Analyse du graphe de développement logiciel mondial

Antoine Pietri

Inria, Paris

June 9th, 2022

Software Heritage

Software Mining

Definition

Software mining: studying existing software repositories to help improve software development processes and practices.

Applications

- Software health, software evolution
- Automated bug detection
- Automated vulnerability repair
- Code autocompletion
- Clone detection
- License compliance
- ...

Universal Software Mining

Current scale of software mining studies

- Individual projects
- Up to thousands of popular repositories (e.g., “top 1000 by stars”)
- Entire ecosystems (app stores, package managers, ...)

Universal software mining

Next step: a framework to run empirical studies on **all the public software repositories**?

- Less repetitive, no need to crawl the data for each study
- Easier to replicate studies
- High-level view of social processes in software development

In my thesis...

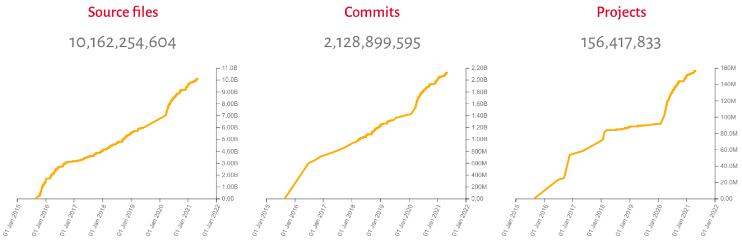
I study how to organize the **graph of public software development**, a comprehensive dataset of software development data, to make it **accessible for software mining research**.

Research direction: Working towards a research platform for Universal Software Analysis.

Antoine Pietri, Stefano Zacchiroli
Towards Universal Software Evolution Analysis
BENEVOL 2018

Corpus: The Software Heritage Archive — archive.softwareheritage.org

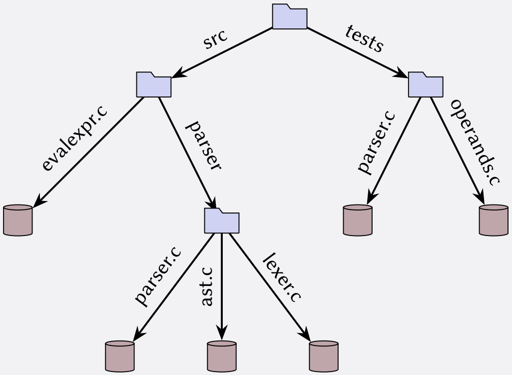
- We use the **Software Heritage archive** as our best approximation of the entire corpus of public software development.
- Largest public source code archive in the world (more than 900 TB, growing daily).



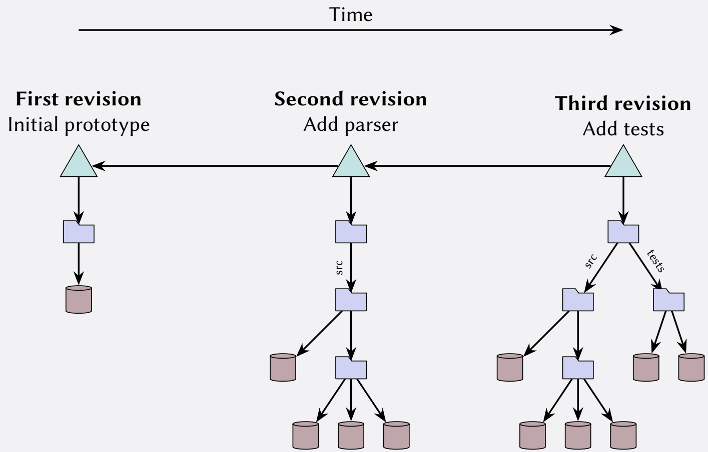
Bitbucket · R · debian · Framagit · GitHub · GitLab · GITORIOUS · Google code · GNU · Guix · HAL archives-ouvertes.fr · Inria · IPOL Journal · npm · NixOS · python Package Index

A source code directory

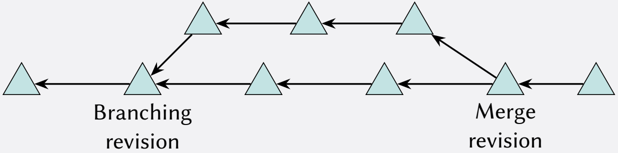
```
/
├── src
│   ├── evalexpr.c
│   └── parser
│       ├── ast.c
│       ├── parser.c
│       └── lexer.c
└── tests
    ├── eval.c
    └── operands.c
```



- **Revisions** (or "commits") keep track of successive states of a source directory.

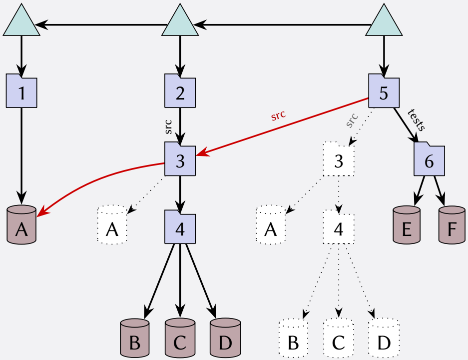


Developers can use "branches" to work on different features simultaneously.



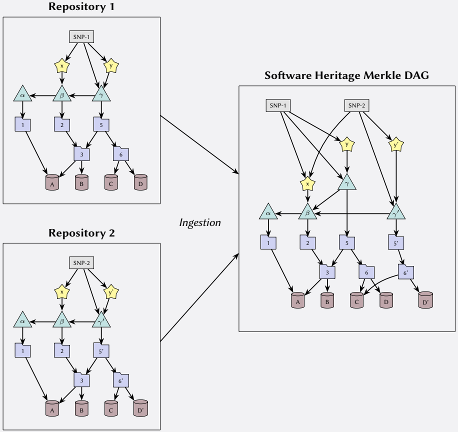
Deduplication

- Instead of copying the nodes between each revision, we can identify & deduplicate them with **cryptographic hash functions** (e.g., SHA-1)
- Each object is identified by a unique identifier ("hash") computed from its entire subtree



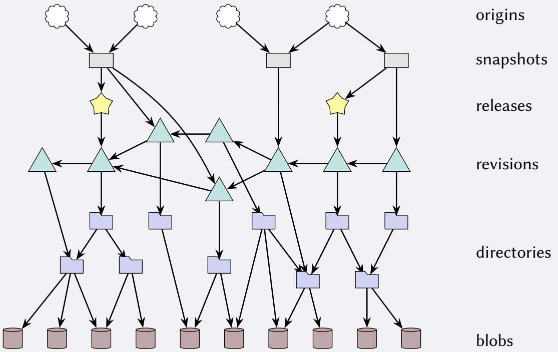
Consolidation in a single archive

- In Software Heritage, *all* the repositories are consolidated into a single archive
- Software artifacts are deduplicated *across different repositories*
- The result is a single graph providing a **global, unified view** on **all the software development artifacts** from version control systems
- Helpful analogy: like a single Git repository but with all the public code in the world.



Software Heritage Merkle DAG

- Hash-based deduplication applied on every node in the graph ⇒ **Merkle DAG**
- Persistent structure: append only, great for archival



- 25B nodes
- 375B edges

Requirement analysis for Empirical Software Engineering

Identifying researchers need

Literature review of **54 papers** from the Mining Software Repositories conference (MSR 2019).

Categories of requested data

- Blobs
- Filesystem hierarchy (*file names, directories*)
- History graph (*revisions*)
- Content search (*full-text search index*)
- Provenance (*backwards index*)
- Commit diffs
- Community graph (*revision authors*)
- Dependency data

Data volume challenges

Local analysis

Handling data at that scale is a hard practical problem for researchers:

- Data does not fit on a single machine
- Downloading this volume of data can take months
- High deduplication: entangled structure, hard to parallelize

Approaches addressed in my thesis

- Sampling: access limited amounts of data
- Scale-out: platform for distributed computing
- Scale-up: compression

The Software Heritage Graph Dataset

The **Software Heritage Graph Dataset**: a snapshot of the entire graph of software development (without the file contents).

Antoine Pietri, Diomidis Spinellis, Stefano Zacchiroli
The Software Heritage graph dataset: public software development under one roof
Mining Software Repositories 2019

Format: A set of *relational tables* in columnar format (Apache ORC) for scale-out processing and graph analysis platforms

Availability

- Downloadable for local use
- Cloud processing platforms: Amazon Athena, Azure Databricks

Most frequent first commit words

```
SELECT COUNT(*) AS c, word FROM (
  SELECT LOWER(REGEXP_EXTRACT(FROM_UTF8(
  message), '^\w+')) AS word FROM revision)
WHERE word != ''
GROUP BY word ORDER BY COUNT(*) DESC LIMIT 5;
```

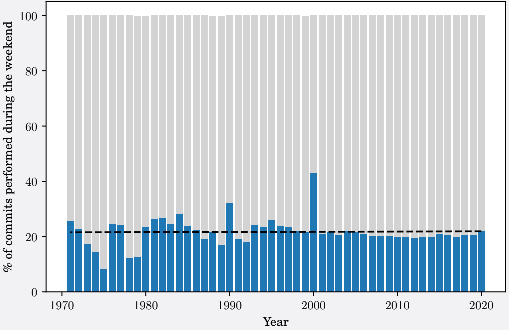
Count	Word
71 338 310	update
64 980 346	merge
56 854 372	add
44 971 954	added
33 222 056	fix

Analyzes 1.1 billion revision messages in 30 seconds.

Example queries

Weekend work

```
WITH revision_date AS
  (SELECT FROM_UNIXTIME(date / 1000000) AS date
  FROM revision)
SELECT yearly_rev.year AS year,
  CAST(yearly_weekend_rev.number AS DOUBLE)
  / yearly_rev.number * 100.0 AS weekend_pc
FROM
  (SELECT YEAR(date) AS year, COUNT(*) AS number
  FROM revision_date
  WHERE YEAR(date) BETWEEN 1971 AND 2020
  GROUP BY  YEAR(date) ) AS yearly_rev
JOIN
  (SELECT YEAR(date) AS year, COUNT(*) AS number
  FROM revision_date
  WHERE DAY_OF_WEEK(date) >= 6
      AND YEAR(date) BETWEEN 1971 AND 2020
  GROUP BY  YEAR(date) ) AS yearly_weekend_rev
  ON yearly_rev.year = yearly_weekend_rev.year
ORDER BY  year DESC;
```



Analyzes 1.1 billion revision timestamps in 7 seconds.

Recursive queries

- This approach works really well for **embarrassingly parallel** queries
- Scale-out solutions are less efficient for **recursive queries** that exploit the hierarchical/structured nature of the graph
- BFS Traversal of the graph on Spark: 4 hours, 80 nodes (!), 5000 USD

Research question

Can recursive graph algorithms be performed in an accessible and cost-efficient way?

Compression approach

Objective: Analyzing the *entire graph of public software development* on a single machine.

Paolo Boldi, Antoine Pietri, Sebastiano Vigna, Stefano Zacchiroli
Ultra-Large-Scale Repository Analysis via Graph Compression
SANER 2020, 27th Intl. Conf. on Software Analysis, Evolution and Reengineering. IEEE

Advantages

- Simpler for prototyping, no need to write distributed algorithms
- Cheaper than scale-out processing
- Allows us to run exhaustive analyses quickly

Compression techniques

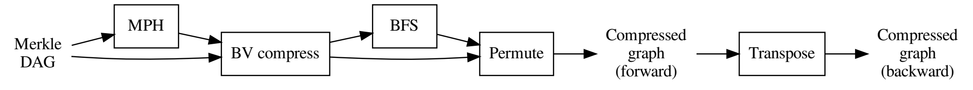
Existing compression algorithms used with the **graph of the Web**.

Compression pipeline

Web graph → Software development graph: (re)establishing locality

Key for good compression of adjacency lists is a node ordering that ensures **neighbor locality**.

- Lexicographically-ordered URLs in the Graph of the Web have this property.
- It is *not* the case with cryptographic Merkle IDs...
- ...but is the case *again* after a breadth-first traversal



- MPH: minimal perfect hash, mapping Merkle IDs to 0..N-1 integers
- BV compress: Boldi-Vigna compression (based on MPH order)
- BFS: breadth-first visit to renumber
- Permute: update BV compression according to BFS order

Compression results

We ran the compression pipeline on the input corpus using the **WebGraph** framework (Boldi, Vigna 2004).

- Server equipped with 24 CPUs and 750 GB of RAM
- **Compression time**: 138 hours (6 days)
- **Compression efficiency**: 6 TiB edge file $\longrightarrow$ 91 GiB forward, 83 GiB transposed

Benchmark

Full traversal: 1h48min (1.81 M nodes/s) on a single thread
$\Longrightarrow$ Huge improvement over Spark (4 h, 80 nodes, 5000 USD)

LLP compression

Layered Label Propagation: algorithm to uncover better locality-preserving node orderings (Boldi et al. 2010)

- Algorithm to uncover locality information
- Propagates labels on random nodes to discover neighborhoods
- Even more impressive compression ratio (91 GiB $\longrightarrow$ 60 GiB, reduced by ~35%)
- Compression requires more runtime memory

Graph Attributes

Node attributes

- The compressed in-memory graph structure has no attributes
- Usual data design is to exploit the 0..N-1 integer ranges to memory map *node* attributes from secondary storage (node ID ⟶ node attribute)
  - We do this for node types (mapping: 4 GiB), timestamps (mapping: 149 GiB), etc.
  - Data structures: integer/byte arrays, front-coded string lists, etc.

Edge attributes

- Built-in WebGraph support for attributes on the edges (generally integers)
- We convert *file names* to integers using a MPH

Graph Querying

Option 1: Write a traversal algorithm using Java graph primitives

```
HashSet<Long> visited = new HashSet<>();
Stack<Long> stack = new Stack<>();
stack.push(srcNodeId);
visited.add(srcNodeId);

while (!stack.isEmpty()) {
    long currentNodeId = stack.pop();
    LazyLongIterator it = graph.successors(currentNodeId);
    for (long neighborNodeId; (neighborNodeId = it.nextLong()) != -1; ) {
        if (!visited.contains(neighborNodeId)) {
            stack.push(neighborNodeId);
            visited.add(neighborNodeId);
        }
    }
}
```

- Efficient but low-level & requires local access to the graph server.
- Simpler/remote querying $\Longrightarrow$ need to build traversal query language

Option 2: HTTP API for simple graph traversals

- Generic remote API for graph traversals, Java/Python/aiohttp backend
- Limited to simple DFS from a single node (forward or backward graph)
- Traversal types: neighbors, leaves, all nodes, all edges
- Supports edge-type filtering

```
> GET /leaves/swh:1:rev:f39d[...]2a35?direction=backward
swh:1:ori:634a2b699d442aa9abd5008f379847816f54ab85
swh:1:ori:571a86b198c6c66ef33025249f7e455b529aae65
swh:1:ori:c15194d6cb59a6d32777ca3b287ea6664d540df3
...

> GET /visit/nodes/swh:1:rev:c6df[...]fc28?edges=rel:rev,rev:rev
swh:1:rel:c6df0a7ef73ca90825f1472b8a3c5f7a2ce3fc28
swh:1:rev:c8448ff2f9234332f0bc25dc3a13031f8ab3c73c
swh:1:rev:4b63dbd4e782e74bdc050c4579381d29b4bd41c0
...
```

Graph Topology: Research Questions

The Software Heritage Graph Dataset materializes a *network of relationships between software artifacts* which has not yet been empirically studied as a whole.

Research questions

- What is the network topology of the graph of software development?
  Network topology metrics: Degree distributions, connected components, distance between roots and leaves, clustering coefficient.
- What do these metrics tell us about this graph and its layers?
  - Best approaches for large scale analysis?
  - Methodological implications for software mining?

The **compressed graph framework** allows us to answer these questions experimentally.

Antoine Pietri, Guillaume Rousseau, Stefano Zacchiroli
Determining the intrinsic structure of public software development history
Mining Software Repositories 2020

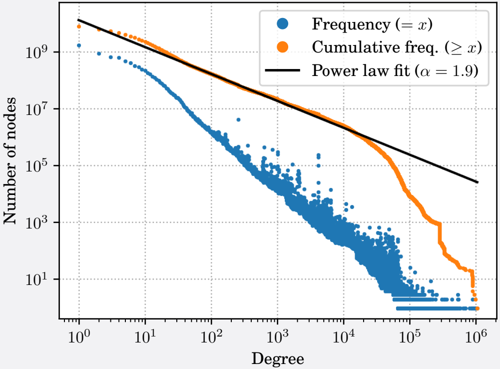
Average degree

Average number of neighbors of all the nodes in the graph

Dataset	Average degree
swh-2020-commit	1.022
bitcoin-2013	6.4
dblp-2011 (Co-authorship)	6.8
swh-2020	11.0
swh-2020-filesystem	12.1
twitter-2010	35.2
clueweb12	43.1
uk-2014 (Web)	60.4
fb-2011 (Facebook)	169.0

Out-degree distributions: filesystem layer

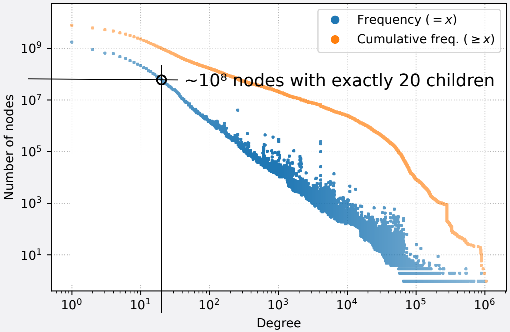
Distribution of the number of entries of each directory in the graph



$\Longrightarrow$ No characteristic number of entries in a directory.

Out-degree distributions: filesystem layer

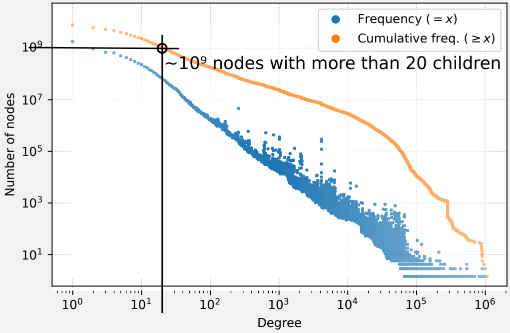
Distribution of the number of entries of each directory in the graph



⟹ No characteristic number of entries in a directory.

Out-degree distributions: filesystem layer

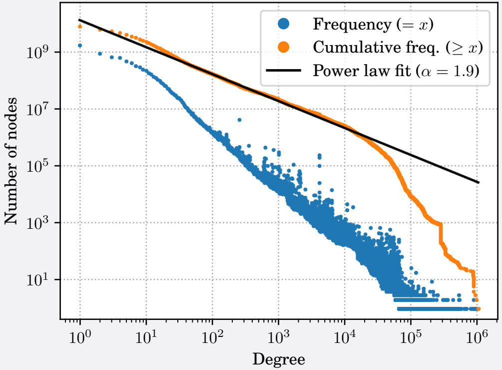
Distribution of the number of entries of each directory in the graph



$\Longrightarrow$ No characteristic number of entries in a directory.

Out-degree distributions: filesystem layer

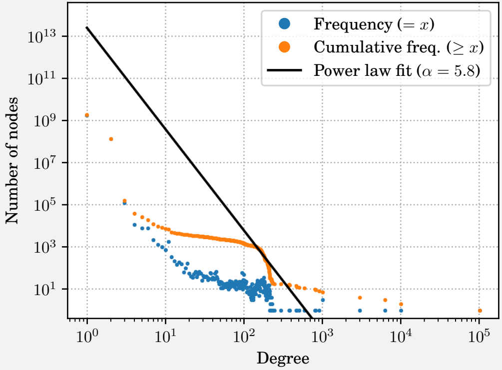
Distribution of the number of entries of each directory in the graph



⟹ No characteristic number of entries in a directory.

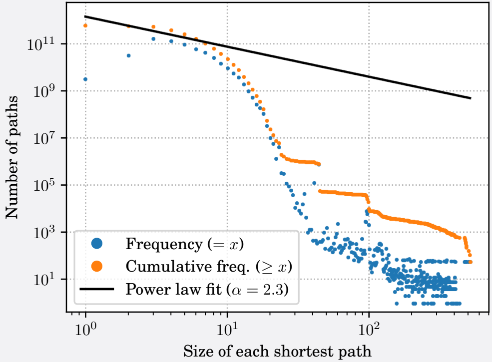
Out-degree distributions: commit layer

Distribution of the number of parents of each commit in the graph

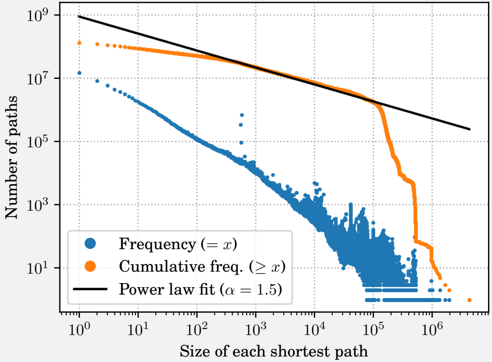


$\Longrightarrow$ Characteristic number of parents due to development patterns.

Distance between roots and leaves

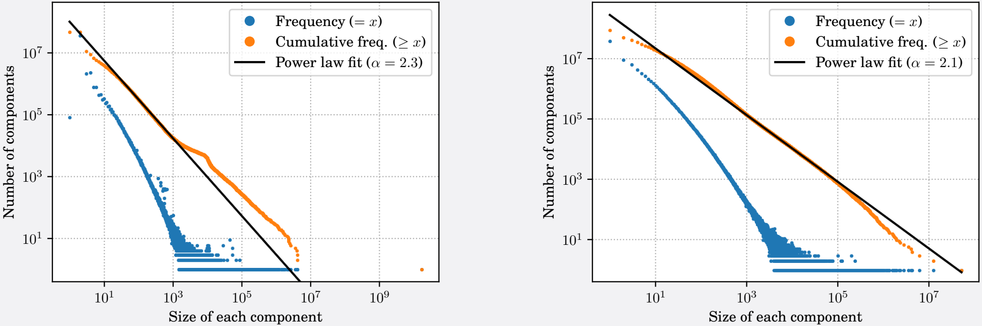


(a) Depth of files in directory trees



(b) Length of commit chains

Connected components



(a) Filesystem layer

(b) Commit layer

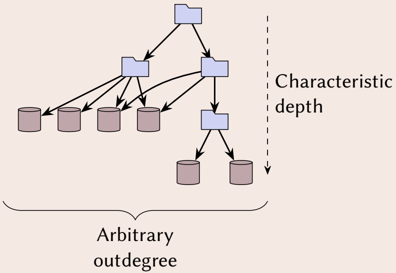
Layer	# of WCC	Size of largest WCC	% in largest
Full graph	33 104 255	18 902 683 142	97.79%
Filesystem layer	46 286 502	16 565 521 611	97.16%
Commit layer	88 031 649	51 543 944	2.61%

Filesystem / commit layer duality

The filesystem and commit layers have almost opposite topological properties.

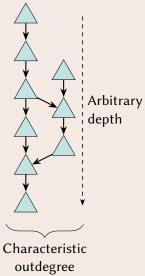
Filesystem layer

- Dense, non-partitionable (giant WCC)
- Characteristic depth
- Arbitrary out-degree



Commit layer

- Sparse, partitionable (max WCC = 3%)
- Arbitrary depth
- Characteristic out-degree (degenerate)



Implications for software mining research

Layers

- Large disparity in the topological structure of layers
- Important to study layers separately to understand the graph structure

Methodology

- No obvious threshold to “filter” outliers in many distributions
- Highlights the importance of exhaustive approaches

Distributed analysis

- No natural partitioning in small connected components
- Need for more subtle approaches?

Conclusion

Main contributions to universal software mining

- Making the graph available for research
  - Graph dataset (MSR 2019)
  - Graph compression (SANER 2020)
- Used for the **first exhaustive study on the graph structure of public software development**.

Future work

- Incremental graph compression
- Expressive query language for graph querying
- Derived graphs: commit diffs, co-authorship graph

Thanks!

All this work is open {source, data, access, ...}.

https://forge.softwareheritage.org https://github.com/seirl/thesis

- Antoine Pietri and Stefano Zacchiroli. "Towards Universal Software Evolution Analysis". In: *Proceedings of the 17th Belgium-Netherlands Software Evolution Workshop, Delft, the Netherlands, December 10th - to - 11th, 2018.* Ed. by Georgios Gousios and Joseph Hejderup. Vol. 2361. CEUR Workshop Proceedings. CEUR-WS.org, 2018, pp. 6–10
- Antoine Pietri, Diomidis Spinellis, and Stefano Zacchiroli. "The Software Heritage Graph Dataset: public software development under one roof". In: *Proceedings of the 16th International Conference on Mining Software Repositories, MSR 2019, 26-27 May 2019, Montreal, Canada.* Ed. by Margaret-Anne D. Storey, Bram Adams, and Sonia Haiduc. IEEE, 2019, pp. 138–142
- Antoine Pietri, Diomidis Spinellis, and Stefano Zacchiroli. "The Software Heritage Graph Dataset: Large-scale Analysis of Public Software Development History". In: *MSR '20: 17th International Conference on Mining Software Repositories, Seoul, Republic of Korea, 29-30 June, 2020.* Ed. by Sunghun Kim, Georgios Gousios, Sarah Nadi, and Joseph Hejderup. ACM, 2020, pp. 1–5
- Paolo Boldi, Antoine Pietri, Sebastiano Vigna, and Stefano Zacchiroli. "Ultra-Large-Scale Repository Analysis via Graph Compression". In: *27th IEEE International Conference on Software Analysis, Evolution and Reengineering, SANER 2020, London, ON, Canada, February 18-21, 2020.* Ed. by Kostas Kontogiannis, Foutse Khomh, Alexander Chatzigeorgiou, Marios-Eleftherios Fokaefs, and Minghui Zhou. IEEE, 2020, pp. 184–194
- Antoine Pietri, Guillaume Rousseau, and Stefano Zacchiroli. "Forking Without Clicking: on How to Identify Software Repository Forks". In: *MSR '20: 17th International Conference on Mining Software Repositories, Seoul, Republic of Korea, 29-30 June, 2020.* Ed. by Sunghun Kim, Georgios Gousios, Sarah Nadi, and Joseph Hejderup. ACM, 2020, pp. 277–287
- Antoine Pietri, Guillaume Rousseau, and Stefano Zacchiroli. "Determining the Intrinsic Structure of Public Software Development History". In: *MSR '20: 17th International Conference on Mining Software Repositories, Seoul, Republic of Korea, 29-30 June, 2020.* Ed. by Sunghun Kim, Georgios Gousios, Sarah Nadi, and Joseph Hejderup. OSF registration available online at: `https://osf.io/7r2w4`. ACM, 2020, pp. 602–605
- Thibault Allançon, Antoine Pietri, and Stefano Zacchiroli. "The Software Heritage Filesystem (SwhFS): Integrating Source Code Archival with Development". In: *43rd IEEE/ACM International Conference on Software Engineering: Companion Proceedings, ICSE Companion 2021, Madrid, Spain, May 25-28, 2021.* IEEE, 2021, pp. 45–48

Why not...?

Comparison with other datasets

- GHTorrent, Github on BigQuery: Github only
- source{d}: obsolete, top-bookmarked, Github only
- World of Code: Git only, mapping-oriented data model
- CodeDJ: GitHub only, model includes platform-specific metadata, interesting query system
- DejaVu: GitHub only, contains duplicate mappings but not the actual software objects

Graph databases

- Neo4J, Amazon Neptune, GraphFrames $\longrightarrow$ Interesting to make them available, but costly. Scalability concerns?

Graph Subdatasets

Generating representative subgraphs

- Useful for smaller-scale experimentation, prototyping
- Focusing analysis on a relevant subset
- Representative samples ⟶ transitive closure of a subset of origins
- Use a fitted log model to estimate the size of the resulting subgraph