LAGOON: An Analysis Tool for Open Source Communities

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ABSTRACT
This paper presents LAGOON – an open source platform for understanding the complex ecosystems of Open Source Software (OSS) communities. The platform currently utilizes spatiotemporal graphs to store and investigate the artifacts produced by these communities, and help analysts identify bad actors who might compromise an OSS project’s security. LAGOON provides ingest of artifacts from several common sources, including source code repositories, issue trackers, mailing lists and scraping content from project websites. Ingestion utilizes a modular architecture, which supports incremental updates from data sources and provides a generic identity fusion process that can recognize the same community members across disparate accounts. A user interface is provided for visualization and exploration of an OSS project’s complete sociotechnical graph. Scripts are provided for applying machine learning to identify patterns within the data. While current focus is on the identification of bad actors in the Python community, the platform’s reusability makes it easily extensible with new data and analyses, paving the way for LAGOON to become a comprehensive means of assessing various OSS-based projects and their communities.

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CCS CONCEPTS
Information systems → Graph-based database models; Human-centered computing → Open source software; Social networks; Security and privacy → Human and societal aspects of security and privacy; Computing methodologies → Machine learning.

KEYWORDS
data streams, sociotechnical system, spatiotemporal graph, model observations, dashboard

1 INTRODUCTION
Open source software (OSS) is responsible for many of the productivity advancements in modern software engineering, essentially by expanding the author list of any software project considerably. However, OSS can also directly cause failures in the projects that rely on them, with examples such as the unpublishing of Leftpad [3], the corruption of Faker.js [10] and the pushing of malicious code to UA-Parser.js [6]. Understanding what motivates the maintainers of high-quality OSS projects – and being able to identify when such a project might become derelict or compromised – is paramount to avoiding this class of supply-chain disruptions, which at best affects service uptime or requires considerable developer hours to remedy, and at worst can introduce subtle security bugs that compromise users.

On one hand, OSS communities produce many artifacts, such as source code or mailing list messages, that can help understand
the state of each project; on the other hand, such analysis is difficult due to its scope. Successful OSS communities tend to be large, distributed and highly interconnected. Two issues further complicate matters: (1) the list of authors actively contributing to an OSS project changes over time, which needs to be taken into account to contextualize a community’s dynamics [18, 21, 26]; and (2) many community members make significant contributions outside of the code base, such as ideas and discussions, requiring an analysis platform capable of ingesting and merging multiple, disparate data sources. Available tools to help with this analysis are limited.

We present the Leveraging AI to Guard Online Open Source Networks (LAGOON) platform – an open source, reusable tool to ingest, analyze and visualize temporal, sociotechnical graph data, in a way that allows for the assessment and analysis of OSS projects and communities. Specifically, LAGOON’s analyses are focused on detecting cyber-social operations targeting OSS developer communities, though its modular design allows for additional use cases. LAGOON can currently be pointed at arbitrary OSS code repositories or other sources of information, and users can create and add their own ingest modules or analyses. LAGOON is available at https://github.com/GaloisInc/SocialCyberLAGOON, and can be cited as [16]. The URL includes a link to a publicly available backup of our database for the CPython project and its associated community artifacts, which form the primary case study for our analyses.

Notably, LAGOON is a partner project to the Open-source Complex Ecosystem And Networks (OCEAN) data collection effort [32] – a partnership between Google Open Source and the University of Vermont. OCEAN provides standardized data from mailing lists of several OSS communities, including 954, 287 messages from the Python community, which formed a key part of the data we ingested and analyzed in LAGOON.

1.1 Overview of LAGOON

Fig. 1 gives an overview of the LAGOON platform. For a complete view of a sociotechnical system such as an OSS community, LAGOON supports the ingest and combining of data streams from multiple different sources representing the system into a spatiotemporal graph database, which is used for analyses.

Disparate sources are handled via an entity and observation model. That is, each unique entity is created as a node in the graph; entities are intransient. At different points in time, two entities might interact or a single entity might be measured in some way: these are recorded into the graph as observations, and always have timestamps (though NULL might be used to indicate an intransient observation). For example, Person A (an entity) might author on July 2nd, 2020 (an observation) Message B (another entity). Both entities and observations can have arbitrary data attached for convenience; e.g., Person entities have a username and e-mail address.

Entities and observations are ingested from each data source as part of a batch, independently from all other data sources. That is, ingesting a git repository creates a set of user entities which are completely separate from the user entities produced during a mailing list ingest. This allows for data sources to be individually re-ingested or updated to include new features without requiring the entire database to be re-ingested.

Dealing with duplicate or aliased entities from disparate sources of data has been discussed in literature [7, 9, 33]. As the final step of database preparation, LAGOON ingest batches are merged under a fusion process that de-duplicates entities across different batches by creating a single FusedEntity to represent them.

The end result is a database ready for analysis, providing a unified view of the disparate data sources created by OSS communities.

LAGOON contains a Python library for querying the database. This library has been used to derive all of our results, as well as some results for OCEAN. LAGOON is also packaged with a user interface (UI) for inspecting and analyzing the graph, as well as a command line interface (CLI) for ad hoc queries.

1.2 Related work

The popularity of the graph format have led to a profusion of graph datasets for machine learning (ML) purposes [14, 15, 20, 22, 25], some of which deal with code analysis and OSS communities [15, 25]. We make the key distinction that these are datasets, not tools. In the tool space, there are several commercial / enterprise software for dealing with graphs [11, 12, 27, 30], as well as open source efforts with predominantly visualization functionality [4, 5, 8], or analysis functionality [23]. LAGOON, as already described, is an open source tool which can ingest, visualize and analyze graph data. There have been efforts which have performed data analysis on OSS data, such as [1, 2, 35]; these efforts do not include a comprehensive platform which also supports data ingest, and are in a similar vein to the results we present in Sec. 4.

2 THE LAGOON PLATFORM

LAGOON is a tool built using Python and contains a PostgreSQL database [13] accessed using SQLAlchemy [28]. Fig. 2 gives a detailed example of the platform ingesting data from an OSS project. Data sources (a) are processed into batches (b), which can be cross-linked (c) and fused (d) to form a final sociotechnical graph (e). An example database is provided with LAGOON, which contains artifacts relating to CPython, the reference implementation of Python.

2.1 Ingest

LAGOON currently supports several ingestion modules. Users can also extend LAGOON with their own custom ingestion modules.

2.1.1 Ingesting from repositories. As entities, this module pulls in (1) people (i.e. maintainers) with their name and email address; (2) commits with their hash, commit time and message; and (3) files within the repository. Observations are used to link maintainers to the commits they created, and commits to the files they changed.

Example: The blue batch in Fig. 2(b) ingests from a repository two maintainers – Walt Woods and Sourya Dey – each of whom has made one commit.

2.1.2 Ingesting from mailing lists. As entities, this module pulls in messages with their time, subject, body and source mailing list; and people (i.e. authors), as from repositories. Observations are used to link authors to messages, and messages referencing each other.

Example: The red batch in Fig. 2(b) ingests from a mailing list two authors – W. Woods and Sourya Dey – each of whom has written one message, with the latter’s referencing the former’s.
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2.1.3 Ingesting from web scrape – PEPs. As entities, this module pulls in Python Enhancement Proposals (PEPs) [19] with their title, number and other information as obtained from the leading table of a PEP’s webpage\(^1\); and people (i.e. PEP authors), as described above. Observations link authors to PEPs, and associated PEPs together.

As a separate batch, this module links the ingested PEPs to previously ingested batches containing entities which mention that PEP by number.

Example: The green batch in Fig. 2(b) ingests two PEPs – 693 created by Walt Woods and 682 created by Sourya Dey, with PEP 693 superseding PEP 682. Then, the orange batch in Fig. 2(c) creates observations to link entities from previous batches to the PEPs. In this case, there was one commit message in the blue batch and one mailing list message in the red batch which contained ‘PEP 693’.

2.1.4 Ingesting toxicity attributes. This module analyzes messages from previous batches for toxic language, and attaches attributes to the respective entities. Our current database uses toxicity lists from [24]. Toxicity analysis was separated from, e.g., mailing list ingest, to minimize the runtime of each separate step.

Example: The purple batch in Fig. 2(c) identifies ‘shit’ and ‘hell’ as toxic words and attaches them to the respective entities – one commit and one message. Note that this attaching is not done via creating observations (hence the arrows are not solid), instead the attributes dictionary of the respective entities are augmented.

2.2 Entity fusion

LAGOON fuses person entities if any of these criteria are met:

- Emails are identical and valid (i.e. not part of a generic mailing list address).
- Names are identical, and the names have a space in them and are longer than 5 characters.
- Names, on passing through PostgreSQL’s pg_trgm\(^*\)’s metaphone function, have a similarity of > 0.95 according to pg\(_{\text{trgm}}\)’s similarity function. This allows for names with slight typos and/or missing accents to be merged.

\(^*\)See https://www.python.org/dev/peps/pep-0435/ for an example

![Figure 2](image2.png)

Figure 2: A complete example of LAGOON’s different ingestion processes and fusion. Should be viewed in color. (a) Data sources. (b) Data is ingested from repositories (blue), mailing lists (red), and web scraping of PEPs (green) in independent batches. (c) As separate batches, ingested messages are linked through observations to the PEPs they reference (orange), and toxicity attributes are added to existing messages (purple). (d) Finally, person entities are fused (brown). (e) The final graph with all data co-existing. Note: Batches within each of the subfigures (b), (c), (d) can be reordered, but the ordering (b)→(c)→(d) is required.

![Figure 3](image3.png)

Figure 3: Small example screenshot from UI, with key parts annotated by bold orange lines. (1) Focus locking, which can be used to quickly query displayed entities. (2) Pause/resume of continuous layout. (3) time range displayed from the database; observations at the start of this range are colored dark purple, while observations at the end of this range are bright yellow. (4) Name of currently focused entity, which can be clicked to search. (5) Entities show up as different colors and shapes of nodes based on their type and properties.

Entity fusion finalizes the database by replacing entities and observations with FusedEntity-es and FusedObservations. Our most recent CPython database contains about a million FusedEntity-es and 4 million FusedObservations (as of 2022-01-24).

Example: Entities inside each brown box in Fig. 2(d) are fused. Note that ‘Sourya Dey’ is fused with ‘Souryå Dey’ since the two names are similar, and ‘Walt Woods’ is fused with ‘W. Woods’ since their emails are the same. The final data in the graph is shown in Fig. 2(e), which combines all the steps from Fig. 2(a).

2.3 User Interface

LAGOON is packaged with a UI for inspecting and analyzing the ingested open source community. The UI was constructed with the Vue 3 framework [34].
An example of the UI is shown in Fig. 3. To lay out the entities and observations, Cytoscape.js [8] was used. To deal with the uniquely large graph databases for OSS communities, time filtering is applied. When an entity has observations outside of the current time window, two special nodes are created, with the most recent preceding and following observation times, to allow for crawling the complete graph without memorizing times of interest.

Currently, the UI supports a limited family of runtime plugins which can be implemented outside of the core LAGOON code. These plugins can add additional details to an entity being viewed. This has been used for, e.g., providing user access to ML models.

2.4 Analysis Scripts and Reports

The LAGOON platform includes a library for querying the underlying database. Example usage includes querying the commit density and neighboring subgraph of each contributing community member at different points in time, and subsequently training an ML model to predict future disengagement from the project based on current events. LAGOON is also packaged with scripts which generate reports on collaborations amongst contributors, as a way of better understanding interactions within the community.

3 ACCESSING AND RUNNING LAGOON

LAGOON is available as a public repository at https://github.com/GaloisInc/SocialCyberLAGOON. Users are strongly encouraged to refer to the README.md file for complete guidance on operating LAGOON and making it useful for other projects. Generally, all commands may be run through “./lagoon_cli.py”, which supports tab completion and documentation via the “typer” package [29].

As mentioned in the README, pre-populated databases that we have used can be downloaded from a publicly shared folder. Once the database is set up, the user can run “./lagoon_cli.py shell” to interact with the database in an IPython environment using SQL queries. For example, “sess().query(sch.FusedEntity).first()” will print out the first entity. Fig. 4 shows other example queries and their outputs.

4 OUR ANALYSES ON LAGOON DATA

We used a graph convolutional network (GCN) [17] enhanced with a transformer [31] to predict contributor disengagement. This approach filtered the batch of toxicity attributes attached to messages to focus on those linked to a particular contributor (spatial analysis) over a particular period of time (temporal analysis). Disengagement was defined as the reduction in a contributor’s activity from one time window to the next. Combining toxicity with vector embeddings for each type of entity in the graph led to an 11.7% improvement over a naive predictor, as shown in Fig. 5. Additional analyses, such as on PEPs, might be presented in future work, but are out of scope for this paper.

5 CONCLUSION

We have presented LAGOON – an open source, reusable tool for analyzing OSS communities. The key highlights include various ingestion modules, data layering, entity fusion, a UI, and predictions on the health of OSS communities.

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**Figure 4:** Two example database queries and their outputs (limited to one result for ease of display). Top – Find observations made in 2018 that modified files. This is an example of time filtering. Bottom – Find messages that contain the term ‘hell’. This is an example of detecting toxicity.

**Figure 5:** Prediction quality across varying levels of data inclusion. Numbers below 100% indicate effective generalization from learning to contributors for which no instability information was included in the training data. Overall, including type and bad word counts as a proxy for toxicity led us to outperform a naive prediction of disengagement by 11.7% on average; outlier detection in the box plot demonstrates a greater improvement when considering the median.

The future of LAGOON comprises adding more ingestion modules and increasing the power of the platform to predict threats to OSS communities. The authors are happy to accept pull requests and extensions to LAGOON, and hope that the broader community can benefit from using it.

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