LogLess:

A Logging Paradigm for Serverless Applications

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Abstract

Logging is a prominent practice followed in software development. Without sufficient and appropriate logging, isolating bugs, debugging problems, and maintaining best security practices become increasingly difficult.

Current logging mechanisms in serverless platforms can sometimes become cumbersome for developers. In case of any failures or debugging, spotting the issues can become difficult due to inadequate logging. Additionally, the auto-generated system-wide logs, by cloud platforms, are not descriptive enough to help debug an application error. There are indeed some logging tools and utilities available in the market, which can be configured to an application's needs. However, they still need developers to write the logging statements apart from the code.

We propose LogLess, a new paradigm in logging, which can automate the logging mechanism. With this approach, the developers will be able to publish logs of their serverless applications without writing the log statements manually within the code. LogLess utilizes the "decorator" objects in a programming language. These decorators will be used to parse the function arguments and every underlying block or line of code within the function. LogLess will categorize every block/line of code based on the function it is performing such as variable assignment, API call request/response, connection to external databases, etc. Upon categorizing these lines of codes, LogLess will assign them to a corresponding "pattern group/sub-group". Once the pattern group has been assigned, it will fetch the corresponding values of all the underlying variables in each block/line of code and generate an appropriate log.

Keywords

Cloud Computing, Distributed Systems, Serverless Computing, Logging, Programming Languages, Decorators

I. INTRODUCTION

LogLess is a one-of-a-kind logging model and makes use of the fact that functions are "first-class objects" in programming languages, like Python, JavaScript, Java, Golang, etc. This allows functions to be passed as arguments to decorators which are functions themselves, to be used by LogLess. LogLess advances knowledge by offering a unique perspective and approach to how logging can be produced. In contrast to the traditional methodology of writing time-consuming logging statements in every block of code, this proof of concept offers a *log-less* decorator-based approach that will automate a range of logging methods for serverless applications. Ultimately, this idea can provide a quick, customizable, and developer-friendly logging model.

Currently, developers write individual logging statements in code blocks which could lead to missing key statements or heavily duplicate messages across the platform. LogLess would offer a contribution that simplifies logging by enabling developers to focus on their code. LogLess would enforce standardization on statement messages so that they can be reused.

Different development environments may require differing requirements for logging. LogLess will provide a novel contribution in that a logging mode can be selected from a list of modes. A logging mode will vary in terms of the number of log statements, what parameters get logged, and which log levels are supported. In addition, various modes can be configured namely – dev-mode, safe-mode, and prod-mode. Each mode will serve a different purpose in the software development lifecycle and won't need any additional changes to the actual code for debugging and logging. This configuration can provide better logging flexibility and design to applications.

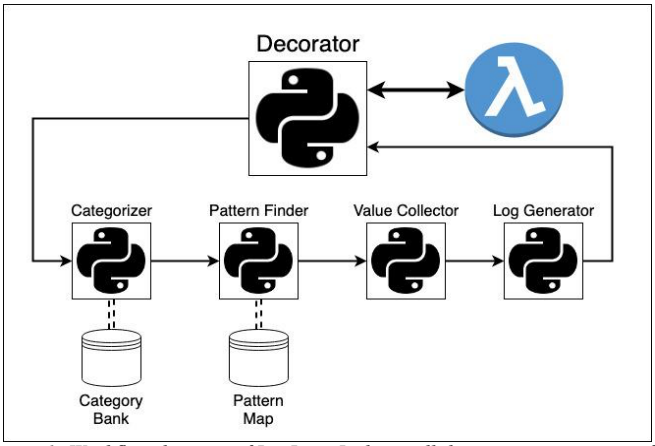


Figure 1: Workflow diagram of LogLess. It shows all the major components of the model

Many serverless platform providers have predefined logging of their cloud services. For example, in AWS, a

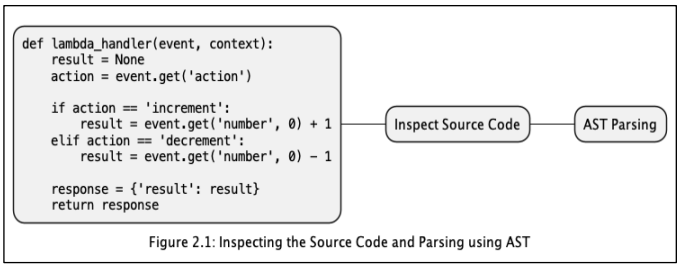


Figure 2.1: Inspecting the Source Code and Parsing using AST

connection between a lambda function and DynamoDB is logged into CloudWatch. However, this logging is restricted to only AWS-provided services and is not inclusive of any external communications. Moreover, CloudWatch logs do not provide in-depth knowledge of variables and values used within a Lambda application or offer any customization opportunities. LogLess will offer more efficient, granular, and customized logging that will augment such in-built logging tools.

This project can provide a broader benefit to the serverless development community, which includes computer science students, development teams in the workplace, and open-source contributors. While we plan to experiment with LogLess using Python, it can be implemented in other programming languages, thus impacting a larger community.

II. THE DECORATOR

In most modern programming languages, such as Python, Java, and JavaScript, functions are first-class citizens and can be passed around as variables. This means, all these objects can have attributes, member functions, and they can be passed as arguments.

Using this knowledge about functions we implement LogLess by developing a Python *Decorator* function which wraps the application code (decorated function).

This is a parsing module, which parses the functions within the serverless deployed application. It traverses through every code-block within the function and passes them to the code categorizer [1].

A. Code Categorizer

- This module traverses through each code-block and categorizes the code according to the predefined categories. It utilizes *inspect* and *ast* modules of Python3 package. These categories will be looked up from a code category bank. This code category will then be passed to a pattern finder.

B. Code Category Bank

- This data bank will consist of various categories of code that might occur in a serverless architecture. This will categorize various programming functionalities like variable assignment, conditionals, loops, etc. Additionally, it will also contain categories defined based on extensive research on the available functionalities across various Serverless providers and their respective FaaS services.

C. Pattern Finder

- This module will determine the pattern of the categorized code and based on the category and pattern

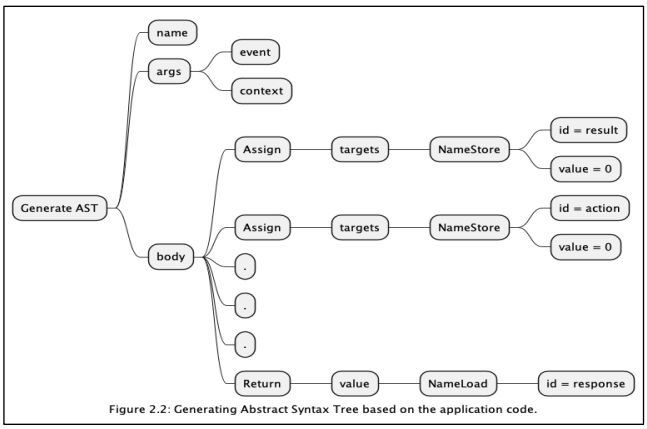


Figure 2.2: Generating Abstract Syntax Tree based on the application code.

map; it will determine the type of logging needed for that code category.

D. Pattern-Category Map

- This module will map the code category with its relevant logging pattern. This pattern will be created based on extensive research and experimentation for various types of applications running over serverless platforms.

E. Value Collector

- This module will store the values of all the variables occurring within a particular line/block of code.

F. Log Generator

- It takes the pattern and the variables and their corresponding values as an input, will generate an appropriate log, which will be descriptive and informative for developers and code reviewers.

III. THE IMPLEMENTATION

We define a wrapper function which serves as a decorator for the function(s) in the application code. We named the decorator of our *LogLess* package – *decolog*.

A. Code Categorizer

To categorize every line of code of the decorated function, we first utilize the *inspect* module [2] of Python3 package to retrieve the *source-code* as text. Then, we parse the generated *source-code* to generate the Abstract Syntax Tree (AST) of the code in hierarchical structure. For this we are utilizing *ast* [3] which is also present as a python module and available as part of the standard python distribution.

The AST module helps Python applications to process trees of the Python abstract syntax grammar (Figure 2.1 & 2.2). It helps to find out programmatically what the current grammar looks like for the underlying python code.

Once the AST of the code is generated, we do a semantic analysis of the AST and categorize the various code blocks using Code Modeling, Syntax, and Semantics [*$VI.C*] along with a few Machine Learning models [*$VI.D*]. The categorization process utilizes a predefined set of rules and category database.

B. Code Category Bank

In order to assign a category to semantically categorize code for writing the logging, we created a light-weight database. This database comes in-built as part of the LogLess package and is based on *SQLite* [4, 5].

SQLite is a C library that provides a lightweight disk-based database that doesn't require a separate server process and allows accessing the database using a nonstandard variant of the SQL query language. The *sqlite3* python module was written by Gerhard Häring. It provides an SQL interface compliant with the DB-API 2.0 specification described by PEP 249 [6], and requires SQLite 3.7.15 or newer.

IV. EXPERIMENTATIONS

For experimentation, we plan to research a variety of applications currently prevalent on serverless platforms for their type of built-in functionalities. Based on that research we plan to create a data bank of all programming concepts and functions which are frequently used in serverless applications. We will also populate the categorization data bank with serverless utility-specific methods, and functions.

Once we have a data suite ready, we will have a robust and extensive set of unit tests to verify the functionality of logging and what is expected for each category of code and functions. The team plans to perform black box testing through equivalence partitioning and boundary value analysis. In addition, the team will utilize a code coverage tool to carry out white box testing. In testing the team plans to use tools such as *pytest* and *Coverage.py*.

V. LITERATURE SURVEY

The project's primary concern regarding software logging will be log instrumentation. This stage consists of including log statements in the application and maintaining them throughout the software development lifecycle. The logging approach, Logging Utility (LU) integration, and Logging Code (LC) composition are the steps of log instrumentation. The logging approach is the high-level workflow of how logging will be performed. The next component of LU integration involves deciding which tool to adopt (example: SLF4J for Java) and how to configure it. Finally, LC composition requires addressing where logging should occur, what should be logged, and how to log with high quality [7]. Documentation of these steps will be critical for this project.

Software logging with security practices is of paramount importance. To follow and implement best security practices when designing an application, vulnerabilities must be looked at. Insufficient logging is one example that can complicate bug identification and expose security vulnerabilities. The Open Web Application Security Project (OWASP) identified insufficient logging as one of the top ten security risks in 2017 [8,9]. In a serverless architecture, pinpointing bugs can become challenging if there are not enough log statements in the functions.

In addition, malicious attackers may have had attempts to steal sensitive information, but it could go unnoticed if the pertinent logging is absent [10]. For this project, understanding this vulnerability will be important to design the logging module; brainstorming the LC composition design effectively can help prevent or mitigate it. If our team plans to test this model in a distributed system consisting of multiple serverless functions, adapting some aspects of a shared log may be helpful. A team from the University of Texas have proposed a serverless runtime, Boki, that outputs a shared log API. This approach consists of building an ordered log that can be accessed concurrently, and is known to achieve scalability, strong consistency, and fault tolerance [11,12].

VI. RELATED WORK

There has been extensive work being done in the application logging. We have conducted a comprehensive survey of works in this area, and identified a number of related works which in some way mark the stepping stones for the LogLess approach .

A. Platform Agnostic

Today most serverless platforms along with their logging and analysis tools are locked into a provider, for example, Lambda functions can only be used on AWS. Fear of provider lock-in has led to platforms such as *KNative*. KNative is an open-source, extensible, and flexible serverless platform built on top of Kubernetes. However, in the case of KNative more informative and fine-tuned logging requires other log services such as FluentBit to be configured [13]. Our tool offers a novel platform-agnostic logging tool that can provide informative and personalized logging to developers.

Diving into KNative more, this platform is managed by three core components: autoscaler, placement engine, and load balancer. In practice, development with KNative can consist of writing functions from a list of supported languages. These functions get deployed into worker pods, which comprise the queue proxy and function containers. The mentioned components will manage these worker pods throughout the lifecycle. Mittal and team leverage these KNative components to develop a resource management framework for the edge cloud environment [14].

B. Logging

Witt is a visual tool that takes serverless execution logs to present to the developer. With this, they present a timeline that explains the performance, structure, and data flow of a serverless function [15].

Alves and colleagues showcased that the benefits of logging can be evident through an examination of existing open-source repositories. Identifying the popularity of logging libraries can assist new development teams and researchers select one suitable for their projects. Another critical component of logging is surveying what type of information to log. This survey can be accomplished by extracting logger calls from existing repositories and persisting metadata associated with them, such as project name, context, verbosity, and message. In addition to this information, it can be beneficial to track the percentages for both logger calls and number of unique message words. Enumerating the list of top words for the different verbosity levels can benefit new development to

adapt these descriptive logging words to offer a better level of standardization and log analysis [16].

Gu and team performed a comprehensive systematic mapping study (SMS) of logging practices. This study was an amalgamation of logging-based research topics, solution approaches, and research issues. It mainly identifies that most existing research has answered the "where" and "what" should be logged, but there are limited studies on answering "why" and "how" well to log. Improper usage of log levels, lack of crucial information, and low density of logging are further limitations that display the necessity for better logging guidance. A core recommendation from this study was that logging intentions and concerns should be followed; this includes examining contextual factors, performance overhead limits, and source. This study can supplement our research problem such that holistic considerations including the "why" and "how" questions of logging can be included when designing the logging module [17].

A project concern for software logging will be log instrumentation. This stage consists of including log statements in the application and maintaining them throughout the software development lifecycle. Logging approach, logging utility integration, and logging code composition are the steps of log instrumentation [7].

C. Code Modeling, Syntax, and Semantics

With various syntactic structures and user-defined functions successfully modeling code for our tool is challenging. Turning to prior works, Abstract syntax trees (AST) are the standard starting point for code modeling in code analysis. Furthermore, in-built AST conversion modules such as *ast* module in Python provides specific error messages as well as line location for syntactically invalid code [18]. Structural language modeling or SLM is an example of ASTs being used as a starting point. SLM takes AST as a base input and then applies decomposition to present partial trees in the form of paths [19].

In addition to this to capture code fully, semantics along with syntax must be taken into consideration. Code clone detection research completed by *Kalita* and *Sheneamer* [20] shows when adding both syntactic and semantic features to their model performance improves by 19.2% across all classification algorithms. CC-GGNN is an example that both takes AST as a starting point and leverages the importance of semantic features to create a code completion tool that outperforms most current state-of-the-art methods [21].

D. Machine Learning

Machine learning is commonly used for code classification, its usage can be noted in various tools that aid in code clone detection and review comments for example. Transformer-Based Code Classifier or TBCC is a proposed tool that uses deep learning classification over tree structures to accurately identify approximately 96% of C and Java code clones [22]. Research conducted by *Arafat*, *Sumbul*, and *Shamma* to categorize the quality of review comments also uses machine learning focusing on the semantics of the comments instead of the code which led to the models' poor performance [23].

More specifically natural language processing is utilized frequently in code analysis, industry examples of this include GitHub's Copilot. Copilot uses deep learning to provide the ability to autofill repetitive code, suggest test code, and convert comments to code [24]. Copilot is built using Codex which is a generative pre-training transformer language model made by OpenAI. In a paper released by OpenAI the authors note the benefits of using open-source code available on GitHub and code from programming competitions to train and assess their model [25].

Li and colleagues develop a model that recommends whether a given block of code should have a logging statement or not. The implementation consists of examining an AST of the source code and passing the features of it as arguments to the machine learning model. The team tested with a combination of syntactic and semantic features, and ultimately found that high usage of syntactic features resulted in a high balanced accuracy. Six code block categories are identified for classification through the model, such as catch, branch, and iteration. This paper addresses the limitation of limited logging recommendations in existing studies, which can benefit our project in the selection of a ML model for the pattern finder component [26].

Zhu and team explore and develop a tool, LogAdvisor, that provides actionable suggestions on where logging statements should be inserted. This implementation focuses on strategic logging placement to capture significant runtime information. With this intention, it is also worth noting that unintended consequences should be avoided, such that minimal logging can circumvent important information and excessive logging can both increase resource consumption and cause information masking. The machine learning workflow consists of instance collection, label identification, feature selection, model construction, and logging suggestion. Our project involves adding critical logging statements for users, so leveraging ideas from the LogAdvisor tool can benefit us in pinpointing logging locations [27].

Our tool plans to utilize machine learning techniques to aid in the classification of code and provide helpful logging to developers. Furthermore, as far as our research shows we are the first to use this to provide an open source serverless logging platform.

E. Security

Currently, there are only a few studies on security for serverless applications. To address this concern, Kim and colleagues have devised a set of guidelines and examples for designing a serverless environment in order to avoid security vulnerabilities. The team set up a set of services in AWS and performed a threat analysis using the STRIDE methodology. This analysis resulted in a set of common vulnerabilities that occur in serverless applications.

The insufficient logging vulnerability is one relevant example from the set that can make problem identification take a longer time and enable attacks to go unnoticed. This vulnerability is relevant to our project, and we can leverage the paper's suggestions to ensure our logging library writes

important information that can fast track the surveillance of malicious attacks and monitoring process for analysis [10].

MILESTONE 3: PROGRESS REPORT

VII. Main Methodology

We are developing a solution, LogLess, that does the logging work for developers. This solution addresses prevalent issues found in software development. First, inadequate logging can occur based on software development team practices and it is highly undesirable. Teams undeniably don't want security issues or bugs to occur unnoticed. Additionally, teams may simply misuse logging statements and levels. With LogLess, developers don't have to be concerned about writing logging statements. Second, some commonly utilized cloud platforms don't output sufficient logging information. Teams that rely on serverless platforms should get the logs they need for operation. LogLess is planned to be supported for serverless platforms, so users would have both the solution's logs and the auto-generated logs at their disposal.

VIII. Research Approach

In most modern programming languages, such as Python, Java, and JavaScript, functions are first-class citizens and can be passed around as variables. This means, all these objects can have attributes and member functions, and they can be passed as arguments. Using this knowledge about functions we implement LogLess by developing a Python Decorator function that wraps the application code (decorated function).

Our research approach also used qualitative methods to address the problem. We surveyed research papers that studied logging practices. In one study, the info and error levels used more descriptive and domain-specific words than other levels. This specificity indicates more variability, and the paper mentions that these levels had the highest percentage of unique words. In contrast, the debug verbosity level showed more repeatable words across projects. This finding offers our team a high-level sense of how logging statements can be constructed based on the verbosity level [16].

Similarly, another part of the qualitative research approach was understanding the popular words or statements in the different log levels. Using the previous study as an example, the debug level is utilized to present results and common words for it include "updated", "resulted", and "set". Likewise, the info level usually indicates ongoing events, with words such as "sending", "creating", and "deleting". Such findings should assist our team in planning for storing a collection of such static strings per verbosity level and intelligently selecting them for the final logging statements.

IX. LogLess Design

The LogLess design is based on the decorator functionality, Abstract Syntax Tree (AST), and source code traversal. It employs the code categorizer and pattern finder modules backed by a data bank, which is created on a lightweight SQLITE3 database. Upon getting the pattern based on the code category, the log is created based on the type of mode (SAFE, DEV, PROD) and respective configuration (INFO, DEBUG, ERROR, etc).

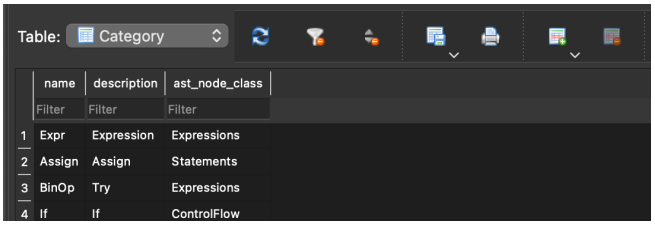
X. Unique Contribution

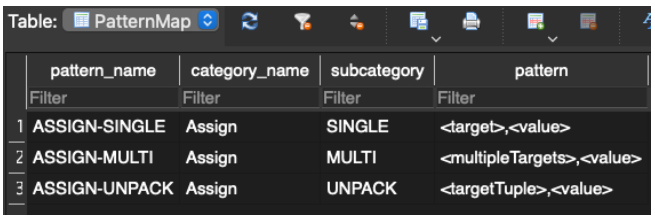
LogLess offers a serverless, platform-agnostic logging decorator. The novelty of LogLess comes from its ease of use, customizability of logging, and development modes. By providing different preset development modes, LogLess allows for quick, easy, and safe logging that facilitates the developer instead of creating additional work. This solution is enabled to be customized for each developer's logging needs by supporting more granular configurations such as log levels, frequency, and logging values.

XI. Progress Details

Thus far our team has created a basic working prototype of the LogLess decorator as well as an initial setup for the testbed. All the prototype code as well as DB data can be found at the following link. https://github.com/kushagrasoni/LogLess_Logging/tree/milestone3.

LogLess can be broken down into six main components as mentioned in section II. The current version of LogLess includes the working implementations of the code categorizer (A), code bank (B), and log generator (F). The pattern finder (C), pattern-category map (D), and value collector (E) are in progress. Briefly, the current module implementations work as follows. The code categorizer takes each AST node as input and categorizes the code based on the AST grammar categories. The said categories are defined in SQL in the code bank module, as well as the AST grammar patterns which will be used in the pattern matcher module. Below are screenshots of said SQL files.





Lastly, the log generator has been created with an instance of a logger, custom logging configurations, custom mode configurations, pattern output from the pattern finder, and variables from the value collector. This component is responsible for generating and outputting an appropriate

logging message for each pattern depending on the verbosity level and mode type (SAFE, DEV, and PROD)

The LogLess testbed will be built upon OpenWhisk, which is an open-source serverless platform that supports standalone and distributed serverless nodes. Together with OpenWhisk, we plan to use Python-lambda-local to run serverless applications and example code provided by Serverless on Github to test with https://github.com/serverless/examples.

Traversing the AST using the ast.walk() functionality was not possible as it does a breadth-first traversal of the tree which does not respect the order of code. To overcome this we created ASTVisitor() which uses ast.NodeVisitor() base class.The ast.NodeVisitor() does a depth-first traversal of the descendants and keeps the order of the code.

Below is an example of how node traversal is implemented. The line of code

```
action_event = event.get('action')
```

calls an attribute of a variable and then assigns the value of the call to a "target". The main functions used in the ASTVisitor() code, the response and diagram is below.

```
class ASTVisitor(ast.NodeVisitor):
    """ example recursive visitor """

    def recursive(func):
        """ decorator to make visitor work recursive """
        global parent_level, child_counter
        parent_level = 0

        def wrapper(self, node):
            global child_counter, parent_level
            child_counter = 0

            func(self, node)
            for child in ast.iter_child_nodes(node):
                self.visit(child)

        return wrapper
```

```
@recursive
def visit_Assign(self, node):
    """ visit a Assign node and visits it recursively"""
    print(
        f'{type(node).__name__}\n\tTotal Targets: {len(node.targets)}\n\tTargets: {node.targets}\n\tValue: {node.value}')
```

```
@recursive
def visit_Call(self, node):
    """ visit a Call node and visits it recursively"""
    print(
        f'{type(node).__name__}\n\tFunction: {node.func}\n\tTotal Arguments: {len(node.args)}\n\tArguments: {node.args}\n\tKeywords: {node.keywords}')
```

```
@recursive
def visit_Attribute(self, node):
    """ visit a Assign node and visits it recursively"""
    print(f'{type(node).__name__}\n\tValue: {node.value}\n\tAttribute: {node.attr}\n\tContext: {node.ctx}')
```

```
Assign
        Total Targets: 1
        Targets: [<ast.Name object at 0x10672bd90>]
        Value: <ast.Call object at 0x10672bdc0>
Name
        Id: action_event
        Context: <ast.Store object at 0x105e71a90>
Call
        Function: <ast.Attribute object at
        0x10672bd60>
        Total Arguments: 1
        Arguments: [<ast.Constant object at
        0x10672b3a0>]
        Keywords: []
Attribute
        Value: <ast.Name object at 0x10672be20>
        Attribute: get
        Context: <ast.Load object at 0x105e71a30>
Name
        Id: event
        Context: <ast.Load object at 0x105e71a30>
Constant action
```

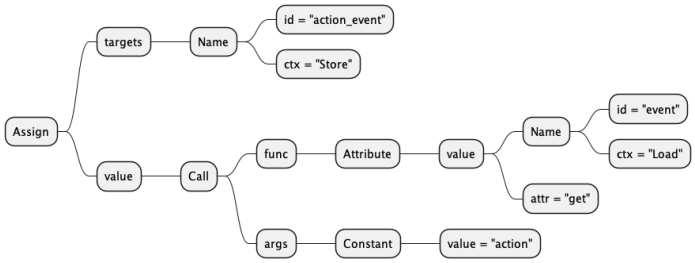


Figure 3: Generating Abstract Syntax Tree for Assign type AST.

Initially, we planned to use machine learning algorithms to define design patterns to aid our logging. However, upon further research and consideration, we decided to drop this functionality as defining design patterns and selecting the features to focus on would require a lot more time as well along with a substantial dataset for training. As this is not viable in our timeframe, we have decided to use machine learning to detect similar code blocks and will add this as an additional feature, time permitting. Finally setting up local environments initially caused slowdowns but we were able to overcome these issues by troubleshooting and helping each other set up.

XII. TIMETABLE

Week	Task	Deadline
17th October - 23rd October	• Continue researching as needed for development • Outline tasks and goals for milestone 3 • Develop Logless features on a smaller scale or smaller scope to prove working	

	concepts. Features include: ○ Decorator ○ Code categorizer ○ Code category bank ○ Pattern finder ○ Pattern-category map ○ Value collector ○ Log generator	
24th October - 30th October	• Continue to develop a working prototype of LogLess • Work on milestone 3 report	Sunday 30th - Milestone 3
31st October - 6th November	• Expand on the working prototype to finalize LogLess • Design test bed	
7th November - 13th November	• Finalize LogLess • Execute tests and collect results	
14th November - 20th November	• Work on nice to have features such as ML • Execute tests and collect results on nice to have features as needed • Work on milestone 4 report	Sunday 20th - Milestone 4
21st November - 27th November	• Analyze results • Improve or adjust Logless as needed • Improve or adjust tests as needed	
28th November - 4th December	• Polish project • Begin work on final report	
5th December - 9th December	• Finalize all work • Review and polish final paper	Friday 9th - Milestone 5 (Final paper)

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