be problematic or missing, therefore a continuous process of checking the database for missing or incorrect data is needed. We plan to add a missing object recovery service that identifies missing commits, blobs, and trees, and retrieves and stores them (in case they are still available online).

3.5 Update

The process of cloning all GitHub repositories takes an increasing amount of time with the growth in size of existing repositories and the emergence of new ones, given fixed hardware. Currently, to clone all Git repositories (over 90M including forks), we estimate the total time to require six hundred single-thread servers running for a week and the result would occupy over 1.5PB of disk space. Fortunately, Git objects are immutable and we can leverage that to simplify and speed up the updates. More generally, to get acceptable update times, we use a combination of two approaches:

- Identify new repositories, clone and extract Git objects
- Identify updated repository and retrieve only newly added Git objects

The work flow is illustrated in Fig. 4.

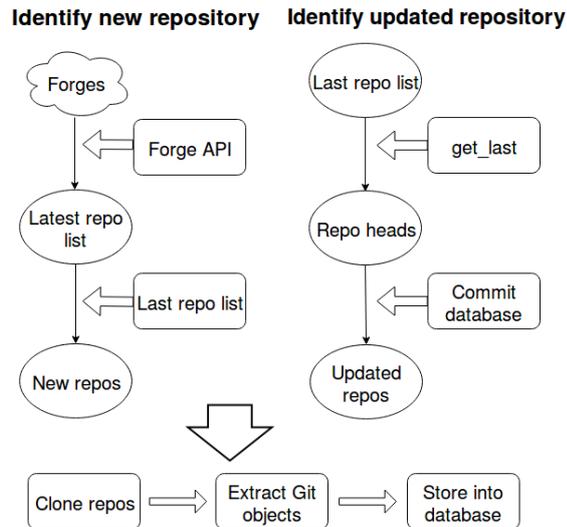


Fig. 4 Update workflow

In fact, only approximately three million new projects were created and an additional two million updated during Dec, 2018.

3.5.1 Procedures for new repositories

Forge-specific APIs are utilized to obtain the complete list of public repositories as described above. A comparison with prior extract yields new repositories. The list may include renamed repositories and forks. We can exclude forks for GitHub, since it is an attribute returned by GitHub API.⁶ Other forges contain fewer repositories, so the forks are not large enough to be a concern.

3.5.2 Procedures for updated repositories

First we need to identify updated repositories from the complete list of repositories. Since we are not sure how GitHub determines the latest update time for a repository, we use a forge-agnostic way of identifying updated repositories. We modified the *libgit2* library so that we can directly obtain the latest commit of each branch in a Git repository for an arbitrary Git repository URL, without the need to clone the repository. If any of the heads contain a commit that is not already in our database, the repository must have had updates and needs to be obtained.

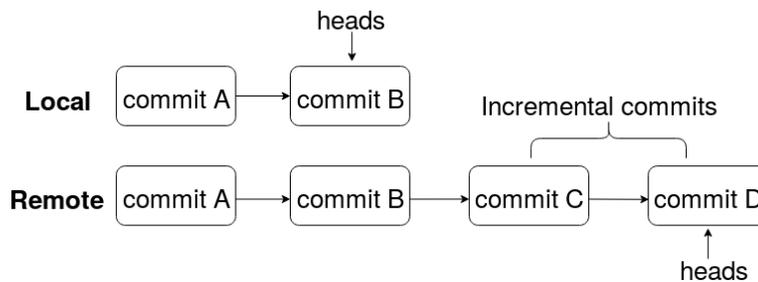


Fig. 5 Incremental commits

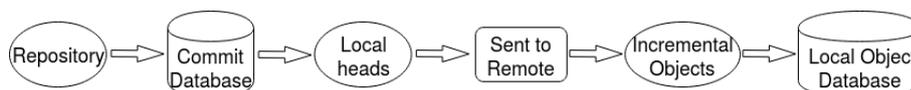


Fig. 6 Future workflow

We are working on a strategy to reduce the amount of bandwidth needed to do the updates. Instead of cloning an updated repository, we'd like to retrieve only incremental Git objects (see Fig. 5) that are generated during the time gap between two consecutive updates. This can be easily done via “git fetch” for a Git repository, but since we do not keep the original Git repository and it is time consuming to pre-populate it with Git objects, we plan to customize “git fetch”

⁶ The exclusion only happens when all the conditions are met: a GitHub project has not been seen in the project list in a previous update, GitHub marked this project as a fork, and all the heads already exist in our database.

protocol by inserting additional logic in order to use our database backend that comprises Git objects from all repositories. The procedure consists of two steps:

1. Customize “git fetch protocol”⁷ to work without Git’s native database.
2. Keep track of the heads for each project that we have in our database so that we can identify latest commits to the modified “git fetch”.

For the second step, the database backend will use the project name as input and provide the list of heads for the project. These heads are then sent to the remote so that the set of latest commits (and related trees/blobs) will be calculated out and transferred back as illustrated in Figure 6. By following this strategy, we could drastically speed-up mining incremental Git objects from repositories in each update.

3.6 Data Reorganization

objects in Git are organized in a way for fast reconstruction of a repository at each commit/revision. In fact even the seemingly simple operation of identifying what files changed in a commit is computationally intensive. Furthermore, there is no consideration for the projects, files, or authors as first-class objects. This limits the usability of the Git object store for research and suggests the need for an alternative data design. Since our objective is to obtain relationships among projects, developers, and files, we have created an alternative database that allows both a rapid lookup of these associations and sweeps through the entire database that make calculations based on such relationships.

3.6.1 Analytic Database

The scale of the desired database limits our choices. For example, a graph database⁸ like neo4j would be extremely useful for storing and querying relationships, including transitive relationships. However, it is not capable (at least on the hardware that we have access to) of handling hundreds of billions of relationships that exist within the entire FLOSS. In addition to neo4j, we have experimented with more traditional database choices. We evaluated common relational databases MySQL and PostgreSQL and key value databases or NoSQL [50] databases MongoDB, Redis, and Cassandra. SQL like all centralized databases [2] has limitations handling petabyte datasets [65]. We, therefore, focus on NoSQL databases [57] that are designed for large scale data storage and for massively parallel data processing across a large number of commodity servers [57].

For the specific needs of the cache database and for key value stores for the analytics maps we use a C database library called TokyoCabinet (similar to Berkeley_db) using a hash-indexed as described above, to provide approximately ten times faster read query performance than a variety of common key value databases such as MongoDB or Cassandra. Much faster speed and extreme portability lead us to use it instead of more full-featured NoSQL databases.

⁷ “git fetch” downloads only new objects from the remote repository

⁸ a database that uses graph structures for semantic queries with nodes, edges and properties to represent and store data

3.6.2 *Maps*

Apart for the general requirement to be able to represent global relationships among code, people, and projects, we also consider the basic patterns of data access for several specific research tasks as use cases in order to design a database suitable for accomplishing research tasks within a reasonable time frame. The specific use cases are:

1. Software ecosystem research would need the entire set of repositories belonging to a specific FLOSS sub-ecosystem, e.g., the set of all repositories that use Python language.
2. Developer behavior research would need to identify all projects that a specific developer worked on, the files they authored, and software technologies they used.
3. Code reuse research would need to identify all projects where a specific piece of code occurs and determine how it got there.

To support the first task, a mapping from file names to project names would be necessary. The second task would require author to project, file, and to content of the versions of the file authored by that developer (in order to access the source code and identify what components or libraries were employed). The last task would require a map between blobs (that contain snippets of code) and projects. It would also require a map between blobs and commits in order to identify the time when the specific piece of code was introduced.

We have identified a number of objects and attributes of interest here: projects, commits, blobs, authors, files, and time. The complete set of possible direct maps for an arbitrary pair is 30. Since author and time are properties of the commit and are not properties of projects, blobs, or files, it makes sense to place commit at the center of this network database. The author-to-file map can then be constructed as a composition of author-to-commit and commit-to-file maps; and author-to-project map can be constructed via author-to-commit and commit-to-project maps. We also need to associate file names with the corresponding blobs since a single commit may create multiple files. Out of the 12 maps,⁹ only 10 need to be instantiated because commit-to-author and commit-to-time maps are embedded as the properties of the commit object.

In addition to having the commit at the center, for certain tasks we also needed to have a blob-to-file map as well. For example, we want to identify module use in Python language files. First, we need to identify relevant files via suitable extension (e.g., .py), then we can determine all the associated commits via file to commit map. These commits, however, may involve other files and if we use commit to blob map to identify associated blobs, we would get blobs not just for “python”, but also for all files that were modified in commits that touched at least one “python” file. The file-to-blob map allows us to reduce the number of blobs that need to be analyzed dramatically.

In addition to these basic maps we create additional maps, such as the author ID to author ID map for IDs that have been established to belong to the same person (see Section 5.2), and project to project maps to adjust for the influence

⁹ bidirectional maps between the commit and five objects/attributes and between file and blob

of forking. Project-to-project maps are based on the transitive closure of the links induced between two projects by a shared commit. Explicit forks that can be obtained as a GitHub project property do not generalize to other forges and, even on GitHub, represent only a fraction of all repositories that have been cloned from each other and then developed independently. Project-to-project map also handles instances where repositories exist on multiple forges or when they are renamed.

As with the original data we utilize multiple databases and use compressed files for sweep operations and TokyoCabinet for random lookup. We separate maps into 32 instead of 128 databases we use for the raw objects since maps tend to be much smaller in size than, for example, blobs. For commits and blobs we use the first character of SHA1 for database identification. For authors, files, and projects, we use the first byte of FNV-1a Hash.¹⁰ Both approaches yield quite uniform distribution over bins.

As noted above, the maps from commit to metadata are not difficult to achieve because most of the metadata is part of the content of a commit object. However, Git blobs introduced or removed by a commit are not directly related to the commit and need to be calculated by recursively traversing trees of the commit and its parent(s). A Git commit represents the repository at the-state-of-world and contains all the trees (folders) and blobs (files). To calculate the difference between a commit and its parent commit, i.e., the new blobs, we start individually from the root tree that is in the commit object, traverse over each subtree and extract each blob. By comparing two sets of blobs of each commit, we obtain the new blobs for the child commit. This step requires substantial computational resources, but the map from the commit to the blobs authored in a commit is used in numerous research scenarios and, therefore, is necessary. On average, it takes approximately one minute to obtain changed files and blobs for 10K commits in a single thread. With 1.5B commits, the overall time for a single thread would take 104 days, but it needs to be done only on approximately 20-40M new commits generated each month.

4 Architecture for research workflows

To make WoC more easily usable in a wide variety of research scenarios, we have designed an architecture to help simplify, support, and evaluate the implementation of research tasks. This section describes that architecture, along with critical performance benchmarks to inform the users on the computational tasks for alternative implementations.

4.1 Architecture

The research workflow architecture is illustrated in Figure 7. The figure shows the application layer, built on top of the three lower layers:

Application Layer: This layer is where the research tasks are implemented by use of WoC. We provide a library of applications to illustrates various types of research analyses that can be implemented using WoC.

¹⁰ <http://www.isthe.com/chongo/tech/comp/fnv/index.html#FNV-1a>

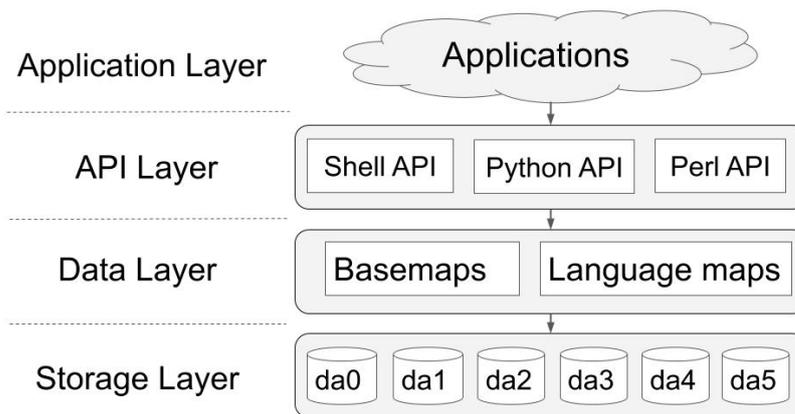


Fig. 7 Architecture of the Tool

API Layer: The applications may use Shell or Python API, or may reuse or modify Perl files (used to support Shell API) to access and process the WoC data. A more detailed description of the Shell and Python APIs can be found in Section 4.2.

Data Layer:

As described above, to be able to identify the relationships rapidly we constructed several types of relationships (or basemaps) that cross-reference the Git objects and other properties. In particular, we treat *project*, *commit*, *blob*, *author*, *file name* as the first class objects and map them to their properties (e.g., time, parent commit, head commit, child commit, etc.). In addition to these basemaps, we also construct technical dependencies that are derived from importing external dependencies for several languages (Language Maps). These dependencies are calculated based on each version of a file. The data is described in more detail in Section 4.3.

Storage Layer All the data are hosted on six servers, which are connected to each other through NFS (network file system). Users can login to any of the servers (da0 to da5) and run their applications on multiple servers.

4.2 API

We support three primary APIs for WoC users to access the dataset: Shell, Python, and Perl. Presently, running an application requires being logged in to one of the hosting servers.

4.2.1 Shell API

For the lowest level access we provide Shell API that is modeled after core philosophy of Unix:¹¹ have a set of specialized commands that are connected in a

¹¹ https://en.wikipedia.org/wiki/Unix_philosophy

workflow through their standard input and output and via creation of files, E.g., according to Doug McIlroy: “Make each program do one thing well. To do a new job, build afresh rather than complicate old programs by adding new features”. The entire application workflow can be built using exclusively shell and standard Unix utilities such as ‘join’, ‘sort’, ‘cut’, ‘uniq’, ‘sed’, and ‘wc’ with added specialized commands to extract data from key-value databases. The key information for this API is the knowledge of how to use shell and standard Unix command and the description of the databases. To enable this approach we also provide all databases as key-sorted (and compressed) text files that can be used with ‘grep’, ‘join’, or ‘sort’ to produce any desired queries. We also add a random lookup operation `getValue mapname` to access values of a key object in the provided `mapname`. In addition, we add the command `showCnt type` to access the content of each Git object given in the standard input where `type` is one of `tag`, `tree`, `commit`, `blob`. A few examples are listed below:

- Checking the content of a Git object given a SHA:

```

1 # (on da3) e.g., show a commit SHA's content:
2 echo e4af89166a17785c1d741b8b1d5775f3223f510f | showCnt commit
3 # Output Formatting:
4 # Commit SHA;Tree SHA;Parent Commit SHA;Author;Committer;Author Time;
   Commit Time
5 e4af89166a17785c1d741b8b1d5775f3223f510f;
   f1b66dcca490b5c4455af319bc961a34f69c72c2;
   c19ff598808b181f1ab2383ff0214520cb3ec659;Audris Mockus <audris@utk.
   edu>;Audris Mockus <audris@utk.edu>;1410029988 -0400;1410029988 -0400

```

- Given an object, check its related objects:

```

1 # (on da3) e.g., show the names of the projects associated with a given
   commit SHA:
2 # "getValue" command takes a database name as an argument and keys
   presented as standard input and produces key-value pairs as output.
3 echo e4af89166a17785c1d741b8b1d5775f3223f510f | getValue /da0_data/
   basemaps/c2pFullP
4 # Output Formatting: Commit SHA;ProjectNames
5 e4af89166a17785c1d741b8b1d5775f3223f510f;W4D3_news;chumekaboom_news;
   fdac15_news;fdac_syllabus;igorwiese_syllabus;jaredmichaelsmith_news;
   jking018_news;milanjpatel_news;rroper1_news;tapjdey_news;
   taurytang_syllabus;tennisjohn21_news

```

4.2.2 Python API

At the top level of abstraction, we provide Python API via package `oscar`¹² that implements the key notions of author, file, project, commit, blob, and tree as the corresponding classes. The enumeration below describes Python classes that were created by wrapping up data objects 2. Each of the classes has a couple of methods attached to access corresponding properties. For the methods that contain slash(/), the method before slash returns actual data in string, while the one after return a generator of corresponding “python” instances. E.g. `Author.commit_shas()` re-

¹² <https://github.com/ssc-oscar/oscar.py>

turns a list of the SHAs of commits that the person authored; `Author.commits()` returns a generator of Commit objects built from those SHAs.

1. `Author(...)` - initialized with a combination of name and email, e.g. "Albert Krawczyk <pro-logic@optusnet.com.au>"
 - `.commit_shas/commits` - all commits by this author
 - `.project_names` - all projects this author has committed to
2. `Blob(...)` - initialized with SHA of blob
 - `.commit_shas/commits` - commits creating or modifying (but not removing) this blob
3. `Commit(...)` - initialized with SHA of commit
 - `.blob_shas/blobs` - all blobs in the commit
 - `.child_shas/children` - the commit that follows this commit
 - `.changed_file_names/files_changed`
 - `.parent_shas/parents` - the commit that this commit follows
 - `.project_names/projects` - projects this commit appears in
4. `Commit_info(...)` - initialized like `Commit()`
 - `.head`
 - `.time.author` - the commit time and its author
5. `File(...)` - initialized with a path, starting from a commit root tree. This represents a filename, regardless of content or repository; e.g. `File(".gitignore")` represents all `.gitignore` files in all repositories.
 - `.commit_shas/commits` - All commits that include a file with this name
6. `Project(...)` - initialized with project name/URI
 - `.author_names` - all author names in this project
 - `.commit_shas/commits` - all commits in this project

4.2.3 Perl APIs

While the Python API provides high level of abstraction, it is not very computationally efficient. In order to provide an intermediate level of efficiency between that of Python and Shell APIs, we also provide a way to implement applications or their components in Perl language. For example, the shell commands `getValue` and `showCnt` are both implemented in Perl. The Perl API instead of creating classes of objects as in Python, it handles the maps directly. To support writing WoC workflows in Perl we provide a variety of utility functions in package 'WoC.pm.' We also have, over the course of evolving WoC, created a number of applications that can be used as templates and modified by the users for their needs. For example, we can parse the content of the commit to obtain its tree, parent commit, author, and time:

```

1 use WoC;
2 my ($tree, $parent, $authName, $authEmail) = ("", "", "", "");
3 my ($pre, @rest) = split(/\n\n/, $code, -1);
4 for my $l (split(/\n/, $pre, -1)){
5     $tree = $l if ($l =~ m/^tree (.*)$/);
6     $parent .= ":$l" if ($l =~ m/^parent (.*)$/);
7     ($authName, $authEmail) = gitSignatureParse($l) if ($l =~ m/^author (.*)$/);
8 }
9 ($auth, $sta) = ($1, $2) if ($auth =~ m/^(.*)\s(-?[0-9]+\s+[\+\-]*\d+)/);
10 $parent =~ s/~/:/ if defined $parent;

```

We also have examples on how to parse, for example, a snippet of “python” source code to obtain the dependencies defined by the import statements. A “segment” is shown below:

```

1 for my $l (split(/\n/, $code, -1)){
2   if ($l =~ m/^\s*import\s+(.*)/) {
3     my $rest = $l;
4     $rest =~ s/\s+as\s+.*//;
5     my @mds = $rest =~ m/(\w[\w.]*[\,\s]*)*/;
6     for my $m (@mds) { $matches{$m}++ if defined $m;
7   }
8   if ($l =~ m/^\s*from\s+(\w[\w.]*)\s+import\s+(\w*)/) {
9     if ($2 ne ""){ $matches{"$1.$2"} = 1; }
10    else{ $matches{$1} = 1; }
11  }
12 }

```

For more detail please refer to the tutorial page of our repository.¹³

4.3 Description of the WoC Data

We use abbreviated object names for WoC data and basemaps as shown in Table 2. As noted above, types of basemaps are created to represent relationships among these objects, which are illustrated in Figure 8. Notice that some maps are missing in Figure 8, because initially we built maps with commit being the core, and other maps were built as certain research tasks the users were attempting to do would benefit from them. The basemaps are stored in TokyoCabinet databases for random queries and key-sorted compressed text files of these basemaps are also created to enable quick sweeps over the whole dataset and to enable the shell API.

In addition to the basemaps, programming language based maps are created to enable language oriented analytic and applications. These contain mappings that list repositories, and the modules they depended on, at a given UNIX timestamp under a specific commit. The format of each entry in these maps are like the following, where `module1;module2;...` represent the modules that repository depended on at the time of that commit:

```
commit;repository_name;timestamp;author;blob;module1;module2;...
```

At the time of writing, 12 maps are ready including C, C#, Java, JavaScript, Python, R, Rust, Go, Swift, Scala, and Fortran with more language maps anticipated to be added in the future.

Table 2 Naming Conventions

Object Abbreviation	Annotation	Entity Type
a	author	string
b	blob	SHA
c	commit	SHA
f	file name	string
p	project	string

¹³ <https://bitbucket.org/swsc/lookup/src/master/>

¹⁴ ‘File’ in this figure refers to ‘File name’

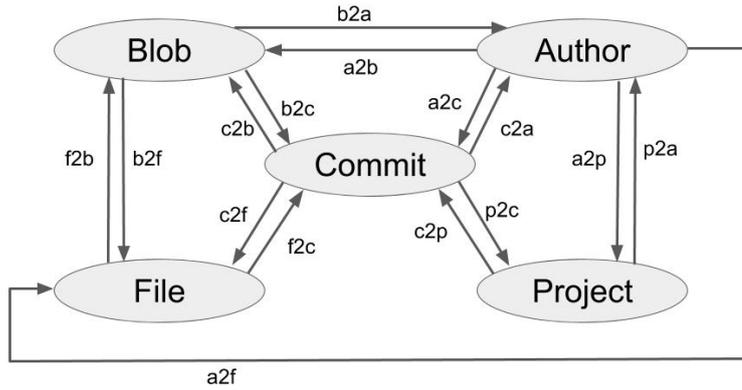


Fig. 8 Maps between primary objects¹⁴(Basemaps)

Table 3 Maps Size

Map Type	Map Size (GB)	Text Dump Size (GB)	# of Records (Billion)
a2b	311	232	9.9
a2c	169	50	2.0
a2p	44	28	3.7
a2f	282	191	31.2
b2a	1102	679	9.9
b2c	1317	1152	40.7
b2f	1099	588	35.2
c2a	192	91	2.0
c2b	970	998	40.7
c2f	695	449	60.1
c2p	1127	797	101.2
f2a	1955	380	31.2
f2b	1574	1085	35.2
f2c	2393	1176	60.1
p2a	84	52	3.7
p2c	1982	2283	101.2

4.4 Performance Benchmark

The anticipated workflow of a specific research task involves a set of queries that proceed from selecting an initial sample of interest such as a set of files related to a specific language, a set of projects or authors with certain properties or other collection. This is typically followed up by one or more network operation such as identifying blobs associated with the selected files, projects associated with the initial set of developers and so on. These tasks can typically be implemented in numerous ways, each leading to different computer memory, disk IO, and computational overheads. To help users decide upon the the best way to proceed and, more generally, to gauge the time needed for their desired workflow, we set up experiments to test our WoC infrastructure performance on such queries. Our existing basemaps should meet users' need in most cases by a query of a single map (e.g. author to commit). However, in cases where a map is not ready (e.g. file to project in Figure 8), users might need to combine/join two or more maps

to achieve their goal. We, therefore, tested the performance of both single map queries and combined map queries, and present the results below.

Since the file¹⁵ to project map is not pre-computed, we can start from the file to commit map to test single map query performance and then join the results with the commit to project map to test the combined map query. We randomly selected 100, 1K, 10K, 100K, and 1M file names from our dataset, and used the Python and Shell APIs without any other task being run on the server to find the corresponding commits in which the files were modified and the projects those commits belong to. We collected the time it took to run each test and show them in Figure 9 for the single map queries, and Figure 10 for the combined map queries.

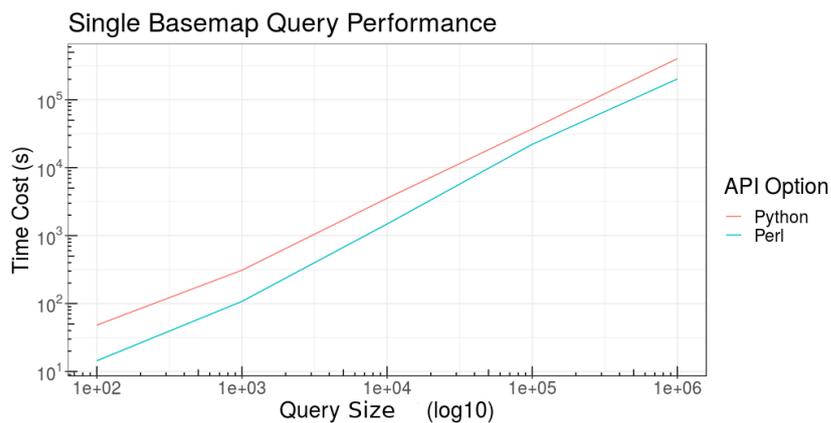


Fig. 9 Single Map Query Performance

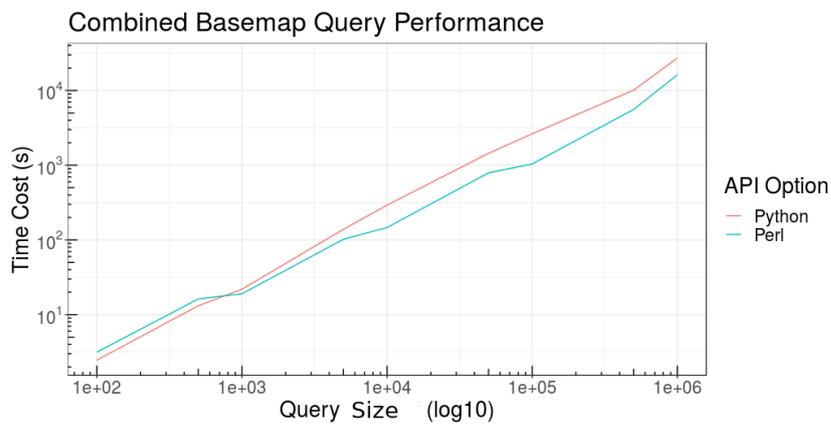


Fig. 10 Combined Maps Query Performance

¹⁵ By file, we refer to the file name (including folder path) in the rest of our paper.

From Figures 9 and 10, we see that the run time increases linearly as the task size increased, highlighting the scalability of the WoC infrastructure. We also found Shell API to be three to four times faster than Python API (Figure 9 and right part of Figure 10), for the same query. One hypothesis is the interpreted nature of Python. Specifically, the data access parts of Shell API are implemented in Perl. While Perl is an interpreted language just as Python, many of the functions are implemented natively in C language, while in Python more performance-critical code is interpreted.

It is worth noting that the x-axis on Figure 10 represents the number of queries, which in this scenario is the sum of the number of file to commit queries and the number of commit to project queries.

We tested the performance of the tool for 100 to 1M queries. If a research workflow involves the initial sample of objects for a very large part of the WoC database, we recommend leveraging the database in the form of compressed text for key-value basemaps instead, because as the number of random access queries increases, it exceeds the time it takes to sweep the entire database using efficient shell commands such as `grep`. In fact, a single sweep of the file to commit compressed data only takes 38 hours while 1M queries of the file to commit basemap takes 56 hours using Shell API.

5 Applications

To evaluate if the experimental platform is capable of supporting research tasks conducted as a part of actual investigations and to provide a set of vignettes for other researchers, we conducted two types of studies. First, we implemented several basic and involved research tasks that require the entirety of FLOSS data as a part of the investigation. Furthermore, we also recruited three researchers external to our group to either conduct investigations of their own utilizing WoC or to provide us with their research problems that can only be solved by using WoC. Below we report both the experiences and results from these experiments.

5.1 Use of programming languages

Language popularity may influence developers decisions as it may affect the market for their software as well as their job prospects. For example: What language-specific API should developer provide for their component? What language should the developer use to implement their product?

To plot, for example, Java language use trend we use WoC to identify all files with `.java` extension. Then, via file-to-commit map, obtain the complete set of commits authoring these files. Commit dates are used to plot the time trends of language-specific commits, authors (property of a commit), projects (via commit to project map) and, if desired, lines of code changed. The entire process is highly parallelizable since each map is separated into 32 instances and can be processed independently. The entire calculation, while not interactive on our hardware, can be performed in tens of minutes. For illustration, we show the ratio of the number of commits over the number of developers (a measure of productivity) each year in Fig. 11. The ratio decreases for most languages, perhaps because as a language

becomes more popular, the less experienced contributors join and lower the average productivity.

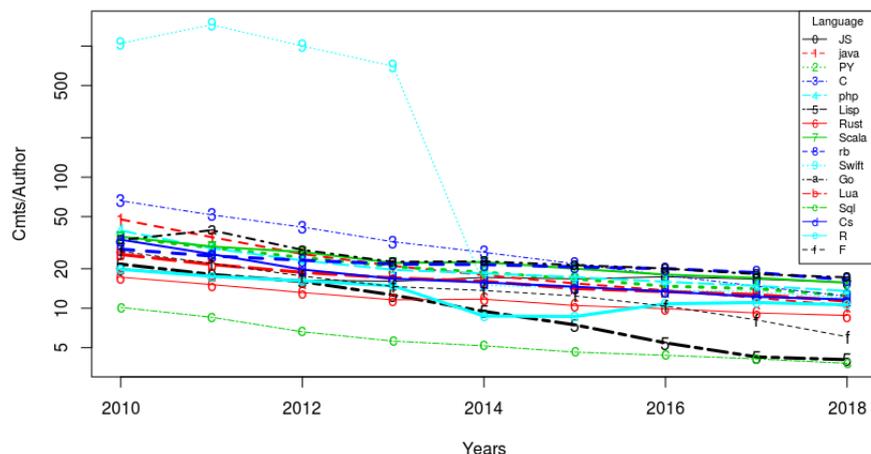


Fig. 11 Productivity by Language

5.2 Correcting Developer Identity Errors

One of the particularly troubling data quality issues with version control systems is developer name disambiguation. Often, names and emails of developers are missing, incomplete, misspelled or duplicate [9,36]. Performance of any disambiguation algorithm depends on the distribution of the actual misspellings in the underlying data. In order to design and evaluate corrective algorithms, it is important to study a large collection of actual data and unearth patterns of irregularities that compromise data quality. WoC contains a nearly complete collection of Git author ids (name and email combinations) and is, thus, more representative of such irregularities than any specific project.

To obtain author IDs we use author-to-commit map containing roughly 30 million distinct author IDs. Common error patterns include organizational ids and emails (Mozilla, Linux, Google etc), names of tools and projects (OpenStack, Jenkins, Travis CI), roles such as (admin, guest, root etc.) and words that preserve anonymity (student, nobody, anonymous etc) as a part of their credentials. We also found a large number developer IDs to be misspelled.

Traditional identity correction approaches rely on the misspelling patterns of author ID (the full name and email) [9,73,74]. With WoC data, we can enhance the traditional string matching with behavioural comparison, by creating similarity measures between author IDs using files modified by developers, time patterns

of commits, and writing styles in commit messages. For illustration — two author IDs that modify a similar set of files may suggest that these IDs belong to the same developer. To implement file-based similarity, we used author to commit and commit to file maps to obtain the set of files modified by a single author ID. Then file-to-commit and commit-to-author maps were used to calculate similarity using weighted Jaccard measure. Commit message text was used to fit a Doc2Vec [49] model to associate each author ID with their writing style. Traditional and behavioural similarities were used to train highly accurate machine-learning model [5].

This experiment demonstrates the utility of WoC data for designing tools to solve common and vexing data quality problems when constructing developer networks. It is also an example of how WoC can be enhanced by incorporating such techniques and providing corrected data to researchers.

5.3 Cross-ecosystem comparison studies

A second research group used the database to gather comparative statistics about different software ecosystems. In that research, “ecosystem” was defined as the set of packages provided by a (usually single language) package management system such as CRAN (for the R language) or npm (for Node.js packages). The purpose was to supplement other comparative data about such package ecosystems in support of a study of how ecosystem tools and practices influence development behavior. The ecosystem study involved a survey, interviews, and data mining over 18 ecosystems whose repositories listed more than 1.2M packages. Some questions about ecosystem practices could be mined from metadata available elsewhere; for example detailed information about dependencies, release frequency, and version numbering practices can be easily extracted from libraries.io.¹⁶ However deeper questions about project content would have been out of reach without WoC; independently building the mechanism to collect all of these projects, building a database of blobs, files, projects, and authors, and comparing them using various metrics would have been too much work for too little gain without the availability of this research platform.

5.3.1 *File cloning across ecosystems*

One such statistic is rate of file cloning. It was theorized that in ecosystems with more flexible support for dependencies and a tolerance for the risk of breaking changes, developers would be more likely to use dependency management tools to make use of functionality from other projects, rather than copying those files in directly; hence in such ecosystems we should find relatively few commits adding a blob that already exists in any other project available through the ecosystem’s dependency management system.

Using WoC, this analysis was straightforwardly accomplished by joining blob-to-commit and commit-to-project mappings, filtering for blobs that appeared in multiple projects, and identifying pairs with one commit in the time frame, and at least one older commit. Such blobs were discarded when the files were very small

¹⁶ <https://libraries.io/>

(since these often turned out to be empty or trivial files duplicated by chance or by tools) resulting in a set of duplicates that, on visual inspection of a sample, did appear to represent genuine examples of reuse-by-cloning.

Contrary to our expectations, the ecosystem with the most propensity for cloning was the one with the modern and flexible dependency system: npm. Despite the strengths of npm’s dependency management system, there is a strong tradition of copying dependencies like jQuery into projects rather than letting npm retrieve them. Figure 12 summarizes the findings for a selection of ecosystems.

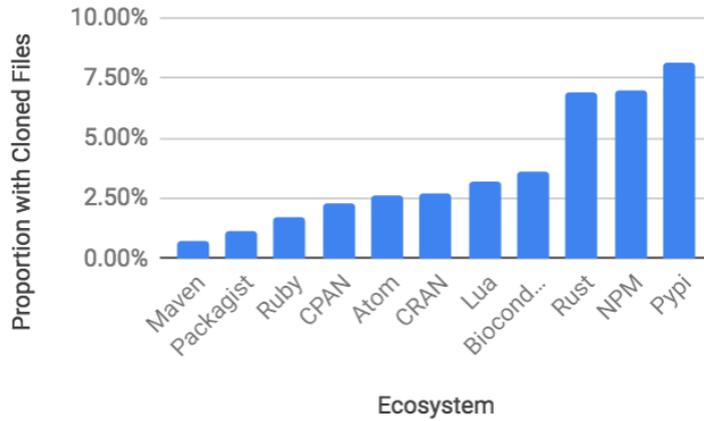


Fig. 12 Proportion of repository packages that added at least one cloned code file over 1kb in 2016.

5.3.2 Developer migration across ecosystems

Another metric of interest was developer overlap between ecosystems. Our ecosystem comparison had included a survey of values and practices in the 18 ecosystems of interest, and we hypothesized that ecosystems might be similar if many developers were actually working in both ecosystems, or had migrated from one to the other.

This question was answered by joining author-to-commit and commit-to-project data for the 1.2M projects in our study, and relying on the identity matching technique described in Sec 5.2.

Over all pairs of ecosystems, we found a sizable correlation between similarity of average responses on ecosystem *practice* questions (things like frequency of updating, collaboration with other projects, means of finding out about breaking changes), and overlap in committers to those ecosystems (Spearman $\rho = 0.341$, $p < .00001$, $n = 16$ ecosystems). Interestingly, perceived *values* of the ecosystem (such as a preference for stability, innovation, or replicability) do *not* seem to align with developer overlap ($\rho = -0.05$, $p = 0.44$). While more research is needed, we hypothesize that developers may carry practices over from other languages and platforms they have used in the past, in a sometimes cargo-cult-like way, despite recognizing that a new ecosystem is designed to accomplish different ends.

In our very large-scale, wide-ranging study, these questions of developer migration and cloning were of great interest, but would likely have been too expensive to pursue alongside other lower-hanging fruit, absent WoC’s prepared set of precomputed maps between files, blobs, authors, projects, and timestamps. The dataset with its analytical maps was not designed with these particular ecosystem comparison in mind, but its design happens to make such ecosystem questions relatively easy to answer.

5.4 Python ecosystem analysis

An external researcher wanted to use WoC to investigate open source sustainability by identifying source code repositories for packages in PyPI ecosystem and to measure package usage directly. While over 90% of npm packages provide repository URLs, less than 65% of Python Package Index (PyPI) packages do.

The researcher obtained all packages from PyPi and calculated blob SHA1s for *setup.py* file of the first PyPI releases of each package. We filter out resulting 101584 blobs to exclude empty or uninformative blobs (blobs that appear in more than one commit using blob-to-commit map). The 54218 informative blobs are then mapped to 54062 unique commits and commits to 51924 unique projects (adjusted for forking as described in Section 3.6). Repositories were recovered for 96% of the 54218 original packages in approximately 20 minutes of computation. To ensure that these repositories are, in fact, used to version control corresponding packages, they can be matched via additional blobs for *setup.py* and other files obtained from PyPi for that package.

Another problem being solved by this researcher was identifying which of the seemingly abandoned projects may be “feature complete,” i.e. already have the intended scope and do not require further maintenance [13]. Feature complete projects should be widely used in contrast to abandoned projects. Proxies of project usage, e.g., GitHub stars or forks can be used to identify such projects [13]. WoC, however, lets us measure the extent of use directly. As described in Section 5.1, all commits modifying Python files are identified (file-to-commit map) and the resulting commits are mapped to projects (commit-to-project map). Blobs associated with these commits (commit-to-blob map) are then used to extract imports from these files. The entire procedure could be completed in approximately four hours using the parallelism of the analytic maps (32 databases) and blob content maps (128 databases).

The reported usage was compared to project development activity, i.e the total number of adoptions versus the total number of commits. In some cases, usage was not accurately reflected in the number of commits. Common examples are packages providing console scripts and CMS-like projects. In the former case, packages are not reused in programmatic code and thus don’t get into statistics. In the latter case, website builders often do not publish their code and thus such usage remains unobserved. Therefore, while the number of public reuses provides some extra information about package use, it should be adjusted for package type.

5.5 Repository filtering tool

Millions of repositories on GitHub and other forges also include projects that are completely unrelated to software development. GitHub is widely used for education and other tasks such as backing up text files, images, or other data. Researchers investigating education may need to focus on tutorials, while other researchers may need a sample of actual software development projects. Furthermore, a way to select specific subsets of software development projects in order to conduct, for example, "natural experiments" would also be highly beneficial. WoC can support such project segmentation tasks in a variety of ways. An external education researcher wanted to understand the impact of self-administered programming tutorials. To do that, WoC was used to identify developers who participated in tutorials by searching the set of projects in WoC via keywords related to education: "assignment", "course", "homework", "class", "lesson", "tutorial", "syllabus", "mooc", "udacity". The search yields over 1M projects. While it is only a small fraction of all projects in WoC but it represents a large sample in absolute terms. Further filtering was needed to find developers who also worked on actual software projects to measure the impact of self-administered tutorials. The project-to-commit map identified 605K users of tutorials and, when these users were mapped to all projects they participated in, we determine that only half of them contribute to non-tutorial projects. These 300K individuals are potential subjects of tutorial-impact study. Further information (such as their commit activity and project participation) can be obtained from WoC and combined other data, be used in this research. WoC can be extended with other approaches to segment projects¹⁷. For example, identification of projects with sound software engineering practices [58] relies on a combination of factors easily obtainable in WoC, such as history, license, and unit tests.

5.6 Other Applications

A number of research publications have utilized the WoC database, including:

- The relationship between dependencies of NPM packages, collected using the WoC infrastructure, and their popularity was discussed in [17]. A related work exploring the interrelationship between software quality and popularity was discussed in [18, 20]
- The effort contribution and demand patterns of the contributors to the NPM ecosystem was discussed in [16].
- The investigation of what attributes drive the adoption of a software technology was discussed in [53].
- The effect of overall expertise of software developers, extracted using WoC data, and other social and technical factors on the chance of their pull requests getting accepted was discussed in [21, 22], and the related dataset was made available at [19].
- A method of representing the medium-granularity expertise of developers using a "skill-space" based on the APIs they use, and its usefulness in addressing a number of important SE research questions was explored in [15].

¹⁷ Section 5.2 shows how WoC can also be used to improve them

6 Archetypal Usage of WoC

To increase the utility of this project to a wider research community, we would like to prioritize easy access to the World of Code to other interested parties. In this section, we provide a brief introduction and an overview of the World of Code and how to use it. Moreover, there are some resources already in place that were designed to assist in this process, which can be found in a public repository.¹⁸

After describing WoC and its applications, in this section we demonstrate how to actually use WoC to implement a specific analysis. A couple of approaches presented here leverage the WoC tool to implement the Java language trend analysis, as described in Section 5.1.

1. Identify Java files based on ‘.java’ extension, collect commits that changed these files, and deduplicate the commits. Now we have all commits where one or more java files were created/modified. The source code of the custom `lsort` command is presented in Appendix B.

```

1 #start from basemap dump("file to commit" dump, P represents version),
2 for i in {0..31}; do zcat /da0_data/basemaps/gz/f2cFullP.$i.s | awk -F ";"
   "/.java;/{print $2 }" done | ~audris/bin/lsort 10G -u | gzip >
   JavaCommits.gz

```

2. For each commit in commit collection, we can use either Python or Perl API to find related author and commit time, and then calculate the number of authors and commits by year – the trend

```

1 # Using Python
2 import gzip
3 from datetime import datetime
4 from collections import defaultdict
5
6 year2commit_count = {}
7 year2commit_count = defaultdict(lambda: 0, year2commit_count)
8 year2author_count = defaultdict(set)
9 java_commits = gzip.open("JavaCommits.gz", "r")
10 for commit in java_commits:
11     time, author = Commit_info(commit).time_author
12     year = datetime.fromtimestamp(int(time)).year
13     year2commit_count[year] += 1
14     year2author_count[year].add(author)
15 print(year2commit_count)
16 for year, authors in year2author_count.items():
17     print("Year: " + str(year) + "# of authors: " + str(len(authors)))

```

```

1 # Using Perl
2 # we can run /da3_data/lookup/showCmt.perl on every commit and extract
   author and time info from there
3 # A simpler way is to utilize basemap c2taFullP.{0..31}.tch (i.e., the
   basemap from commit to author and commit time) by calling Cmt2ATShow.
   perl (see source code in Appendix)
4 zcat JavaCommits.gz | perl Cmt2ATShow.perl | gzip > JavaYearAuthor.gz
5 # count records for each year, we get the number of commits by year. E.g.,
   for year 2014:

```

¹⁸ <https://github.com/ssc-oscar/lookup>

```

6 zcat JavaYearAuthor.gz | grep "^2014;" | wc -l
7 # after deduplication, count records for each year and we get the number
  of authors by year. E.g., for year 2014:
8 zcat JavaYearAuthor.gz | sort -u | grep "^2014;" | wc -l

```

In fact, directly using language maps is more efficient when implementing this analysis, since language specific information have already been extracted from base maps and stored as language maps for use.

```

1 # Alternatively, we use language map: c2bPtaPkgPjava, which consists of commit,
  blob, project name, time, author, etc.
2 zcat c2bPtaPkgPjava.{0..31}.gz | cut -d\; -f3,4 | gzip > JavaYearAuthor.gz
3 # now follow the similar approach in Perl example shown above to get the final
  result

```

7 Platform Comparison

In this section, we compare different platforms and datasets to better highlight the unique features of WoC. In particular, we provide the basic size comparisons¹⁹ (see Table 5) and data categories (see Table 4) for Software Heritage, GHTorrent, WoC, BOA, and GHArchive.

Table 5 shows that WoC is comparable in size of various data components to Software Heritage, GHArchive, and GHTorrent. All four are much larger than BOA dataset.

Because the platforms have different goals, they collect and index different kinds of data; Table 4 summarizes some of the differences in data content, indexing, and services. While WoC attempts to be comprehensive in capturing source code and source code change history and authorship, it does not capture some of the social interaction associated with open source software engineering, such as bug reports, patch submissions, and code reviews: GitHub enables these interactions, and they are captured by pure Github archives like GHArchive and GHTorrent. WoC, on the other hand, provides more comprehensive cross-indexing of software artifacts than the other platforms do, and provides services for the common research steps of merging duplicate repositories and duplicate user identities. WoC and Software Heritage also capture the actual content of software files, which GHArchive and GHTorrent do not attempt to do, to keep their data set sizes tractable. WoC manages the size by provisioning a very large storage space on a set of linux servers and giving researchers command-line accounts on these servers. Software Heritage in contrast provides an open API for querying file contents one at a time, which makes access easier for a wider group of researchers, but at the cost of making it difficult for outside researchers to run analyses over large numbers of source files. Note that BOA is omitted from this table, since BOA is a tool that could, in theory, be applied to the task of capturing any of this data, and indexing it in any of these ways.

¹⁹ The size information for Software Heritage, GHTorrent and WoC is directly obtained from their official websites. GHArchive, on the other hand did not provide such detailed information, and we looked into its dataset and checked the author ID field and project ID field.

	WoC	SH	GHA	GHT
Metadata				
commit	yes	yes	yes	yes
authors	yes	yes	yes*	yes*
filenames	yes	yes	no	no
trees	yes	yes	no	no
blob SHA	yes	yes	no	no
Issues, PRs, comments	no	no	yes	yes
branches	no	yes	no	no
repositories	yes	yes	yes	yes
Indexing				
authors	yes	yes	no	yes
commits	yes	yes	no	yes
filenames	yes	yes	no	no
blobs	yes	yes	no	no
repositories	yes	yes	no	yes
commit to parent	yes	yes	no	yes
commit to filenames	yes	yes	no	no
commit to head	yes	no	no	no
commit to root	yes	no	no	no
blob to first commit/author	yes	no	no	no
time of the commit	yes	yes	yes	yes
Other features				
language use	per blob	no	per repo	per repo
Blob accessible for analysis en masse	yes	no	no	no
Blob contents	yes	yes	no	no
Deforking	yes	no	no	no
Merge user identities	yes	no	no	no

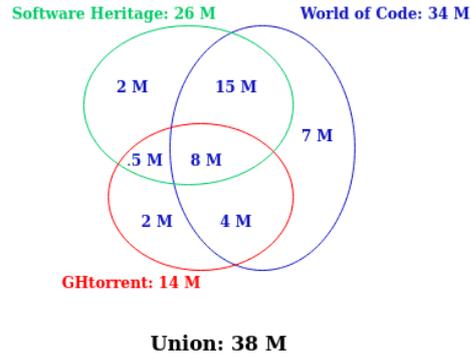
Table 4 Features for comparable repositories: WoC= World of Code; SH = Software Heritage; GHA = GithubArchive; GHT = GHTorrent. ‘*’: GithubArchive and GHTorrent only collect github identities as authorship information. The ‘Metadata’ section describes information that is captured by the platform; ‘Indexing’ describes what indexes are provided for efficiently making connections. For example although it is possible in Software Heritage to iteratively trace a chain of commits to the chain’s root, there is not a table directly connecting them; thus “commit to root” has “no” in column SH.

Moreover, we conduct a performance comparison for specific tasks across BOA and WoC, and report the result in Section 7.3. In order to understand the data completeness of different datasets, we compared the corresponding author Id (name and email) dataset for Software Heritage, GHTorrent and WoC, and present the result in Figure 13. We found that over a total number of 38 million author IDs, WoC captured a majority part (34 million), which is much larger than the other two datasets (26 million and 14 million). Note that this comparison was conducted in November 2019, which does not represent the current status. Also, GHArchive and ghTorrent also capture users who have not made any code changes, hence such users will not be present in WoC or Software Heritage datasets that deal exclusively with the source code and its changes.

In below, we briefly describe the features of each platform, and provide functionalities comparison with WoC.

Table 5 Dataset Comparison

Platforms	Date	No. of Blobs	No. of Files	No. of Folders	No. of Commits	No. of Authors	No. of Projects	No. of Releases
Software Heritage	July 11, 2020	NA	8.5B	7.3B	1.8B	36.4M	132.0M	14.8M
GHTorrent	June, 2019	NA	NA	NA	1.4B	32.4M	125.4M	NA
BOA (GitHub set)	October, 2019	NA	484.9M	NA	23.2M	NA	NA	7.8M
WoC	Mar, 2020	7.9B	12.4B	8.3B	2.0B	42.1M	123.8M	NA
GH Archive	Dec, 2019	NA	NA	NA	NA	26.9M	126.6M	NA

Name/Email matches across three platforms**Fig. 13** Developers ID match across WoC, Software Heritage and GHTorrent platforms.

7.1 GHTorrent

GHTorrent [41] captures GitHub’s event stream and uses the captured data to reconstruct GitHub’s object model of software interaction history that is visible to GitHub users. Its focus is thus more on software process than content: it captures the identities of projects, users, and commits, as well as their interactions in the form of issues, pull requests, comments, and their starring, labeling, and joining of projects. GHTorrent does not capture the actual contents of files in the projects.

Its main advantage over World of Code is that it captures a significant dimension of non-coding work that happens in projects: bug reporting and design discussions that happen in pull request and issue threads. It is less suited to research involving the actual content of code files, since it does not contain or index the files contained in the projects. It also is limited strictly to GitHub data.

Further, GHTorrent’s method for collecting data has inherent limitations [47]: GitHub’s event stream has changed in format over time, has produced buggy or inconsistent data in the past, and has had outages; thus GHTorrent provides only a best-effort reconstruction of Github-based software development.

7.2 Software Heritage

Software Heritage(SH) [27, 60] has aims and methods that are similar to that of World of Code: they aim to collect “all publicly available source code, with all its development history, organizing it into a canonical structure, and providing unique,

intrinsic identifiers for all its parts, enabling its better fruition while ensuring its long term preservation.” [27].

Like WoC, this platform also collects software on an ongoing basis from multiple sources, including Github, Gitlab, the Debian package repository, Gitorious, Google code, and PyPi [60]. They collect commits, authors, repositories, directories, filenames, and the blobs themselves. Unlike WoC, they also collect branches and releases, in a cross-VC representation they call “snapshots”.

SH holds this archive of data on a set of servers, with a web interface designed around its role as a preservation archive – it is convenient for users to register new code bases and examine historical ones one at a time, but it is not designed to allow the public to do arbitrary research queries. For research purposes, they offer a large (1TB) graph database of metadata [60]; this makes a broader range of metadata queries possible, but the files/blobs themselves are still only accessible one at a time, via an API; there would be no efficient way to run analysis on the content of large numbers of blobs in order to, for example, search for a particular method name or language feature use.

7.3 BOA

The Boa system provides a commendable option in regards to Git analysis. However, it does have some issues when analyzing complex research questions due to inherent complexities related to querying. More specifically, Boa’s data storage format [46] requires the use of MapReduce, a complex model used for batch processing large datasets, which becomes worse when the desired data requires multiple uses of MapReduce.

Hung [46] provides an interesting attempt to subvert this issue by providing what they characterize as “Materialized Views”, which allows users to access the results of previous queries from other users as a way to simplify the data retrieval process. This approach helps future users for accessing data that have been previously requested by others, however, chaining successive MapReduces for complex tasks is still acquired for the initial request. The WoC platform, on the hand, provides basemappings as direct connections between various data categories. These basemappings are stored in a constant time database which ensures the data retrieval process maintains a linearity in speed.

Another drawback of Boa is that it only provides datasets that were compiled using Java and Python. Although Boa has code that supports additional languages (e.g. PHP, XML, CSS), no datasets are provided with these languages so far. Furthermore, Boa only provides data associated with GitHub, and additional efforts are required if users are want to create new datasets from a manually selected set of Git repositories out of GitHub. The latest Boa dataset was compiled in October 2019, and contains around 7.8M projects, 380K Code Repositories, 23.2M Revisions, 146.4M Unique files, 485M File snapshots, and 71.8B AST Nodes.

We implemented a speed test on the same machine (to maintain comparability) to perform a comprehensive comparison between these two systems. We installed the Python boa-api client on this machine, which also has access to WoC basemappings. We took as an example counting the total number of committers in each project, which is explicitly described in the list of examples on the Boa

official webpage²⁰. Given the substantial difference in the number of projects contained within each platform, we chose to randomly select 7,830,023 (the number of projects in Boa) projects from WoC for comparison. We leveraged Perl API and project-to-author map and completed this task at a time cost of 259 seconds. We directly ran the source code of the example provided on Boa webpage, and finished the same task in 383 seconds. Based on our test, we believe that WoC platform can provide better performance on specific tasks than Boa given that the WoC selection task was run on an order-of-magnitude larger dataset.

7.4 GH Archive

GH Archive is a project to record the public GitHub timeline of events, archive it, and make it easily accessible for further analysis²¹. New public GitHub events/activities are collected every hour, and have been archived since Feb 12, 2011. Users can access these data sets either by directly downloading each hourly compressed collection, or by running BigQuery in Google Cloud Platform where the full data set is stored as SQL tables.

By selecting unique repos over the nine databases representing years from 2011 until 2019, we found that GHArchive contains around 126.6 million projects.

GH Archive data has supported several research projects, visualizations and talks, such as GitHub Analytics²² and GitHut²³. Compared to other platforms, GH Archive has advantages for research that studies a specific time range, requires publicly available services (cloud service) and most recent data access (quick hourly update). However, there are drawbacks as well: this archive contains only the log of visible events, not the blobs and files they represent. Parsing these logs is nontrivial, as log formats are complex and have changed subtly over the years; and furthermore, relationships among development components (e.g., what are the commits made by a specific developer) are not directly represented, and must instead be collected and indexed by the user.

8 Hackathon Event

In early November, 2019, we hosted a hackathon event at the Carnegie Mellon University campus, during which a number of researchers in software domain from all over the world gathered and participated to further explore the potentials of WoC platform, propose missing services that would be beneficial for their researches, and, overall, to familiarize themselves with WoC. In this section, we report the hackathon event workflow, a brief summary of projects proposed and implemented during this hackathon, and a published research work (extension of one of the projects).

²⁰ <http://boa.cs.iastate.edu/examples/index.php#scheme-use>

²¹ <https://www.gharchive.org/>

²² <https://github.com/harishvc/githubanalytics>

²³ <https://githut.info/>

8.1 Event Workflow

We hosted a pre-hackathon event virtually in October 2019, where we shared the instructions on the setting up of WoC environment, and went through a live tutorial of WoC together with participants. By offering this training opportunity, we hope that the participants could become familiar to WoC services and dataset before attending the official event.

The official event started on the evening of Nov 1st. After a short introduction to WoC, participants were asked to brain storm for ideas where WoC could be leveraged to assist. These ideas were further classified into a few categories (software risk, ecosystem study, API usage, developer migration, infrastructure improvement, etc.) and participants were asked to pick one of the topic at will to contribute. In the end, four groups emerged, and each group was expected to finalize the project road map, collaborate efficiently and present their work by the noon of Nov 3rd.

During this event, we received a number of requests for certain functionalities that were missing. Due to the practical impacts, these services become our priority focus to be implemented since then.

8.2 Event Projects

We briefly describes each project in the hackathon event as follows.

- Bot detection²⁴: This group was tasked with detecting code-commits bots that are active various social-coding platforms.
- Bridge²⁵: This group consists of members from the Software Heritage project, members familiar with the GHTorrent project, and WoC. The main objective was to compare datasets across different platforms, and build a joint service/entrance as a bridge to facilitate and enable the access to these platforms.
- Workers Comprehension²⁶: This group was tasked with determining knowledge transfer between developers when changes were made to files within a project. If multiple authors had made changes to a file it was hypothesized that the knowledge transfer between those developers could be determined by analyzing the commit messages and lines of code modified.
- TAP²⁷: This project was focused on the understanding of developers trajectory on language usage, and gender distribution among languages.

8.3 Bot Detection

This project was conceived during the hackathon event with the goal of detecting bots that commit code in various social-coding platforms. The presence of bots in datasets used to explore questions related to empirical software engineering can be a nuisance, since it can significantly skew the measures of productivity, team

²⁴ https://github.com/ssc-oscar/BIMAN_bot_detection

²⁵ <https://github.com/woc-hack/thebridge>

²⁶ <https://github.com/woc-hack/Workers-Comprehension>

²⁷ <https://github.com/woc-hack/TAP>

size, project activity etc. However, detecting bots is not an easy task, since every developer in the entire open-source community has to be examined to determine whether that developer is actually a bot. Due to the size of the data, the only practical method for dealing with this problem was using a combination of some heuristics and some fine tuning. We used a combination of three heuristics, the result of which was combined using an ensemble model. We call our proposed bot detection method **BIMAN** — *Bot Identification by commit Message, commit Association, and author Name*.

The first heuristic was based on the observation that the bots sometimes have the word “bot” in their name or email. The data obtained from WoC had the names and email addresses of all the developers who contributed code to OSS, so we used regular expressions to search for the presence of the word “bot”, and found that sometimes, the word was there in the name, and sometimes it was in the email ID of the authors. Datasets like GHTorrent, GH Archive etc. typically do not have the name and email address of the developers, only their GitHub ID, which would likely mean that we would have missed a number of true bots. Moreover, GHTorrent does not have any information about the GitHub Apps, which are responsible for making a large number of commits, and are almost always bots. As such, having access to both the names and email addresses of the developers, and having access to the data about the Apps through WoC helped us broaden our search and find more bots using this heuristic.

The second heuristic is based on the observation that bots typically use some type of a template for creating the commit messages for their commits. Through WoC, it is easy to get access to all commit messages created by a developer using the map from authors to commits (*a2c*) and commits to commit contents. While this data is available and can be obtained from GHTorrent, it is only limited to data from GitHub, while WoC has access to data for all OSS projects that use git, which significantly broadens the scope for the research. Having access to WoC helped us examine the entire OSS ecosystem (that use git) with ease and discover a number of bots using this heuristic.

The basis of the third heuristic was the empirical observation and hypothesis that the files modified by a commit and the projects it is associated with will have a different pattern for the commits created by bots and for those created by humans. To validate this hypothesis, we collected data on a number of measures for each developer, viz. the total number of files changed by the developer, the number of unique file extensions modified by them, standard deviation of number of files per commit, mean number of files per commit, the total number of unique projects commits have been associated with, and the median number of projects the commits have been associated with (includes duplicates). While this data can be easily calculated by WoC using the authors to commits (*a2c*), commits to files (*c2f*), and commits to projects (*c2p*) maps, these measures would be difficult to calculate quickly (or at all) for the other existing databases.

Having access to WoC gave us the unique opportunity to apply these heuristics on the entire OSS ecosystem in a timely manner, and discover a number of code-commit bots. We examined more than 34 million developers who have committed code to a GitHub repository, along with detailed information for approximately 1.6 billion commits made by them. The final ensemble model combining these three heuristics achieved an AUC of 0.90, and the result was published in the Mining Software Repositories conference, 2020 [24]. We also compiled a

dataset with information about 461 bots, detected by **BIMAN** and manually verified as bots, each with more than 1,000 commits, along with detailed information about 13,762,430 commits made by these bots, which is available at [DOI 10.5281/zenodo.3610205](https://doi.org/10.5281/zenodo.3610205) [23]. An extension of the work was published in [26], and a dataset containing a mapping between bot commits, projects, files, and blobs was made available at [25].

9 Future work

To have an impact on research practice, the WoC prototype needs to be exposed via reliable services that help with research and do not overwhelm the platform. Currently, we only have Python and Perl API available. However, more languages will be supported in the future. Comparatively small pre-extracted relations will be stored into relational database to extend our accessibility to users who are used to SQL. WoC should also accommodate additional data and computational procedures needed for discovering, correcting, cleaning, augmenting, and modeling the underlying data. Processing hundreds of terabytes of data on powerful clusters may be out of reach for most research groups. Therefore, to accommodate massive queries WoC would require more powerful hardware. Such hardware can be obtained from cloud vendors, but the costs of hosting and analyzing data on these platforms might be high. An alternative might be a few high-throughput services that work on the hardware we currently employ.

The differentiating features of WoC are the completeness of the collection and access to global relationships. Specifically, two basic services would be difficult to replicate outside WoC, yet be capable of high throughput on the limited hardware. First, a reporting service that considers prevalence of certain features, such as languages, tools, and other technologies as well as the information about contributors might provide services akin to those provided by a population census. The second basic service would focus on identifying all entities linked to a specific entity, such as files modified by a developer, all repositories containing a specific code, or all files that use a specific module or technology. These two capabilities, in conjunction with MSR technology already in use, would provide both, population-level data and complete links within entire FLOSS ecosystem. It would then be up to researchers to retrieve additional data on individual projects based on the stratified samples from the first service or derived from the relationships obtained from the second service.

10 Limitations

We tried to make the assumptions and rationale for specific decisions clear within each section but it is important to reiterate at least some of the limitations. Despite a large size (the collection contains over 1.45B commits), there is no guarantee it closely approximates the entirety of public version control systems as the project discovery procedure is only an approximation. Our focus on Git (due to the simplified global representation) excludes older version control systems that have not been converted to Git yet. We regularly identify issues with data being incomplete due to collection, cleaning, or processing and we are working on an approach to

continuously validate and correct it. The particular design decisions were focused on the particular computing capabilities that were available to us at the time and could/should be revisited as the prototype evolves. The entirety of research tasks that WoC provides is not exhausted by the few examples we have investigated and certain tasks may require different solutions. We do, however, think that the micro-services approach allows for simpler addition/extension/replacement of components as needs or opportunities arise than would be possible with a more monolithic architecture.

How to reliably clean, correct, integrate, and augment the collected data so that the resulting analyses accurately reflect the modeled phenomena is a concern. To ensure the performance of the analytics layer certain objects are filtered from it. For example, some of the public repositories are created to test the performance/-capabilities of Git and contain many millions of files/blobs in a single commit. Such commits are excluded from the analytics layer to speed-up the commit-to-file and commit-to-blob maps. The nature of the data may also create performance problems. For example, the most common blob is an empty file. Mapping such blobs to all commits that create them or to all files does not make sense, since there are millions of commits that have created empty files. These performance-related modifications may affect some arguably superficial analyses, e.g., what are the commits with the largest number of files? We explicitly highlight these modifications in the WoC code to minimize potential confusion.

Reproducibility may pose an issue in a constantly updated database. Since Git objects are added incrementally and order in which they are stored is preserved, we can reconstruct any past version of the object store. For the analytic layer, which depends on the set of Git objects available at the time, we create versions, where each of the maps described above is tagged with a version identifying the state of Git object store. Preserving these past versions ensures reproducibility of the results obtained from them.

The research use cases presented do not constitute an empirical evaluation of WoC usability but, instead, focus on presenting vignettes that are effective for these scenarios. Some of these vignettes went through several iterations until the simplest and fastest implementations were obtained.

11 Conclusions

We introduce WoC: a prototype of an updatable and expandable infrastructure to support research and tools that rely on version control data from the entirety of open source projects and discuss some of the research problems that require such global reach. We discuss how we address some of the data scale and quality challenges related to data discovery, retrieval, and storage. We enable wide data access to collected data source by providing a tool built on top of the infrastructure, which scales well with completion to query in linear time. Furthermore, we implement ways to make this large dataset usable for a number of research tasks by doing targeted data augmentation and by creating data structures derived from the raw data that permit accomplishing these research tasks quickly, despite the vastness of the underlying data. Finally, we validated WoC by conducting actual research tasks and by inviting researchers to undertake investigations of their own. In summary, WoC can provide support for diverse research tasks that would be

otherwise out of reach for most researchers. Its focus on global properties of all public source code will enable research that could not be previously done and help to address highly relevant challenges of open source ecosystem sustainability and of risks posed by this global software supply chain. Transforming the WoC prototype into a widely accessible platform is, therefore, our immediate priority.

All source codes can be found in a public repository.²⁸

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Appendix A Source Code for Cmt2ATShow.perl

```

1  #!/usr/bin/perl -I /home/audris/lib64/perl5 -I /home/audris/lib/x86_64-linux-gnu/
    perl
2  use strict;
3  use warnings;
4  use Error qw(:try);
5  use TokyoCabinet;
6  use Compress::LZF;
7
8  sub toHex {
9      return unpack "H*", $_[0];
10 }
11 sub fromHex {
12     return pack "H*", $_[0];
13 }
14
15 my $split = 1;
16 $split = $ARGV[1] + 0 if defined $ARGV[1];
17
18 my %c2at;

```

```

19 for my $sec (0..($split-1)){
20     my $fname = "$ARGV[0].$sec.tch";
21     $fname = $ARGV[0] if ($split == 1);
22     tie %{$c2at{$sec}}, "TokyoCabinet::HDB", "$fname", TokyoCabinet::HDB::OREADER,
23         16777213, -1, -1, TokyoCabinet::TDB::TLARGE, 100000
24         or die "cant open $fname\n";
25 }
26
27 while (<STDIN>){
28     chop ();
29     my $c = fromHex($_);
30     my $ss = pack 'H*', substr ($_, 0, 2);
31     my $sec = (unpack "C", $ss)%$split;
32     if (defined $c2at{$sec}{$c}) {
33         my ($time, $author) = split(/;/, $c2at{$sec}{$c});
34         my @parts = localtime($time);
35         my $year= $parts[5] + 1900;
36         print $year.";".$author."\n";
37     }
38 }
39 for my $sec (0..($split-1)){
40     untie %{$c2at{$sec}};
41 }

```

Appendix B Source Code for the custom lsort command in tutorial

```

1 #!/bin/bash
2 export LC_ALL=C
3 export LANG=C
4 sz=${1:-10G}
5 shift
6 sort -T. -S $sz --compress-program=gzip $@

```