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Growth and Duplication of Public Source Code over Time: Provenance Tracking at Scale

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June 17, 2019

Abstract

We study the evolution of the largest known corpus of publicly available source code, i.e., the Software Heritage archive (4B unique source code files, 1B commits capturing their development histories across 50M software projects). On such corpus we quantify the growth rate of original, never-seen-before source code files and commits. We find the growth rates to be exponential over a period of more than 40 years.

We then estimate the multiplication factor, i.e., how much the same artifacts (e.g., files or commits) appear in different contexts (e.g., commits or source code distribution places). We observe a combinatorial explosion in the multiplication of identical source code files across different commits.

We discuss the implication of these findings for the problem of tracking the provenance of source code artifacts (e.g., where and when a given source code file or commit has been observed in the wild) for the entire body of publicly available source code. To that end we benchmark different data models for capturing software provenance information at this scale and growth rate. We identify a viable solution that is deployable on commodity hardware and appears to be maintainable for the foreseeable future.

1 Introduction

Over the last three decades, software development has been revolutionized under the combined effect of the massive adoption of free and open source software (FOSS), and the popularization of collaborative development platforms like GitHub, Bitbucket, and SourceForge [34], which have sensibly reduced the cost of collaborative software development and offered a place where historical software can be stored [33]. One important consequence of this revolution is that the source code and development history of tens of millions of software projects are nowadays public, making an unprecedented corpus available to software evolution scholars. We will refer to this corpus as *public source code* in this paper.

Many research studies have been conducted *on subsets* of all public source code, looking for patterns of interest for software engineering, ranging from the study of code clones [32, 35, 36] to automated vulnerability detection and repair [18, 24, 27], from code recommenders [40, 41] to software licence analysis and compliance [38, 39].

Scaling up similar studies to the whole corpus, and making them reproducible, is a significant challenge. In the absence of a common infrastructure providing a *reference archive* of pubic source code development, scholars have used popular development platforms like GitHub as surrogates. But development platforms are not archives: projects on GitHub come and go,[1] making repro-

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[1] For example, hundreds of thousands of projects migrated from GitHub to GitLab.com in the days following the acquisition of GitHub by Microsoft in summer 2018, see https://about.gitlab.com/2018/06/03/movingtogitlab/.

ducibility a moving target. And while GitHub is the most popular development platform today, millions of projects are developed elsewhere, including very high profile ones like GNOME.[2]

Software Heritage [1, 10]—with its mission to collect, preserve, and make accessible all public source code together with its development history—offers an opportunity to change this state of affairs. The project has amassed the largest public source code corpus to date, with more than 80 millions software projects archived from GitHub, GitLab, PyPI, and Debian, growing by the day.

In this paper we leverage Software Heritage to perform the first study on the evolution of public source code. First, we look into the production of *original* source code artifacts over time, that is, the amount of source code files or commits that have never been published before (e.g., in other VCS repositories or distributed tarballs/packages) across the entire corpus. Our first research question is:

RQ1 how does the public production of *original*, i.e., never published before, source code artifacts, and in particular files and commits, evolve over time? what are the respective growth rates?

To answer this we perform an extensive study of the Software Heritage archive, continuing a long tradition of software evolution studies [6, 7, 20, 21, 26], which we extend by several orders of magnitude and perform over a period of more than 40 years. We show evidence of stable *exponential growth* of original commits and files published over time.

Second, we study the number of *different contexts* in which original code artifacts re-appear over and over again, e.g., the same unmodified source code file found in different commits, or the same commit distributed by different repositories. By doing so we quantify the *multiplication* of public source code artifacts, addressing our second research question:

RQ2 to what extent the same source code artifacts, and in particular file and commits, can be found in different contexts (commits and repositories, respectively) in public source code?

We find evidence of a combinatorial explosion in the number of contexts in which original source code artifacts appear, which is particular significant in the multiplication of identical source code files across different commits.

In the last part of the paper, we explore the implications of such multiplication on the problem of *software provenance tracking* [14, 15] for public source code. We ask ourselves: is it feasible to keep track of all the different contexts in which a given file or commit occur across the entire corpus?

To address this practical question we evaluate three different data models for storing provenance information, which offer different space/time trade-offs. We evaluate them on more than 40 years of public source code development history and find that one of them—which we call the *compact model*—allows to concisely track provenance across the entire body of public source code, both today and in the foreseeable future.

Paper structure we review related work in Section 2 and address **RQ1** in Section 3; in Section 4 we attack **RQ2**, studying the multiplication factor of original source code artifacts across different contexts; provenance tracking representations are studied in Section 5, leading to the compact model, which is experimentally validated in Section 6; threats to validity are discussed in Section 7 before concluding in Section 8.

Reproducibility note given the sheer size of the Software Heritage archive (≈200 TB and a ≈100 B edges graph), the most practical way to reproduce the findings of this paper is to first obtain a copy of the official Software Heritage Graph Dataset [30] and then focus on the source code revisions that we have analyzed for this paper. The full list of their identifiers is available on Zenodo (DOI 10.5281/zenodo.2543373) (20 GB); the selection criteria are described in Section 3.

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[2] See `https://www.gnome.org/news/2018/05/gnome-moves-to-gitlab-2/`

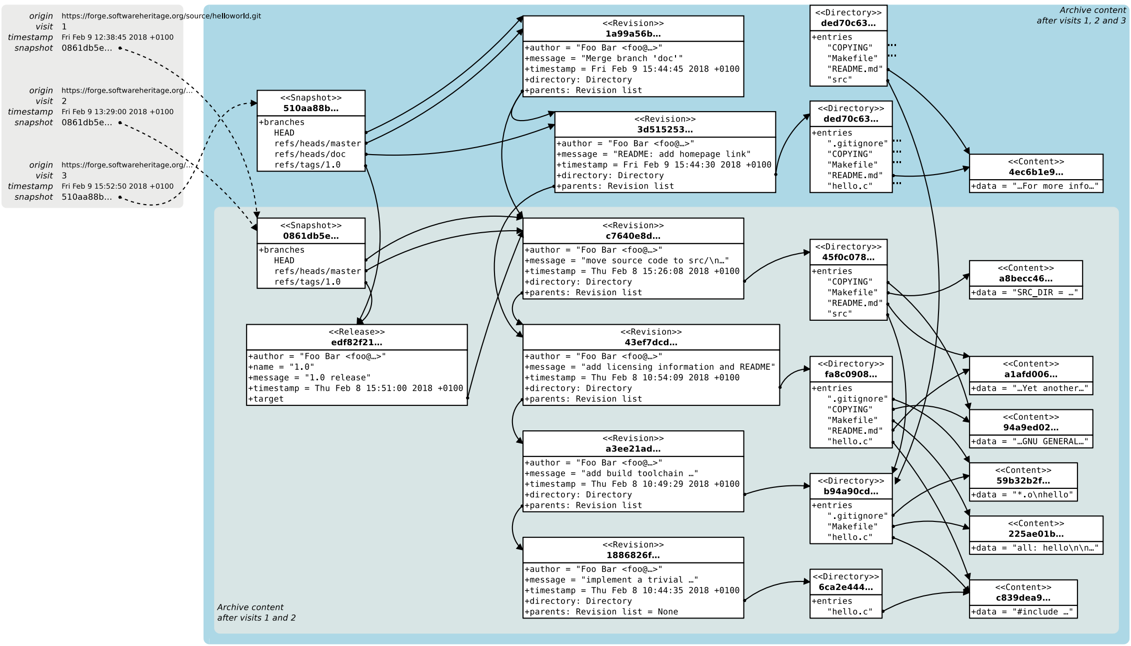

Figure 1: Software Heritage Merkle DAG with crawling information.

2 Related Work

The study of software evolution has been at the heart of software engineering since the seminal "Mythical Man Month" [5] and Lehman's laws [23]. The tidal wave of FOSS, making available a growing corpus of publicly available software, has spawned an impressive literature of evolution studies. Some 10 years ago a comprehensive survey [7] showed predominance of studies on the evolution of individual projects. Since then large scale studies have become frequent and the question of how Lehman's laws need to be adapted to account for modern software development has attracted renewed attention, as shown in a recent survey [21] that advocates for more empirical studies to corroborate findings in the literature.

While Mining Software Research (MSR) research [19] is thriving, realizing large-scale empirical studies on software growth remains a challenging undertaking depending on complex tasks such as collecting massive amounts of source code [29] and building suitable platforms for analyzing them [12, 37]. Hence, up to now, most studies have resorted to selecting relatively small subsets[3] of the full corpus, using different criteria, and introducing biases that are difficult to estimate. For instance, an analysis of the growth of the Debian distribution spanning two decades has been performed in [6], observing initial superlinear growth of both the number of packages and their size. But Debian is a collection maintained by humans, so the number of packages in it depends on the effort that the Debian community can consent.

A recent empirical study [20] has calculated the compound annual growth rate of over 4000 software projects, including popular FOSS products as well as closed source ones. This rate is sensibly in the range of 1.20–1.22, corresponding to a *doubling in size every 42 months.* In this study, though, the size of software projects was measured using lines of code, without discriminating between original contents and refactored or exogenous code reused as-is from other projects.

Not many of these studies take into account the amount of code duplication induced naturally by the now popular pull-request development technique [17] and more generally by the ease with which one can create copies of software components, even without forking them explicitly. The

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[3] Some studies have analyzed up to a few million projects, but this is still a tiny fraction of all public source code.

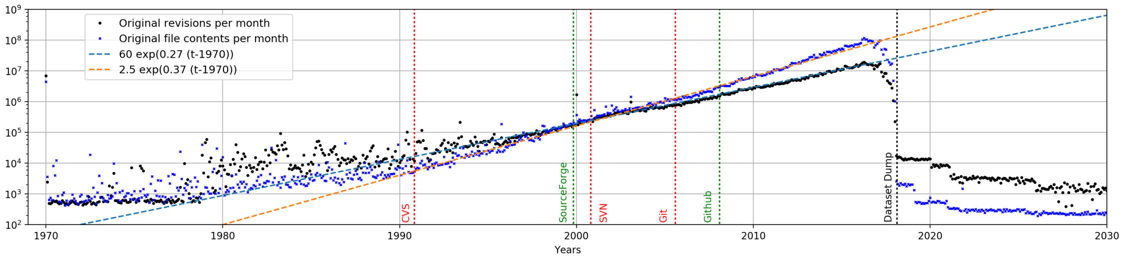

Figure 2: Global production of original software artifacts over time, in terms of never-seen-before revisions and file contents (lin-log scale). Major events in the history of version control systems and development forges are materialised by vertical bars.

amount of exogenous code in a project can be extremely important, as shown in [25], which analyzed over 4 million non-fork projects from GitHub, and showed that almost 70% of the code consists of file-level exact clones. This paints a very interesting picture of cloning in a subset of GitHub at the time it was performed; it would be interesting to know how cloning evolves over time, and how it impacts the growth of the global source code corpus.

Software provenance tracking is an essential building block of several studies, in particular on vulnerability tracking, license analysis [13], and reuse [22]. Provenance can be looked at different granularities [8]. On one end of the spectrum, tracking the origin of code *snippets* is useful when studying coding patterns across repositories [3, 13]. On the opposite end, tracking the origin of whole *repositories* is useful when looking at the evolution of forks or project popularity [4]. In between, tracking *file*-level provenance has been for more than a decade a key element of industrial tools for license compliance offered by companies like BlackDuck, Palamida, Antelink, nexB, TripleCheck, or FossID, leading to patent portfolios [31].

With few exceptions [15], though, file-level provenance has received little attention in the research community. We believe this is due to the lack of a reference archive of public source code on which file-level provenance tracking can be implemented once and then reused by other researchers. In the final part of this paper we discuss the implications of our findings about public source code and explore the feasibility of such "provenance service" approach, relying on Software Heritage as a proxy of public source code.

3 Public Source Code Growth

Current development practices rely heavily on duplicating and reusing code [17, 25], which makes it non trivial to estimate how much *original* software is being produced: summing up the usual metrics—such as number of source code files or revisions (also known as *commits*)—across a wealth of software projects will inevitably end up in counting the same original source code artifacts multiple times.

In this section we report on the first large scale analysis of the growth of original software artifacts, in terms of revisions and contents, that we have performed leveraging the fully-deduplicated data model that underlies Software Heritage, briefly recalled below.

Terminological note: we adopt in the following a technology-neutral terminology to refer to source code artifacts: we use "content" for "[source code] file" and "revision" for commit. The next subsection can be referred to for the intended meaning of those terms.

3.1 The Software Heritage data model

A toy yet detailed example of the Software Heritage data model is shown in Figure 1; full details can be found in [9, 10]. The key principle is to deal with code artifacts duplication by storing them in a single, huge Merkle direct acyclic graph (DAG) [28], where every node is thoroughly deduplicated. Different types of nodes are present in the graph:

Contents raw file contents as byte sequences. Contents are anonymous; “file names” are given to them by directories and are context dependent.

Directories lists of named directory entries. Each entry can point to content objects (“file entries”), to other directories (“directory entries”), or even to other revisions (“revision entries”), capturing links to external components like those supported by Git submodules and Subversion externals). Each entry is associated to a name (i.e., a relative path) as well as permission metadata and timestamps.

Revisions (or *commits*) point-in-time states in the development history of a software project. Each revision points to the root directory of the software source code at commit time, and includes additional metadata such as timestamp, author, and a human-readable description of the change.

Releases (or *tags*) particular revisions marked as noteworthy by developers and associated to specific, usually mnemonic, names (e.g., version numbers or release codenames). Releases point to revisions and might include additional descriptive metadata.

Snapshots lists of pairs mapping development branch names (e.g., “master”, “bug1234”, “feature/foo”) to revisions or releases. Intuitively each snapshot captures the full state of a development repository, allowing to recursively reconstruct it if the original repository gets lost or tampered with.

Deduplication happens at node granularity for all source code artifacts: each file content is stored exactly once and referred to via cryptographic checksum key from multiple directories; each commit is stored once, no matter how many repositories include it; up to each snapshot, which is stored once no matter how many identical copies of repositories in exactly the same state (e.g., pristine forks on GitHub) exist.

This arrangement allows to store in a uniform data model both specific versions of archived software (pointed by release nodes), their full development histories (following the chain of revision nodes), and development states at specific points in time (pointed by snapshot nodes).

In addition to the Merkle DAG, Software Heritage stores *crawling information*, as depicted in the top left of Figure 1. Each time a source code origin is visited, its full state is captured by a snapshot node (possibly reusing a previous snapshot node, if an identical repository state has been observed in the past) plus a 3-way mapping between the origin (as an URL), the visit timestamp, and the snapshot object, which is then added to an append-only journal of crawling activities.

3.2 Key figures on the Software Heritage dataset

At the time we used it for this paper, the Software Heritage archive was the largest available corpus of public source code [1, 10], encompassing:

- a full mirror of GitHub, constantly updated
- a full mirror of Debian packages, constantly updated
- a full import of the Git and Subversion repositories hosted on Google Code at shutdown time
- a full import of Gitorious at shutdown time
- a one-shot import of all GNU packages (*circa* 2016)

Table 1: Graph characteristics of the reference dataset: a Software Heritage archive copy as of February 13th, 2018.

(a) archive coverage

46.4 M software origins

(b) nodes

node type	quantity
content	3.98 B
revision	943 M
release	6.98 M
directory	3.63 B
snapshot	49.9 M
total	8.61 B

(c) edges

edge type	quantity
revision → directory	943 M
release → revision	6.98 M
snapshot → release	200 M
snapshot → revision	635 M
snapshot → directory	4.54 K
directory → directory	37.3 B
directory → revision	259 M
directory → file	64.1 B
total	103 B

For this paper we used the state (called *reference dataset* in the following) of the full Software Heritage archive as it was on February 13th, 2018. In terms of raw storage size, the dataset amounts to about 200 TB, dominated by the size of content objects. As a graph, the DAG consists of ≈9 B nodes and ≈100 B edges, distributed as shown in Table 1; note how this corpus is orders of magnitudes larger than previously analyzed ones [6, 25, 26].

3.3 Evolution of original revisions and file contents

We have analyzed the entire reference dataset (see Table 1), processing revisions in increasing timestamps order, and keeping track for each file content the timestamp of the *earliest* revision that contains it, according to the commit timestamp. A revision is *original* if the combination of its properties (or, equivalently, its identifier in the Merkle DAG) has never been encountered before. Results are shown in Figure 2. They provide very rich information, answering **RQ1** for both revisions and file contents.

We discuss first a few outliers that jump out. Data points at the *Unix epoch* (1/1/1970) account for 0.75% of the dataset and are clearly over-represented. They are likely due to forged revision timestamps introduced when converting across version control systems (VCSs). This is probably also the main reason behind revisions with timestamps in the "future", i.e., after the dataset timestamp (0.1% of the dataset). The sharp drop before the dataset timestamp is a consequence of the lag of Software Heritage crawlers w.r.t. its data sources.

Focusing on the core part of the figure we remark that in the early years, before the introduction of forges and advanced VCSs, the number of revisions is relatively small (tens to hundreds of thousands only), and their evolution is rather irregular.

After the creation of the first popular forge, SourceForge (1999), we observe on the other hand a remarkably regular exponential growth lasting twenty years. For original revisions, growth can be accurately approximated by the fit line $60e^{0.27(t-1970)}$; at this rate **the amount of original revisions in public source code doubles every ≈30 months**. For original contents, growth is accurately approximated by the fit line $2.5e^{0.37(t-1970)}$; at this rate **the amount of original public source code files doubles every ≈22 months**.

This information is precious to estimate the resources needed for *archiving* publicly developed software: taking into account the long term evolution of storage costs[4] this growth looks managable, provided that deduplication is applied. The sustainability of provenance tracking remains potentially challenging, though, because artifact *occurrences* in different contexts cannot

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[4] see, e.g., `https://hblok.net/blog/storage/`

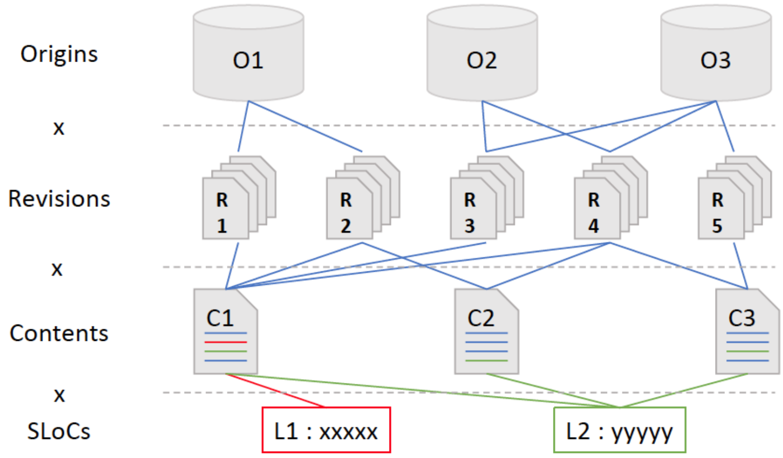


Figure 3: The three layers of multiplication in public source code: SLOCs occurring in source code files (contents), contents occurring in commits (revisions), revisions found at different distribution places (origins).

be deduplicated. We will quantify source code artifact multiplication in the next section.

The growth rate of original contents and revisions suggests that both the production of source code and its derived graphs are interesting evolving complex networks [2,11]. Their nature—scale-free or not—as well as the role of phenomena like preferential attachment in the growth dynamics between edges and nodes, potentially leading to accelerating growth [2], are important subjects for further investigation.

Finally, we remark that the *difference* in the growth rates of original revisions and original file contents means that over the past twenty years **the average number of original file contents per revision has been doubling every ≈7 years**. Whether this comes from the availability of better tools that can easily handle large commits, from different development practices, or other causes is another interesting open question.

4 Public Source Code Multiplication

We now look into *public source code multiplication*, i.e., how often the same artifacts (re-)occur in different contexts. Figure 3 depicts the three layers of this phenomenon: a given line of code (SLOC) may be found in different source code files; a given file content may appear in different revisions (e.g., different commits in the same repository); and a given revision may be found at multiple origins (e.g., the same commit distributed by multiple repositories and source packages).

To study this phenomenon and answer **RQ2** we perform in the following focused analyses on the Software Heritage Merkle DAG. They will lead to quantitatively evaluate the *multiplication factor* of source code artifacts at each multiplication layer of Figure 3.

4.1 Content multiplication factor

In order to assess the *content* multiplication factor, i.e., the amount of duplication of file contents among revisions, we took a random sample of about 1 million unique contents (all contents whose hash identifiers start with `aaa`. For each content in that sample we counted how many revisions contain it in the reference dataset. The resulting distribution of the multiplication factor is shown in the upper part of Figure 4, together with the corresponding cumulative distribution.

Looking at the cumulative distribution it jumps out that the average multiplication factor is very high. It exhibits a characteristic decreasing power law ($\alpha \simeq -1.5$), only limited by an exponential cut-off. There are hence over a hundred of thousand contents that are duplicated

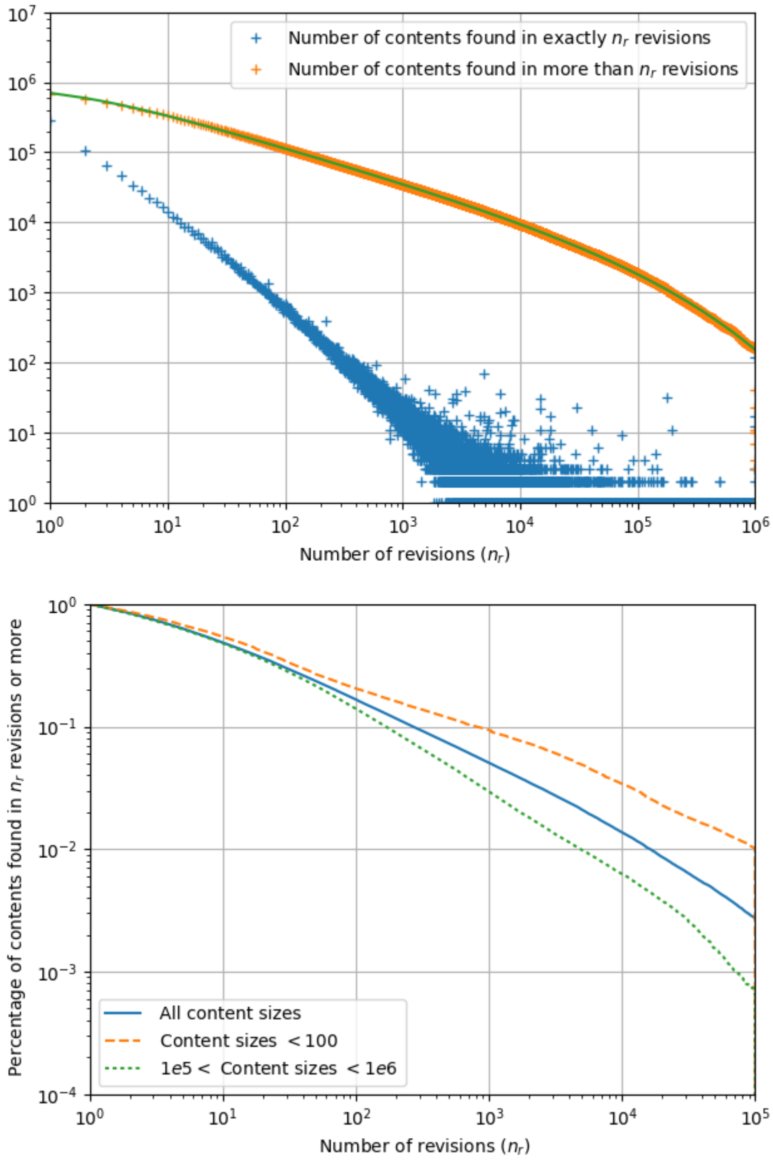


Figure 4: Top: cumulative (upper curve) and simple (lower curve) multiplication factor of unique file contents across unique revisions. Bottom: normalized cumulative content multiplication factor for the same sample (solid line) and two random samples of about 1 M contents each, with content sizes up to 100 bytes (dashed line) and between 10^5 and 10^6 bytes (dotted line).

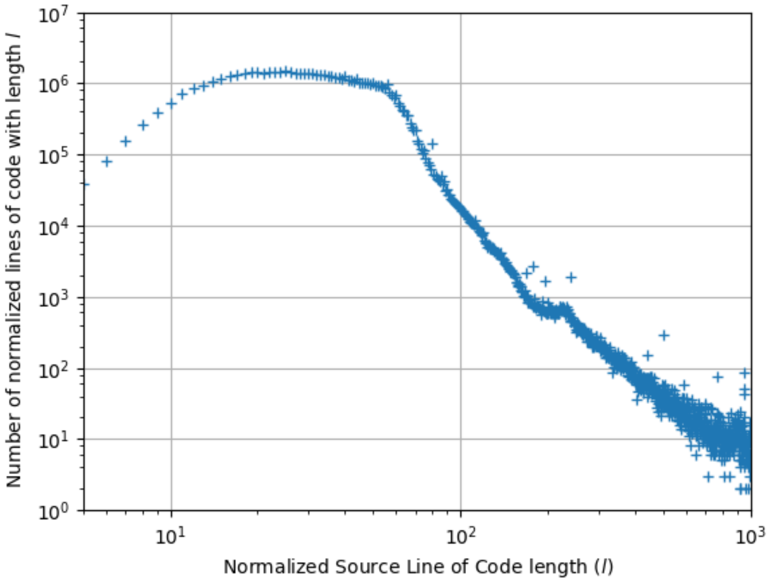


Figure 5: Distribution of normalized SLOC lengths in a sample of 2.5 M contents that appear at least once with `.c` extension.

more than one hundred times; tens of thousand contents duplicated more than a thousand times; and there are still thousands of contents duplicated *more than a hundred thousands times*! Space-wise, keeping track of all the occurrences of the content→revision layer of Figure 3 is a highly nontrivial task.

We did not resist investigating the side question of whether the *size* of a file content impacts the multiplication factor. We hence took two new random samples of about 1 million contents each, one with content sizes up to 100 bytes and one with sizes between 10^5 and 10^6 bytes, and performed the same analysis as for the previous sample.

The resulting normalized cumulative multiplication factors are shown on the bottom of Figure 4. We can see that *the multiplication factor of small contents is much higher* than that of average-sized and large contents. Hence, keeping track of the content→revision occurrences only for files larger than, say, 100 bytes, is a significantly simpler problem than its fully general variant. Omitting small files is indeed a technique often used by state-of-the-art industry solutions for software provenance tracking: we provide evidence on why it is effective (at the expense of completeness).

4.2 SLOC length and multiplication factor

We now turn our attention to the bottom layer of Figure 3: SLOC→content. Since lines of code are hardly comparable across languages, we focused on the C language, which is well-represented in the corpus. We took a random sample of ≈11.4 M unique contents occurring in revisions between 1980 and 2001, and selected from it contents that appear at least once with `.c` extension and with sizes between 10^2 and 10^6 bytes, obtaining ≈2.5 M contents. We then split contents by line and, to remove equivalent formulations of the same SLOC, *normalized* lines by removing blanks and trailing `";"` (semicolon). We obtained ≈64 M normalized SLOCs.

The multiplication factor of SLOCs across unique contents is shown in Figure 6. We observe a much faster decrease w.r.t. the multiplication factor of contents in releases ($\alpha \simeq -2.2$), hinting that keeping track of SLOCs→content occurrences may be less problematic than content→revision.

We also computed the distribution of normalized SLOC lengths between 4 and 1000, shown in Figure 5. We observe that lines with length 15 to 60 normalized characters are the most

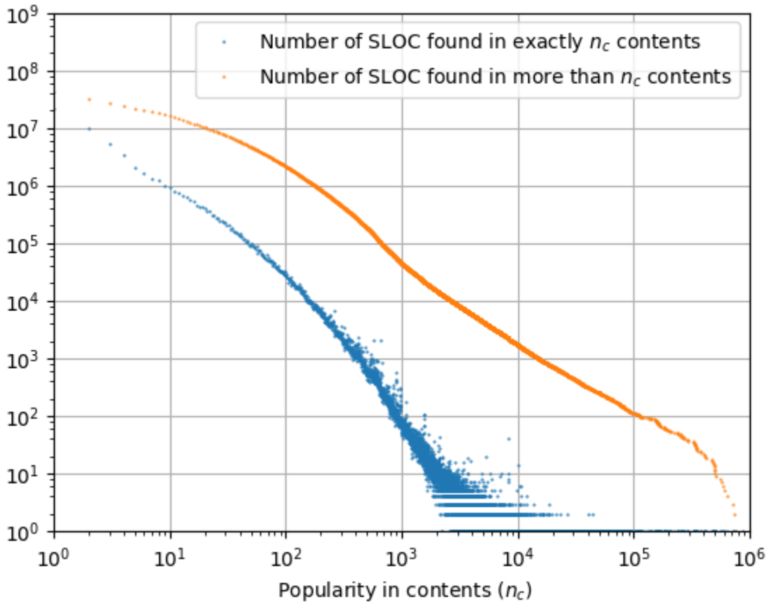


Figure 6: Multiplication factor of normalized SLOCs as the number of unique contents they appear in. Dataset: same of Figure 5.

represented, with a fairly stable presence within that range, and a steep decrease for longer lines. Hence, for SLOC→content occurrences there does not seem to exist any obvious length-based threshold that would reduce their amount.

4.3 Origin size and multiplication factor

Finally we look into the revision→origin layer of Figure 3. To that end we took a sample of ≈12% of the origins, which contain ≈29% of the revisions (or about 5.4 M origins and 272.5 M revisions) and replicated the previous study of content duplication onto revisions. Results are shown in Figure 7.

Revision multiplication shows an erratic behavior near the end of the range, but decreases steadily before that, and way more steeply ($\alpha \simeq -1.9$) than it was the case for content→revision multiplication (see Figure 4 for comparison): the multiplication factor of revisions in origins is way smaller than that of contents in revisions.

While this result is sufficient to assess the respective impact on public source code multiplication of the considered layers, we dug further into origin sizes to better understand *which* origins participate into revision→origin multiplication.

We have considered two different measures of origin size. One that simply counts the number of revisions found at each origin. Another that associates revisions found at multiple origins *only to the origin that contains the largest number of revisions*, and the count them as before. When a project is forked, the second measure would always report a revision as belonging to the fork with the most active development, which is a good approximation of the "most fit fork", while stale forks would decay. This measure has many good properties: it will follow forks that resurrect projects abandoned at their original development places, it does not rely on platform metadata for recognizing forks, and is hence able to recognize *exogenous forks* across unrelated development platforms (e.g., GitHub-hosted forks of the Linux kernel that is not natively developed on GitHub).

Figure 8 shows the impact that the "most fit fork" measure has on the number of revision→origin occurrences. Starting with relatively small repositories, (≈100 revisions) the number of occurrences to track is lower than for the simpler measure, with a difference growing up to a full order

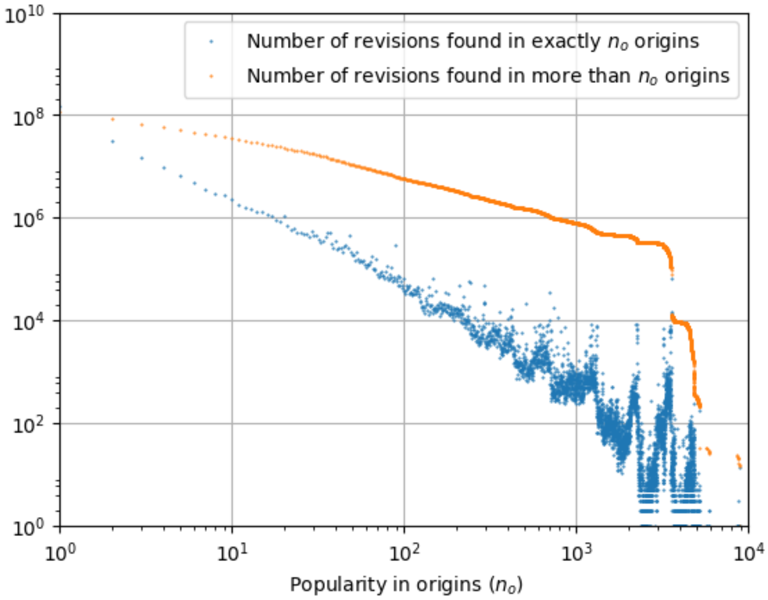


Figure 7: Duplication of revisions across origins.

of magnitude for repositories hosting 10 K revisions.

5 Compact Provenance Modeling

We now consider the problem of tracking software provenance across a corpus as large (and as fast growing) as all public source code. In short, the goal is to keep track of all the different places (contents, revisions, origins) in which any given source code artifact (SLOC, content, revision) can be found—more detailed requirements are given below in Section 5.1.

What are the implications of our findings on public source code growth and multiplication, on the *feasibility* of maintaining such a complete provenance index? An important fact that emerges from the analyses is that, size-wise, the most challenging part is the layer associating file contents to all the revisions they appear in, because contents are duplicated across revisions much more than revisions across origins.

Hence in the following we will focus on concisely representing the content→revision mappings; the revision→origin ones will be a straightforward and fully modular addition. SLOC-level provenance tracking is left as future work.

5.1 Requirements

Supported queries At least two queries should be supported: first occurrence and all occurrences. The *first occurrence* query shall return the earliest occurrence of a given source code artifact in any context, according to the revision timestamp. The *all occurrences* query will return all occurrences. The two queries answer different use cases: first occurrence is useful for prior art assessment and similar intellectual property needs; all occurrences is useful for impact/popularity analysis and might be used to verify first occurrence results in case of dubious timestamps.

Granularity It should be possible to track the provenance of source code artifacts at different granularities including at least file contents and revisions.

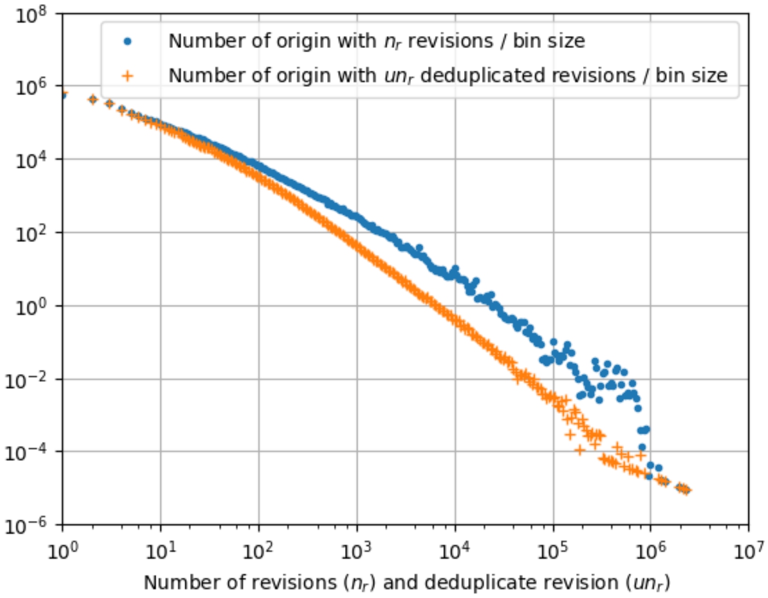


Figure 8: Distribution of origin size as the number of revisions they host.

Scalability It should be possible to track provenance at the scale of at least Software Heritage and keep up with the growth rate of public source code. Given that the initial process of populating provenance mappings might be onerous, and that some use cases require fresh data (e.g., impact/popularity), we also require *incrementality* as part of scalability: the provenance index must support efficient updates of provenance mappings as soon as source code artifacts (old or new) are observed in new contexts.

Compactness It should be possible to store and query provenance information using state-of-the-art consumer hardware, without requiring dedicated hardware or expensive cloud resources.

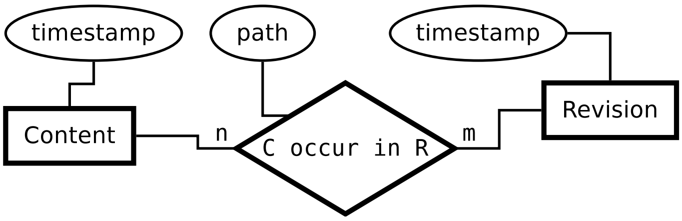
Streaming For the *all occurrences* query a significant performance bottleneck is the transfer time required to return the potentially very large result. A viable provenance solution should hence allow to return results incrementally, piping up the rest for later.

5.2 Provenance data models

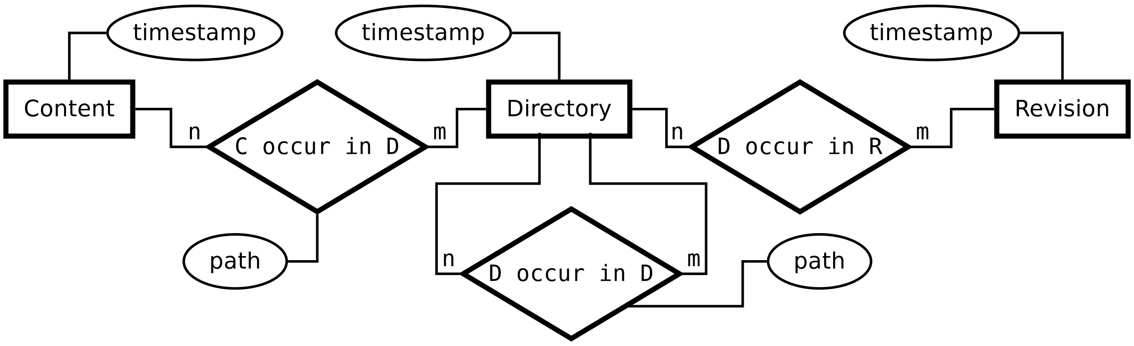
We study three different data models for provenance tracking, that we call respectively *flat*, *recursive*, and *compact*. Their Entity-Relationship (E-R) representations are shown in Figure 9.

Flat model this is our baseline for tracking provenance, shown in Figure 9(a). In this model provenance mappings are "flattened" using a single C(ONTENT) OCCUR IN R(EVISION) relation, that also keeps track of file paths relatively to the root directory of the associated revision. The cardinality of C OCCUR IN R is n-m (rather than 1-n), because the same content might appear multiple times in a given revision at different paths. Each revision carries as attribute the revision timestamp, in order to answer the question of *when* the occurrence happened. Each content carries as attribute the timestamp of its earliest occurrence, i.e., the minimum timestamps among all associated revisions.

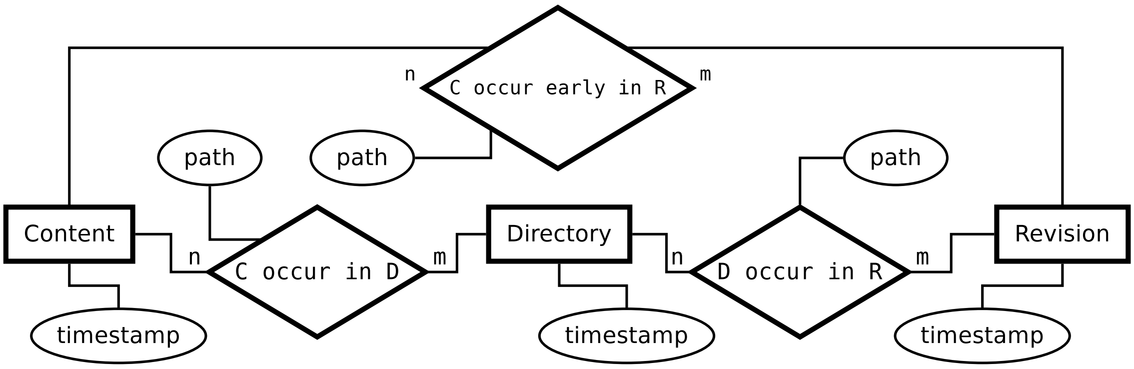
Given suitable indexing on content identifiers (e.g., using a B-tree), the flat model adds no read overhead for the all occurrences query. Same goes for first occurrence, given suitable indexing on timestamp attributes, which is required to retrieve path and revision.



(a) flat model



(b) recursive model



(c) compact model

Figure 9: Provenance tracking models, entity-relationship (E-R) views

Updating provenance mappings when a new revision comes in requires traversing the associated directory in full, no matter how many sub-directories or contents in it have been encountered before, and adding a relationship entry for each of its nodes.

Recursive model while the flat model shines in access time at the expenses of update time and compactness, the recursive model shown in Figure 9(b) does the opposite. It is intuitively a "reverse" Merkle DAG representation, which maps contents to directories and directories to revisions.

Each entity has a timestamp attribute equal to the timestamp of the earliest revision in which the entity has been observed thus far. When processing an incoming revision r_{t_2} (with timestamp t_2) it is no longer necessary to traverse in full the associated directory: if a node n is encountered that is already present in the model with a timestamp $t_1 < t_2$, recursion can stop because the subtree rooted at n, which is already present due to the Merkle DAG properties, has already been labeled with timestamps earlier than t_2 and needs not be updated; we just need to add an entry in the corresponding occurrence table for n with timestamp t_2.

Thanks to the sharing offered by the directory level, the recursive model is as compact as the original Merkle structure, with no flattening involved. The all occurrences query is slow in this model though, as for each content we need to walk up directory paths before finding the corresponding revisions. Response time will hence depend on the average directory depth at which queried contents will be found. First occurrence is faster, but still incurs some read overhead: given a content we have to walk up all directories and then lookup the corresponding revisions whose timestamps equate the timestamp of the content being queried.

Compact model Figure 9(c) shows a compromise version between the flat and recursive models, which is both storage-compact and capable of quickly answering the required queries. The tables for the content, directory, and revision entities are progressively populated as the structure is built, with a timestamp attribute denoting the earliest known occurrence, as before. To understand how the compact model is built and used we introduce the following notion:

Definition 1 (Isochrone subgraph) *given a partial provenance mapping $\mathcal{P}$ associating a timestamp of first occurrence to each node in a Merkle DAG, the* isochrone subgraph *of a revision node R (with timestamp t_R) is a subgraph rooted at R's directory that only contains directory nodes whose timestamps in $\mathcal{P}$ are equal to t_R.*

Intuitively, when processing revisions chronologically to update the entity tables and the provenance mappings, the isochrone subgraph of a revision starts with its root directory and extends through all directory nodes containing never-seen-before source code artifacts. Due to Merkle properties each directory containing at least one novel element is itself novel. Everything outside the isochrone subgraph has been observed before, in at least one previously processed revision.

Given this notion, the upper part of the compact model (C OCCUR EARLY IN R in Figure 9(c)) is filled with one entry for each content attached to any directory in the isochrone subgraph. As a consequence of this, the first occurrence of any given content will always be found in C OCCUR EARLY IN R although other occurrences—depending on the order in which revisions are processed to update provenance mappings—may also be found there.

The relation D OCCUR IN R is filled with one entry, pointing to the revision being processed, for each directory *outside* the isochrone subgraph that is referenced by directories *inside* it, i.e., D OCCUR IN R contains one entry for each directory→directory edge crossing the isochrone frontier. Finally, the relation C OCCUR IN D is filled with one entry for each content (recursively) referenced by any directory added to the D OCCUR IN R relation.

Filling the compact model is faster than the flat model: when we reach a directory d at the frontier of an isochrone subgraph, we only need to visit it in full the first time, to fill C OCCUR IN D, and we need not visit d again when we see it at the frontier of another isochrone subgraph in the future.

It is slower than the recursive model case, though, as we still need to traverse the isochrone subgraph of each revision. Read overhead for first occurrence is similar to the flat model: provided suitable indexing on timestamps we can quickly find first occurrences in C occur early in R. Read overhead for all occurrences is lower than the recursive model because all content occurrences will be found via C occur in D without needing to recursively walk up directory trees, and from there directly linked to revisions via D occur in R.

5.3 Discussion

Intuitively, the reason why the compact model is a good compromise is that we have many revisions and a very high number of file contents that occur over and over again in them, as discussed in Section 4.1. Consider now two extreme cases: (1) a set of revisions all pointing to the same root directory but with metadata differences (e.g., timestamp or author) that make all revisions unique; (2) a set of revisions all pointing to different root directories that have no file contents or (sub)directories in common.

In case (1) the flat model would explode in size due to maximal duplication. The recursive model will need just one entry in D occur in R for each revision. The compact model remains small as the earliest revision will be flattened (via C occur early in R) as in the flat model, while each additional revision will add only one entry to D occur in R (as in the recursive model).

In case (2) the flat model is optimal in size for provenance tracking purposes, as there is no sharing. The recursive model will have to store all deconstructed paths in D occur in D. The compact model will be practically as small as the flat model: all revisions are entirely isochrones, so the C occur early in R relation will be the same as the C occur in R of the flat model, and the only extra item is the Directory table.

Reality will sit in between these two extreme cases, but as the compact model behaves well in both, we expect it to perform well on the real corpus too. The experimental evaluation reported in the next section validates this intuition.

6 Evaluation

To compare the size requirements of the provenance data models described in Section 5, we have monitored the growth of each model while processing incoming revisions to maintain provenance mappings up to date.

Specifically, we have processed in chronological order revisions from the reference dataset with timestamps strictly greater than the Unix epoch (to avoid the initial peak of forged revisions discussed in Section 3) and up to January 1st, 2005, for a total of ≈38.2 M revisions. For each revision we have measured the number of entities and relationship entries according to the model definitions, that is:

Flat model one entity for each content and revision; plus one C occur in R entry for each content occurrence

Recursive model as it is isomorphic to the Merkle DAG, we have counted: one entity for each content, directory, and revision; plus one relationship entry for each revision→directory, directory→directory, and directory→content edge

Compact model after identifying the isochrone subgraph of each revision, we counted: one entity for each content and revision, plus one entity for each directory outside the isochrone graph referenced from within; as well as one relationship entry for each content attached to directories in the isochrone graph (C occur early in R), one D occur in R entry for each directory→directory edge crossing the isochrone frontier, and one C occur in D entry for each content present in directories appearing in D occur in R.

Table 2: Size comparison for provenance data models, in terms of entities and relationship entries. Same dataset of Figure 10.

	Flat	**Recursive**	**Compact**
entities	80 118 995 rev: 38.2 M cont: 41.9 M	148 967 553 rev: 38.2 M cont: 31.9 M dir: 68.8 M	97 190 442 rev: 38.2 M cont: 31.9 M dir: 17.1 M
rel. entries	654 390 826 907	2 607 846 338 cont–dir: 1.29 B dir–rev: 38.2 M dir–dir: 1.28 B	19 259 600 495 cont–dir: 13.8 B dir–rev: 2.35 B cont–rev: 3.12 B
rel. ratios	$\frac{\mathit{flat}}{\mathit{compact}} = 34.0$	$\frac{\mathit{flat}}{\mathit{rec.}} = 251$	$\frac{\mathit{compact}}{\mathit{rec.}} = 7.39$

Processing has been done running a Python implementation of the above measurements on a commodity workstation (Intel Xeon 2.10GHz, 16 cores, 32 GB RAM), parallelizing the load on all cores. Merkle DAG information have been read from a local copy of the reference dataset, which had been previously mirrored from Software Heritage. In total, revision processing took about 4 months, largely dominated by the time needed to identify isochrone subgraphs.

Final sizes, measured in terms of entities and relationship entries are given in Table 2. They show, first, that the amount of relationship entries dominate that of entities in all models, from a factor 18 (recursive model) up to a factor 8000 (flat). Dealing with mappings between source code artefacts remains the main volumetric challenge in provenance tracking. As further evidence of this, and as a measure of the overall amplitude of provenance tracking for all public source code, we have also computed the number of relationship entries for the flat data model *on the full reference dataset*, obtaining a whooping $8.5 \cdot 10^{12}$ entries in C occur in R.

Second, sizes show that the Merkle DAG representation, isomorphic to the recursive model, is indeed the most compact representation of provenance information, although not the most efficient one to query. The compact model is the next best, 7.39 times larger than the recursive model in terms of relationship entries. The flat model comes last, respectively 251 and 34 times larger than recursive and compact.

Figure 10 shows the evolution of model sizes over time, as a function of the number of unique contents processed thus far. After an initial transition period, trends and ratios stabilize making the outlook of long-term viability of storage resources for the compact model look good.

Furthermore, the comparison between the compact (orange line) and flat (blue) model shows that, at the cost of a small increase in the number of entities, the compact model performs much better in terms of relationship entities. And even if, in terms of entities a small divergence can be observed over time (1/10 of an order of magnitude), the gain in terms of relationship entries makes it worthwhile (1.5 orders of magnitude).

In order to relate these figures to real-world storage requirements, we have also filled a MongoDB-based implementation of the compact model—including all attributes of Figure 9(c) and needed indexes—while processing revisions to perform the above measurements. Extrapolating the final MongoDB size to the full reference dataset we obtain an on-disk size of 13 TB. While large, such a database can be hosted on a consumer workstation equipped with ≈4000$ of SSD disks, without having to resort to dedicated hardware or substantial investments in cloud resources. Using the compact model, universal source code provenance tracking can lay at the fingertips of every researcher and industrial user!

7 Threats to Validity

Internal validity The main concern for internal validity is that we did not have the resources available to perform all estimates and experiments on the full Software Heritage archive. While

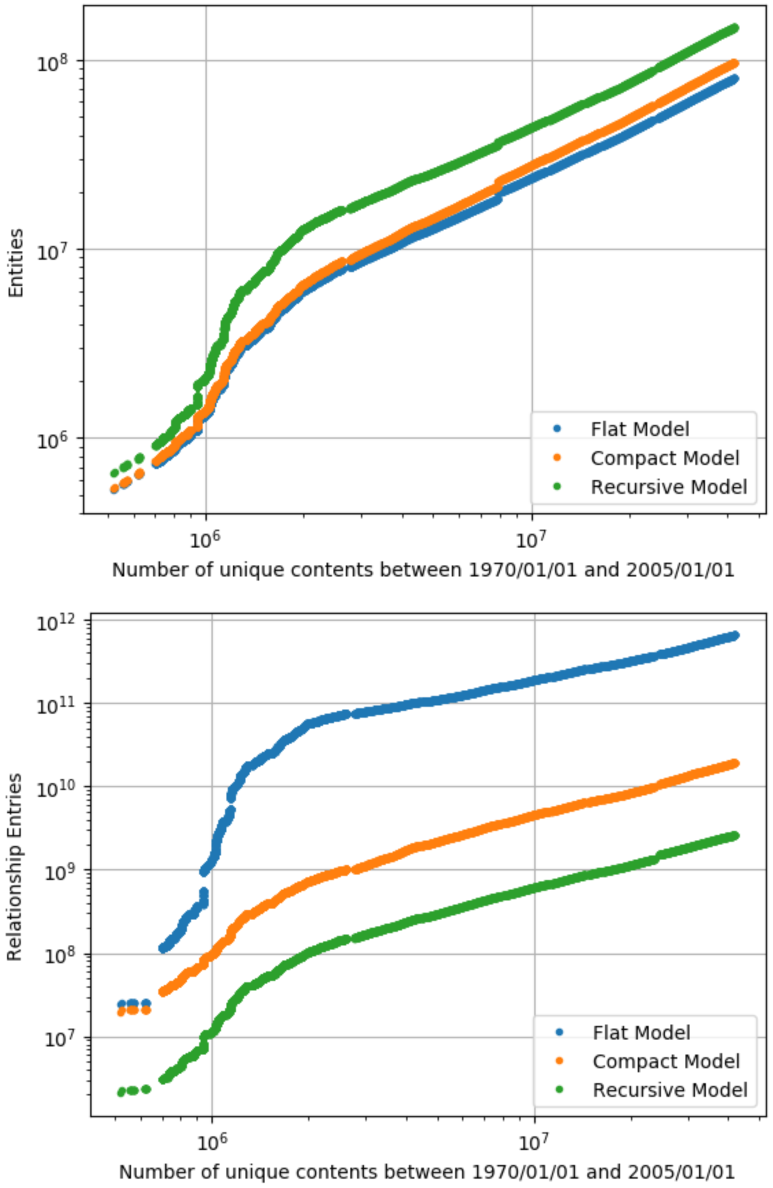


Figure 10: Evolution over time of the sizes of different provenance data models, in terms of entities (top) and relationship entries (bottom). Data for Software Heritage revisions up to 2005-01-01, excluding Unix epoch.

our main growth results are measured on the full reference dataset, other results are extrapolated from smaller subsets. To counter potential bias, we have used random samplings and sizeable samples.

When comparing provenance data models we have quantitatively estimated sizes, but only qualitatively estimated read overhead—rather than benchmarking it in production—in order to remain technology-neutral.

Finally, we have trusted commit timestamps to determine first occurrences, even if it commit timestamps can be forged. This approach is consistent with previous software evolution studies that consider timestamp forging a marginal phenomenon. We also remark that for evaluating the performance of the provenance model we only need to single out *a* "first" occurrence, no matter how it is determined.

External validity While Software Heritage does not cover all existing free/open source software, it is the largest source code archive in the world and spans the most popular code hosting and development platforms. We therefore consider that this is the best that can be done at present.

Finally, we acknowledge the habit of using *software* development platforms for collaboration tasks other than software development (e.g., collaborative writing), particularly on GitHub, but we did not try to filter out non-software projects. On the one hand we expect software development to be the dominant factor, and on the other hand non-software projects might still contain interesting code snippets that are worth tracking. Also, as demonstrated in the paper, it is not *necessary* to filter out non-software project in order to build a practical provenance tracking solution.

8 Conclusion

The emergence of Software Heritage as a comprehensive archive of public source code, spanning tens of millions of software projects over more than 40 years, enables analysis of the evolution of software development at a novel scale.

The first contribution of this paper is a quantitative analysis of the growth of public software development, factoring out exact code clones. Since the advent of version control systems, the production of unique original revisions doubles every 30 months, and the production of unique original file is even faster, doubling every 22 months. Besides confirming the perceived overall growth of the public software ecosystem, these results open up a wealth of new research questions.

The second contribution is a quantitative assessment of the amount of duplication of both original file contents across different commits and of original commits across different software origins, gaining precious preliminary insights into the deep structure of public software development and distribution.

The third and final contribution is the development and comparison of three data models designed to answer the software provenance questions of "what are the first/all occurrences of a given file content/commit?". The *compact* data model, based on the novel notion of isochrone subgraphs, provides a time/space trade-off that allows to track software provenance at the scale of Software Heritage on consumer hardware.

In future work we intend to extend the compact data model to allow tracking provenance at the granularity of individuals lines of code, and explore how other types of original source code artifacts evolve over time. We also intend to study the characteristics of provenance graphs as naturally-occurring, evolving complex networks.

8.1 Notice

We strongly believe that it is essential to make available to other researchers the data on which is based this kind of analysis. The core of the work presented here has been performed between January 2017 and August 2018, but the unprecedented size of this dataset has required significant time and effort to comply with our principles, and this has delayed the disclosure of our work much longer than what we wanted or expected. Now that the Software Heritage Graph Dataset is available to all [30], we are finally able to share results that can be independently verified by other researchers.

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