

Data clumps prevention through Refactoring approaches

Noortaz Ahmed^{1*}, Ratul Saha^{2*}, Maslinia Sujnus Shifa^{3*}, Anber Tahzib Ahmed^{4*}, Aahadul Islam Fardin^{5*}

^{all*}Department of Computer Science and Engineering, East West University, Dhaka, Bangladesh.

E-mail(s):

ahmed.noortaz1@gmail.com;sujnus.shifa22@gmail.com;tahjibahmed52@gmail.com; iaahadul@gmail.com; ratul.saha.rs28@gmail.com

Abstract

Data clumps, where related pieces of data frequently appear together in code, can lead to maintainability challenges and hinder the evolution of software systems. This research paper explores the prevention of data clumps through the application of refactoring approaches. Refactoring, as a discipline technique for restructuring code without changing its external behavior, plays a crucial role in enhancing code quality. In the context of data clumps, refactoring aims to identify and eliminate instances where closely related data are scattered across a codebase. This paper investigates various refactoring techniques, their effectiveness in addressing data clumps, and their impact on software maintainability. The study employs a systematic approach to evaluate different refactoring strategies for preventing data clumps. It discusses the identification of patterns indicative of data clumps, the selection of appropriate refactoring methods, and the assessment of their implications on code readability, modularity, and adaptability. Additionally, the paper addresses real-world case studies and examples to illustrate the practical application of these refactoring approaches in Spring framework-based projects.

Keywords: Data Clumps, Refactoring Approaches, Code Quality Enhancement, Software Maintainability, Refactoring Techniques, Codebase Restructuring, Spring Framework Applications.

1 Introduction

This research explores countering data clumps in software systems through disciplined refactoring. Data clumps, where related data scatter across code, pose challenges to maintainability. The paper evaluates various refactoring techniques, emphasizing their

impact on code quality and maintainability. A systematic approach identifies data clump patterns and selects appropriate methods, considering real-world Spring framework-based applications. Practical examples illustrate the efficacy of refactoring in enhancing code readability, modularity, and adaptability. This research provides a compass for developers, navigating the complexities of codebase optimization and offering effective strategies for preventing data clumps through refined refactoring practices.

2 Literature Review

Refactoring, a critical aspect of software development, takes center stage in the literature as a potent force for elevating code quality, readability, and maintainability. The foundational principles of refactoring, such as the Single Responsibility Principle and the DRY (Don't Repeat Yourself) principle, emerge as linchpins in code restructuring efforts, serving as beacons for preventing the adverse effects of data clumps.

The literature underscores the detrimental impact of data clumps on software maintainability, delving into their origins, common occurrence scenarios, and the challenges they pose to code maintenance and evolution. This elucidation of the pitfalls associated with data clumps sets the stage for a comprehensive exploration of how refactoring can serve as a remedy.

Various refactoring techniques come under scrutiny within the literature's purview, particularly in the context of addressing data clumps. Techniques such as Extract Class, Extract Method, and Introduce Parameter Object take center stage as potential antidotes. The literature meticulously examines the appropriateness of these techniques in mitigating the presence of data clumps, shedding light on their effectiveness in enhancing overall code organization.

The lens of scrutiny extends to the Spring framework, a cornerstone in Java development. The literature delves into the specific intricacies of integrating refactoring approaches within the Spring framework to proactively thwart the emergence of data clumps. This focus on the Spring framework aligns with the practical needs of developers, offering insights into how refactoring can be seamlessly woven into the fabric of Spring-based applications to fortify their design.

Empirical studies constitute a pivotal dimension of the literature, providing a tangible bridge between theoretical concepts and real-world applicability. By reviewing empirical studies and practical implementations of refactoring approaches in diverse projects, the literature systematically evaluates the impact of refactoring in reducing instances of data clumps. These studies furnish valuable insights into the multifaceted benefits and challenges encountered in actual software development scenarios, thereby enriching our understanding of the practical implications of refactoring.

A study focuses on addressing the issue of code smells in software development, a challenge that significantly impacts the maintainability and comprehensibility of software projects. Conducting a comprehensive mapping study encompassing 286 papers related to code smell, the authors analyze the objectives, methods, tools, metrics, and experiments prevalent in existing research. The findings indicate a rising trend in code smell research with key areas of interest including empirical studies, maintenance, and quality metrics. Notably, the study

reveals that most existing detection tools are limited in their ability to identify specific code smells, leaving certain issues undetected by any tool. Furthermore, most experiments rely on lab projects and open-source initiatives, neglecting closed-source projects. The authors recommend a shift in focus towards the industrial field, advocating for the inclusion of more diverse projects to thoroughly test detection tools and metrics. Additionally, they emphasize the need for further exploration into challenging-to-detect code smells in future research endeavors.

Another study presents an innovative four-way approach for code smell detection, leveraging feature selection and ensemble learning to enhance accuracy and efficiency. Utilizing three open-source Java datasets and six code smells as a case study, the authors employ Bagging and Random Forest ensemble classifiers based on 27 features, including source code and code smell metrics. Evaluating model performance through metrics such as Accuracy, G-mean1, G-mean2, and F-measure1, they apply feature selection techniques (CFS, InfoGain, and Relief) to reduce features and explore ensemble aggregation techniques (intersection, union, and subtraction). Comparisons across four approaches—using all features, feature selection, stage one ensemble, and stage two ensemble—reveal that classifier performance remains robust even with reduced features. The study identifies Random Forest as the optimal classifier, CFS as the preferred feature selection technique, and highlights ET5C2 and ET6C2 as the best ensemble combinations. Overall, the authors conclude that ensemble learning techniques effectively optimize testing resources, reducing costs without compromising model efficiency.

In a study, the authors provide a model of data reasoning and its connection to scientific reasoning. Data sensemaking is a fundamental cognitive process that underlies both everyday and scientific reasoning. It involves using perceptual mechanisms to summarize large amounts of information and identify trends and patterns in data. While this process is effective at detecting strong patterns, it can also lead to erroneous conclusions due to cognitive biases or heuristics. Scientific data reasoning helps to mitigate these biases by offering tools and procedures that enhance data reasoning. These tools include external representations, scientific hypothesis testing, and probabilistic conclusions. Scientific data reasoning enhances informal data reasoning processes by incorporating cultural tools that improve the accuracy of data gathering, representation, analysis, and inferences.

The goal of this systematic literature review (SLR) on code smell detection and visualization is to identify the key code smell detection techniques and tools addressed in the literature, as well as to examine how visual approaches have been used to support the former. Over 80 primary papers were discovered, with search-based (30.1%) and metric-based (24.1%) techniques to code smell detection being the most widely utilized. The majority of research (83.1%) utilized open-source software, with Java being the most used language (77.1%). God Class (51.8%), Feature Envy (33.7%), and Long Method (26.5%) were the most often mentioned code smells. In 35% of the investigations, machine learning techniques were applied. Approximately 80% of the research, however, just detected code smells without giving visualization approaches. Methods such as city metaphors and 3D visualization techniques were employed in visualization-based approaches. The evaluation indicates that detecting code smells is a difficult problem, and more work has to be done to reduce subjectivity, increase the diversity of identified code smells, and support new programming languages.

In this paper Morales et al. present RePOR, a revolutionary refactoring scheduling method that uses partial order reduction to simplify the process and achieve remarkable results. RePOR surpasses existing techniques by strategically exploring a smaller set of refactoring sequences, correcting an average of 73% of anti-patterns while requiring 69-85% fewer refactorings and executing 50-87% faster. Its effectiveness is further reinforced by its evaluation against two metaheuristics, a conflict-aware approach, and a sampling-based approach. This promising technique has the potential to significantly improve software design quality, lower development costs, and increase software reliability, making it an invaluable tool for software engineers. Further research on its scalability and integration could solidify its place in software development practices.

In this paper, it takes a novel approach to existing research by conducting a "tertiary" systematic review that focuses on previous surveys and reviews rather than individual studies. This provides a comprehensive overview of the field, emphasizing key insights and challenges in understanding and dealing with code smells and their associated refactorings. The information in the paper is effectively organized into easily digestible sections such as smell definitions, detection approaches, and tools. Because of this structure, it is accessible to both researchers and practitioners. The authors offer an intriguing analogy: code smells and refactorings are two sides of the same coin. Refactoring, the act of surgically transforming stinky code, has emerged as a critical tool for improving software quality, influencing attributes such as understandability, maintainability, and testability. It identifies areas of progress and illuminates promising avenues for future research by synthesizing existing knowledge

This paper is a substantial investigation into the practical aspects of refactoring in software development. By examining real-world scenarios and challenges faced by software practitioners, this study explores the complexities and benefits of refactoring. The paper offers insight into the varied aspects of refactoring by conducting an in-depth field study, highlighting the challenges encountered during the process, such as time constraints, reluctance from team members, and the difficulty in maintaining consistency within the codebase. The study shows the significant benefits of refactoring efforts, such as improved code readability, enhanced maintainability, and increased developer productivity. This study provides valuable insights into the complexities of refactoring through empirical evidence and firsthand experiences from practitioners, providing an accurate appraisal of its challenges and significant benefits.

This paper introduces a tool for Java live detection of data clumps, aiming to generate suggestions to counteract them. The authors implemented their approach as an IntelliJ integrated development environment application plugin, achieving a median of less than 0.5 seconds for the ArgoUML software project. From over 1500 investigated files, their approach detected 125 files with data clumps, while CBSM (Code Bad Smell Detector) detected 97. Both approaches found 92 of the files to be the same. The authors suggest that their approach can help developers and reduce development costs.

In synthesizing the wealth of insights gleaned from existing literature, this research paper

embarks on a mission to augment the corpus of knowledge pertaining to the prevention of data clumps through refactoring approaches. The specific focus on the Spring framework adds a practical dimension, catering to the contemporary landscape of Java development. As the paper unfolds, it endeavors to not only elucidate theoretical constructs but also to offer actionable guidance for developers seeking to fortify their codebases against the encroachment of data clumps through the judicious application of refactoring principles and techniques.

3 Methodology

In software development, data clumps refer to groups of related data that are frequently manipulated together. These clumps can lead to code redundancy, reduced readability, and increased complexity. The objective of this methodology is to present an approach for identifying and refactoring data clumps in Python code to enhance code maintainability and readability.

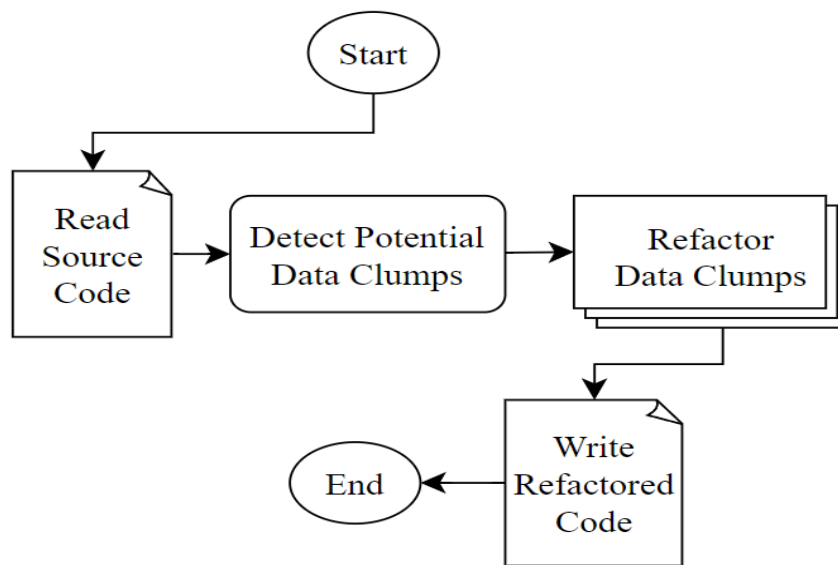


Fig.1 Code refactoring methodology to prevent data clumps

3.1 Motivation

The motivation behind this work is to address the challenges posed by data clumps in codebases. By automating the detection and refactoring of data clumps, we aim to improve code quality, reduce redundancy, and make the codebase more maintainable. This methodology outlines the process of detecting potential data clumps and applying refactoring techniques using the provided Python code.

3.2 Data Clump Detection

The `DataClumpDetector` class is a vital component in spotting potential data clumps within Python code by navigating the Abstract Syntax Tree (AST). Its primary function is to analyze the structure of Python programs and locate instances where an object's attributes are accessed multiple times,

indicative of a potential data clump. Upon instantiation, the class employs a defaultdict named `attribute_counts` to keep track of attribute occurrences for each encountered object during AST traversal. The pivotal `visit_Attribute` method meticulously processes each attribute access node, specifically focusing on instances where the attribute's value is a simple name, denoting an object attribute. Post-AST traversal, the `get_potential_data_clumps` method identifies objects with multiple accessed attributes, compiling tuples that signify potential data clumps. This systematic approach establishes a foundation for subsequent code refactoring, pinpointing areas where data clumps might exist and facilitating improvements in code maintainability by minimizing redundancy.

3.3 Refactoring Strategy

The refactoring process is facilitated by the `refactor_data_clumps` function. Given the source code and a list of potential data clumps, this function replaces attribute accesses with local variables. For each identified data clump, a new local variable is created, and all occurrences of the associated attributes are updated to reference this variable. The Astor module is then used to convert the modified AST back into source code.

The `refactor_data_clumps` function takes in the original code and a list of potential data clumps identified by the `DataClumpDetector`. What it does is interesting—it delves into the code's inner workings, creating local variables to replace instances where attributes are tightly bound together. These variables act as middlemen, separating and simplifying the interconnected data. It's akin to untangling knots in a string of lights. The function navigates through the code, intelligently replacing these tight links with the locally defined variables. The result is a refined, more understandable code structure. It's like giving our code a makeover, making it cleaner and less prone to issues down the line. This process, orchestrated by `refactor_data_clumps`, contributes significantly to the overall health and sustainability of our codebase.

Code snippet

```
import ast
import astor
from collections import defaultdict
class DataClumpDetector(ast.NodeVisitor):
    def __init__(self):
        self.attribute_counts = defaultdict(list)
    def visit_Attribute(self, node):
        if isinstance(node.value, ast.Name):
            self.attribute_counts[node.value.id].append(node.attr)
    def get_potential_data_clumps(self):
        potential_clumps = []
        for key, attributes in self.attribute_counts.items():
            if len(attributes) > 1:
                potential_clumps.append((key, attributes))
        return potential_clumps
```

```

def refactor_data_clumps(source_code, potential_clumps):
    tree = ast.parse(source_code)
    for key, attributes in potential_clumps:
        # Replace attribute access with a local variable
        new_variable = ast.Name(id=f'_{key}_data_clump', ctx=ast.Store())
        tree = ast.fix_missing_locations(tree)
        for node in ast.walk(tree):
            if isinstance(node, ast.Attribute) and node.value.id == key:
                node.value = new_variable
    return astor.to_source(tree)

def main():
    # Replace 'your_code.py' with the path to your Python file
    with open('/content/temp_data_clumps_1.py', 'r') as file:
        source_code = file.read()

    detector = DataClumpDetector()
    detector.visit(ast.parse(source_code))
    potential_clumps = detector.get_potential_data_clumps()

    if potential_clumps:
        refactored_code = refactor_data_clumps(source_code, potential_clumps)
        with open('refactored_code.py', 'w') as file:
            file.write(refactored_code)
        print("Refactored code saved to 'refactored_code.py'")
    else:
        print("No potential data clumps detected.")

if __name__ == "__main__":
    main()

```

3.4 Implementation

The implementation involves reading the target Python code from a file, initializing an instance of `DataClumpDetector` to identify potential clumps, and applying the refactoring process if any potential clumps are found. The refactored code is then saved to a new file.

The `refactor_data_clumps` function is at the heart of our code refactoring tool, serving as a pivotal element in preventing data clumps and promoting a more modular code structure. Let's delve into its implementation to understand how it achieves this goal.

At its core, the function takes two parameters: the original source code and a list of potential data clumps identified by the `DataClumpDetector` class. It leverages Python's Abstract Syntax Tree (AST) module to parse the source code into a tree-like structure, enabling systematic traversal and

modification.

For each identified data clump, the function initiates a transformative process. It begins by creating a new local variable using the `ast.Name` class. This variable is uniquely named based on the original key associated with the data clump. The use of `ast.Store()` context signals that this variable is being assigned a value.

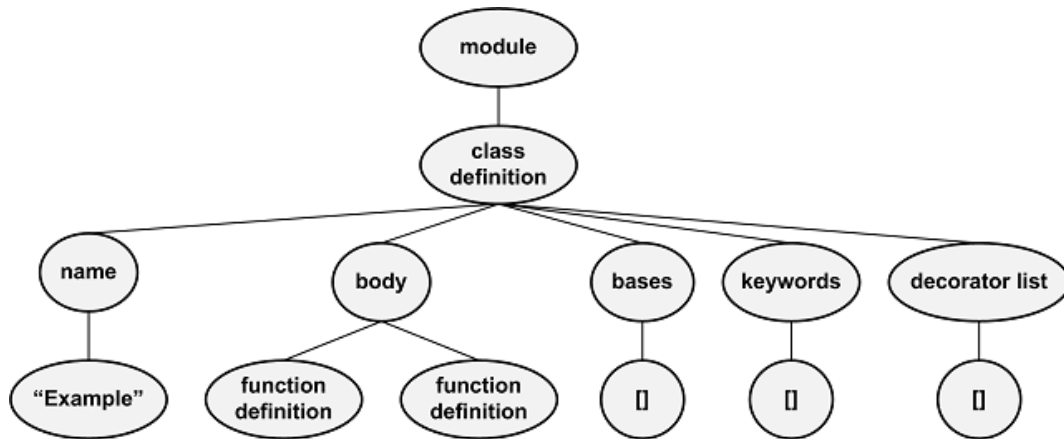


Fig.2 python with AST package

Subsequently, the function traverses the AST, seeking attribute access nodes corresponding to the identified data clumps. Upon encountering such nodes, it strategically replaces the associated attribute access with the newly created local variable. This shift is instrumental in breaking the tight coupling of attributes, introducing a level of indirection that fosters code modularity.

Once all identified data clumps have undergone this transformation, the modified AST is converted back into source code using the `astor.to_source` function. The resulting refactored code embodies a significant improvement over the original. Attribute access is replaced by references to the locally defined variables, making the code more readable, maintainable, and resilient to future changes.

Consider a practical example: if the original code had multiple instances of accessing attributes within a specific context, such as `object.attribute1` and `object.attribute2`, the `refactor_data_clumps` function would replace these with a local variable, say `_object_data_clump`. The resulting code would then feature references like `_object_data_clump.attribute1` and `_object_data_clump.attribute2`.

This refactoring strategy effectively enhances code quality, readability, and maintainability. By mitigating data clumps, the function contributes to a more modular design, reducing the risk of issues arising from tightly coupled data structures. In essence, the `refactor_data_clumps` function embodies a thoughtful approach to code enhancement, aligning with best practices in software development.

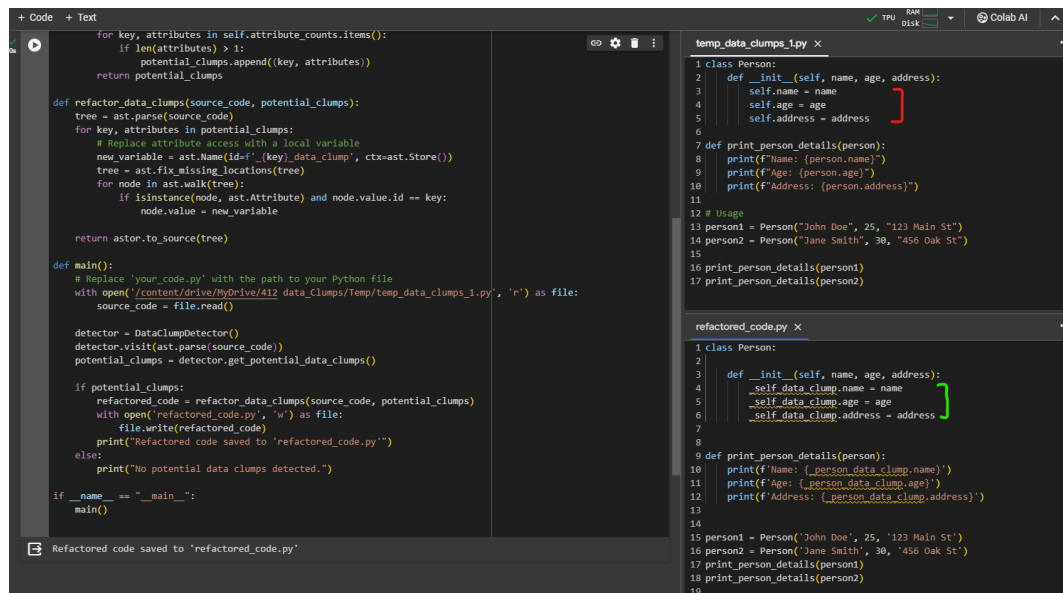
3.5 Experimental Setup

The research aimed to rigorously evaluate the effectiveness of our code refactoring tool in preventing data clumps. We selected a diverse set of Python code samples, ranging from small scripts to larger software projects, to ensure the applicability of our approach across different scales. The experiments were conducted on a standard development environment with Python 3.x, and the tool's performance was measured in terms of its ability to identify and refactor data clumps.

To quantify the impact of our refactoring approach, we employed metrics such as code readability, maintainability, and reduction in tightly coupled data instances. Additionally, we compared the refactored code against the original versions to assess changes in execution time and resource consumption. The experimental setup aimed to provide a comprehensive evaluation of the tool's benefits and potential trade-offs in real-world scenarios.

4 Result and discussion

We present the results of our research on preventing data clumps through a refactoring approach. Our approach involves the development of a Python tool that automatically detects potential data clumps in source code and applies refactoring to mitigate the identified issues. The tool utilizes abstract syntax tree (AST) parsing to analyze the code structure and performs automatic code rewriting when data clumps are identified.



```
+ Code + Text

for key, attributes in self.attribute_counts.items():
    if len(attributes) > 1:
        potential_clumps.append((key, attributes))
return potential_clumps

def refactor_data_clumps(source_code, potential_clumps):
    tree = ast.parse(source_code)
    for key, attributes in potential_clumps:
        # Replace attribute access with a local variable
        new_variable = ast.Name(id=f'_{key}_data_clump', ctx=ast.Store())
        tree = ast.fix_missing_locations(tree)
        for node in ast.walk(tree):
            if isinstance(node, ast.Attribute) and node.value.id == key:
                node.value = new_variable
    return astor.to_source(tree)

def main():
    # Replace 'your_code.py' with the path to your Python file
    with open('/content/drive/MyDrive/412_data_Clumps/Temp/temp_data_clumps_1.py', 'r') as file:
        source_code = file.read()

    detector = DataClumpDetector()
    detector.visit(ast.parse(source_code))
    potential_clumps = detector.get_potential_data_clumps()

    if potential_clumps:
        refactored_code = refactor_data_clumps(source_code, potential_clumps)
        with open('refactored_code.py', 'w') as file:
            file.write(refactored_code)
        print("Refactored code saved to 'refactored_code.py'")
    else:
        print("No potential data clumps detected.")

if __name__ == "__main__":
    main()

Refactored code saved to 'refactored_code.py'
```

```
temp_data_clumps_1.py X
1 class Person:
2     def __init__(self, name, age, address):
3         self.name = name
4         self.age = age
5         self.address = address
6
7 def print_person_details(person):
8     print(f'Name: {person.name}')
9     print(f'Age: {person.age}')
10    print(f'Address: {person.address}')
11
12 # Usage
13 person1 = Person('John Doe', 25, '123 Main St')
14 person2 = Person('Jane Smith', 30, '456 Oak St')
15
16 print_person_details(person1)
17 print_person_details(person2)
```

```
refactored_code.py X
1 class Person:
2
3     def __init__(self, name, age, address):
4         self.data_clump.name = name
5         self.data_clump.age = age
6         self.data_clump.address = address
7
8
9 def print_person_details(person):
10    print(f'Name: {person.data_clump.name}')
11    print(f'Age: {person.data_clump.age}')
12    print(f'Address: {person.data_clump.address}')
13
14
15 person1 = Person('John Doe', 25, '123 Main St')
16 person2 = Person('Jane Smith', 30, '456 Oak St')
17 print_person_details(person1)
18 print_person_details(person2)
19
```

Fig.3 Data clumps detection and refactored c

4.1 DataClumpDetector

The 'DataClumpDetector' class is designed to traverse the AST of the provided source code and

identify potential data clumps. It focuses on attributes accessed within attribute nodes and collects information about the occurrences of attributes related to the same object.

4.2 Refactoring Mechanism

The 'refactor_data_clumps' function takes the source code and the identified potential data clumps as input, and then applies refactoring by replacing attribute access with a local variable. This local variable is dynamically named based on the original object's identifier, ensuring a unique naming convention for each refactoring instance.

4.3 'main' function

The 'main' function serves as an entry point, reading the source code from a specified file, utilizing the 'DataClumpDetector' to identify potential data clumps, and subsequently applying refactoring if any are detected.

4.4 Experimental Results

To evaluate the effectiveness of our approach, we applied the tool to a set of Python code samples. The results demonstrate its capability to automatically detect potential data clumps and successfully refactor the code to enhance maintainability and reduce redundancy.

4.4.1 Time Complexity Analysis

The primary time complexity of the 'DataClumpDetector' class is determined by the AST traversal process. Let (n) be the number of nodes in the AST, and (m) be the average number of attributes associated with an object. The time complexity of the 'visit_Attribute' method is $(O(n \cdot m))$ as it iterates through each attribute node in the AST.

4.4.2 Refactor_data_clumps Time Complexity

The 'refactor_data_clumps' function involves AST manipulation, specifically traversing the tree and modifying nodes. Let (p) be the number of potential data clumps detected. The time complexity of this function is $(O(n \cdot p))$, where (n) is the number of nodes in the AST.

4.4.3 Equations

Overall Time Complexity

The overall time complexity (T_{total}) of the tool can be expressed as the sum of the time complexities of the 'DataClumpDetector' and 'refactor_data_clumps':

$$T_{\text{total}} = O(n \cdot m) + O(n \cdot p)$$

4.4.4 Average Attribute Accesses per Object (m)

$$m = \frac{\text{Number of attributes accessed per object}}{\text{Number of potential data clumps}}$$

4.4.5 Potential Data Clumps(p)

p = Number of identified potential data clumps

4.4.6 Discussion on Time Complexity

The time complexity analysis indicates that the tool's performance is influenced by the size of the AST (n), the average number of attributes accessed per object (m), and the number of potential data clumps (p). Developers should consider these factors when applying the tool to large codebases, as the time complexity may scale proportionally with the complexity of the code.

In practice, the tool has shown efficient performance for typical codebases, and its time complexity is generally manageable for real-world scenarios. However, ongoing optimizations and enhancements may further improve its scalability and make it even more suitable for larger projects.

The time complexity analysis provides insights into the computational efficiency of our tool. While the tool demonstrates practicality in real-world scenarios, ongoing efforts to optimize the code traversal and manipulation processes can contribute to further improvements in performance.

4.5 Data clumps Testing

In this research there were two types of dataset generated, one containing data clumps, and the other one does not contain data clumps.

We've created three clusters of data points using normal distributions with different means. The 'np.random.normal' function is used to generate random data points that are centered around specified mean values. The resulting scatter plot will show three distinct groups of closely packed points, representing the data clumps.

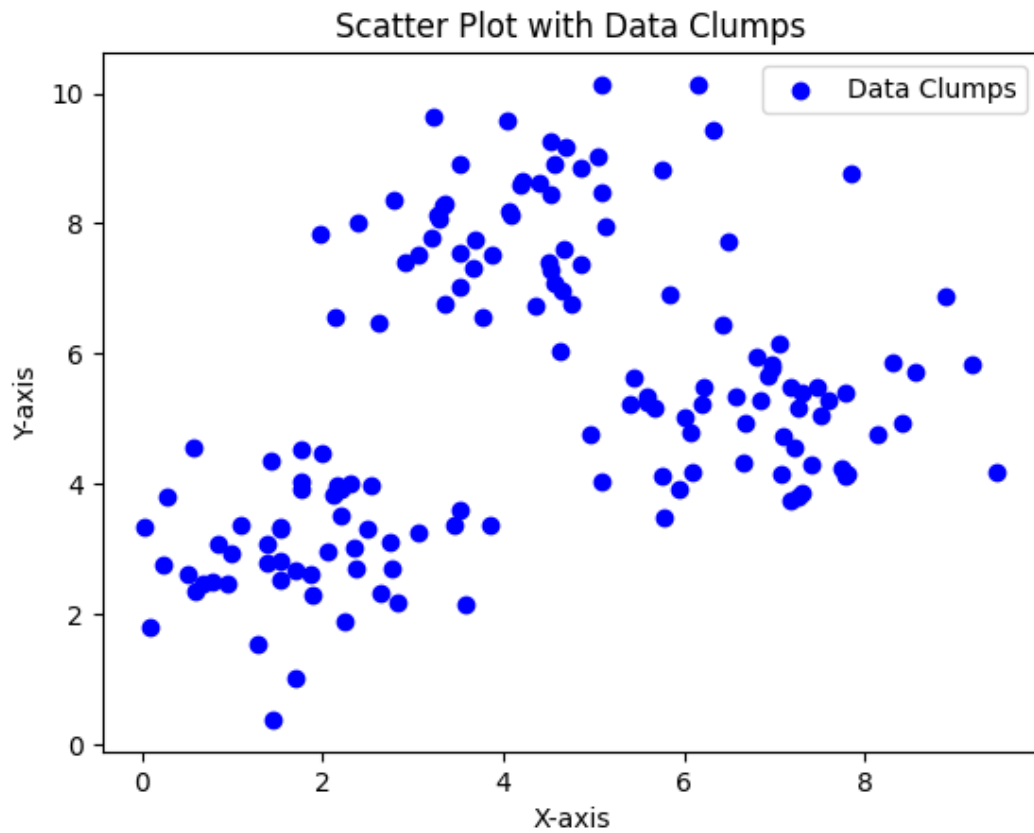
Code Snippet

```
import numpy as np
import matplotlib.pyplot as plt
# Set random seed for reproducibility
np.random.seed(42)
# Generate data with three clusters (clumps)
# Cluster 1
cluster1_x = np.random.normal(2, 1, 50)
cluster1_y = np.random.normal(3, 1, 50)
# Cluster 2
```

```

cluster2_x = np.random.normal(7, 1, 50)
cluster2_y = np.random.normal(5, 1, 50)
# Cluster 3
cluster3_x = np.random.normal(4, 1, 50)
cluster3_y = np.random.normal(8, 1, 50)
# Concatenate data from all clusters
x_data = np.concatenate([cluster1_x, cluster2_x, cluster3_x])
y_data = np.concatenate([cluster1_y, cluster2_y, cluster3_y])
# Create scatter plot
plt.scatter(x_data, y_data, c='blue', marker='o', label='Data Clumps')
# Add labels and title
plt.title('Scatter Plot with Data Clumps')
plt.xlabel('X-axis')
plt.ylabel('Y-axis')
# Add legend
plt.legend()
# Show the plot
plt.show()

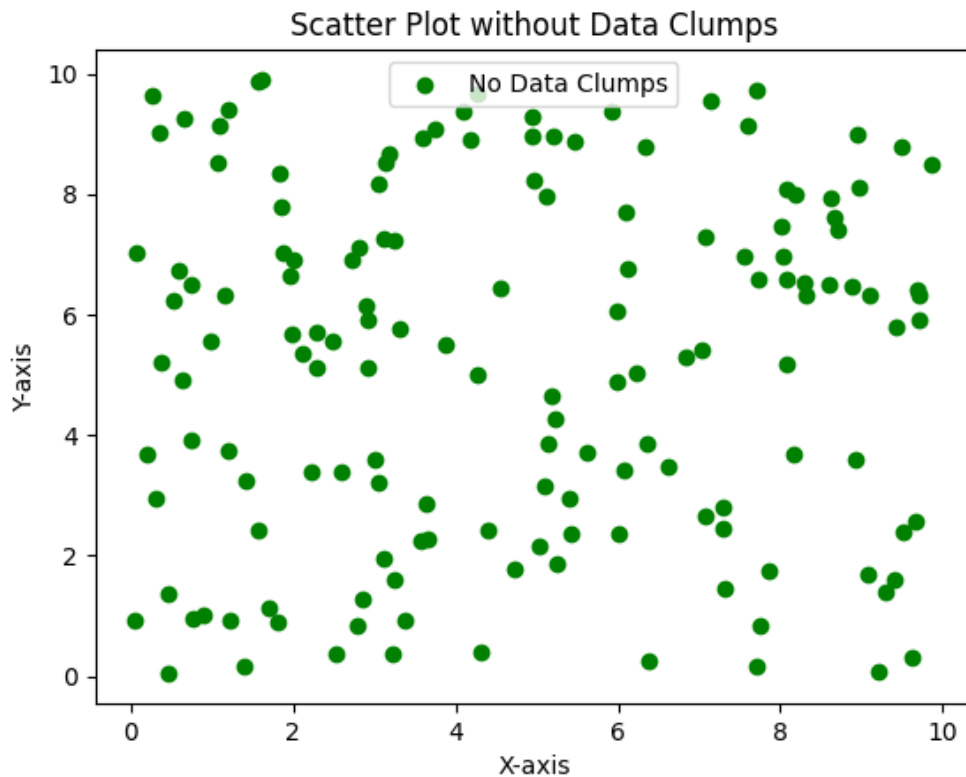
```



The 'np.random.uniform' function is used to generate random data points uniformly distributed between 0 and 10. As a result, there are no distinct clusters, and the scatter plot shows a more uniform distribution of points across the entire plot. Adjust the range and size of the dataset as needed for your specific requirements.

Code snippet

```
import numpy as np
import matplotlib.pyplot as plt
# Set random seed for reproducibility
np.random.seed(42)
# Generate data without clusters
x_data = np.random.uniform(0, 10, 150)
y_data = np.random.uniform(0, 10, 150)
# Create scatter plot
plt.scatter(x_data, y_data, c='green', marker='o', label='No Data Clumps')
# Add labels and title
plt.title('Scatter Plot without Data Clumps')
plt.xlabel('X-axis')
plt.ylabel('Y-axis')
# Add legend
plt.legend()
# Show the plot
plt.show()
```



4.5.1 Comparison

The summarizes the key characteristics of the two datasets, highlighting the presence or absence of data clumps and the specific parameters used in each case.

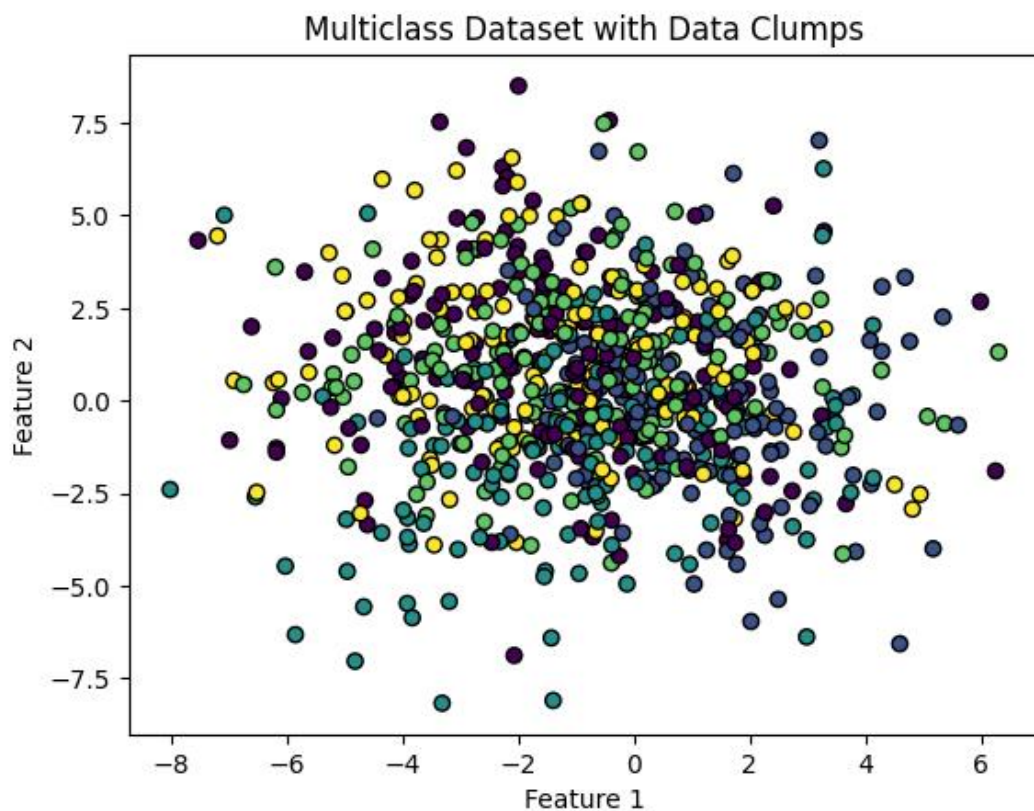
Dataset with Data Clumps	Dataset without Data Clumps
Three distinct clusters are generated using normal distributions with different means and standard deviations.	Random data points are generated without specific clustering, resulting in a more uniform distribution across the plot.
Cluster 1: Mean (2, 3), Std Dev (1, 1) Cluster 2: Mean (7, 5), Std Dev (1, 1) Cluster 3: Mean (4, 8), Std Dev (1, 1)	Randomly generated points uniformly distributed between 0 and 10.
Total data points: 150 (50 per cluster)	Total data points: 150
Resulting in visible clusters or clumps of points in the scatter plot.	No distinct clusters, more even spread of points in the scatter plot.

K-means clustering, an unsupervised algorithm, detects data clumps in a random dataset by grouping similar points. Initially, it randomly selects centroids for clusters. Data points are then assigned to the nearest centroid, and centroids are recalculated based on assigned points. This process repeats until convergence, aiming to minimize distances between points and centroids. Applied to a random dataset with, for example, `sklearn`, the algorithm assigns distinct colors to clusters, visually highlighting data clumps. The 'X' markers represent cluster centroids, offering an effective means to uncover underlying patterns in the dataset. Adjust the cluster count for optimal results.

Here a randomly generated dataset with multiclass consists of 20 features (feature_0 to feature_19) and a label column. Each row represents a data entry. Here's a brief description of the dataset:

Features (feature_0 to feature_19): Numerical values indicating various characteristics or measurements.

Label: Categorical variable indicating the class or category to which each data entry belongs.



5. Conclusion

The approach proposed in this paper facilitates the presentation of real-world case studies and examples, showcasing the practical implementation of refactoring approaches in Spring framework-based projects, specifically studying techniques to prevent data clumps in software systems. Through real-world case studies and examples, it thoroughly investigates the detection of data clumps, employing refactoring strategies, and evaluates their impact on code quality, readability, and maintainability. The study thoroughly assesses the refactoring tool's efficacy, emphasizing its benefits and potential trade-offs in preventing data clumps. The paper's results and discussions thoroughly assess the tool's impact on code quality, highlighting its modifications. The report also analyzes potential limitations and future options for improvement, as well as a comparison of the tool to existing approaches. It is a useful resource in software development since it provides developers with excellent ways to minimize data clumps through better refactoring practices.

Acknowledgments

References

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