COMP3023J Software Methodology Research Group11

1st Jinpeng Zhai
Software Engineering Year of 2021
Beijing-Dublin International College
Beijing, China
jinpeng.di@ucdconnect.ie

2nd Ziqi Yang
Software Engineering Year of 2021
Beijing-Dublin International College
Beijing, China
ziqi.yang@ucdconnect.ie

3rd Yiran Zhao
Software Engineering Year of 2021
Beijing-Dublin International College
Beijing, China
ZhaoYiran@emails.bjut.edu.cn

Abstract—**This paper, authored by Group 11, serves as a midterm checkpoint for the COMP3023J Software Methodology course research assignment. It is important to note that a comprehensive abstract will be provided upon the completion of the entire manuscript.**

Index Terms—**Python, tracing, visualization**

I. Introduction

Python is widely recognized as one of the most popular programming languages in contemporary computing. Its popularity stems from its exceptional flexibility, ease of learning, and the extensive selection of libraries available [1]. Python's widespread adoption is not limited to well-established fields such as web development, data analytics, and scientific computing; it has also gained prominence in emerging areas, notably in the domain of machine learning [2]. This increasing popularity has led to a growing community of developers and researchers.

However, as Python projects expand in size and complexity, they encounter fresh challenges associated with both development and maintenance. These challenges encompass intricacies in code organization, the emergence of "hot code" leading to performance bottlenecks, and the escalating intricacies of ongoing maintenance [3]. Consequently, there arises a compelling need for code analysis and optimization for large Python projects [4].

Previous studies have emphasised the efficacy of employing code tracing and code coverage techniques within Python projects in tackling these problems. Code tracing refers to the action of following the flow of program execution. It shares some similarities with deterministic profiling and debugging, in that in the context of Python, this is usually accomplished via placing a hook function into the Python interpreter via the provided `sys.settrace()` method, that is then called to record the exact detail of program execution. Among these, CPython's Lib.trace.py module provides robust capabilities in tracing the execution of native Python code [5]. This module adeptly traces function calls and furnishes comprehensive code coverage reports, thus facilitating the identification of inadequately tested code and performance bottlenecks.

Simultaneously, a growing trend in recent years has witnessed the adoption of visualization tools to enhance code analysis, presenting findings in an intuitively accessible format [6], [7]. This trend serves to further enhance code quality and bolster the maintainability of large Python projects.

Of note is that due to the converging interest in developing better techniques for the visualization of profiling results, in recent years popular visualization packages have instead opted for extending either the `pdb`, the Python debugger module, or various deterministic profilers, traditionally either the `profile` or the `cProfile` packages. The merits of some of these options will be explored later in this report.

Consequently, this research aims to explore and compare various options for tracing Python code visualization, and demonstrate the use of these techniques for a better understanding of complex Python projects.

II. Previous Art

Lib/trace.py is the tool bundled with CPython, the reference implementation for Python language [8]. Written in the early 2000s, it has been part of the official library from as early as Python 2.2. It provides both program execution tracing and code coverage analysis functionality, and even a limited profiling ability. Implementation-wise, it attaches a tracing funciton (via `sys.settrace()`), written in Python, that is attached to the evaluation mechanism in the underlying Python interpreter, and is called during the normal execution of CPython [9]. Although the module itself does not provide for much in terms of visualization, in recent years a few projects that employs similar techniques for the generation of visualization has emerged. We will examine two such projects, the more established `pycallgraph`, and a more recent work, `vizTracer`.

Various Python profilers, in particular profiling tools bundled with CPython as part of the standard library, the `profile` and the C implementation `cProfile` are also of some interest. As deterministic profilers, they records and expose the Python call stack for each evaluation, allowing program execution tracing to be inferred. Due to the wealth of information recorded, over the years, many projects that visualizes program execution has built upon its output. Notable ones includes:

1) `RunSnakeRun`. Generates a tree map.
2) `GProf2Dot`. Generates a directed arrow-and-box graph.

3) `flameprof`. Generates a flame graph.

Of note is that not all profilers are suitable for our purposes. In particular, non-deterministic profilers works by sampling, at set intervals, the memory layout of the Python interpreter, thus they are suitable for low overhead programm profiling, but unsuitable when capturing function calls for analysis are required, since there is no guarantee of the completeness of the resulting capture. Solutions based on these will be ignored for the purpose of this study.

Finally it bears mentioning that an emerging technique employed in the visualizaiton of tracing information is that of static code analysis. In particular, sophisticated models have been proposed in academica to analyze Python code that has demonstrated limited ability to infer call relation without running the code [10]. However, due to the dynamically typed, interpreted nature of Python, this approach has met some challenges when met with complex code structure, dynamic or conditional imports, and deep class hierarchies.

III. Methodology

For the purpose of this research, we first constructed a Python project consisting of multiple modules that emulates various code structure and exeucte common operations that is encountered in Python projects. From there, multiple types of graphs were generated, and the merits of the resulting graphs are compared, with a particular focus a few select criterion aspects that pertains to the ability of a programmer to use the generated result as a source for the comprehension of the underlying code structure.

`thermal` is a collection of Python scripts that is bundled as part of an open source interior ballistic solver, hosted on Github [11]. Minor manipulation was required to convert it to the format of a Python package. At roughly 2400 lines long (with comments) across 7 files, it is inteded to represent a medium sized, scientific computing oriented Python project.

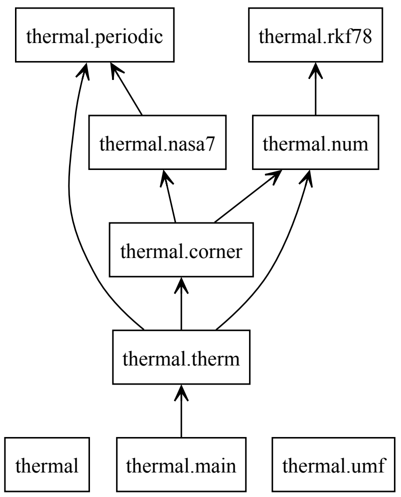


Fig. 1. Package Organization of the `thermal` scripts. Generated using `pyreverse` tool.

A short explanation of the package may help with the appreciation of the visualization developed later in this report.

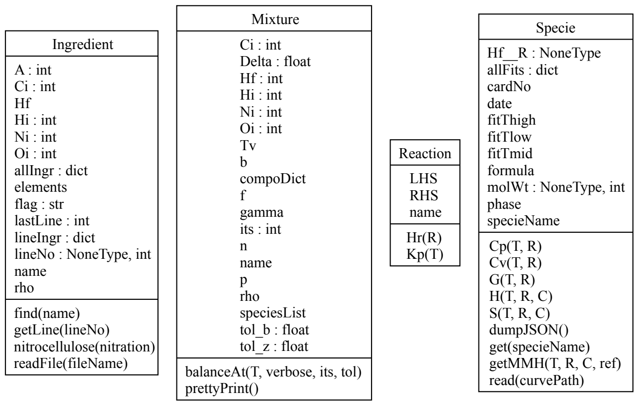


Fig. 2. Class Diagram and of the `thermal` scripts. Generated using `pyreverse` tool.

In `nasa7.py`, `Species` class is defined with objects of this class storing information which allows the calculation of thermalchemical properties, via substitution back into curve-fitted polynomial. Objects of this class are created by reading from a thermalchemical punch-card record, at `data/PEPCODED.DAF`. Within the same file, `Reaction` object represents a chemical reaction involving a certain number of `Species` as reactants and products, and facilitates the calculation of enthalpy, entropy and gibbs free energy change of reaction.

Within `therm.py`, The `Ingredient` allows the representation of energetic materials. Objects of this class are created by reading a thermalchemical database record in a specific format, at `data/nasa7.dat`, or via user definition. `Mixture` class objects represents a combination of `Ingredient` at varying ratios, and implements calculation of derived thermalchemical properties, in turn relying on calling function in `corner.py` which uses the information supplied via `Ingredient` instances to construct `Reactions`, calling to it for the calculation of corresponding chemical equilibrium. Several other files contains support functions and data values that are used in support of the afore-described core functionalities.

As per Python programming conventions, most scripts or modules contains are likely to contain its own entry point.

```python
# code executed if imported to other scripts
if __name__ == "__main__":
    # code executed if this script is run
    independently
```

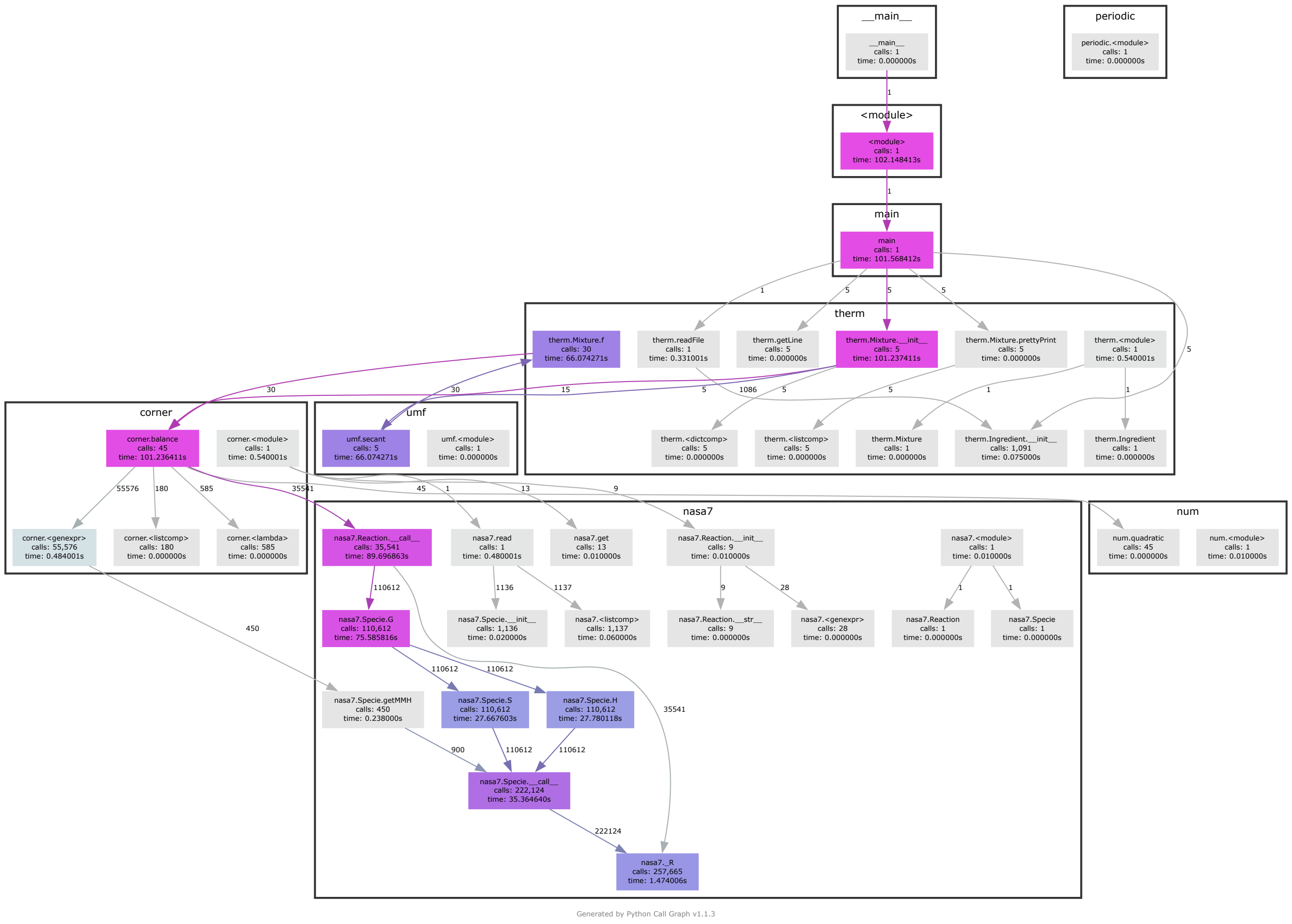
Listing 1. Entry Point for Python Scripts

These serve as convenient locations for script or module-specific tests or examples, often written alongside the module itself. Using these as entry points can be useful when attempting to visualize an unknown project. Although, it is more often the case that these have been pruned out for more established projects, in which case it is necessary to either set up the testing environment as per the project guidelines (often using libraries like `pytest`), or find minimum working examples provided. For the convenience of this report we have assumed that this is the case, and an working example that may serve as the entry point for visualization is provided as `main.py`, which will serve just this purpose for further analysis.

IV. Experiments and Results

A. `pycallgraph`

`pycallgraph` [12] is a relatively established module for the generation of callgraph for Python projects, with the first trackable commit on Github dating back to 2009. The mechanism by which this works is similar to `Lib.trace` in that a custom tracing function is defined (in Python), and attached to the interpreter via `system.settrace()`. This function is then invoked on every line evaluation, exception raised and function returns. Finally, the data is processed by `pycallgraph`, into the final grpahical information. The graphical backend `graphiviz` is then used to convert the generated `.dot` file into presentable image formats such as `.png` or `.svg`. Although by all metrics a popular package, this package has been archived due to lack of maintenance (and is currently unusable . This research instead employs a maintained, backward compatible fork known as `pycallgraph2` [13], which is publically available from PyPI, the Python package index. Running on `main.py` generates a callgraph as below:



__main__
__main__ calls: 1 time: 0.000000s
periodic
periodic.<module> calls: 1 time: 0.000000s
<module>
<module> calls: 1 time: 102.148413s
main
main calls: 1 time: 101.568412s
therm
therm.Mixture.f calls: 30 time: 66.074271s
therm.readFile calls: 1 time: 0.331001s
therm.getLine calls: 5 time: 0.000000s
therm.Mixture.__init__ calls: 5 time: 101.237411s
therm.Mixture.prettyPrint calls: 5 time: 0.000000s
therm.<module> calls: 1 time: 0.540001s
therm.<dictcomp> calls: 5 time: 0.000000s
therm.<listcomp> calls: 5 time: 0.000000s
therm.Mixture calls: 1 time: 0.000000s
therm.Ingredient.__init__ calls: 1,091 time: 0.075000s
therm.Ingredient calls: 1 time: 0.000000s
corner
corner.balance calls: 45 time: 101.236411s
corner.<module> calls: 1 time: 0.540001s
corner.<genexpr> calls: 55,576 time: 0.484001s
corner.<listcomp> calls: 180 time: 0.000000s
corner.<lambda> calls: 585 time: 0.000000s
umf
umf.secant calls: 5 time: 66.074271s
umf.<module> calls: 1 time: 0.000000s
nasa7
nasa7.Reaction.__call__ calls: 35,541 time: 89.696863s
nasa7.read calls: 1 time: 0.480001s
nasa7.get calls: 13 time: 0.010000s
nasa7.Reaction.__init__ calls: 9 time: 0.010000s
nasa7.<module> calls: 1 time: 0.010000s
nasa7.Specie.G calls: 110,612 time: 75.585816s
nasa7.Specie.__init__ calls: 1,136 time: 0.020000s
nasa7.<listcomp> calls: 1,137 time: 0.060000s
nasa7.Reaction.__str__ calls: 9 time: 0.000000s
nasa7.<genexpr> calls: 28 time: 0.000000s
nasa7.Reaction calls: 1 time: 0.000000s
nasa7.Specie calls: 1 time: 0.000000s
nasa7.Specie.getMMH calls: 450 time: 0.238000s
nasa7.Specie.S calls: 110,612 time: 27.667603s
nasa7.Specie.H calls: 110,612 time: 27.780118s
nasa7.Specie.__call__ calls: 222,124 time: 35.364640s
nasa7._R calls: 257,665 time: 1.474006s
num
num.quadratic calls: 45 time: 0.000000s
num.<module> calls: 1 time: 0.010000s
Generated by Python Call Graph v1.1.3

Fig. 3. Callgraph Generated by `pycallgraph2` from `main.py`

It is seen that in the callgraph, function calls are represented with boxes, and functional invocation is represented via arrow, pointing from the caller to the callee, with a numeral indicating the number of times this particular relation has occured. Of note is that we have chose to enable the option for grouping calls based of file here to illustrate this feature. The cells can be colored based on either total-time, the cumulative time spent within this function, or self-time, which is the total time sans the time spent in subsequent calls to other functions. The hue is approximately lograithmic colored. Setting it to former, will illustrate the main branch of execution. Setting it to the latter will help to illuminate performance bottlenecks. The above graph has been colored according to total-time.

It can be seen that the callgraph, as generated by pycallgraph, aptly reproduced the call activity and their hierarchy for the underlying code. Starting from the first __init__ node, program execution transfers to main(), from which point it can be inferred that five Ingredient and Mixture objects were initiated via calling to their __init__ constructor methods directly. Additionally, more Ingredient objects are created through therm.readFile() function call, which after being called from main() called the constructor Ingredient.__init__() 1086 times. Finally, the main() function also called therm.getLine() and Mixture.prettyprint() method five times.

This illustrates a weakness of the functional call-graph visualization, in that it does not allow the visualization of discrete objects, instead the existence and manipulation of objects must be completely inferred from the graph. In particular, in code it can be seen that, while in code, the initialization and manipulation of objects are clearly linked through identifier:

```python
ATKPRDS22 = Mixture(
    # .... definition elided for brevity
) # object initialization
ATKPRDS22.prettyPrint() # object manipulation
```

In the call graph, these operations have been illustrated separately, like the following: Given that the use of objects for the

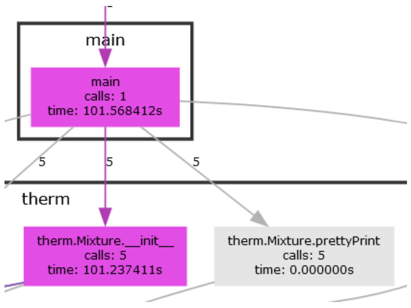


Fig. 4. Closeup of Figure 3

organization of data and operations being one of the primary benefit for object oriented programming, the visualization fails in this regard to associate the two together, impairing the programmer's ability to gain insight into the behavior of code, especially if objects-logic drives the program execution flow, and may differ depending on data, such as this example. Additionally, it appears that a particular failing of pycallgraph is the inability to distinguish between class or static methods, and global functions. For example, in reality, therm.getLine() is defined as:

```python
class Ingredient:
    # .... other functions elided for brevity
    @classmethod
    def getLine(cls, lineNo):
        #.... code elided for brevity
```

This is inconsistent with what the programmer might expect, for example therm.Ingredient.getLine().

Following the main branch of execution, calls to Mixture.__init__() triggers evaluation of corner.balance(), and to umf.secant(), which in turn calls a function Mixture.f() and from there also the corner.balance() function. The import statement executes the nasa7.read function, defining 1136 new nasa7.Species, and 9 nasa7.Reactions.

gprof2dot.

V. Discussion

Originally, the research was planned to be of a larger scope, where code from common libraries would be tested.

VI. Conclusion

General statement and ending thoughts about the topic.

VII. Project Management

Throughout the course of this research project, effective project management practices were diligently implemented to ensure the successful execution of the study and the attainment of its research objectives. This section offers insights into key aspects of project management, including team management, the presentation of milestones through Gantt charts, individual team member contributions, and potential future research directions.

A. *Team Management*

Effective team management is paramount for the success of a research project, ensuring that all team members work cohesively towards common goals. In the context of this study, several strategies were meticulously employed to promote efficient teamwork:

- **Cohesive and Collaborative Team:** Our research team thrived on a culture of cohesiveness and collaboration. Team members actively engaged in learning about each other's work, encouraging knowledge sharing, and fostering an environment of continuous improvement. Mutual respect, inclusivity, and honesty were the cornerstones of our interactions. We recognized and celebrated each team member's distinct attributes and strengths, resulting in a balanced and complementary team.
- **Regular Team Meetings:** The project team scheduled and adhered to regular meetings to facilitate thorough discussions on various aspects of the research. These meetings became a platform for deliberating project progress, addressing issues, and setting forth objectives for the upcoming stages. The consistency of these meetings ensured that all team members were continuously aligned with the research objectives and were aware of the project's evolving dynamics.
- **Effective Team Organization:** Organizational structures significantly impact the decision-making process within a team. Effective communication is the cornerstone of our team management strategy. In addition to scheduled meetings, we established digital communication platforms, specifically WeChat and Telegram group chats, to facilitate real-time communication and information sharing among team members. These platforms allowed for swift discussions and collaborative decision-making,

ensuring that everyone was on the same page regarding project developments.

- **Shared Resource Management:** To facilitate efficient collaboration and resource accessibility, the research team adopted modern tools and platforms. A dedicated GitHub repository was established for streamlined code sharing and collaboration on experimental components. This central repository allowed team members to work on project software with version control and simplified issue tracking. Additionally, Overleaf, an online platform for collaborative writing, was used to create and edit the research paper collectively. This real-time collaboration improved the efficiency of document creation and review. These modern tools ensured easy access to project resources, including code and research documentation, enhancing collaboration, version control, and issue resolution for the success of the research project.

Our team management practices were instrumental in fostering a collaborative and productive environment, which ultimately played a pivotal role in the successful execution of this research project. The harmonious teamwork, communication, and resource management strategies allowed us to efficiently navigate the complexities of the research process and achieve our project objectives.

B. Milestone Showcase with the Gantt Chart

As illustrated in Figure 5, the Gantt chart is an instrumental graphical representation that offers a structured overview of the project's chronological progression and key milestones. This visual representation is an essential tool for effective project management, aiding in the tracking of tasks, allocation of resources, and adherence to project timelines.

C. Team Member Contributions

Each member of the research team made substantial and equitable contributions to the success of the project. It is worth noting that the team unanimously acknowledges that each member's contributions to the research project were fundamentally equal and characterized by active engagement. Below is a detailed breakdown of the tasks and responsibilities that each team member undertook:

- Jinpeng Zhai
  - Actively engaged in the implementation of the research plan, transforming initial concepts into concrete project components.
  - Took the lead in formulating and developing the research methodology, playing a crucial role in crafting the research approach presented in the paper.
  - Contributed significantly to the writing of the research's methodology and approach sections in the paper, ensuring its thoroughness and accuracy.
- Ziqi Yang
  - Demonstrated proactiveness in conducting extensive research to identify available tools and the latest research methods.
  - Presented innovative ideas for implementation and actively participated in the design and development phases of the research.
  - Contributed to the creation of project components and the development of research solutions, enriching the research's technical foundation.
- Yiran Zhao
  - Formed and efficiently managed the research team, facilitating regular team meetings and fostering effective communication.
  - Contributed to the research paper, including creating the overleaf template and drafting the introduction section and project management section.
  - Thoroughly reviewed relevant literature, bringing a wealth of knowledge and insights to the research. Introduced innovative ideas and approaches that enriched the research process and contributed to the research's overall success.

The entire team is in unanimous agreement that each member's commitment and contributions to the research project were equitable and integral to its success. The collaborative and complementary efforts of all team members were essential in achieving the project's goals.

D. Future Research Directions

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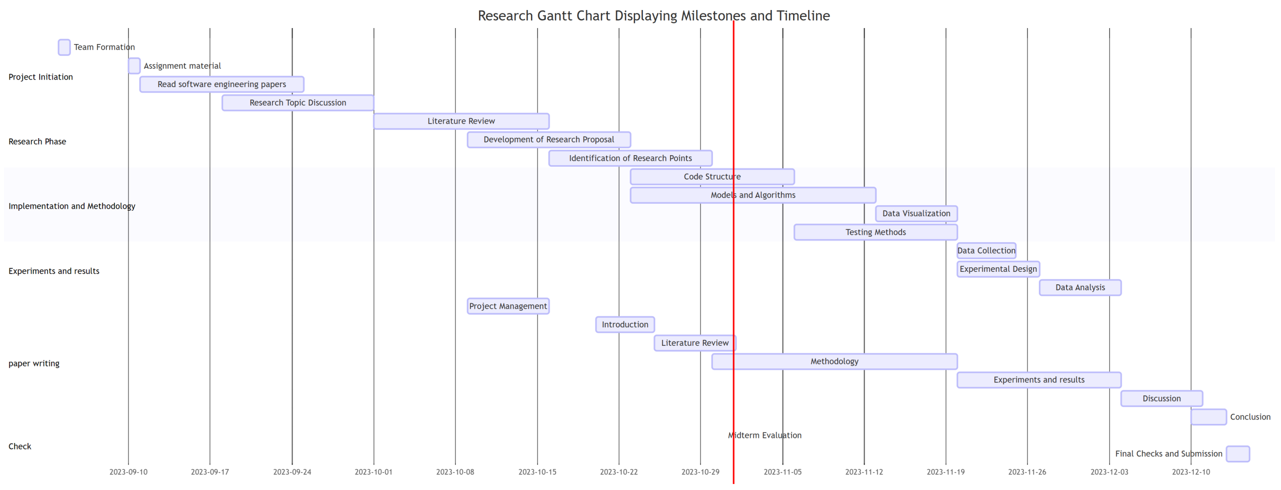

Fig. 5. Research Gantt Chart Displaying Milestones and Timeline