A Clustering Approach to Classify Lock Contention Fault Types Utilizing Run-time Performance Metrics for Java Intrinsic Locks

by

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Abstract

Locks are essential in java-based multi-threaded applications as this mechanism provides a proper solution to synchronizing shared resources. However, improper management of locks and threads can lead to contention; as a result, it causes performance bottlenecks and prevent java application from further scaling. These types of faults are challenging to debug because they are caused by complex interactions among the threads and can only be detected at run time. Nowadays, performance engineers use legacy tools and their experience to determine causes of lock contention. In this research, a clustering-based approach is presented to help identify the type of lock contention fault to facilitate the procedure that performance engineers follow, intending to support developers with less experience eventually. The classifier is based on the premise that if lock contention exists it is reflected as either **a) threads spend too much time inside the critical section and/or b) threads' high frequency access to the locked resources**. Our results show that a classifier can be effectively trained to detect lock contention caused by high hold time and contention due to high frequency with which threads send access requests to the locked resources.

Keywords— Java, Locks, Monitors, Contention, Concurrency, Run-time Faults, Localisation, JLM, Linux Perf, Clustering, Classification, Software Engineering

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Statement of Contributions

I performed the majority of the synthesis, testing of membrane materials, and writing of the manuscript.

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Chapter 1

INTRODUCTION

1.1 INTRODUCTION

Java programming language has multi-threading capabilities for concurrent programming. It provides an Application Programming Interface (API) for managing multi-threaded concurrency processing known as an intrinsic lock or monitor lock that observes the behaviour of threads and enforces exclusive access to any object's state [30]. Every object in java has an inherent lock that monitors the threads' movements trying to access shared resources. However, Java Virtual Machine implements this built-in locking mechanism inside in it that provides the opportunity of thread synchronization for concurrent programming [27].

Although, synchronization is essential in multi-threaded applications, it introduces some level of thread contention when applies. In a thread contention scenario, threads are being blocked by multiple threads when two or more threads try to access the same shared resources to avoid data inconsistency. These multiple threads then undergo a slow operation and sometimes even suspend execution entirely. This can result in the poor performance of a multi-threaded application. This performance degradation is typically known as a contention fault or performance bottleneck due to contention.

It is also known that contention faults are caused by two primary issues [20] described by Brian

Goetz in his book that are:

- Type 1 - Threads spend too much time inside the critical sections.
- Type 2 - High frequency with which threads send access requests to the locked resources.

In a critical section, introducing few additional and unnecessary computations makes one thread hold the lock longer than expected time. This indicates the first type of fault. According to the Brian Goetz book if an operation holds a lock for more than equal to two milliseconds then no matter how many idle processors are there, the throughput of the application never exceed five hundred operations per second [20]. On the other hand, when many shared resources are tighten up in a single lock increases the access frequency by threads when they are increases in number, creates the second type of contention fault scenario.

Leaving these type of patterns in a concurrent code-base creates performance bottlenecks, which is difficult to find using any static analysis approach. Therefore, the run-time metrics help developers identify the actual cause for contention hidden at the code level. With this in mind we are interested in developing a contention classifier that assists in identifying contention fault types throwing some proper recommendations.

It is hard to write concurrent programs and developers usually come back to refactor the portion of the code where the concurrency feature resides to make their concurrent code more efficient. A recent study reports that more than 25% of all critical sections are changed at some point by the developers, both to fix correctness bugs and to enhance performance [37] [22]. The motivation for our work is to automate the contention fault detection and identification by leveraging on the fact that there are 2 potential causes for contention faults as described by Brian Goetz [20].

In this research we focus on contentions caused by the improper use of java intrinsic locks. Improper use of intrinsic lock implies leaving two types of harmful patterns in the concurrent section of code-base. We use a run-time analysis approach over static code analysis because these faults surface at run-time. Even though contention bottlenecks have been investigated in the software community for a while they are still difficult to detect and analyze and usually it is a job performed by an experienced performance engineer. Typically application developers do not have the skill set that a performance engineer has. To detect contention bottlenecks, performance engineers usually use some legacy tools such as JLM (Java Lock Monitor) and Linux *perf* and follow the steps below:

- **Step 1:** Run the Linux *perf* command and collect the raw *perf* data.
- **Step 2:** Run a script to make the *perf* data human-readable.
- **Step 3:** Analyse the *perf* log and look for possible symbols related to significant lock-contention and degradation in the application's performance. Also they look for some OS routines that was transferred by JVM as it fails at some point to handle the situation.
- **Step 4:** Run JLM and collect the logs output, if the perf output confirms there are possible lock contention situation.
- **Step 5:** Analyse the JLM log and look for the possible contented monitors
- **Step 6:** Search for possible bottlenecks based on available symbols, OS routines and JLM monitors.

First of all these tools fail to distinguish the contention fault types either holding the lock more than expected time or high frequency with which threads send access requests to the locked resources, and secondly, fail to produce recommendations or suggestions about the cause of the contention. However, our preliminary research has found that these fault types tend to leave some patterns in the run-time logs depending on their behaviors. Therefore, we believe that it is possible to classify contention fault types into these 2 causes using a clustering approach that will identify the essential features from the JLM and *perf* run-time metrics. We also believe that the classifier can identify cases where contention is minimal or non-existent with the overall goal of lessening the human effort in identifying the contention bottlenecks.

1.2 MOTIVATION

The traditional approaches [11] [15] [38] [9] [36] [19] [31] fail to distinguish the difference between the two fault types, Type 1 and 2. These approaches present different thread activities, blocked thread lists, and lock-monitor statistics that do not provide insight into these two faults. Therefore, developers struggle to identify the actual reason for faults and can not distinguish which fault needs to be addressed. In addition, it is difficult to check the fault's reason manually at run-time. However, contention metrics (e.g., GETS, TIER2, TIER3, and AVER_HTM) can benefit developers from identifying the fault types during the run-time.

Therefore, we propose to automate the fault identification using machine learning from the contention metrics. In our approach, we create a dataset considering different features that are responsible for occurring these faults. We use a clustering approach to classify the fault types so that developers can easily recognize and resolve the faults.

1.3 CONTRIBUTIONS

The main contributions of our research are:

1. Classifying contention fault types of java-based concurrent application through clustering techniques utilizing the run-time metrics that come from performance analyzer tools.

2. Generation of a dataset containing contention statistics and formalization of the experiments so that by leveraging this formalization one can enrich dataset with new sets of contention faults.

1.4 ORGANIZATION OF THE PAPER

Our research paper is organized by the following chapters. In Chapter 2 we introduce the reader to some related works discussing their approaches. There are quite a few related works listed that have been dealing with java performance degradation due to contention bottlenecks. We end the chapter by introducing the readers to the current traditional approaches that are being used to analyze lock contention faults or bugs. It describes how performance engineers operate IBM health center and what the steps are, how performance engineers deal with another popular tool called YourKit. We also list the current approaches' limitations at the end of this chapter.

We continue in Chapter 3 where we present our methodology for our approach. First, we present a high-level workflow of our approach, then we try to explain the three main method steps that are essential to classify the lock contention faults. The very first step describes performance metrics acquisition secondly, metrics aggregation and filtering, and lastly, how we perform data preprocessing and classification.

In Chapter 4 we try to present the dataset generation process and the environment we set up for the experiment, and it has the details of both the hardware and software configuration. In terms of software configuration, it describes the java version and JVM we use and the tools we installed to capture performance metrics and continue our work. The chapter includes a detailed explanation of the log generation process and how we perform an automated generation process. Later this chapter, we detail the test formalization where we describe how the example code was configured to exercise and what parameters we changed during the experiment. In the end, the dataset information is discussed.

We present the clustering results in Chapter 5. In this chapter, we discuss the high-level observation of JLM and perf data with different example code configurations. We analyze the correlation matrix output of the heatmap and analyze essential features for our dataset. Before jumping into the clustering process, in this chapter, we also try to show some verification and validation using popular R and Python packages that the data we generated is cluster-able. After that, we continue our work applying KMeans, PCA, and DBSCAN algorithms, and before that, we verify the actual cluster number using silhouette coefficient and elbow method. Finally, we end our chapter by evaluating the performance of our model.

Our next Chapter 6 discusses the mechanism we introduce to label the fault types leveraging the test parameters such as the number of threads and sleep time we record during the experiment. Plotting the threads and sleep time help us to label the fault types. The end of this chapter illustrates the advanced analysis of the metrics that are useful for further classification. And it has a short discussion about why the analysis and dominant metrics are crucial to the performance engineer as well as developers.

Our final Chapter 7 has the full overview of our work. We include the limitations of our current work and lastly it is ended with discussing the future work that we have in our bucket list.

Chapter 2

Background and Related Work

2.1 Introduction

Analyzing lock contention performance issues and locating and resolving them is a hot topic and has been investigated by developers and researchers for more than a decade. Because of the independent threads and their movements, it is hard to detect the locking issues, and it is more problematic when there are more independent state variables to be locked. Moreover, these lock-related issues are only be detected at run-time. Many approaches and tools have been published in order to deal with resolving contention and java performance degradation due to contention. Most of them discuss identifying contention or critical section pressure, and some of them have dealt with detecting and locating the contention region. Although these methods are extensive and efficient, they still fail to discuss the two fault types, which is holding the critical section for a long period of time and high frequent requests to the locked resources by threads. Moreover, these approaches lack analyzing the contention statistics and performing any classification process as we present in this work. However, in this chapter, we divide the content into two main sections a) discussing some approaches to deal with contention issues, b) discussing some popular methods and tools that have the solution to resolve contention and performance degradation.

2.2 Related Work

Lock contention performance bottlenecks have been investigated in the the past few years with researchers primarily focusing on detecting and locating the root cause of the lock contention Very few papers though have attempted to categorize the lock contention as we are investigating.

Nathan R. Tallent et al. [35] detail three approaches to gaining insight into performance losses due to lock contention. Their first two approaches used call stack profiling and proved that this profiling does not yield insight into lock contention. The final approach used an associated lock contention attribute called thread spinning that helps yielding insight into lock contention. Although the paper's analysis is based on ”C” concurrent programs, their approaches are similar to ours. We are also considering run-time logs for the analysis and determining run-time metrics directly related to the contention fault and impacting the bottlenecks.

Another similar by Peter Hofer et al., [23], proposed a novel approach to detect lock contention in a Java application by tracing the locking events extracted from JVM. Tracing call chains of both the blocked and blocking threads confirms the contention causes and severity of the running application. The main difference between their work and ours is the metrics we extracted from the run-time traces and that bear the potential weight for contention severity measurement.

Florian David et al. proposed a profiler named ”free-lunch” that measures critical section pressure (CSP) and the progress of the threads that impede the performance [11]. In this work, they modified the JVMTI and captured the thread progression. This paper also stated that they failed to determine the correlation among the metrics extracted from IBM JLA (Java Lock Analyzer) while we have been able to observe some relations between the performance metrics and the lock contention. This paper also lacks a description of the metrics related to different contention fault types.

A different style of approach was proposed by E. Farchi et al. [15] where they create or find patterns that describe issues in the code and attempt to match those to real code examples. The paper used a tool called ”ConTest” to test their assumption. They found that their system was able to enhance the ”ConTest” tool’s ability to locate concurrent bugs.

Sangmin Park et al. [32] proposes a tool named FALCON that dynamically analyses concurrent programs and attempts to locate problematic data-access patterns based on memory-access sequences among threads. It does this by observing memory access during the code execution and assigns them a pass or fail based on the pattern, the pass/fail ratio is then used to calculate a suspicion rating of the code. The tool is different from others because it captures both order violations and atomic violations.

R. Gopalakrishnan et al. [21] proposed a system that identifies problems in code structure and is able to provide a solution without having to first execute the code. It uses machine learning and text mining algorithms to mine the source code multiple open-source projects and identify the “source code topics” which are correlated with architectural tactics, these are then used to predict what the program should have based on the requirements that the machine learning model predicts. This is not the type of classification that we are using, however it is a interesting approach to the problem.

Chen Zhang et al. [38] implemented a static synchronization performance bug detection tool that detects critical section identifier, loop identifier, inner loop identifier, expensive loop identifier, and pruning component. They collected 26 performance bugs from three real-world distributed systems HDFS, Hadoop MapReduce, and HBase, to detect performance bugs, and their detection tool performed well on these. The main difference between this method and our is static and dynamic analysis. Also, they did not analyze the log trace and classify the fault types.

The IBM Health Center [9], a powerful tool, is built for internal use and quite good enough to deal with detecting the lock contention in a java-based application.JLM is listed under this tool but it requires manual observation and intervention to detect and locate the contention related bottlenecks.

2.3 Traditional Approaches

In our related work section, we attached several traditional approaches that analyze lock contention bottlenecks, but none had ever gone with the clustering approach like ours. The benefits of clustering techniques are many. It reduces human intervention, reveals insight into the contention-related performance metrics, reveals new classes of fault types. However, there are several lock contention monitoring tools & techniques published out there. Among them, some popular tools are widely used, such as ”IBM Performance Inspector” [9], ”YourKit Java Profiler” [36] etc. In this section we intend to go through these tools and their approaches for detecting lock contention bottlenecks in case it occurs.

2.3.1 IBM Performance Inspector

IBM Performance Inspector is a performance benchmark-suite under IBM Health Center. Tools such as JPROF, JLM, TPROF etc, are available under this performance inspector to profile java application health. However, JLM is efficient enough to detect any contention bottlenecks in a java application. In order to detect contention related performance issue, performance engineers usually follow some manual steps while using these tools. These steps are:

1. **Observe Perf data:** Let’s assume, our example code `synchronized task` has a performance issue with comparatively low throughput. As a performance engineer, one should go for the perf testing before going for any other tools. However, perf tool records the kernel’s memory footprint and collects the samples of the symbols printed on the memories. The sweet spot of the perf recording is, it collects all the symbol names that are either from operating system’s tokens or tokens used in the user space applications such as java application. Moreover, in case of any issues with the application perf trace captures different signatures. Hence, if the application encounters with contention-related issue then those related symbols will be reflected in the perf trace.

   After scanning through the perf data, performance engineers capture the most probable hottest region of the application due to heavy contention along with the contention-related symbols. A single snap-shot of perf data for our example code SyncTask is shown in Figure 2.1. However, if we look carefully then we can see that some symbols related to contention are marked with bluish flag. Additionally it is also visible that the method `run` from the class `SyncTaskThread` is reflected on the perf trace which is the hottest region of the example code.

```
  173    0.55% [unknown:[vdso]]
  204    0.65% omrthread_sleep_interruptable
  227    0.73% update_curr
  228    0.73% update_cfs_group
  277    0.89% flexible_sched_in
  280    0.90% __const_udelay
  305    0.98% ctx_sched_in
  388    1.24% __memmove_avx_unaligned_erms
  422    1.35% bytecodeLoopCompressed
  495    1.58% _raw_spin_lock
  504    1.61% x86_pmu_disable_all
  873    2.79% psi_task_change
 1039    3.32% native_sched_clock
 1780    5.69% VM_BytecodeInterpreterCompressed::run
 2999    9.59% native_write_msr
 3486   11.15% native_read_msr
 3717   11.88% delay_mwaitx
 6711   21.46% visit_groups_merge
31277           --total--
```

Figure 2.1: A single perf snapshot for Sync Task example code indicating high sample counts for some contention-related symbols

2. **Observe JLM data:** Now as we are quite confirmed that the issue is nothing but contention related bottlenecks, it is worth looking at the JLM data next. As a performance engineer one should run then activate the JLM to collect statistical data related to highly contended monitors from its agent. JLM collects contention related stats using the agent and this agent should be included as a run-time argument while running the java application. After capturing the JLM data, performance engineers typically scan through the `Java Inflated Monitors` block to obtain a high level overview of contented monitors and the stats. A single snapshot of JLM data for the `SyncTask` example code is shown in Figure 2.2. Perf log reveals the hottest region, in contrast JLM exposes the monitors that responsible for high contention and possible reason behind the hottest part of the code.

```
    0       0       0       0       0       0       0    0       0  [00007F70280D7680] MM_FreeEntrySi
    0       0       0       0       0       0       0    0       0  [00007F70280D7828] MM_FreeEntrySi
    0       0       0       0       0       0       0    0       0  [00007F70280D7300] MM_MemoryPoolA
    0       0       0       0       0       0       0    0       0  [00007F70280D7198] MM_MemoryPoolA
    0       0       0       0       0       0       0    0       0  [00007F7028056CD8] MM_FreeEntrySi
    0       0       0       0       0       0       0    0       0  [00007F70280DE280] MM_FreeEntrySi
    0       0       0       0       0       0       0    0       0  [00007F70280DE428] MM_FreeEntrySi
    0       0       0       0       0       0       0    0       0  [00007F70280E38D0] MM_MemorySubSp

Java (Inflated) Monitors

%MISS     GETS   NONREC     SLOW      REC    TIER2    TIER3 %UTIL AVER_HTM  MON-NAME

  100       18       18       18        0        0        0    96 2016737495  [00007F6F880027A8] SyncTask2@00

LEGEND:
              %MISS : 100 * SLOW / NONREC
               GETS : Lock Entries
             NONREC : Non Recursive Gets
               SLOW : Non Recursives that Block
                REC : Recursive Gets
              TIER2 : SMP: Total try-enter spin loop cnt (middle for 3 tier)
              TIER3 : SMP: Total yield spin loop cnt (outer for 3 tier)
              %UTIL : 100 * Hold-Time / Total-Time
            AVER-HT : Hold-Time / NONREC
```

Figure 2.2: A single JLM snapshot for Sync Task example indicating contention due to high hold time reflected in key AVER_HTM

After obtaining the JLM data performance engineers go for the analysis such as if the AVER_HTM count is high then it is pretty obvious that the locking issue is related to fault type 1 where the threads are holding the lock more than expected. On the other hand, if the spin related count such as, `TIER2`, `TIER3` etc then it is related to fault type 2 when the locked resources are frequently accessed by the threads. Based on the fault type engineers usually go back to the code base and reduce contention by removing excessive work under critical section if the contention is related to fault type 1. Else they suggest to split the locks and make it more granular as the locked resource are frequently accessed.

3. **Locate Bottleneck Area:** At this stage performance engineers have the JLM contention results and symbol names possibly responsible for the hottest regions of the application, they usually move to the next step, where they dig deeper into the call stacks and search for those

symbols (method names). However, after expanding the call stacks, engineers point out the code blocks responsible for poorly managed concurrent code due to inefficiently managed locks.

2.3.2 YourKit Java Profiler

YourKit [36] is a popular java profiling tool which is a commercial, closed-source software built by YourKit GmbH. This profiler is capable of capturing java applications' profile data and it is widely used by the performance engineers to monitor the java applications' health. YourKit java profiler is also leveraging its agent library to capture the profiling data. It has the options to capture the profile data both for java application / JVM running in local environment or in a remote machine. Similar like other java profiling tool it is also capable of seizing the data for CPU usage, Memory usage, Threads & Monitor activities etc. YourKit profiler comes with a powerful graphical user interface that provides easiest navigation features to the user. Once the profiler starts, it also allows the user to pause and resume capturing profile and events occur in a running VM. As a performance engineer one has to follow the steps below to collect the profiling data using this tool:

1. **Prepare Agent:** Before moving forward, performance engineers have to make the agent library ready for the application to be used as a run-time argument. Several options can be configured for the agent, such as CPU profiling, threads and monitors profiling, exceptions profiling, memory usage profiling etc. In order to enable the agent start collecting data, first one has to select the option from home window that says "Profile local or remote java applications". The home window of the YourKit profiler is shown in Figure 2.3. Under the "Monitor Applications" section of the application UI one can find the listed JVM running in local or remote machine. After completing the agent configuration and run java application with that arguments, YourKit grabs the running java pids and lists under this section to allow user start profiling. See the Figure 2.4.

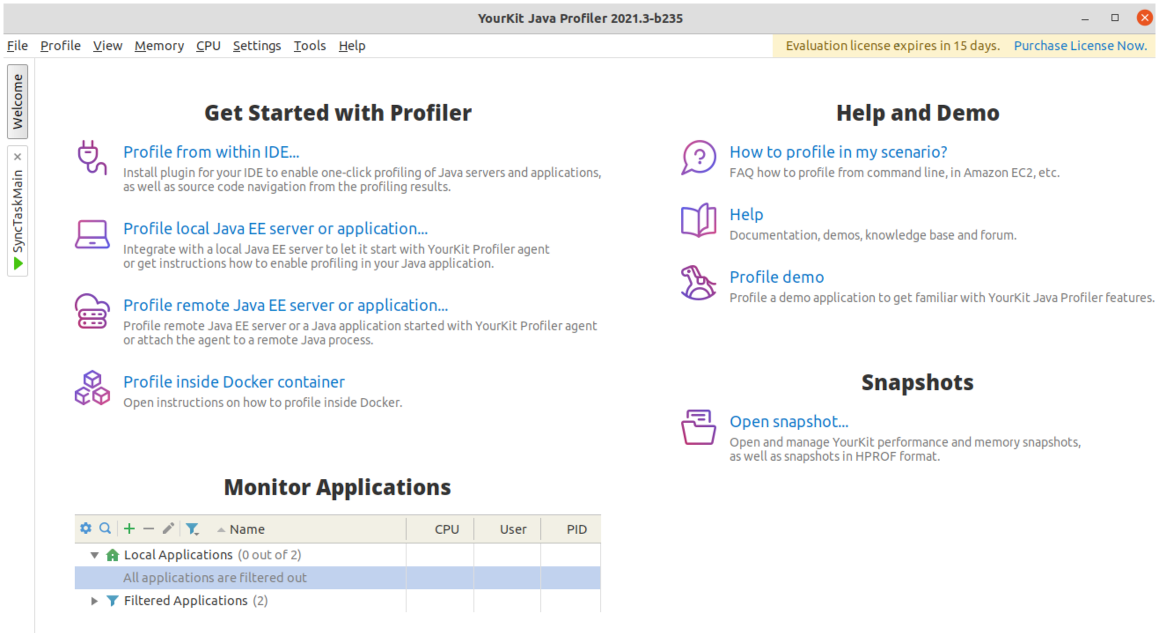


Figure 2.3: Home window of YourKit java profiler allows user to start profiling applications

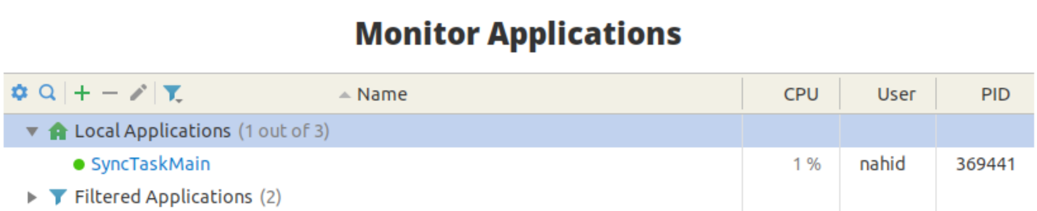


Figure 2.4: Available applications list window of YourKit java profiler allows user to start profiling applications

2. **Capture Profile Data:** After configuring the necessary arguments, the agent is now ready to collect the profiling data. Engineers attach the agent as a run-time argument to the application, and it starts displaying the data to the YourKit application UI. However, there are options in the YourKit application UI to capture the data for specific profiling whenever it is needed. For our example application `SyncTask`, thread activities profiling and monitor

usage profiling are captured. The thread and the monitor profiling are shown in Figure 2.5 and Figure 2.6 respectively.

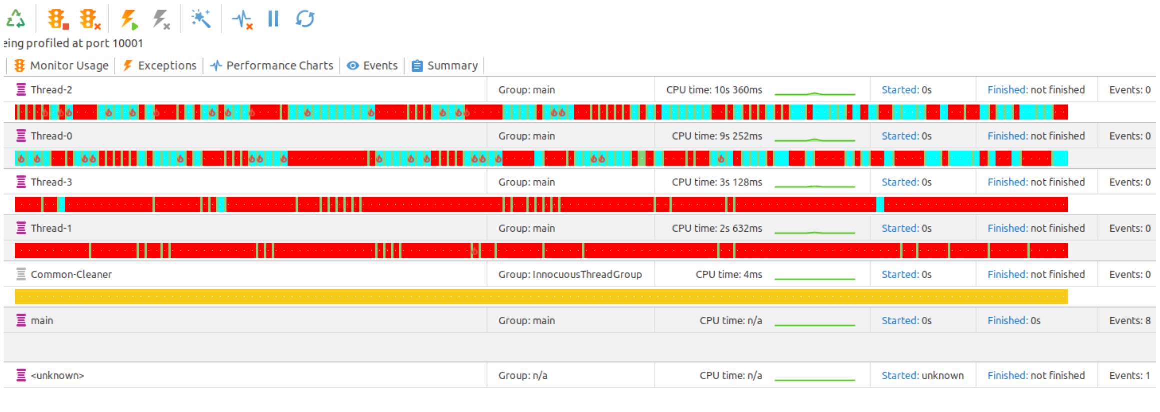


Figure 2.5: Thread activities profiling using YourKit java profiler for SyncTask example

3. **Understanding Contention:** Inspecting the Figure 2.5 we can observe that the profiler shows the thread progression. As the example runs with only four threads, from the figure it is clearly visible that it has four thread progress bars created by our SyncTask example code. However, the progress bars have two different colors and the green color indicates the thread is active and running, and the red time frame for the thread progress bar reflects the blocking state of the thread. If any thread is blocked by some other threads more than usual time then we can confirm that it is the sign of contention. In the thread activity bars, it is visible that the percentage of red color is way more than the other colors, indicating contention. After analyzing the thread activities, it is required to know the contended monitors in our application. The second Figure 2.6 illustrates the high-level overview of monitor uses and the waiting or blocked states of different threads. The corresponding thread for which the other thread is blocked is also noticeable from the monitor usage window of YourKit Profiler.

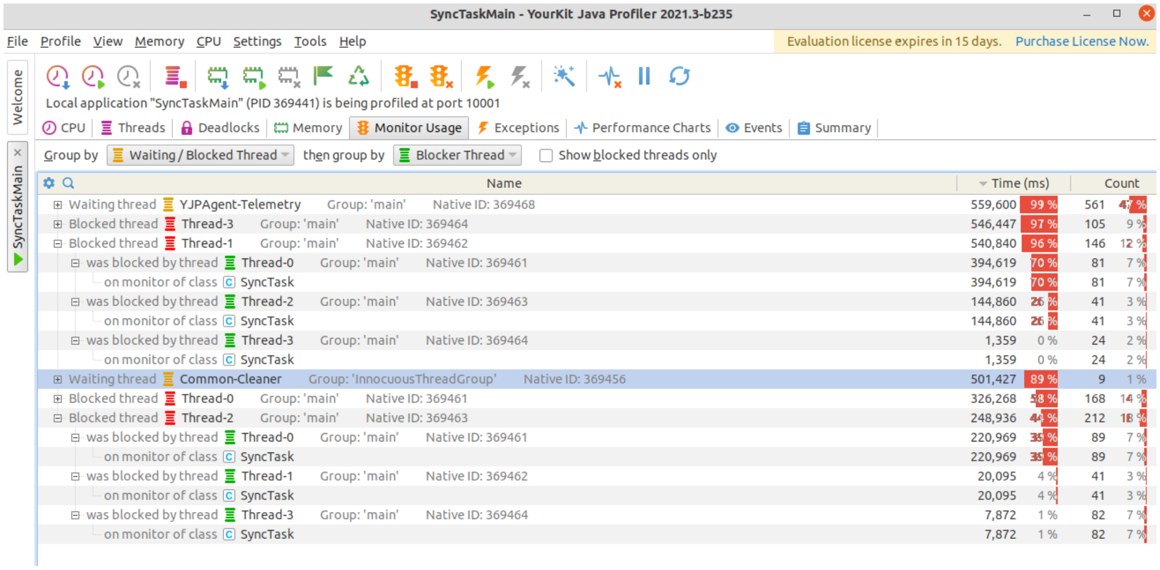


Figure 2.6: Monitor usage profiling for SyncTask example using YourKit java profiler

2.3.3 JProfiler

JProfiler [19] is a closed-source and commercially licensed Java profiling tool available in the market developed by ej-technologies GmbH, targeted at Java EE and Java SE applications. In order to analyze and visualize the lock-related performance issue using JProfiler, performance engineers usually operate the application graphical user interface. It comes with a powerful graphical user interface that let us perform profiling an application with ease. Like other common profiler it provides profiling options to perform analysis for local application as well as applications running in a remote machine. Leveraging dynamically-linked shared library, it enables connecting JVM in either local machine or remote and start profiling and collecting data. It also provides a headless mode that is capable of profiling the application in silent mode and captures necessary logs, then stores them to a desired directory from where one can collect and proceed with the further analysis. Unlike YourKit profiler, this profiler does not require us to prepare agent for it and all the operations are performed through its UI. Another great feature of the JProfiler is of operable as plugin for eclipse development IDE. It enables both memory profiling to assess memory usage and dynamic allocation leaks and CPU profiling to assess thread conflicts. Following are the steps a performance engineer has to perform to profile a java application with contention-related bottlenecks

1. **Initialize New Session:** As a performance engineer one has to start the application executable and open the window where it is possible to initialize the new session or start the session that has been created before. New session refers to the process of collecting logs from beginning discarding the older sessions. Additionally, another option is a the ”Attach” provides the opportunity to connect the profiler directly to a running VM. However, in order to start collecting the profiling data performance engineers have to choose any of these. In case of new session, one has to provide the necessary arguments for the profiler to be started, such as directory of the class or jar file, then command line arguments needed for the java application. And in case of ”Attach” option, choosing running VMs is available in the UI. A snapshot of new session window of the JProfiler is shown in the Figure 2.7

2. **Observe the Thread Activities:** After starting the session or connecting to a running VM, JProfiler usually starts collecting the profile data. In different modules it shows different profile statistics such as under ”Live Memory” window it shows memory usage and ”CPU View” enable profiling CPU usage. However, performance engineers turn on the window of ”Threads” and ”Monitors & Locks” to visualize the contention-related performance. For demonstration purpose, we started our new session with some high number of sleep times and 4 threads that simulates the contention. Looking at the Figure 2.8 it is clearly visible that the threads are running with red colors. Compared to the red colors, the percentage of the green color is really low. Also the yellow color represents the waiting mode of the threads which is also great in numbers.

3. **Observe the Monitors:** Observing poor conditions of the thread activities lead us to inspect the monitors of the application. Performance engineers need to know the monitors that are causing performance issues is listed under ”Monitor Statistics” window of the JProfiler. For

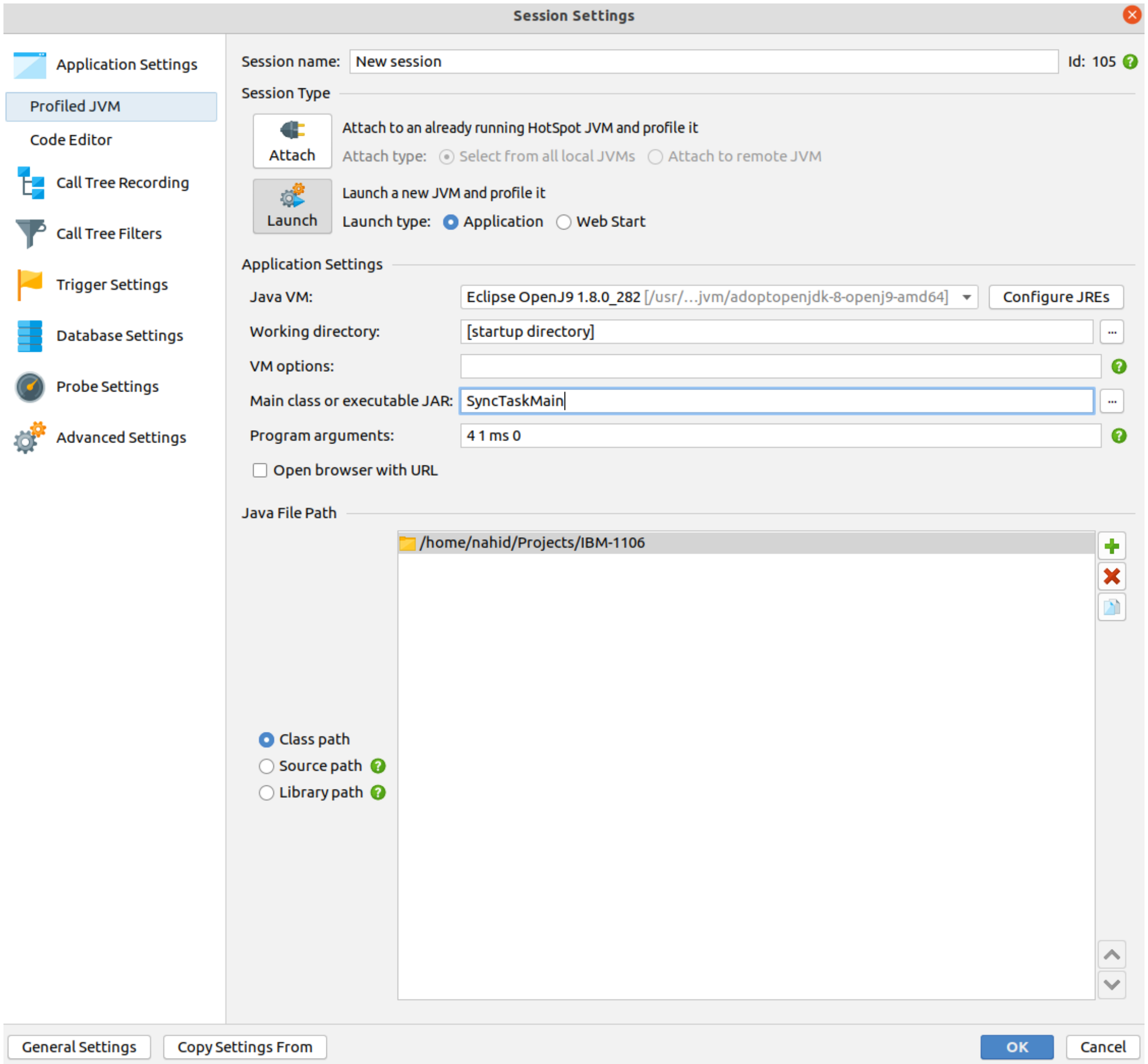


Figure 2.7: A snapshot of JProfiler's new session configuration window

our example SyncTask concurrent code the contended monitors statistics are listed under the monitor history, see Figure 2.9, and the monitor statistics, see Figure 2.10 respectively.

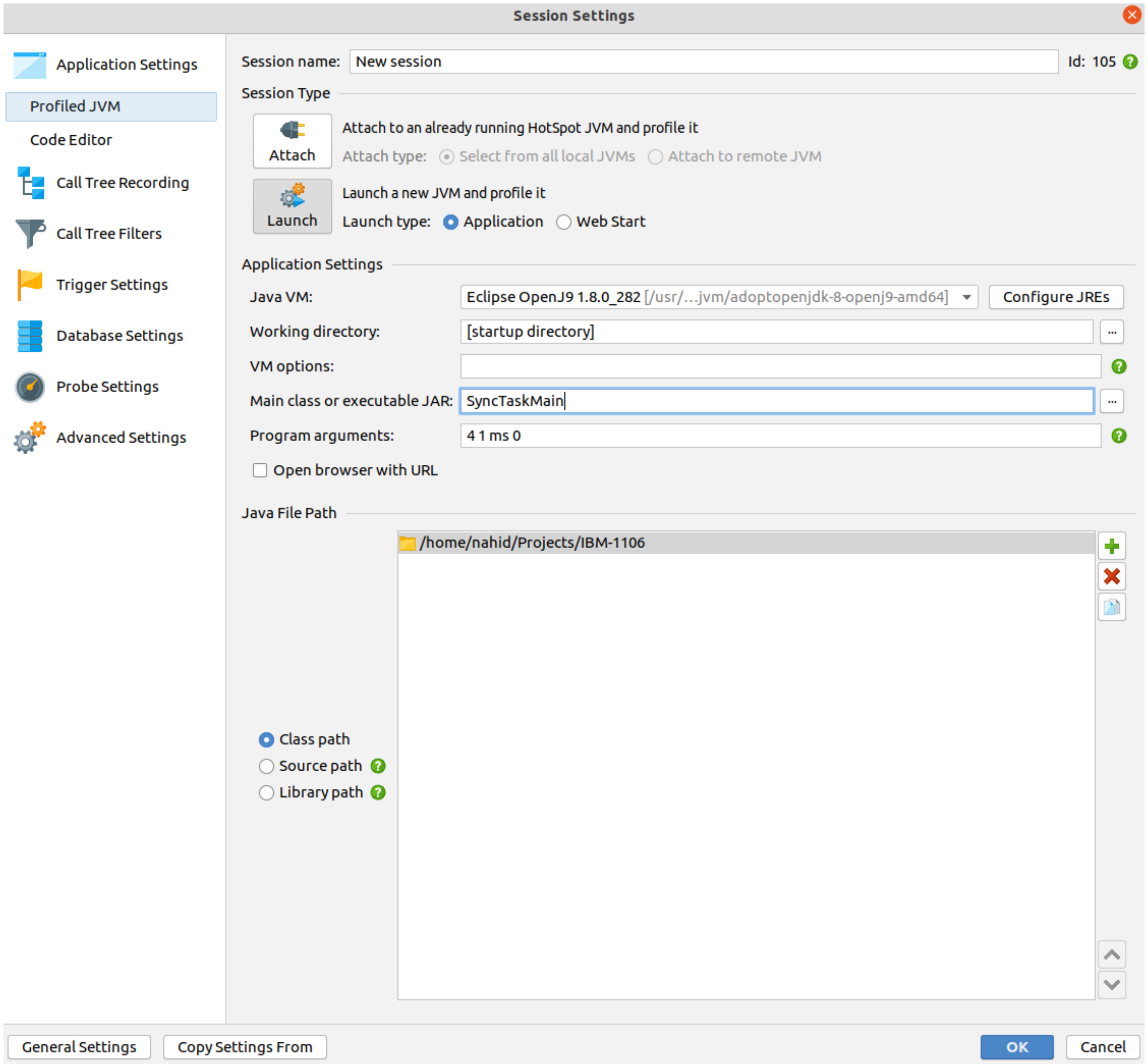


Figure 2.8: A snapshot of JProfiler's thread activities window captured for our SyncTask example code

2.3.4 Visual VM

VisualVM [31] is an open-source tool that provides a visual interface for viewing java applications' performance while they are running on a Java Virtual Machine (JVM) and for troubleshooting problems and profiling them. It has lightweight profiling capabilities designed for both development and

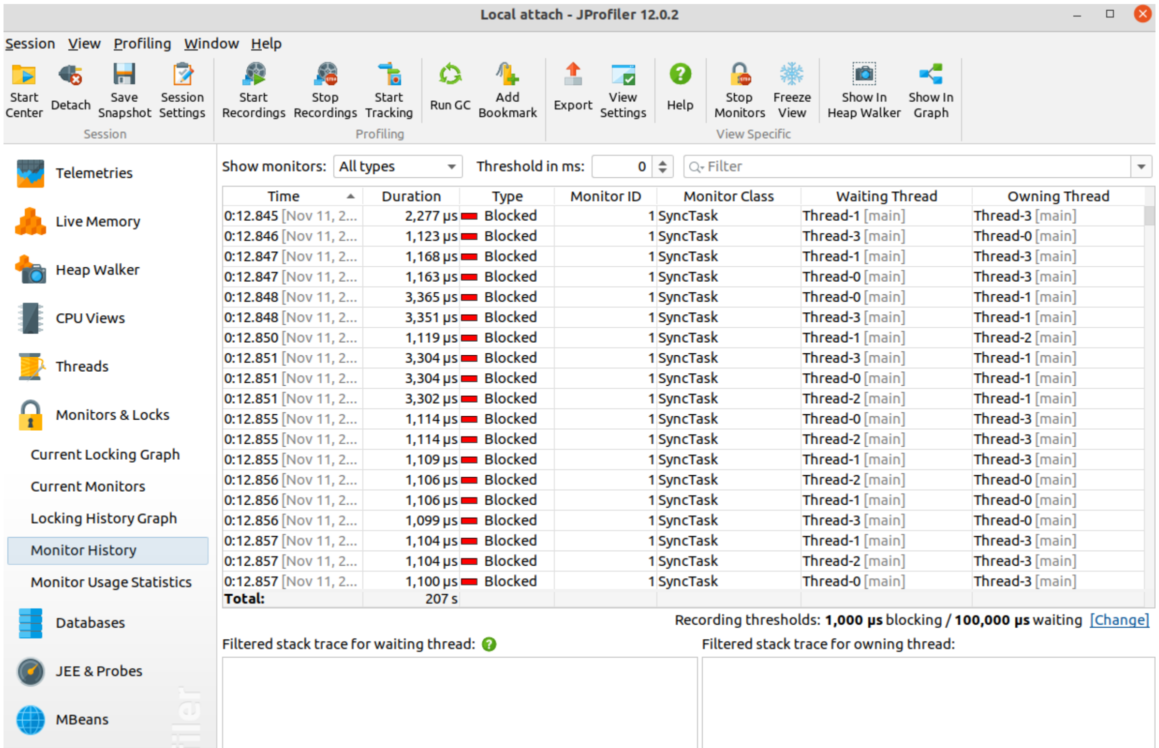


Figure 2.9: A snapshot of JProfiler's monitor history window captured for our SyncTask example code

production time use. Java application developers can use Java VisualVM to troubleshoot applications and monitor and improve the applications' performance. Java VisualVM can allow developers to generate and analyze heap dumps, track down memory leaks, browse the platform's MBeans and perform operations on those MBeans, perform and monitor garbage collection, and perform lightweight memory and CPU profiling. Developed by Oracle, this profiler was integrated with NetBeans IDE and comes as a default performance analyzing tool for java applications. Recently, NetBeans IDE discontinued the idea of integrating Visual VM as a default performance tool. Unlike YourKit profiler, this profiler also does not require us to prepare the agent for it. Instead, it captures the java application automatically running on a local or a remote machine. In the UI, it has a applications list bar where it shows all the captured running java applications. As a performance engineer, one should click on a particular application to start monitoring and profiling.

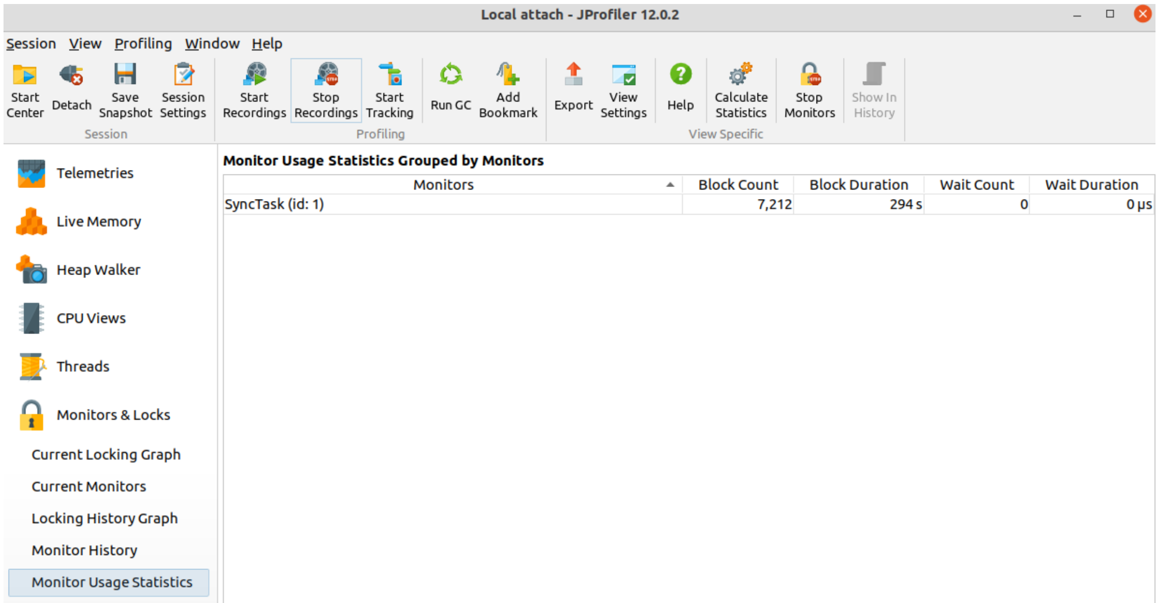


Figure 2.10: A snapshot of JProfiler's monitor statistics window captured for our SyncTask example code

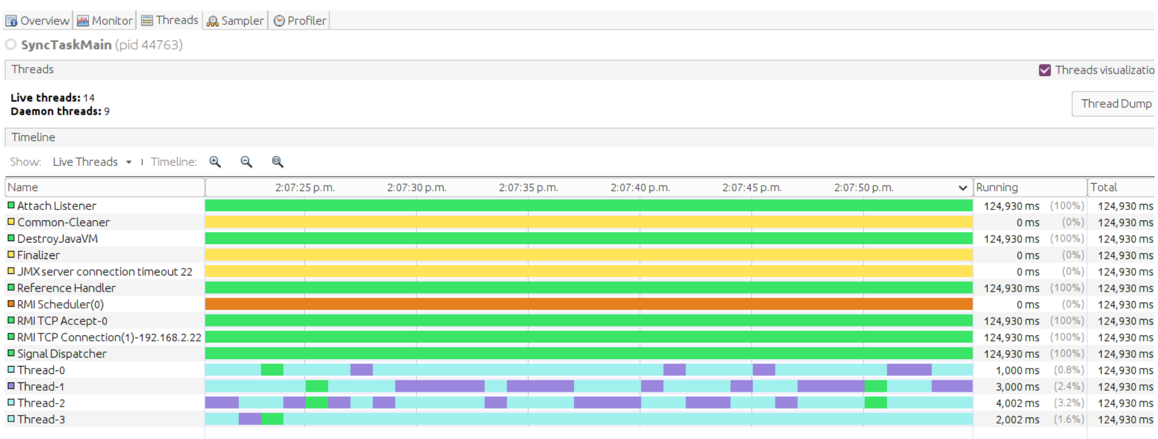


Figure 2.11: Visual VM thread profiling for sync task example

Monitoring the thread activities requires one performance engineer to move to the "Threads" tab of the UI window. Under this window, one can observe the real-time thread activities running in a java application.

A single snapshot of Visual VM is shown in Figure 2.11 where it presents the thread profiling of our example code ”SyncTask” with contention. Thread numbers 0 to 4 are spotted that are being used in our ”SyncTask” example code we are interested in. If we look carefully then it is clearly visible that the running time (green blocks) of 4 threads are noticeably low. Most of the time, they are blocked by each other. Moreover, it is also visible that the percentage of running time for those threads are 0.8%, 2.4%, 3.2% and 1.6% respectively. Additionally, Visual VM provides the option to take the total snapshot of the thread dump. A snapshot of the thread dump of our ”SyncTask” example code is shown in Figure 2.12. Thread activities in the thread dump show that thread-1, thread-2, and thread-3 are blocked and waiting for locking the monitor object. And the thread-4 has gone timed-wait, which means it is sleeping at the particular moment when the thread dump is taken.

SyncTaskMain (pid 53973)

Thread Dump

```
"Thread-0" #12 prio=5 os_prio=0 cpu=481.84ms elapsed=26.76s tid=0x00007fa5103c0800 nid=0xd2e6 waiting for monitor entry
   java.lang.Thread.State: BLOCKED (on object monitor)
        at SyncTask.taskOne(SyncTaskMain.java:34)
        - waiting to lock <0x000000062c01e888> (a SyncTask)
        at SyncTaskThread.run(SyncTaskMain.java:131)

   Locked ownable synchronizers:
        - None

"Thread-1" #13 prio=5 os_prio=0 cpu=886.98ms elapsed=26.76s tid=0x00007fa5103c2800 nid=0xd2e7 waiting for monitor entry
   java.lang.Thread.State: BLOCKED (on object monitor)
        at SyncTask.taskOne(SyncTaskMain.java:34)
        - waiting to lock <0x000000062c01e888> (a SyncTask)
        at SyncTaskThread.run(SyncTaskMain.java:131)

   Locked ownable synchronizers:
        - None

"Thread-2" #14 prio=5 os_prio=0 cpu=448.61ms elapsed=26.76s tid=0x00007fa5103c4000 nid=0xd2e8 waiting for monitor entry
   java.lang.Thread.State: BLOCKED (on object monitor)
        at SyncTask.taskOne(SyncTaskMain.java:34)
        - waiting to lock <0x000000062c01e888> (a SyncTask)
        at SyncTaskThread.run(SyncTaskMain.java:131)

   Locked ownable synchronizers:
        - None

"Thread-3" #15 prio=5 os_prio=0 cpu=920.40ms elapsed=26.76s tid=0x00007fa5103c6000 nid=0xd2e9 sleeping [0x00007fa4d2ff50
   java.lang.Thread.State: TIMED_WAITING (sleeping)
        at java.lang.Thread.sleep(java.base@11.0.11/Native Method)
        at java.lang.Thread.sleep(java.base@11.0.11/Thread.java:334)
        at SyncTask.taskOne(SyncTaskMain.java:35)
        - locked <0x000000062c01e888> (a SyncTask)
        at SyncTaskThread.run(SyncTaskMain.java:131)

   Locked ownable synchronizers:
        - None

"DestroyJavaVM" #16 prio=5 os_prio=0 cpu=113.30ms elapsed=26.76s tid=0x00007fa510028000 nid=0xd2d6 waiting on condition
   java.lang.Thread.State: RUNNABLE
```

Figure 2.12: Visual VM thread dump for sync task example

2.3.5 JDK Utilities

JDK Utilities are mainly command line tools that are handy and provide quicker solution to analyze the thread activities and lock contention by taking a thread dump. Most of the JDK utility tools are available in bin directory under JDK home path. However, thread dump is a snapshot of the state of all the threads in a java process and it is written in plain text. Moreover, the thread dump contains the stack trace of the thread activities that allows performance engineers diagnose the locking-related problems with ease. There are several JDK Utilities available such as `jstack`, `jconsole`, `jcmd`, `kill` etc.

- **jstack:** jstack is operated in command line and requires java process id to capture necessary thread dump. The following command and options are used for jstack.
  jstack [-f][-l][-m] <java_process_pid>
  These -f/l/m flags are optional and have different uses. To capture the dump we can use the following:
  $ jstack -l <java_process_pid>
  It is also possible to redirect the output dump to a file and that requires the following final jstack command:
  $ jstack -l <java_process_pid> > jstack.out

- **kill:** Unix command kill with signal -3 is used to capture the java applications' thread dump. It dumps the output directly to the default java output if any logger is specified. However, it is also possible to redirect the dumps to a separate file which needs adding some run-time arguments before running the application. This kill command also requires java process id and that can be found using `ps aux` command in Unix-like systems. In order to send the kill signal we need to simply follow the command below:
  $ kill -3 <java_process_pid>

In case of redirecting output to a separate file it is required to adjust some java run-time arguments:

$ java -XX:+UnlockDiagnosticVMOptions -XX:+LogVMOutput -XX:LogFile=./dump.log Program.java

```
"Common-Cleaner" #11 daemon prio=8 os_prio=0 cpu=0.11ms elapsed=19.10s tid=0x00007f4800353000 nid=0xdb57 in Object.wait()  [0x00007f47d036f000]
   java.lang.Thread.State: TIMED_WAITING (on object monitor)
        at java.lang.Object.wait(java.base@11.0.11/Native Method)
        - waiting on <0x000000062c389190> (a java.lang.ref.ReferenceQueue$Lock)
        at java.lang.ref.ReferenceQueue.remove(java.base@11.0.11/ReferenceQueue.java:155)
        - waiting to re-lock in wait() <0x000000062c389190> (a java.lang.ref.ReferenceQueue$Lock)
        at jdk.internal.ref.CleanerImpl.run(java.base@11.0.11/CleanerImpl.java:148)
        at java.lang.Thread.run(java.base@11.0.11/Thread.java:829)
        at jdk.internal.misc.InnocuousThread.run(java.base@11.0.11/InnocuousThread.java:134)

"Thread-0" #12 prio=5 os_prio=0 cpu=357.20ms elapsed=19.07s tid=0x00007f48003d1000 nid=0xdb58 waiting for monitor entry  [0x00007f47d026e000]
   java.lang.Thread.State: BLOCKED (on object monitor)
        at SyncTask.taskOne(SyncTaskMain.java:34)
        - waiting to lock <0x000000062c01e888> (a SyncTask)
        at SyncTaskThread.run(SyncTaskMain.java:131)

"Thread-1" #13 prio=5 os_prio=0 cpu=336.29ms elapsed=19.07s tid=0x00007f48003d2800 nid=0xdb59 waiting for monitor entry  [0x00007f47d016d000]
   java.lang.Thread.State: BLOCKED (on object monitor)
        at SyncTask.taskOne(SyncTaskMain.java:34)
        - waiting to lock <0x000000062c01e888> (a SyncTask)
        at SyncTaskThread.run(SyncTaskMain.java:131)

"Thread-2" #14 prio=5 os_prio=0 cpu=709.82ms elapsed=19.07s tid=0x00007f48003d4800 nid=0xdb5a runnable  [0x00007f4793ffd000]
   java.lang.Thread.State: RUNNABLE
        at SyncTaskThread.run(SyncTaskMain.java:131)

"Thread-3" #15 prio=5 os_prio=0 cpu=678.81ms elapsed=19.07s tid=0x00007f48003d6000 nid=0xdb5b waiting for monitor entry  [0x00007f4793efd000]
   java.lang.Thread.State: BLOCKED (on object monitor)
        at SyncTask.taskOne(SyncTaskMain.java:34)
        - locked <0x000000062c01e888> (a SyncTask)
        at SyncTaskThread.run(SyncTaskMain.java:131)

"DestroyJavaVM" #16 prio=5 os_prio=0 cpu=103.44ms elapsed=19.07s tid=0x00007f4800029000 nid=0xdb47 waiting on condition  [0x0000000000000000]
   java.lang.Thread.State: RUNNABLE

"VM Thread" os_prio=0 cpu=9.62ms elapsed=19.15s tid=0x00007f4800264800 nid=0xdb4e runnable

"GC Thread#0" os_prio=0 cpu=2.88ms elapsed=19.17s tid=0x00007f4800041000 nid=0xdb49 runnable

"G1 Main Marker" os_prio=0 cpu=0.44ms elapsed=19.17s tid=0x00007f480007b800 nid=0xdb4a runnable

"G1 Conc#0" os_prio=0 cpu=0.08ms elapsed=19.17s tid=0x00007f480007d000 nid=0xdb4b runnable

"G1 Refine#0" os_prio=0 cpu=0.39ms elapsed=19.16s tid=0x00007f48001ff000 nid=0xdb4c runnable

"G1 Young RemSet Sampling" os_prio=0 cpu=3.37ms elapsed=19.16s tid=0x00007f4800200800 nid=0xdb4d runnable
"VM Periodic Task Thread" os_prio=0 cpu=15.22ms elapsed=19.11s tid=0x00007f4800344800 nid=0xdb56 waiting on condition
```

Figure 2.13: A snapshot of thread dump for sync task example taken using kill -3 command

A snapshot of thread dump is taken using the kill command providing the above arguments and shown in Figure2.13. However, from the figure it is visible that except thread-2 the all other threads are blocked and waiting to acquire the lock at that particular moment. As a performance engineer, one should analyze these thread activities and based on this analysis he/she should conclude whether the current condition of the particular piece of code is well performing or has a severe bottleneck.

2.4 Limitations of Traditional Approaches

The tools listed above and similar approaches have been utilized for more than a decade, helping developers detect bottlenecks and bugs efficiently. As the java language runs on a virtual machine, and sometimes bottlenecks happen due to VM issues, these tools typically come with the java language itself or are integrated with IDE. Thus, these tools were essential from the beginning. However, these tools have some limitations; we can list them below:

1. They need human intervention to debug the problematic situations and locate the places.
2. They are unable to suggest a proper recommendation as they are incapable of analyzing the profile data.

Although these tools are efficient, the recent need of the developers and based on the listed above limitations motivated us to conduct this research as to whether it is possible to throw some proper recommendations along with reducing manual human interventions detecting the problems. For instance, we ran our example code ”SyncTask” with a contention issue. Our example code can be simulated to create both of the two issues a) Type-1: High hold time, b) Type-2: Frequent access. However, we simulated with 4 threads and applied 1 millisecond inside the critical section. In this case, the program experienced a high hold time contention. The tools listed above only can detect which thread is taking too much time and is responsible for contention, but the scenario fails to describe what type of problem it is facing. More precisely, if the contention would happen due to frequent access, these tools fail to make the proper reason and statement.

2.5 Summary

This chapter summarizes the necessary background regarding the java world, java concurrency support, locking bottlenecks, java performance analyzer tools, and some unsupervised machine learning techniques that are helpful to identify lock contention types. In the related works section, we tried to present some works around this area solving contention-related problems, but these approaches never tried analyzing the performance data that can be useful to detect contention bottleneck types. Tools presented at the end of the chapter are efficient enough but limited to describing bottleneck type as well.

Chapter 3

METHODOLOGY

3.1 INTRODUCTION

A hypothesis drives our methodology that a lock can experience performance bottlenecks by producing some amount of contentions under any circumstances. However, contentions can be accelerated by either having some operations that hold the lock more than expected or access the lock more frequently. Based on this hypothesis, we are interested in determining if lock contention faults can be classified into the two potential causes described by Brian Goetz [20] that are:

- Type 1 - Threads spend too much time inside the critical sections, and
- Type 2 - High frequency with which threads access the critical section.

Although we are interested in two classes referring to the two potential faults, our generated data should contain more categories than the two. During exercising our example code and generating data, we varied from low amount of threads to high amount of threads and low sleep time to high sleep time. We expect another class considering low contention besides our expected two fault classes. This is intentional in order to prove the hypothesis to see if we can also detect that condition in the performance of an application. In this chapter, we try to detail our methodology in several steps that are needed to complete our approach. Steps such as acquiring run-time metrics, then filtering and aggregating the metrics into single file from different source files and lastly data preprocessing and classification are part of our approach. These steps are shown in a high-level workflow where we show the data flow from exercising the example code till the classification process. In the run-time metrics acquisition step, we show the process we go through to acquire run-time metrics from exercising the example code. The filtering and aggregation step describes the process where we collected data from different sources and merged them into a single file. It is ideal that the data we fed into an ML model should be streamed from a single source rather than multiple files. And in our last preprocessing and classification step, we show the different phases we followed by applying some data preprocessing algorithms along with some unsupervised fashioned clustering techniques to classify the fault types.

3.2 Approach

As a preliminary approach, our methodology uses several run-time logs from a Linux *perf*, and JLM performance analyzers, then analyze them using a KMeans classifier to determine the existence of different types of lock contention faults. Before analysing the data using pure KMeans, we preprocess our data using Principal Component Analysis (PCA). Instead of feeding the raw data to KMeans this processed data is much more valuable to the KMeans algorithm and those processing help find out the actual clusters out of the dataset. We also call our methodology a preliminary approach because there are no available datasets for this research. First, we collect and create a dataset by running some of the code that creates contention, and then we analyze the dataset using KMeans to understand the insight of the data.

Analyzing the data using KMeans and finding the expected classes falls into unsupervised clustering technique. As a result our methodology has the portion where unsupervised learning technique is introduced to classify the contention types.

Our expected unsupervised classification process depends on several steps that are listed below and further detailed in the following sub-sections and shown in figure 3.1.

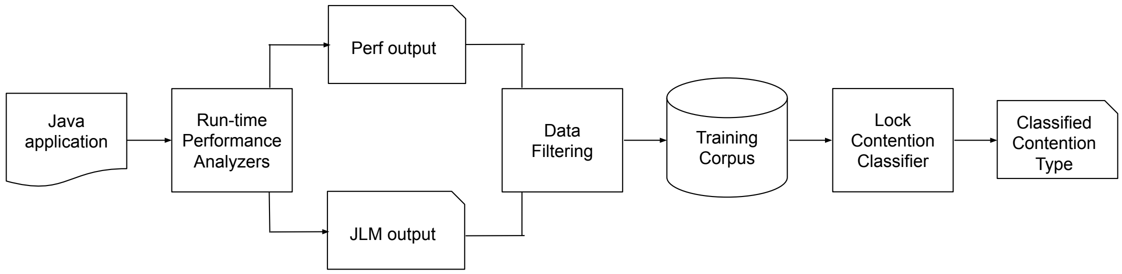


Figure 3.1: High level workflow of our approach

- Run-time performance metric acquisition;
- Aggregation and filtering of the metrics from the logs;
- Data pre-processing and Classification.

3.3 Method Steps

3.3.1 Run-time performance metric acquisition

The Java application listed in Listing 1 is executed in a controlled environment leveraging the *perf* and *JLM* tools that result in particular performance metrics. The code is executed using these performance tools multiple times to reduce the effects of outliers in the metrics and we usually skip the first $10s$ of the execution to avoid the JVM's code optimization and warm-up period. In order to cover a variety of lock-contention scenarios we vary the time that a lock is held by the application as well as the number of threads that use the lock.

Our run-time performance metric acquisition step mainly depends on two performance analyzer tool named *perf* and Java Lock Monitor (JLM).

1. **JLM:** JLM stands for Java Lock Monitor that was previously built for and a part of IBM Performance Inspector [24] tool-suite to diagnose Java application's health. JLM is capable enough to capture the contention statistics when an application experience some level of

contentions. However, a profiling agent associated with JLM called ”JPROF” is a tool mainly added to the argument list prior to running a java application. This agent tool helps capture the information about lock usage for JLM from a running java application among several logs. JLM trace contains the monitor hold time and contention statistics produced by a java applications and JVM. The two stats elaborately listed under labels ”System (Registered) Monitors” & ”Java (Inflated) Monitors” respectively. However, our primary focus remains on the contention statistics related to Java monitors only. Although, JLM provides quite a few metrics related to java inflated monitors but these are not well defined or documented. In order to move forward with these metrics and make ourselves familiar with them better the reader must know the details about them. The details are provided below:

- %MISS: Application locks failure percentage
- GETS: Total number of applications lock = the FAST + SLOW + REC
- NONREC: Total number of non recursive application lock (Non Recursive GETS)
- SLOW: Non recursive that block
- REC: Recursive GETS (thread requests for lock and already acquired it)
- TIER2: On platforms that support 3-layer spin locks, the number of inner loops to obtain locks.
- TIER3: On a platform that supports 3-layer spin locks, the number of cycles in the outer layer to obtain the lock.
- %UTIL : 100 * Hold-Time / Total-Time
- AVER-HTM : Hold-Time / NONREC

When contention occurs JLM lists the java monitors used in our code under the ”JLM Inflated Monitors” with some high counts for each of its metrics. A glimpse of JLM log is shown in the figure 3.2 when contention occurs and it has a high counts in AVER_HTM compared to the low contention shown in Figure 3.3. In case of no contention the java lock monitors do not appear or often appear with all zero values for monitor columns in the JLM log under ”Java inflated monitor” block. When it is a case of low contention then the monitors appear with less counts for monitor column such as AVER_HTM. Heavy Contention due to high hold time is easily distinguishable with the bare eyes and that is why our explanation regarding contention focuses on that specific AVER_HTM column here to provide and an example to the readers. A glimpse of JLM log for sync task example with less contention is shown in the figure 3.3.

```
    0        0        0        0        0        0        0     0        0  [00007F70280D7680] MM_FreeEntrySi
    0        0        0        0        0        0        0     0        0  [00007F70280D7828] MM_FreeEntrySi
    0        0        0        0        0        0        0     0        0  [00007F70280D7300] MM_MemoryPoolA
    0        0        0        0        0        0        0     0        0  [00007F70280D7198] MM_MemoryPoolA
    0        0        0        0        0        0        0     0        0  [00007F7028056CD8] MM_FreeEntrySi
    0        0        0        0        0        0        0     0        0  [00007F70280DE280] MM_FreeEntrySi
    0        0        0        0        0        0        0     0        0  [00007F70280DE428] MM_FreeEntrySi
    0        0        0        0        0        0        0     0        0  [00007F70280E38D0] MM_MemorySubSp

Java (Inflated) Monitors

%MISS     GETS   NONREC     SLOW      REC     TIER2     TIER3 %UTIL AVER_HTM  MON-NAME

  100       18       18       18        0        0        0    96 2016737495  [00007F6F880027A8] SyncTask2@00

LEGEND:
              %MISS : 100 * SLOW / NONREC
               GETS : Lock Entries
             NONREC : Non Recursive Gets
               SLOW : Non Recursives that Block
                REC : Recursive Gets
              TIER2 : SMP: Total try-enter spin loop cnt (middle for 3 tier)
              TIER3 : SMP: Total yield spin loop cnt (outer for 3 tier)
              %UTIL : 100 * Hold-Time / Total-Time
            AVER-HT : Hold-Time / NONREC
```

Figure 3.2: JLM output log of Sync Task example when contention occurs

2. ***perf*** The *perf* tool comes with the Linux distribution by default which is another essential tool has the equal contribution to our research as same as the JLM. The *perf* tool is capable of capturing memory footprints, in other words, symbols from user space along with kernel space. These symbols are mainly method names, variables, or class names usually used in the OS itself or the kernel or in a java application. Additionally, *perf* aggregates the symbol’s

```
    0       0       0       0       0       0       0    0       0  [00007FB6940BE658] MM_MemoryPoo
    0       0       0       0       0       0       0    0       0  [00007FB6940D7680] MM_FreeEntry
    0       0       0       0       0       0       0    0       0  [00007FB6940D7828] MM_FreeEntry
    0       0       0       0       0       0       0    0       0  [00007FB6940D7300] MM_MemoryPoo
    0       0       0       0       0       0       0    0       0  [00007FB6940D7198] MM_MemoryPoo
    0       0       0       0       0       0       0    0       0  [00007FB694056CD8] MM_FreeEntry
    0       0       0       0       0       0       0    0       0  [00007FB6940DE280] MM_FreeEntry
    0       0       0       0       0       0       0    0       0  [00007FB6940DE428] MM_FreeEntry
    0       0       0       0       0       0       0    0       0  [00007FB6940E38D0] MM_MemorySub

Java (Inflated) Monitors

%MISS     GETS   NONREC     SLOW      REC    TIER2    TIER3 %UTIL  AVER_HTM  MON-NAME

  100       18       18       18        0        0        0    93 1973444373  [00007FB6942BF498] SyncTask2@

LEGEND:
               %MISS : 100 * SLOW / NONREC
                GETS : Lock Entries
              NONREC : Non Recursive Gets
                SLOW : Non Recursives that Block
                 REC : Recursive Gets
               TIER2 : SMP: Total try-enter spin loop cnt (middle for 3 tier)
               TIER3 : SMP: Total yield spin loop cnt (outer for 3 tier)
               %UTIL : 100 * Hold-Time / Total-Time
             AVER-HT : Hold-Time / NONREC
```

Figure 3.3: JLM output log of Sync Task example code when less contention occurs

frequency that is useful to predict the fault types. The reference of how the *perf* tool works can be found here [26]. Unfortunately, the raw *perf* data is not human-readable. However, with the help of a script, we can extract a human-readable log containing the following 3 columns of values a) **Sample count**, b) **Percentage in total sample count**, c) **Symbol name**.

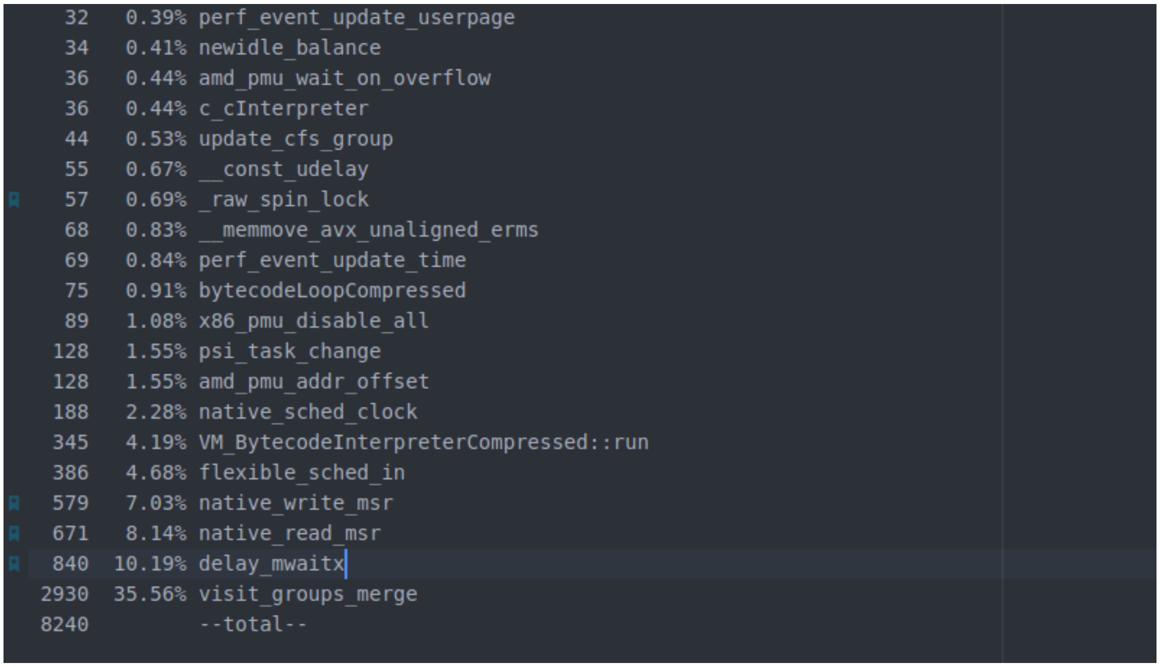
However, perf-record collects lots of symbols that are not related to contention faults. A group of symbols does appear when contention occurs. They usually appear with a high number of samples in case the code experience bad contention and with less on the other hand. After exercising our example code many times, these symbols are in our observation, and we take notes of them. Leveraging these symbols might help us to identify the contention fault types, which is what we expect. In our dataset, the symbols represent the feature and the sample count as the value for the feature. A snapshot of the *perf* log of Sync Task example code is shown in figure 3.4 highlighting the some symbols such as _raw_spin_lock, delay_mwaitx, native_write_msr and native_read_msr that are consuming significant CPU resources compared to the others. However, in case of low contention these symbols often appear with less sample value. A snapshot of the *perf* log of Sync Task example code is shown in figure 3.5 when contention does not occur.

```
  173   0.55% [unknown:[vdso]]
  204   0.65% omrthread_sleep_interruptable
  227   0.73% update_curr
  228   0.73% update_cfs_group
  277   0.89% flexible_sched_in
  280   0.90% __const_udelay
  305   0.98% ctx_sched_in
  388   1.24% __memmove_avx_unaligned_erms
  422   1.35% bytecodeLoopCompressed
  495   1.58% _raw_spin_lock
  504   1.61% x86_pmu_disable_all
  873   2.79% psi_task_change
 1039   3.32% native_sched_clock
 1780   5.69% VM_BytecodeInterpreterCompressed::run
 2999   9.59% native_write_msr
 3486  11.15% native_read_msr
 3717  11.88% delay_mwaitx
 6711  21.46% visit_groups_merge
31277          --total--
```

Figure 3.4: A small portion of the perf snapshot taken for Sync Task code when contention occurs

In manual operation of log generation, we usually run the java application in one terminal. Then in another terminal, we capture the application pid, and both the *perf* record and JLM command need this pid to collect further data. Command ps aux | grep java grabs the pid of the running java process, required as an argument for the perf command. As the Java pid is present, we start capturing *perf* trace using the command perf record, which extracts the perf.data file. Although the perf.data is not human-readable, we use the perf-hottest python script to extract the human-readable perf file.

However, to obtain the log for JLM, we enabled a different JVM run-time argument called



```
  32   0.39% perf_event_update_userpage
  34   0.41% newidle_balance
  36   0.44% amd_pmu_wait_on_overflow
  36   0.44% c_cInterpreter
  44   0.53% update_cfs_group
  55   0.67% __const_udelay
  57   0.69% _raw_spin_lock
  68   0.83% __memmove_avx_unaligned_erms
  69   0.84% perf_event_update_time
  75   0.91% bytecodeLoopCompressed
  89   1.08% x86_pmu_disable_all
 128   1.55% psi_task_change
 128   1.55% amd_pmu_addr_offset
 188   2.28% native_sched_clock
 345   4.19% VM_BytecodeInterpreterCompressed::run
 386   4.68% flexible_sched_in
 579   7.03% native_write_msr
 671   8.14% native_read_msr
 840  10.19% delay_mwaitx
2930  35.56% visit_groups_merge
8240         --total--
```

Figure 3.5: A small portion of the perf snapshot taken for Sync Task code when less contention occurs

agentlib:jprof. After running the java application with the necessary JVM options, we activate the rtdriver to collect the JLM trace from another terminal. rtdriver is also a part of the IBM performance inspector suite capable of seizing the JLM information from either a local machine or a remote one when we specify the machine IP address within the rtdriver command. rtdriver starts collecting the data sending the start signal and stops it when it sends stop command to the targeted machine. The whole tools installation and log generation process is explained in Chapter 4.2.4

Exercising the code and producing the run-time perf and JLM log is a tedious and time consuming one. In order to make the log generation process faster and to generate the data-set, we wrote an algorithm (steps listed below) capable of running the entire process multiple times. The algorithm that helps to run the entire log generation process is shown in the Algorithm 2. Run-time performance metric acquisition process flow-chart is shown in Figure 3.6.

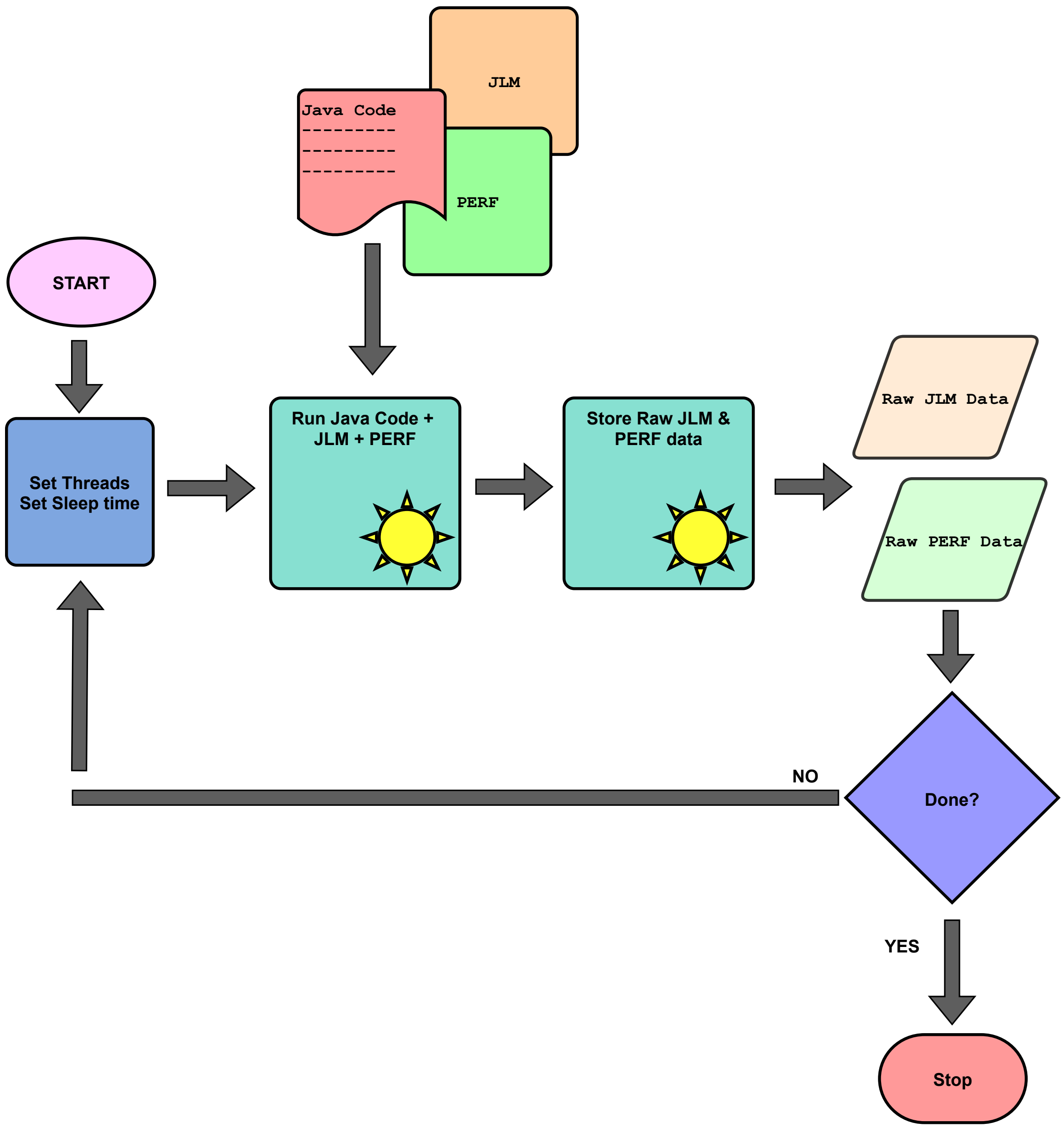


Figure 3.6: Run-time performance metric acquisition

It required to run our code multiple times with different sleep times and thread numbers for simulating the contention type 1 and contention type 2. Algorithm shown in the Algorithm 2 assist us running a single test and collect the necessary JLM and *perf* data and saving them. Therefore, another script is needed to run our previous script multiple times so that dataset can be generated

Algorithm 1: Algorithm to run collect data bash algorithm multiple times to collect JLM data and perf data and store them in a desired directory

```
THREADS ← initialize thread list;
for each THREADS do
    TRIALS ← number_loop;
    DELAY ← delay_value;
    for loop until TRIALS do
        execute Algorithm to collect jlm and perf data;
        DELAY ← DELAY + 100;
    end
end
```

without any human intervention and reducing the exercising time. In this algorithm, we have two loops, when the outer loop iterates over an array of thread numbers and the inner loop is responsible for generating some different sleep time compared to the previous test and run our previous script providing the necessary java application arguments such as total thread numbers, sleep times, sleep time type (whether the java application apply milliseconds to the critical section or nanoseconds) and so on. The second code automation script is shown in the Algorithm 1

- **Auto log generation steps:**
  - Run java program
  - Wait ten seconds
  - Execute *perf* and JLM for ten seconds
  - Terminate java program
  - Repeat n times
  - Repeat with modified processing time in contented region and number of threads

Algorithm 2: Algorithm to run SyncTask example code, after that collect JLM data and perf data and store them in a desired directory

```
compile java program;
run java program with arguments [−Xjit:perfTool, −agentlib:jprof];
java_pid ← capture pid of java program using ps aux | grep | awk;
if java_pid not empty then
    record jlm data using rtdriver;
    sleep 10 seconds;
    record perf data;
    sleep 10 seconds;
    perf_pid ← capture perf pid using ps aux | grep | awk;
    kill perf pid using −SIGINT;
    kill java pid using −SIGKILL;
else
    notify java pid not found;
end
convert raw perf.data to perf.log using perf_hottest;
save jlm.log to desired dir;
save perf.log to desired dir;
```

3.3.2 Aggregation and Filtering

After collecting the data, it is run through a series of algorithms that merge different runs and data sources into one file for ease of access. Before merging the JLM data and *perf* data into a single one, a parser is needed to parse valuable information from these raw data. In order to achieve this we wrote a parser algorithm using python that parses the JLM data, *perf* data and the test information into three different CSV files. Filtering and aggregation process is shown in Figure 3.7. While running a single test we vary the threads and sleep times and those information are needed for the evaluation and verification purposes during classification process, that are the test information we are also collecting. However, we store the JLM, *perf* and test information log containing timestamp in their name to identify them as a single run. JLM data has two main blocks that are, ”System Registered Monitors” and ”Java Inflated Monitors”. We are interested in this java monitors as they come from our java code that are mainly used by the JVM for the locks. An algorithm for parsing the JLM data is shown in the Algorithm 3

Algorithm 3: Algorithm to parse JLM data into a CSV file

```
open_file;
write_file(headers);
;                                          /* GETS,TIER2 ...etc */
for each timestamp do
    iterate_lines ← false;
    lines ← read_file('jlm'+timestamp);
    for each line do
        tokens ← split(line);
        stripped_line ← strip(line);
        if stripped_line == 'LEGEND' then
            iterate_lines ← false;
        end
        if stripped_line == 'Java Inflated Monitors' then
            iterate_lines ← true;
        else
            if line not empty and iterate_lines == true and length(tokens) > 0 then
                new_line ← join(tokens);
                ;            /* Values of GETS,TIER2 ...  etc */
                write_file(new_line)
            end
        end
    end
end
```

We process the *perf* data separately as the perf data is collected from a different source. While this is underway the *perf* data will be filtered so that only the most significant symbols related to lock-contention are kept such as `_raw_spin_lock`, `objectMonitorEnterNonBlocking`, `omrthread_spinlock_acquire` etc. As the perf log has plenty of other symbols we are not interested, we collect only the symbols related to contention. The chosen symbols are listed in the parser and the algorithm filters the symbols using the regular expression. We know what these symbols are based on feedback from experienced performance engineers. Moreover, while exercising

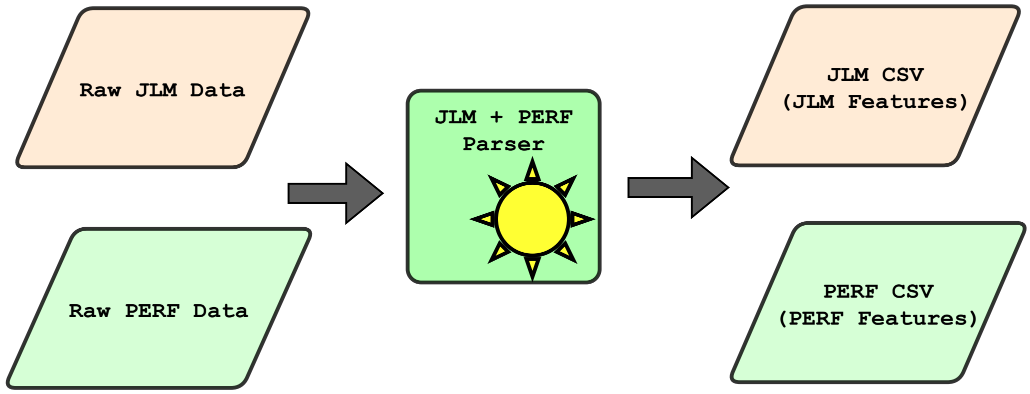


Figure 3.7: Data filtering and aggregation

the example code, some of the symbols appeared most of time due to contention. Additionally, symbols are removed from our raw dataset if they occur on average less than two times. An algorithm to parse *perf* data is shown in the Algorithm 4.

3.3.3 Data Preprocessing and Classification

Data preprocessing and classification is the final step in the methodology. In this step, we perform some processing to our raw dataset and make our dataset ready to be classified. This third step of our methodology is divided into some more sub-steps which are described below:

Merging CSV Files

Typical to most classifiers it is important to perform some data preprocessing prior to training the classifier. Our preprocessing starts with concatenating the three CSV files into one python dataframe. Both the JLM and *perf* CSV data are organized based on timestamps and they are synchronized when merged. However, it is worth mentioning that, we take the help of a popular python library `scikit learn` and its modules to perform all kinds of data preprocessing and classification.

Algorithm 4: Algorithm to parse *perf* data into a CSV file

```
initialize_symbols;
values ← {};
counter ← 0;
for each symbol do
  | values[symbol] ← []
end
for each timestamp do
  | lines ← read_file('perf'+timestamp);
  | lines ← find_chosen_symbols;
  | temp_var ← {};
  | for each line do
  |   | name ← split(line)[2];
  |   | sample ← split(line)[0];
  |   | temp[name] ← {'sample_count' : sample};
  |   | for each key in values do
  |   |   | append temp[key]['sample_count'] into values[key];
  |   | end
  | end
  | counter ← counter + 1;
end
open_file;
header ← join(each key in values);
write_file(header);
for x in range(counter) do
  | temp_values ← [];
  | for key in values do
  |   | append values[key][x] into temp_values;
  | end
  | final_values ← join(temp_values);
  | write_file(final_values);
end
```

Scaling The Data

Next, the data is scaled so that it is more uniformly distributed. To perform scaling we used standard scaler from scikit learn python package. It is required that data should be scaled before feeding the dataset into any clustering algorithms, and without scaling the data, these algorithms usually throw an exception. However, it is essential to know why Standard Scaler is chosen over MinMax Scaler or some other scaler methods. According to this article, [14] if the dataset has different columns representing different units or types, then these values are not comparable anyway. Applying to them the method z-standardizing is the best practice to give equal weight to them. In our dataset, the AVER_HTM is the CPU ticks and other values counts and sample counts. Therefore, we believe choosing Standard Scaler is the right decision for our dataset. After that, leveraging the Heatmap [2] it is possible to view the relationship among the performance metrics. This heatmap technique not only helps view insight into the data, it helps reducing some of the less correlated metrics from dataset or they do not have any correlation at all. Therefore, we take some of the features out after analysing the heatmap.

Applying PCA

In the next phase of our approach we reduce the dimensionality of the data by applying the Principal Component Analysis (PCA) [17]. PCA helps visualize the data in two dimensional form as the data features are reduced to two primary components only. In our approach they are named as `principal_component_1` and `principal_component_2`. In an unsupervised learning, often feature engineering or the feature extraction is done using this PCA analysis as because it finalizes the most important desired N features out of the large dimensions. Hence, in our case these two primary components are the final features which are ready to be fed into the further clustering algorithms. Additionally, plotting these two dimensions in a scatter plot makes the visualization more efficient.

KMeans & Cluster Analysis

Before feeding the data into the clustering algorithms such as KMeans it is important to know the desired clusters and which is an argument we need to pass to the clustering algorithm. However, in order to obtain our desired clusters and our expectation from the dataset is three, we set the argument of cluster number is three for the algorithm. Moreover, this desired cluster number is also verified by some popular methods available such as Elbow method, or Silhouette Coefficients technique. After applying these techniques they respond with the optimal clusters number possible in our dataset. That result is the argument of cluster number for our clustering algorithm we set. Finally the classifier can be trained using the PCA data. We feed PCA data to the KMeans with necessary arguments. The arguments we provide to the KMeans are listed below:

- Number of clusters : 3
- Initialization of centroids : k-means++
- Maximum iteration : 600
- Number of initialization : 10

Classification process was not limited only with the PCA values but we also feed KMeans with the processed final data to find the expected clusters of fault types. However, these two training approaches find the similar kind of results and we verify it with some performance evaluation methods discussed in Chapter 5, Section 5.7. In order to verify whether the clustering algorithms are compatible with our dataset we feed our data to the clustering algorithm called Density-Based Spatial Clustering of Applications with Noise (DBSCAN) [34] [10]. However DBSCAN fails to construct desired clusters or groups out of the dataset we created. Unlike KMeans DBSCAN does not require argument for expected clusters. Instead it requires an argument named ”eps” which is the value for dense area to compute the next neighbour. Initial value of is set to 0.3 for eps and tweaking this value sometimes helps extract desired clusters. Tweaking to a higher value does not improve the clustering performance in this case of dataset. Therefore, we leave it out from our performance evaluation.

After the clustering process, we extract the labels and attach them to the original dataset to observe the dominant features for each cluster. In order to achieve this, we take the assistance of a visualization method called Radial Visualization. Radial Visualization method is a data visualization technique to display multivariate data in a circle. This algorithm plots each feature dimension uniformly around the circumference of a circle then plots points on the interior of the circle such that the point normalizes its values on the axes from the center to each arc [12]. RadViz visualization allows plotting multiple dimensions within the circle, widely exploring the dimensionality of the visualization. Data scientists use this visualization algorithm to know the classes' basic distinction or observe too many outliers. Although utilizing Radial Visualization reveals some insight into the data but it fails to distinguish the dominant features for all the clusters. Results of the Radial Visualization is discussed in Chapter 4, Section 5.6.

As the Radial Visualization fails, we move forward to another type of visualization method called box plot. Box plotting is a visualization method [1] that displays the data distribution based on five-point summary ("minimum", first quartile (Q1), median, third quartile (Q3), and "maximum") [18]. Plotting the features to the box plot reveals the dominant features for each cluster. However, in order to label the clusters, the test parameters (e.g., Threads and Sleep) are mapped back to the processed dataset. According to our hypothesis, one cluster should have a relationship with thread numbers, mainly fault type 2 (high-frequency access by threads). Utilizing box plots and plotting threads in relation to clusters reveals that one cluster falls under a high-frequency access fault. Plotting box plot for Sleep time also reveals that one cluster has a relation to it which is expected according to our hypothesis.

Plotting the other features with a box plot also helps us find the dominant features for each cluster. Observing different metrics utilizing box plots and the discussion of labeling fault type is presented in Chapter 6. The whole preprocessing and classification process is captured in Figure

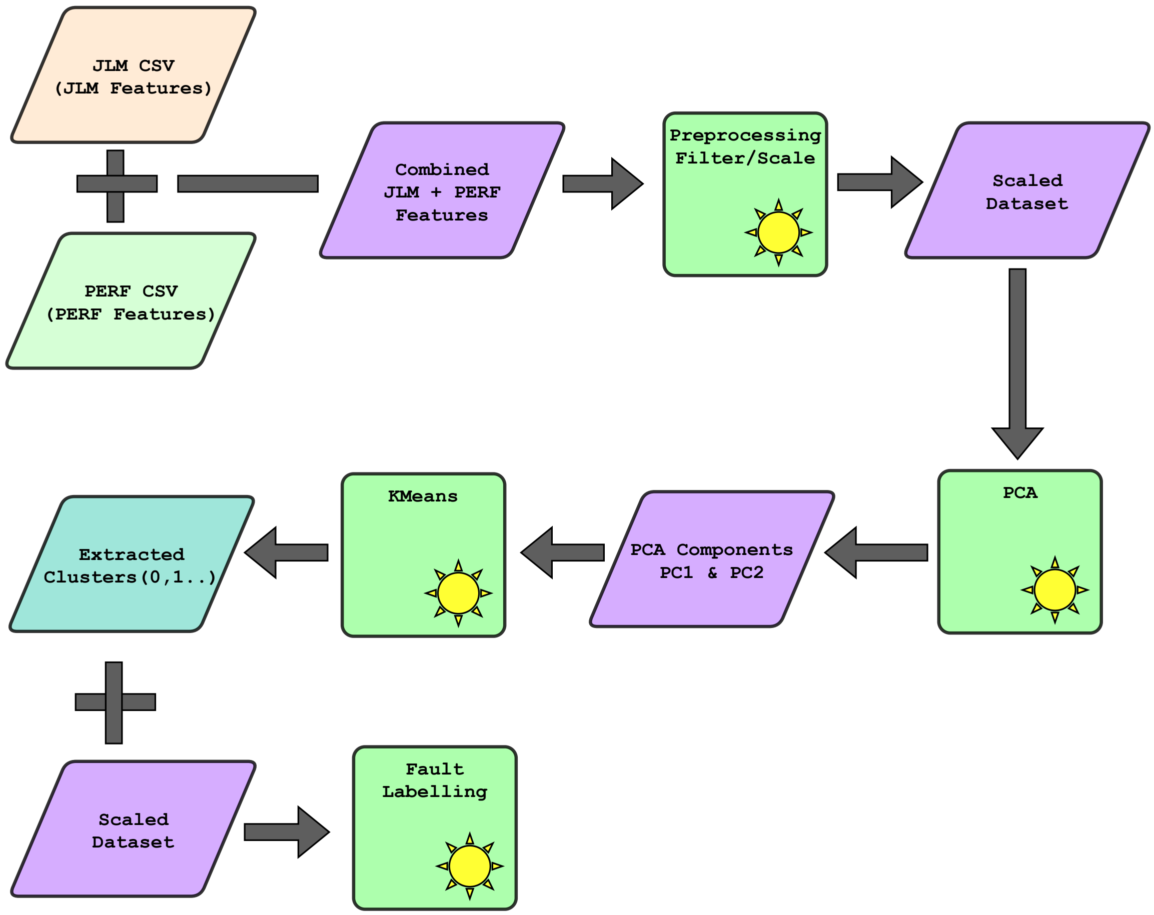


Figure 3.8: Data preprocessing and classification

3.8.

3.4 Summary

The summary of this chapter includes a discussion about the methodology of the research work. The method is driven by a hypothesis that contention faults occurring due to a) heavy hold time inside the critical section or b) high-frequency access by threads can be classified as they leave some patterns in the metrics of the performance analyzer tools. It summarizes the chapter by discussing the main three method steps a) performance metrics acquisition, where it discusses the collection procedures of performance metrics log by exercising the concurrent code. The next step, b) data filtering and aggregation, where it discusses the procedures we take into account to filter out the required data from both the JLM and the *perf*. This step, also discusses how information is merged from multiple JLM files into one by creating a CSV and performing the same for the *perf* CSV. And finally, c) preprocessing and classification step discusses the clustering techniques we performed on our generated dataset to classify our expected clusters of fault types. It also points out the discussion of how a cluster can be labeled back to its actual fault type.

Chapter 4

DATA GENERATION

4.1 INTRODUCTION

Data generation is one of our main contributions in this research. Due to unavailability of the proper dataset it is one of our major concerns to generate dataset on which we can apply the clustering techniques. Besides generating datasets, ensuring proper hardware, machine, and software tools was another big challenge. In this chapter, we also try to mention all the tool-set, hardware, and environment needed to perform our research experiment. Moreover, the chapter describes the experimental setup, describing how we exercise our example code varying some parameters. Stress testing a concurrent Java application through a multi-core processing environment requires a high-performing machine with high memory resources. While running a concurrent application, one must keep in mind that several aspects are running underneath that often experiences overhead. Hence, it is recommended to maintain a quiet environment to run an application with concurrency. In the case of a Java application, JVM performs code optimizations. Then it operates locking mechanisms that require both space and time, and finally, in case JVM fails to manage the locks, context switching occurs between JVM and OS kernel [20]. Moreover, running java code with multiple threads need more resources than a regular java application. Thinking of all these corner cases, we tried to maintain an ideal environment for our experiment. This chapter highlights the environment and experimental setup where we ran our example code. And it has the description of the tool-sets that assist in generating and processing our datasets for this research.

4.2 Environment Configuration

4.2.1 Hardware Configuration

A high-performing machine with a bare-metal operating system installed in it is ideal for generating the run-time contention performance data. Moreover, an isolated environment is also recommended for the execution of *perf* and JLM. We installed these tools on a high-performing Linux machine with the following configurations:

- **CPU:**
  - Product: AMD Ryzen 9 3900X 12-Core Processor
  - Architecture: x86_64
  - CPU(s): 24
  - Frequency: 3800 MHz
- **Memory:** 32 GB

4.2.2 Java Configuration

JLM is compatible with the OpenJ9 JVM [13]. Hence, for the Java environment we used Eclipse Openj9 Virtual Machine. The Java configurations are as follows:

- **JDK:** Openjdk version "1.8.0_292"
- **JRE:** OpenJDK Runtime Environment (build 1.8.0_292-b10)
- **JVM:** Eclipse OpenJ9 VM (build openj9-0.26.0, JRE 1.8.0 Linux amd64-64-Bit Compressed References 20210421_1000 (JIT enabled, AOT enabled)

4.2.3 Performance Metrics Seizing Tools

The following tools were used to capture the run-time performance metrics of the application:

- **Performance Inspector:** The IBM Performance Inspector is a tool-suite that includes some performance measuring tools such as *TPROF* for CPU profiling, *JPROF* for application profiling, and JLM for lock profiling. To capture contention statistics and inflated monitors information we installed this performance inspector in our machine.

- ***Perf* Tool:** *Perf* tool mostly comes with the Linux distributions. In order to capture performance data and symbols from kernel space *perf* tool is installed in our machine. Couple of terminal commands are needed to install this tool in a Linux machine. We ensured proper installation of this tool during running the experiments.

- **Perf-hottest:** Data recorded using *perf* tool is stored in a file named `perf.data` by default. This data is saved in the same directory where perf record command is executed. However, the data extracted from *perf* is not human readable. The Perf-Hottest tool is used to interpret information from the "perf.data" file and translate it into a human-readable form.

4.2.4 Log Generation : Manual Steps

Manual operation to generate log by exercising the example code needs some tools installation. These are all performance analyzer tools that we described in the Subsection above 4.2.3 and capable of profiling a java application. However, in this manual way, we start the java application in one terminal, providing necessary profiling arguments for *perf* and JLM, and in another terminal, we record the *perf* data using the java pid. Extracted raw "perf.data" is converted to a human-readable file leveraging the "perf-hottest" python script. Later, we open another terminal and start the JLM agent to capture contention-related statistics data, which is a raw JLM file. Before running the java application and capturing the other logs we ensured the proper installation of those tools that are described in the above sections. Installation of these tools are described below step by step.

- **Install Adoptopenjdk:** Installing Adoptopenjdk ensures installation of OpenJ9 JVM which we need for our experiment. From the adoptopenjdk download page we download the compressed JDK file and extract it to the desired path of our Linux machine where most of the other versions of JDKs are installed by default. We add this java home path to the `$JAVA_HOME` environment variable. The following terminal commands ensures adoptopenjdk installation.
  $ sudo mkdir -p /path_to_java_home/
  $ sudo cp /home/$USER/Downloads/jdk-11.0.8+10.tar.gz /path_to_java_home/
  $ cd /path_to_java_home/
  $ sudo tar -xvzf jdk-11.0.8+10.tar.gz

- **Install Perf Tool:** *Perf* tool comes with the Linux distro most of the time but we ensure it is installed in case of unavailability. In order to install perf tool following commands are used:
  $ sudo apt install linux-tools-common
  $ sudo apt install linux-tools-generic
  Although, perf tool captures kernel memory trace, which is not permitted for the first time from any other user except root after enabling the perf tool. It is required to grant the permission by changing the kernel settings. This permission is enabled by the following command:
  $ sudo sysctl -w kernel.perf_event_paranoid=1
  $ sudo sysctl -w kernel.kptr_restrict=0

- **Install Performance Inspector:** IBM performance Inspector provides necessary tools such as JPROF, TPROF, or JLM to profile java applications and check their health. In order to capture contention-related data, we ensure installing this tool-suite in our machine. As this tool-suite is a proprietary product and managed by IBM internally, we finally get access to the product with the help of the IBM team. However, after unpacking the product, we need to build this tool-suite to enable all the other modules of it. Building it requires modern C++

compilers and Linux headers and libraries. The prerequisites to install performance inspector are:

- cmake
- binutils-dev
- libiberty-dev

These are installed before installing the tool-suite. Once those are done we place the inspector package to a particular directory of the system. Then we create a new directory called `build` inside the root directory of the suite. Next we perform `cmake` and `make` command to build the inspector. This installation adjusts a `bin` and a `lib` directory under the inspector root. The next requirement for this tool is to attach the `bin` directory to the environment `$PATH` variable and the `lib` directory to the library path of the system. The following commands do all the processing for us:

$ export PATH=/path_to_ibm_pi/bin:$PATH

$ echo "/path_to_ibm_pi/lib" | sudo tee /etc/ld.so.conf.d/ibm.pi.conf

$ sudo ldconfig

4.2.5 Log Generation : Automated Steps

Generating the data and the complete dataset is a time consuming process and we always wanted to reduce the amount of time it consumes. It takes around 40 to 45 seconds to perform a single run and generate the JLM & *perf* data and store them. Therefore, we take the help of a bash script algorithm that is capable of exercising the code and rest of other processing till saving the data. To assist us to generate the data-set with ease we wrote an algorithm (steps listed below) capable of running the entire process multiple times in our configured environment.

- Run java program

- Wait ten seconds
- Execute *perf* and JLM for ten seconds
- Terminate java program
- Repeat n times
- Repeat with modified processing time in contented region and number of threads

4.3 Dataset Creation

In order to train a classifier, lock-contention performance data is required. Unfortunately, this performance data is not readily available, and data-set generation was another concern we had to attend to. The class that simulates the lock-contention faults is shown in the Listing of 1. The driver class that initiates and controls the execution of the thread is shown in the Listing 2. For simplicity, our examples implemented the synchronization instance method only.

Due to the absence of the dataset, we had to focus on the dataset generation process as well. Although the major portion of our research was spent on dataset generation, we successfully overcame this situation in the end. We intended to move forward in an unsupervised way, and because of this, our generated data was unlabeled. We applied different clustering algorithms and mapped the classified data to the original one to strengthen our assumption.

However, we divided and formalized the test scenarios for our experiment and performed them with various configurations such as multiple threads and different sleep times along with slightly modified code to simulate the contention scenario.

4.3.1 Test Formalization for Dataset

In our experiment we tried to formalize the test scenarios in such a way that it can experience cases with minimal contention as well as two different types of contention we described in Chapter 3.

Listing 1 Java Synchronized Task example simulates types of faults

```
class SyncTask {
  public Set<String> set;
  public int sleep_t,

  public synchronized void taskOne(String value){
    try {
      set.add(value);
      Thread.sleep(sleep_t);
    } catch(Exception e) {
      e.printStackTrace();
    }
  }

  public void taskOneV2(String value){
    synchronized(set){
      try {
        set.add(value);
        Thread.sleep(sleep_t);
      } catch(Exception e) {
        e.printStackTrace();
      }
    }
  }
}
```

We varied in the exemplar code, the time spent in the contended region (Sleep time), as well as the number of threads. Our formalized scenarios for the experiment is given below:

We configure a bash script algorithm that takes or generates the necessary values for running the java example code. In the bash script algorithm we add first loop and it iterates through an array of thread values. We operate the whole experiment in multiple configurations and each configuration we take a set of threads in the array. The threads are listed in each phase below. Inside the first loop we add our second loop that iterates through two hundred different sleep times. Our multiple values are being used as the run-time arguments for the java example code and that simulates the low contention to high contention and frequent access to the locked resource.

Listing 2 Java Synchronized Task driver class example controls the thread execution

```
public class SyncTaskMain {
  public static void main(String[] args) {
    int NUM_THREADS = thread_size;
    Set<String> set = new HashSet<String>();
    SyncTask sl = new SyncTask(set);
    ArrayList<Thread> threadList = new ArrayList<Thread>();

    for(int i = 0; i < NUM_THREADS; i++){
      Thread t = new SyncTaskThread(sl);
      threadList.add(t);
      t.start();
    }

  }
}
```

- **Configuration 1:**
  - Threads: [10, 100, 500, 1000]
  - Sleep: From $1ns$ up to $20,000ns$ in $100ns$ increments, with 200 runs
  - Total Data Points: 800
- **Configuration 2:**
  - Threads: [10, 100, 200, 300, 400, 500, 1000]
  - Sleep: From $10ns$ up to $20,000ns$ in $100ns$ increments, with 200 runs
  - Total Data Points: 1600

There is a gap between the two different sleep times we configured, and that is 100 nanoseconds. Leaving this much gap between the two different sleep times is intentional, and it allows us to cover a wide range of sleep times. Collecting data after running a single test is also a time-consuming task, and it takes 40 - 45 seconds to complete one data point collection.

In order to simulate high the contention, low contention, and frequent access, we used large sleep time inside the critical section to be operated, less sleep time for the critical section, and low & high range threads, respectively. However, the large amount of threads mainly maintains a routine to send access to locked resource at the same time that ensures frequent access to the critical section. In order to perform perf recording and JLM recording our example code should run more than twenty seconds and from inside the run method of thread we maintain a tight loop that ensures running the program a little while. This tight loop is set to 100000. When a thread tries to access a locked resource more frequently, the lock acquisition degree metrics such as `TIER2`, `TIER3` increase in number. These counts mainly represent the spinning around the locked resource before acquiring the lock. In order to clarify the configuration to the readers more, we also want to state that we only keep the sleep time in the nanoseconds range. In order to generate the whole dataset, we ran total two configurations for our experiment, which aggregates a total of two thousand and four hundred data points.

Features	**Analyzer Tool**	**Data Type**	**Features**	**Analyzer Tool**	**Data Type**
%MISS	JLM	Numerical	REC	JLM	Numerical
GETS	JLM	Numerical	%UTIL	JLM	Numerical
NONREC	JLM	Numerical	AVER_HTM	JLM	Numerical
SLOW	JLM	Numerical	_raw_spin_lock	PERF	Numerical
TIER2	JLM	Numerical	ctx_sched_in	PERF	Numerical
TIER3	JLM	Numerical	delay_mwaitx	PERF	Numerical

Table 4.1: Lock-Contention Performance Metrics dataset information.

4.3.2 Dataset Information

The final generated dataset has **two thousand and four hundred** data points, and **twelve** features in total. Features %MISS, GETS, NONREC, SLOW, TIER2, TIER3, REC, %UTILand AVER_HTM are collected from JLM. Features _raw_spin_lock, ctx_sched_in and delay_mwaitx are collected from *perf* tool. All of them are numerical data we confirmed. The dataset's features, analyzer tool it comes from and the data type are shown in Table 4.1.

4.4 SUMMARY

This chapter summarizes the data generation procedures through some sections that discuss the environment configuration and tools installation required for data generation for this specific research. A quiet and powerful machine is required to perform the experiment that helps in generating the dataset. We ensure a quiet and powerful machine, of course, and it has necessary java and kernel performance profiling tools installed such as JLM, *perf*, IBM performance inspector, OpenJ9 JVM, and JDK, and some Linux common tools. It also summarizes both manual and automated steps to generate the dataset. It also includes the information of test formalization and configuration that helps generate a dataset of contention statistics-related metrics. We end this chapter by summarizing the information of the dataset, such as the total number of data points and features and the features types.

Chapter 5

CLUSTERING RESULTS

5.1 INTRODUCTION

Applying the clustering techniques and after that observing different clusters including the two potential fault types, is our expectation. However, before applying the clustering techniques, we did some preliminary data analysis while exercising the example code and also when we had the final dataset in our hands. The importance of the preliminary data analysis is that it helps find a high-level insight into the data. Also, this analysis helps to reduce some unnecessary features from the final dataset. In machine learning, it is crucial to extract features that are important cause the unnecessary features increase the chance of performing a model under-fit or often over-fit. In order to work with these, we observed the JLM and perf data carefully each time we got the values from the test. In this chapter, we try to elaborate some preliminary data analysis by observing both the JLM and perf data. After that, we further work with the Heat Map plotting that reveals the essential features for our dataset. It is the correlation between the features that indicate which features are positively correlated to which one. At some point in this chapter, we discuss the results from applying the clustering techniques and the clusters we obtained using the techniques.

5.2 OBSERVE METRICS & CORRELATIONS

A manual and plain human eye observation on the JLM data is necessary to understand the metrics changes based on different contention cases. In the case of non-contention or less contention, the JLM metrics never appear or often appear with low lock competition degree (spin counts) and low average monitor hold time. However, in our manual analysis, we observe that monitor entries appear on the JLM data with a high spin count (GETS, SLOW, TIER2, TIER3) when there are frequent requests to the locked resource by the threads. And lastly, the metrics come with a higher average hold time (Metrics AVER_HTM) in the case when the threads hold the lock for more than expected.

In order to move forward with unsupervised learning and make our hypothesis proven, it is required to find some correlation among the data points. Machine learning is after all data-driven AI, and our model will be as good or as bad as the data we have [8]. Although, some research that we listed under Chapter 2, stated that there is no correlation among or between the features of JLM but our careful observation finds out some interesting insights. JLM metrics do change based on the fault types and keep following some certain patterns after reaching to the threshold points of the parameters such as threads and sleep time.

Our research is driven by the fact that there could be two potential bottlenecks; according to Brain Goetz's book, the data points are changing based on these two factors. In our simulation, we ran some scenarios where an operation held a lock for an excess amount of time. In this scenario, we observed that the AVG_HTM of a monitor increased when the GETS, TIER2 and TIER3 decreased. In contrast, a monitor experienced a higher amount of frequent access to the locked resource only when it spent a shorter period in the critical section. In the case of high hold time and high frequent access, the high hold time conquers the overall situation and reflects to the JLM data. In summary, the higher hold time feature is a dominating feature in this case.

Based on this theory we can construct the following statements:

1. In case of high hold time simulation hold-time-related metrics increase in number,

2. In case of higher hold time the spin related metrics decrease in number,

3. In case of higher spin it increases in number only when the monitor spends shorter. period of time.

5.3 DATA PREPROCESSING

Correlation Heatmap is a data plotting that helps visualize the data and expresses the interconnection between the features. Leveraging the heatmap often data scientists find out the insight into the data such as some features are positively correlated or negatively correlated to each other. Therefore applying the data into a heatmap, the map shows the inner connection between the features. Heatmap correlation for `synchronized task` example is shown in the Figure 5.1. The heatmap plotting is done using our final dataset. Also, the features that we used in heatmap are listed in the index Table 5.1. A heat-map analysis of the performance metrics, see Figure 5.1, found an interesting correlation between the GETS and AVER_HTM columns of the JLM data. We found that spin related metrics such as GETS, TIER2, TIER3, and spinlock_acquire have a positive correlation but there is a negative correlation observed between those metrics and others such as AVER_HTM. This strengthened our believe that the performance metrics could be classified. Also analysing this heatmap plotting assist us sorting out some important features those are used for the final dataset for clustering process.

Before running into KMeans or some other clustering algorithms such as Density-based spatial clustering of applications with noise (DBSCAN) [10], some data preprocessing was required. For this, we wrote an algorithm that parses the run-time data into the form we need. It creates the CSV file using the values from the raw *perf* and JLM data. After that we run the heatmap plotting helps us to remove some columns that are not necessary. For example, the columns `GETS` and `NONREC` are highly correlated to each other and therefore we keep `GETS` in our dataset. The column `%MISS` is all zero values. Hence, we leave out this column. In order to increase the readability of the column

Index	Label
0	GETS
1	NONREC
2	SLOW
3	TIER2
4	TIER3
5	%UTIL
6	AVER_HTM
7	_raw_spin_lock (RAW_SPIN_LOCK)
8	ctx_sched_in (CTX_SWITCH)
9	delay_mwaitx (DELAY_MWAITX)

Table 5.1: Lock-Contention Performance Metrics Indexes

names we also rename the columns that are collected from perf data, such as `_raw_spin_lock`, `ctx_sched_in`,
are renamed to `RAW_SPIN_LOCK`, `CTX_SWITCH` and `DELAY_MWAITX` respectively. The K-Means algorithm requires data to be numerical and tabular. We preformed the following steps in our data preprocessing step to achieve this.

1. Remove unnecessary alphabetical columns.

2. Merge the *perf* and JLM into one data-frame.

3. Remove columns that have 0 values or did not appear in sufficient runs.

4. Remove some unnecessary columns from the dataset after analysing the heatmap.

5.4 Validation : Optimal Number of Clusters

The most crucial part of unsupervised machine learning is analyzing the data and validate clustering tendency prior to the clustering and validating the clustering results after that. It is required to validate the clustering tendency to confirm that the data is well cluster-able. Most of the clustering algorithms normally return with some clusters even if the data does not contain any clusters or

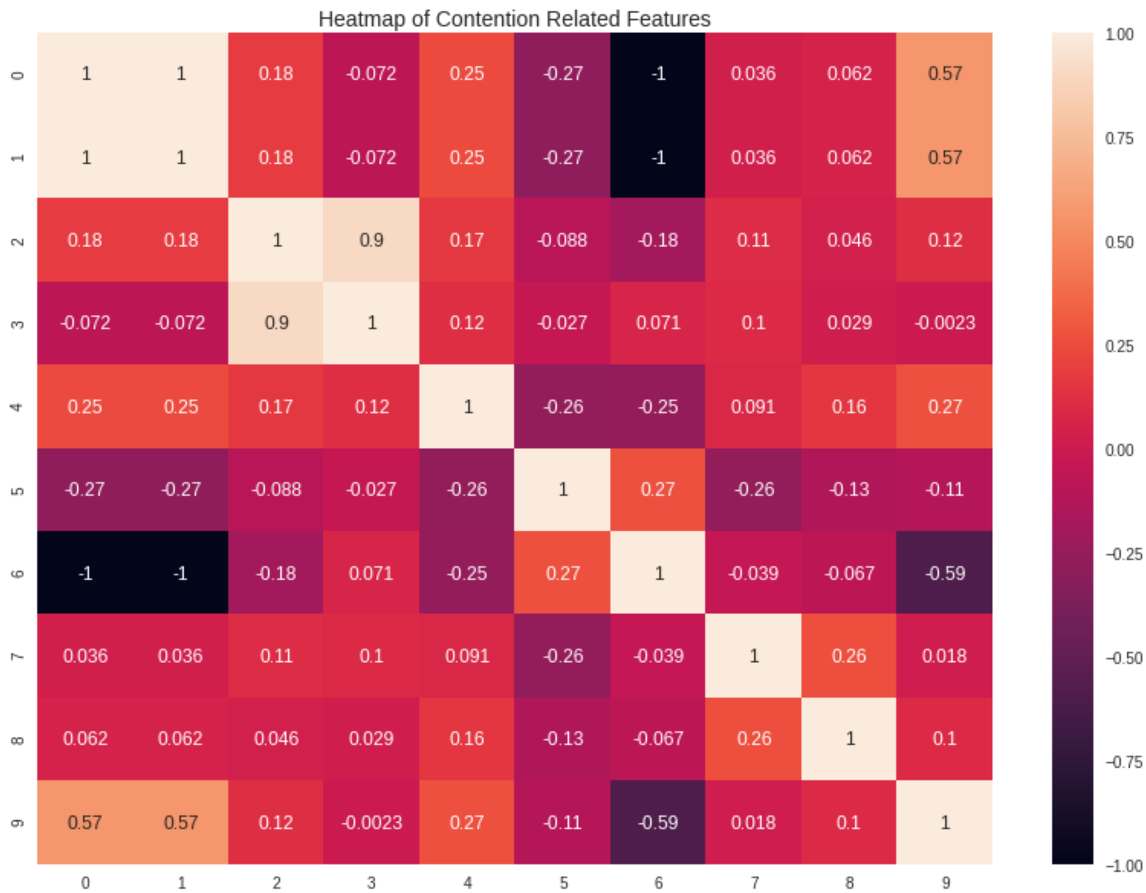


Figure 5.1: Metrics Correlation Heat-map

groups [25]. Therefore, two factors are important in validating clustering approaches **a)** *Assess the clustering tendency before the analysis* **b)** *validate the quality of the clustering results*. In this section we try to validate the clustering tendency and possible optimal number of clusters with the following three techniques:

1. **Assess Clustering Tendency:** This technique determines whether the dataset contains meaningful clusters.

2. **Relative Clustering Validation**: This technique evaluates the structure of the clustering process by varying different parameters of the same clustering algorithm. And this technique

is useful to determine optimal number of clusters can be found in the dataset

3. **External Clustering Validation:** This technique compares the results with the externally known results. This validation assists in determining the appropriate clustering algorithm for the chosen dataset.

5.4.1 Prepare Environment

In order to measure the clustering validation we take the help of R language, and its popular packages such as **cluster**, **factoextra**, **NbClust**. Therefore we prepare the environment and ensure the R language installed in our machine as well as the r-studio, a popular IDE for R developers. When the installation is done we load the each packages in our r-studio and perform the necessary processing to analyze the results with the above three validation techniques. However, before starting the analysis it is required to process our raw dataset using the python data-frame, scale the entire dataset and export to a CSV file. We start our analysis in r-studio loading the CSV data utilizing the R packages.

5.4.2 Assess Clustering Tendency

Typically after applying clustering algorithms on a given dataset, all the clustering algorithms return with clusters even if the data does not contain any meaningful clusters [25]. Therefore, it is mandatory for us to determine whether the data can be partitioned in meaningful groups. In order to achieve that there are some popular methods available such as **a) Hopkins Statistic (Statistical Method)** and **b) Visual Assessment of Cluster Tendency (Visual Method)**. However, applying Hopkins Statistics results in 0.90 for our dataset which is more than 0.5. A good clustering tendency requires Hopkins Statistic value more than 0.5. Therefore, based on this Hopkins Statistical method's result our dataset it highly cluster-able. Hopkins Stat result is shown in Figure 5.2

```
> df = read.csv("./trace4.3.5/trace4.3.5.csv")
> head(df)
  X        GETS      NONREC      TIER2      TIER3        SLOW     X.UTIL    AVER_HTM RAW_SPIN_
1 0  0.830803679  0.830803679 -1.4602945 -0.9336935 -0.05972464 -2.1998673 -0.87606794     2.240
2 1  1.399911505  1.399911505  1.9418446  1.7547678  0.69646072  0.4545729 -1.33363078    -0.522
3 2  0.362159661  0.362159661 -0.8245812 -0.5275893 -0.05972464  0.4545729 -0.44117837     0.081
4 3  0.008151021  0.008151021 -0.6973483 -0.1308946  0.94852251  0.4545729 -0.09484200    -0.522
5 4 -0.182603932 -0.182603932 -0.1699846 -0.3111693  0.44439894  0.4545729  0.09651487     0.081
6 5  1.558464721  1.558464721 -0.5304162 -1.6614937 -0.31178643 -2.1998673 -1.46448009     0.335
> # Compute the number of clusters
> keeps <- c("GETS", "TIER2", "TIER3", "SLOW", "AVER_HTM", "RAW_SPIN_LOCK", "CTX_SWITCH", "DELAY_
> df <- df[keeps]
> df_scaled <- df
> # Compute Hopkins statistic for lock-contention data-set
> res <- get_clust_tendency(df_scaled, n = nrow(df_scaled)-1, graph = FALSE)
> res$hopkins_stat
[1] 0.9040416
```

Figure 5.2: Hopkins Statistic's result shows clustering tendency for our dataset and it is highly cluster-able.

5.4.3 Relative Clustering Validation

In unsupervised machine learning it is required to obtain the clusters in the dataset and it is also required to obtain the optimal number of clusters prior to obtaining the clusters. In this relative clustering validation technique, determining the optimal number of clusters is the primary step that can be done using some popular methods such as **a) Elbow Method** [16], **b) Silhouette Method** [39] and **c) Gap Statistics Method** [25].

Elbow Method (Python & R validation):

To identify the actual optimal number of clusters in our dataset, first of all, we plotted the relationship between the number of clusters and within Cluster Sum of Squares (WCSS), which determines the number of the actual clusters [16]. Optimal number is determined where the change in WCSS begins to level off. WCSS is defined as the sum of the squared distance between each cluster member and its centroid. WCSS is calculated varying the k (expected cluster number) parameter of the KMeans algorithm and storing the model's `inertia_`.

After plotting the WCSS and observing it, a sharp bend at cluster 2 and 3 is visible. Either

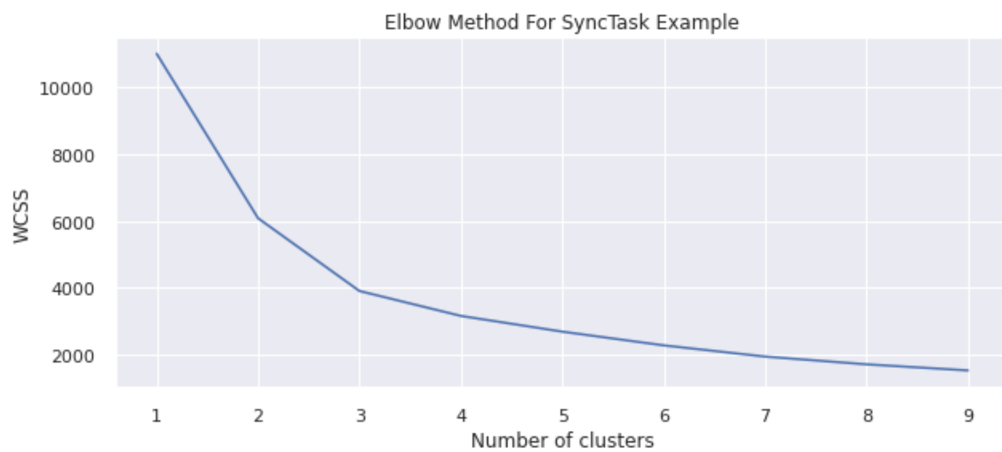


Figure 5.3: Applying K-Means and Elbow Method to obtain possible optimal number of clusters.

of this two number is the expected optimal cluster number for our dataset. Although the sharp bend is visible, it is often difficult to visualize the sharp bend or the elbow point, which needs a programmable calculation. We verified choosing the elbow point of the curve leveraging a Python package, `kneed` [4] [33]. The function `KneeLocator` from the package `kneed` finds out the optimal cluster number in our case is 3. The Elbow method plotting showing the optimal possible cluster number is shown in Figure 5.3. In this figure, it is visible that, y axis plots WCSS score and x axis represents number of clusters (k).

Extracted optimal number of clusters leveraging the R package is 4 for Elbow Method which is shown in Figure 5.4.

Silhouette Method (Python & R validation):

A more advanced algorithm compared to Elbow method to determine the optimal number of clusters in a given dataset is Silhouette Method [39] [25]. The silhouette coefficient is a measurement of cluster cohesion and separation. This method helps decide the assignment of the data points to their proper cluster and how well the data point fits into the assigned cluster. Based on the following two factors, this assignment is done [3]:

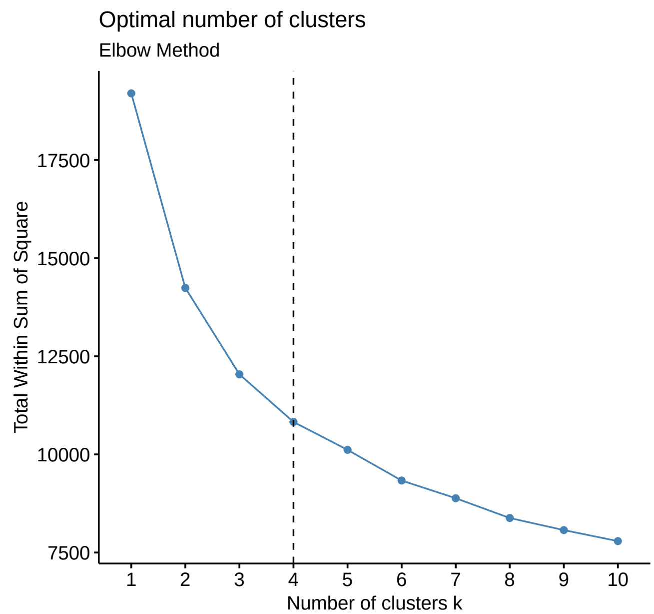


Figure 5.4: R plot of Elbow Method to determine optimal clusters number; which is in this algorithm is 4.

1. How close the data point is to other points in the cluster

2. How far away the data point is from points in other clusters

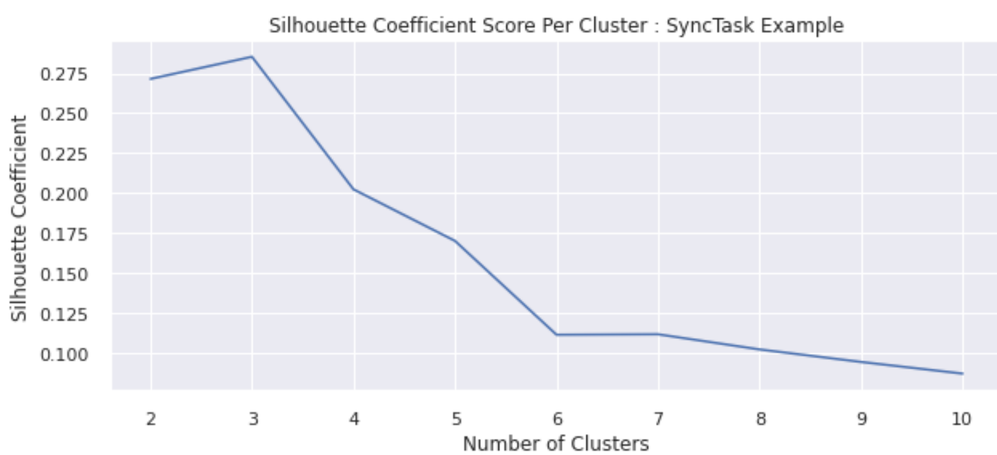


Figure 5.5: Applying K-Means and Silhouette Coefficient to obtain possible optimal number of clusters

We perform python implementation of Silhouette Method to verify the possible optimal number of clusters. Silhouette coefficient values range between -1 and 1. Higher numbers indicate that samples are closer to their clusters than they are to other clusters. The python library `silhouette_score` from sci-kit learn `sklearn.metrics` helps us to apply silhouette scoring. However, the implementation of sci-kit learn-based silhouette coefficient summarizes the average silhouette coefficient from all samples into one score. The scoring function takes a minimum of two clusters as an argument; otherwise raises an error. We maintain the proper arguments while calculating the silhouette coefficient.

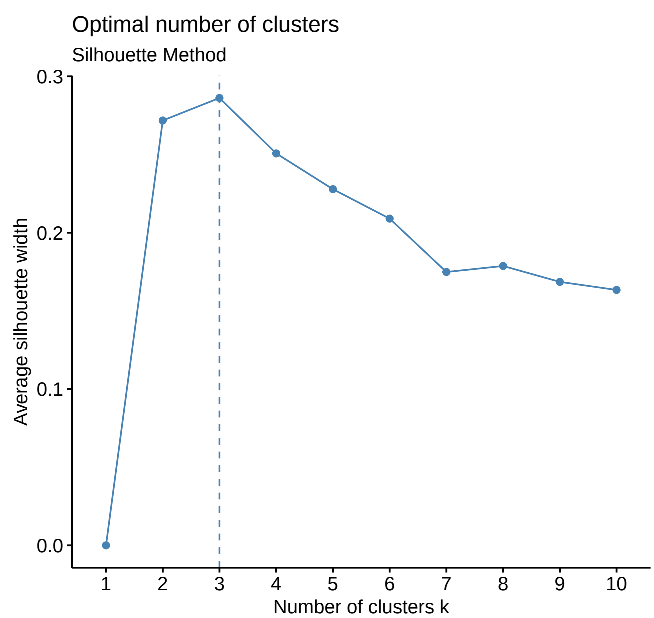


Figure 5.6: R plot of Silhouette Method to determine optimal clusters number; which is in this algorithm is 3.

Similar to Elbow Method, we train multiple KMeans models varying the parameter **K = (expected number of clusters)** and compute the Silhouette's score for each of them. Figure 5.5 shows the optimal number of clusters which is 3 for our dataset. And the score for the cluster number 3 is the highest. The R implementation of Silhouette Method also determines that the optimal number of clusters for our dataset is 3. R plot of Silhouette Method to obtain optimal number of clusters is shown in Figure 5.6. In both Python and R implementation of Silhouette Method show that y axis plots Silhouette score and x axis plots number of clusters k.

Other Methods (R validation):

”Gap Statistic” is another popular method used to find the optimal value for k and has been used for more than twenty years. This method can be used for any clustering algorithm and finds the total within intra-cluster variation (W_k) for each expected cluster number. The largest W_k for a cluster number is the expected optimal number of clusters possible within the dataset. The extracted optimal number determined by the ”Gap Statistic” method is 2. The R plot of Gap Statistic Method's result is shown in Figure 5.7. The y axis for the gap statistic method plots W_k, and the x axis is always k = number cluster.

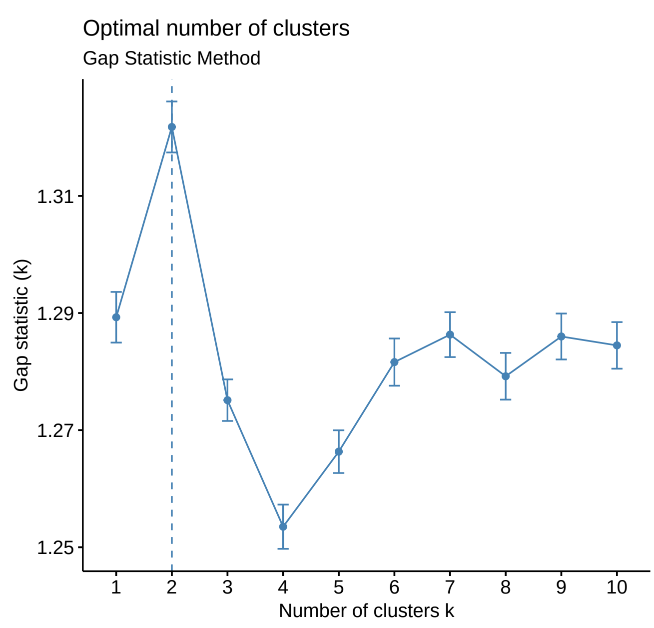


Figure 5.7: R plot of Gap Statistic Method to determine optimal cluster number; which is in this algorithm is 2.

In order to determine optimal number of clusters, more than thirty indices has been published in the literature and the R package `NbClust` [7] has aggregated them in one function. Leveraging this package it is also possible to determine the right number of clusters as the function calls all the thirty indices or methods to obtain the right number of clusters. Among all the indices 11 suggested that the number is 3 for our dataset. The r-studio console result and one of the indices called hubert-index and last of all the plot of suggestions are shown in Figure 5.8, Figure 5.9 and Figure 5.10 respectively.

```
> nb <- NbClust(df_scaled, distance = "euclidean", min.nc = 2,
+                max.nc = 10, method = "kmeans")
*** : The Hubert index is a graphical method of determining the number of clusters.
                In the plot of Hubert index, we seek a significant knee that corresponds to a
                significant increase of the value of the measure i.e the significant peak in Hubert
                index second differences plot.

*** : The D index is a graphical method of determining the number of clusters.
                In the plot of D index, we seek a significant knee (the significant peak in Dindex
                second differences plot) that corresponds to a significant increase of the value of
                the measure.

*******************************************************************
* Among all indices:
* 5 proposed 2 as the best number of clusters
* 11 proposed 3 as the best number of clusters
* 1 proposed 4 as the best number of clusters
* 2 proposed 6 as the best number of clusters
* 1 proposed 9 as the best number of clusters
* 3 proposed 10 as the best number of clusters

                   ***** Conclusion *****

* According to the majority rule, the best number of clusters is  3
```

Figure 5.8: R Studio console shows the statistics of determining optimal number of clusters among all 30 indices.

Analyzing all the methods, we come to a complete conclusion that the optimal number of clusters in our dataset is 3 and the ”number_cluster” argument for any clustering algorithms can be set to 3 after obtaining this result.

5.4.4 External Clustering Validation

Choosing the appropriate clustering algorithm for a given dataset is as important as finding the correct number of clusters in unsupervised machine learning. The means of external clustering validation is selecting the appropriate clustering algorithm which fit the best for a given dataset. In

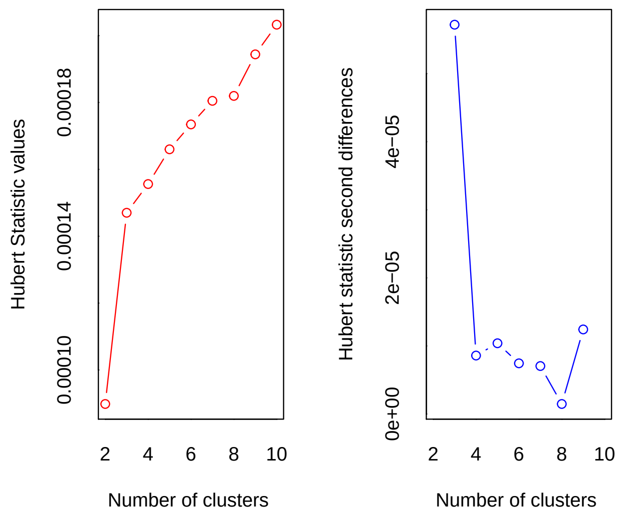


Figure 5.9: R plot of hubert-index, one of the thirty indices shows right number of clusters possible in our dataset.

order to achieve the results, one should measure the clustering statistics of different algorithms to the known results which is the true labels of the classes. The labels for our dataset is absent and not possible prior to the classification, hence this external clustering validation is not applicable in our work. Instead analysing the different algorithms, we choose KMeans and applying enhanced clustering also known as **eclust** from R package **factoextra** helps us partitioning the data into three different classes. The result and plotting of enhanced clustering (eclust) is shown in the Figure 5.11.

5.5 Running Clustering Algorithms

Our clustering process comprises applying several clustering algorithms such as PCA (Principal Component Analysis), KMeans and DBSCAN. These clustering techniques help us to find the hidden clusters within the dataset. Using the Principal Component Analysis (PCA) method, we reduced the dimensions of our data. To achieve that, we used python library `PCA` from `sklearn.decomposition`. As we defined the final output components as two, PCA outputs

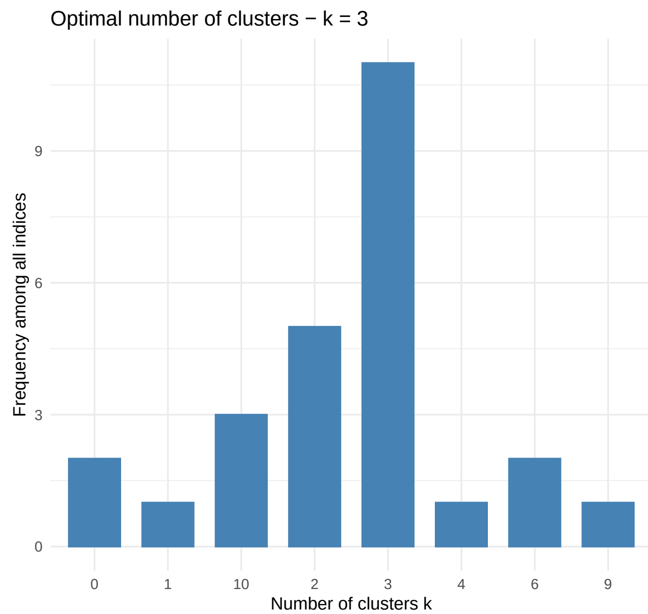


Figure 5.10: R plot of suggestions of thirty indices to obtain optimal number of clusters possible in our dataset; 11 suggested the number is 3.

the two principal components out of ten starting attributes. To obtain a better result, PCA recommends scaled data and we ensured that also using the python library `StandardScaler` from `sklearn.preprocessing`. However, applying PCA and reducing the dimensionality is not the end, when it is essential to run the KMeans right after the PCA to observe the cluster centroids that the KMeans found. As we expected three clusters based on the optimal number of clusters we found, then running the KMeans with the required argument, the demanded cluster number, we found the desired clusters out of the whole dataset. The applied PCA and the KMeans cluster centroids and clusters plotting are shown in Figure 5.12 and Figure 5.13. The Python library `KMeans` from `sklearn.cluster` helps us run the clustering KMeans method after the PCA dimension reduction approach.

Clustering with KMeans requires some arguments before running the algorithm. One of the arguments is the number of clusters that we expect within the dataset. Although, we expect at least two clusters within the dataset, this argument (K = number_cluster) is set to three as our several

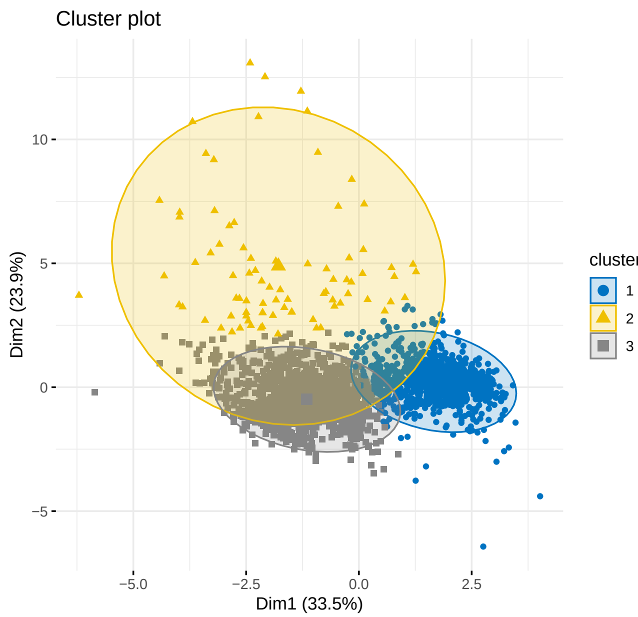


Figure 5.11: R plot of eclust showing clustering is possible using the KMeans clustering algorithm

methods for finding the optimal number of clusters indicate three clusters possible. The argument value K is verified by the several methods including ”Elbow method”, ”Silhouette Method” and more, which are described at Section 5.4. We maintained the following arguments for KMeans algorithm:

- Number of clusters : 3
- Initialization of centroids : k-means++
- Maximum iteration : 600
- Number of initialization : 10

After KMeans, we move forward to the DBSCAN clustering to see whether the DBSCAN clustering algorithm can classify the data from the dataset. Clustering in DBSCAN does not require the expected clusters to be set prior to running the algorithm. However, it requires an argument ”eps”

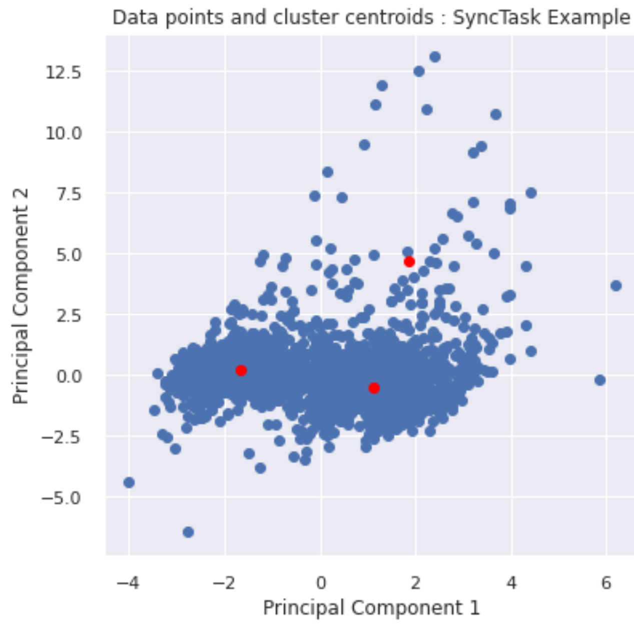


Figure 5.12: Cluster centroids after applying PCA and KMeans, extracted from lock-contention performance metrics

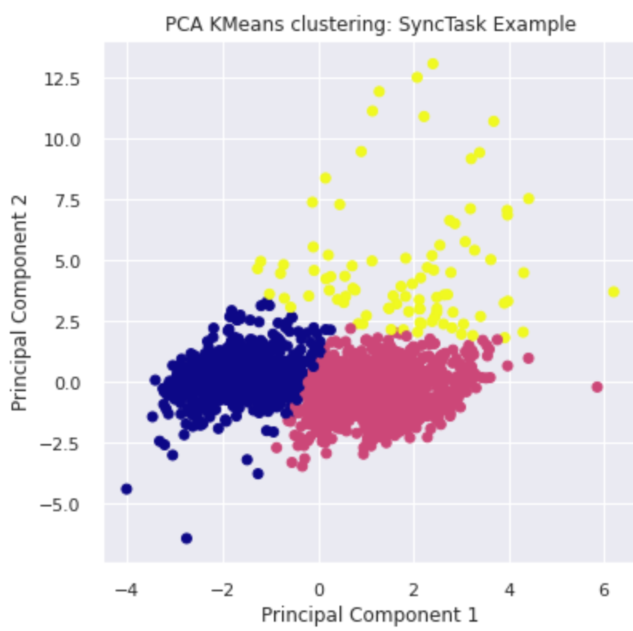


Figure 5.13: Clusters after applying PCA and KMeans, extracted from lock-contention performance metrics

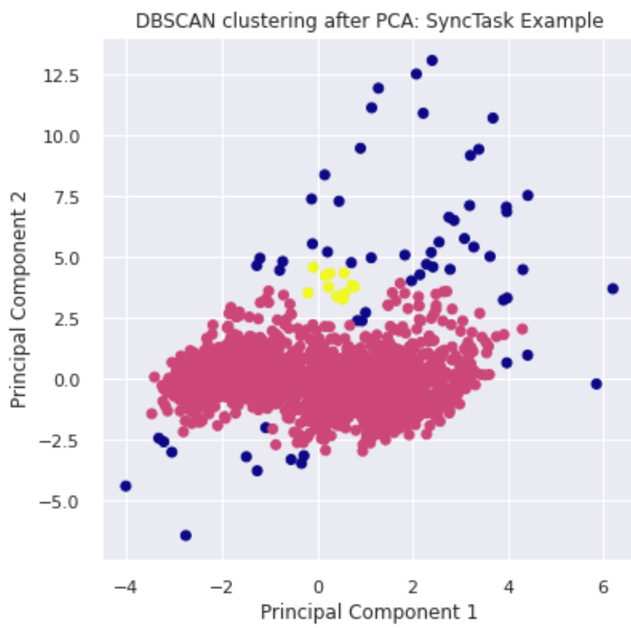


Figure 5.14: Identified clusters from PCA and DBSCAN, extracted from lock-contention performance metrics

(Epsilon). Initially, we set the "eps" argument for the DBSCAN model to 0.3, and it classified more than three clusters which is not expected. However, tweaking the "eps" to 0.4 reduces the number of clusters to five within the dataset. However, we found that two of the clusters are mixed up with the major three clusters identified by the DBSCAN algorithm. The scatter plot of clustering results of DBSCAN using PCA data is shown in the Figure 5.14

5.6 Observing Strong Features

After running all the clustering algorithms, we did reverse engineering to determine the key features in the data for each class. We captured the clusters from the KMeans algorithm and merged the extracted clusters to the original dataset, and plotted the radial visualization [29] which gives us insight into the strength of features in relation to each contention type class. However, we visualize this radial visualization a little bit differently for different extracted clusters this time. First, We merged the PCA+KMeans clusters to the original data-frame and visualize the dominant features for each class, see Figure 5.15.

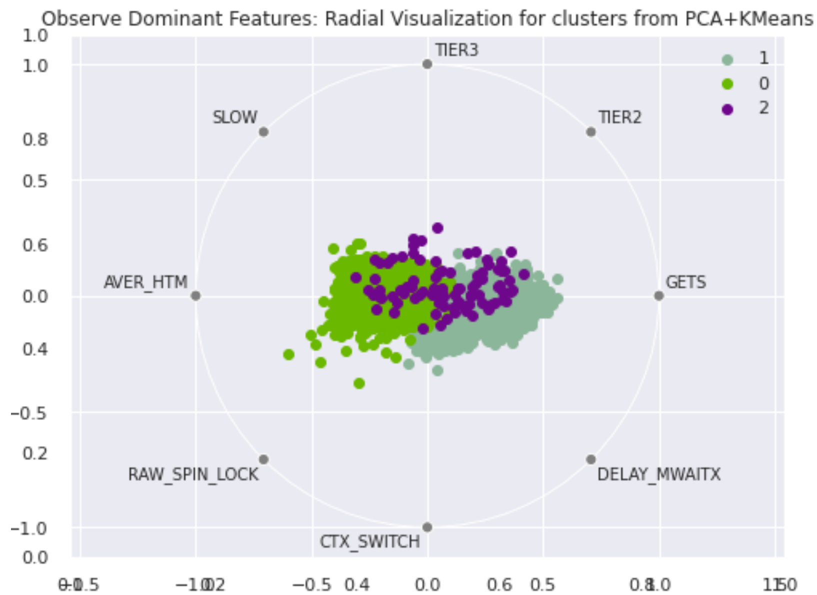


Figure 5.15: Observing key features using 2D Radial visualization for clusters extracted from PCA and KMeans.

Second, we merged the only KMeans applied clusters to the original data-frame and observed the features behaviors, see Figure 5.16.

Third, we go for the PCA+DBSCAN extracted clusters and observe the features, see Figure 5.17.

And lastly we tried with the DBSCAN extracted clusters and observed the strong features related to each class, see Figure 5.18.

The DBSCAN clustering algorithm fails to differentiate the clusters perfectly and therefore we can see from the both Radial Visualization that the clusters are not grouped together nor even they indicate proper dominant feature for each class. Hence the DBSCAN is not a good fit for our approach.

The other Radial Visualization graph clearly shows that some data points are leaning towards

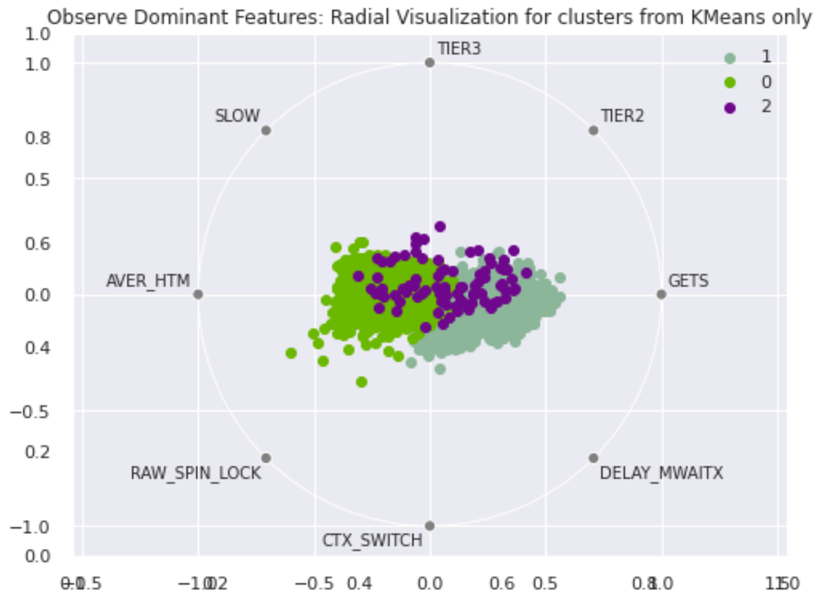


Figure 5.16: Observing key features using 2D Radial visualization for clusters extracted from KMeans algorithm only.

AVER_HTM and which refers to cluster 0 also known as (aka) fault type 1 where threads are holding the lock more than expected time. However, looking at the cluster 1 and cluster 2, it is hard to understand the strong features for them using this Radial Visualization. Although it is visible that cluster 2 is located towards GETS feature but that does not finalize whether this cluster belong to fault type 2.

However, after changing the orientation of the features around the circle of the Radial Visualization, it shows some distinction among the clusters and the dominant features. The new orientation-based Radial Visualization plot for PCA+KMeans extracted clusters is shown in Figure 5.19. Although it is seen from the figure that some data points are inclined towards AVER_HTM, some are towards GETS and some are TIER2 and TIER3, due to large overlapping among the clusters it is difficult to make a decision.

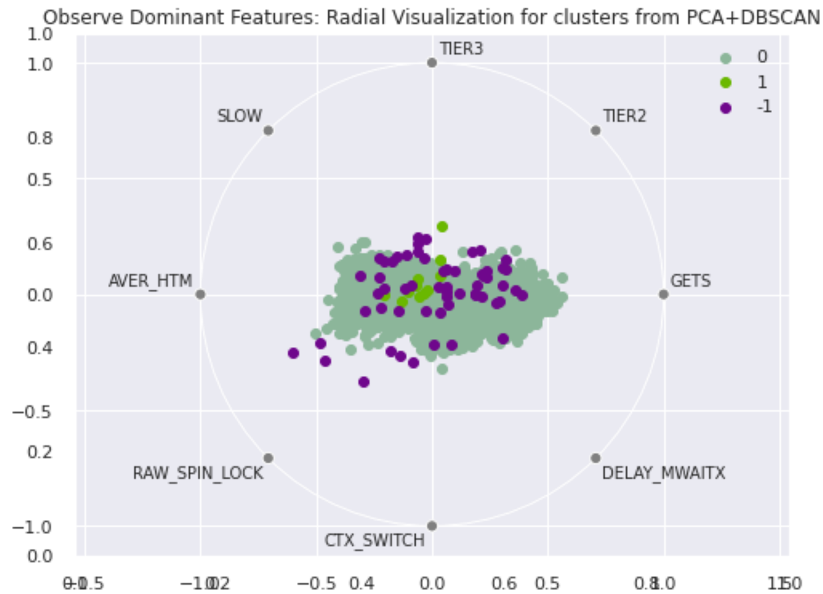


Figure 5.17: Observing key features using 2D Radial visualization for clusters extracted from PCA and DBSCAN algorithms.

5.7 Model's Performance Evaluation

At this moment, we have generated some synthetic dataset by simulating the whole process using an example concurrent codes. Although the whole process is a simulation but our generated data shows some distinct classes on which we performed some model evaluation. However, our PCA+DBSCAN and only DBSCAN failed to show expected performance at the clustering level and hence we left out them from the performance evaluation. We performed two sets of validation, one for the technique where the clustering process is performed using both the PCA and KMeans and the other one is the clusters we extracted using KMeans only. Thus, when we ran the "split into train test" validation, it resulted in the accuracy of 93.61%. In order to perform this split into train test validation we used the method `train_test_split` from the library `sklearn.model_selection`. The other arguments we used for this validation are:

- **Split Into Train Test Validation:**

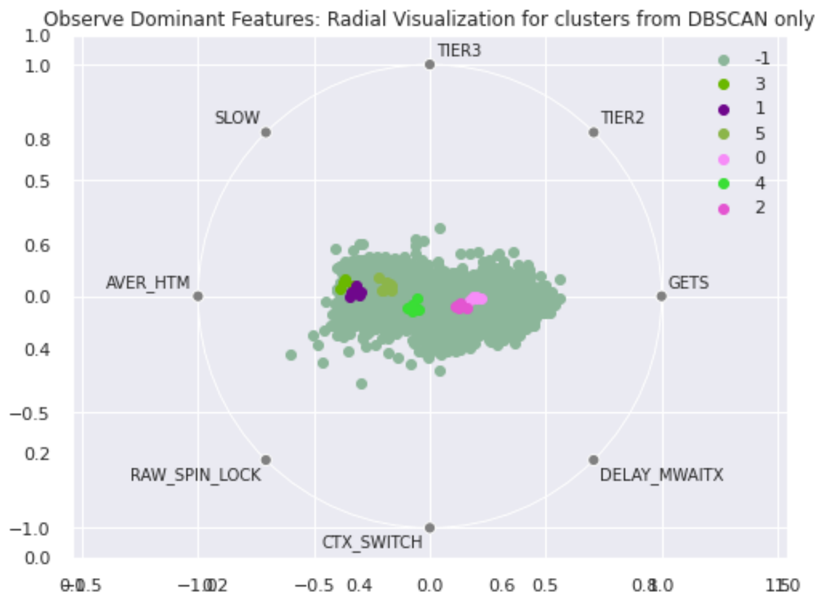


Figure 5.18: Observing key features using 2D Radial visualization for clusters extracted from DBSCAN algorithm only.

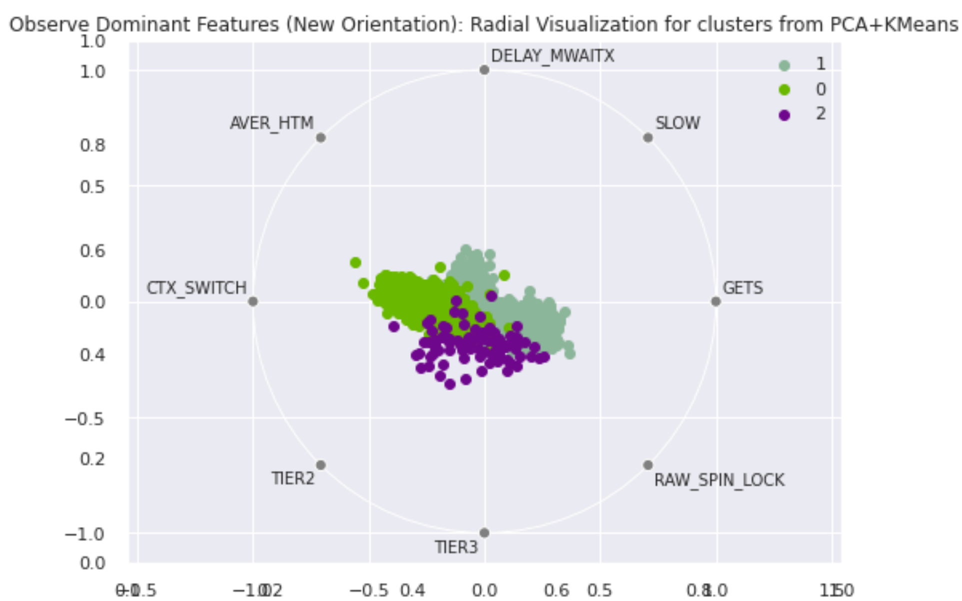


Figure 5.19: Observing key features using 2D Radial visualization for clusters extracted from PCA+KMeans algorithm (New orientation).

  - Test size: 0.25 (25%)
  - Random state: 7 (randomly chosen)

As we have a label for the dataset, we fit our data leveraging widely used Logistic Regression model [6] from the library `sklearn.linear_model`. After that, the method `accuracy_score` from the library `sklearn` helps us determine the prediction's accuracy score. In our second validation for the same PCA+KMeans data-frame, we used the technique called k-fold cross validation. The arguments for the validation are:

- **k-fold Cross Validation:**
  - Number splits: 10 (10-fold cross validation)
  - Random state: 7

However, we used the same Logistic Regression model and the validation resulted in the accuracy of 94.32% (Model performance mean) and 1.80% (Performance deviation). This technique leverages the method `cross_validation_score` from `sklearn.model_selection`. Train test split performance evaluation with the cluster extracted from KMeans only, gives us the accuracy of 96.16% while performance evaluation with the method k-fold cross validation gives us in accuracy of 95.91% (performance mean) and 1.36% (performance deviation). The performance results are listed into the Table 5.2

Data-frame	**Train Test Split**	**K-fold Cross Validation**
KMeans+PCA	93.61%	94.32% (mean), 1.80% (deviation)
KMeans	96.16%	95.91% (mean), 1.36% (deviation)

Table 5.2: Models' performance evaluation on different data-frame

5.7.1 Benchmark Code's Performance Evaluation using Model

It is difficult to find one benchmark application with locking performance bottlenecks in it. Even in this thesis work [5], they used their own created benchmark code like ours. However, we found an example application from this book [28] where it stated an issue regarding lock contention. We collected the JLM and *perf* log while running that benchmark code and ran through the prediction model. Our model assigned the values into the low contention cluster. We believe that the JLM and *perf* trace did not experience contention in our environment as we have a relatively high configured machine with a powerful CPU and memory. See the environment configuration in Chapter 4.2.

5.8 SUMMARY

In this chapter, we try to present all kinds of preprocessing results and validations before the clustering and the final clustering results. However, final clustering results show that three clusters are possible within the dataset we generated, and this is also verified by some methods we use for clustering assessment. Preprocessing starts from heatmap analysis, where we manage to show that some features are highly correlated and some are not. Based on this heatmap analysis, some features are filtered. After that, a series of clustering assessments show that the optimal number of clusters possible within the dataset is three. Scaling is mandatory for clustering techniques, and after that, the dataset dimension is reduced to only two components, PC1, and PC2, by applying principal component analysis. We then feed the KMeans with processed PCA data, and it confirms three clusters. However, we initially try to plot the resulting clusters to a radial visualization to observe strong features for each cluster, but the visualization fails to distinguish those properly.

Chapter 6

Cluster Analysis

6.1 Introduction

Extracted clusters from KMeans have numerical labels, and these do not help us identify the actual label (e.g., fault-1, fault-2, etc.) for each data point. Therefore, a method is required that will assist us in labeling each data point to its actual fault type, which is called semantic labeling. In this chapter, we try to present a procedure to label them by observing the threads and sleep distribution.

Although Radial Visualization with new orientation of the features assists us in showing strong features for the three clusters, it is difficult to identify the dominant features for the clusters precisely as the overlapping among the clusters are high. Therefore we move forward to a different visualization technique to understand the dominant features for each cluster. In order to achieve that, first, we apply necessary clustering algorithms and obtain the clusters, and then we merge the cluster results to the original dataset keeping the data-frame's index unchanged. After that, we plot each feature in a box plot to observe the value distribution for them. Therefore, plotting in a box plot of each feature is a great help to reveal the dominant feature. In this chapter, our primary target is to finalize our hypothesis that our assumption regarding the fault types is correct. These faults are reflected in the run-time logs from where those can be detected leveraging our clustering approach. We try to plot each feature in a box plot and observe their distribution for the different clusters to see which features are dominant for a particular cluster.

6.2 Labeling the Clusters

Before labeling a data point to its actual fault type, we need some preprocessing first. It requires the test parameters such as the number of threads and sleep time we vary during our code exercising. However, we store those parameters information for each run and map back to the original dataset after a successful classification process. Now plotting these number of threads and sleep time should assist us in finding the original fault label for each data point.

During the Threads-Cluster box-plot observation and labeling the cluster, the parameter ”THREADS” is mapped back to the scaled final dataset on which we perform clustering. However, the column ”THREADS” is not scaled and we add the unchanged original value stored during the dataset generation. We follow the same exact procedure for the parameter ”SLEEP” when it is added to the scaled dataset.

According to the hypothesis, the thread number is one of the main differences between the regular contention and contention fault type 2, which is a high-frequency request problem. As the fault type 2 problem depicts itself that too many threads send access requests to the locked resources, hence in the thread distribution, fault type 2 should gain the threads with high value compared to the other contention clusters. After plotting the threads distribution in a box plot for each cluster, it is visible that the fault type 2 has the threads that are high in values. It proves our hypothesis that fault type 2 has the relation to the thread numbers that are high in values. The thread distribution box plot is shown in Figure 6.1.

It implies that cluster 2 may fall under fault type 2, where request frequency from the threads is too high.

In order to prove our next hypothesis that the high hold time fault type should have a relation to the sleep time that is high in values, we plot the sleep times for each cluster to a box plot. The box plot of sleep times shows the distribution, which is shown in Figure 6.2. The figure clearly illustrates

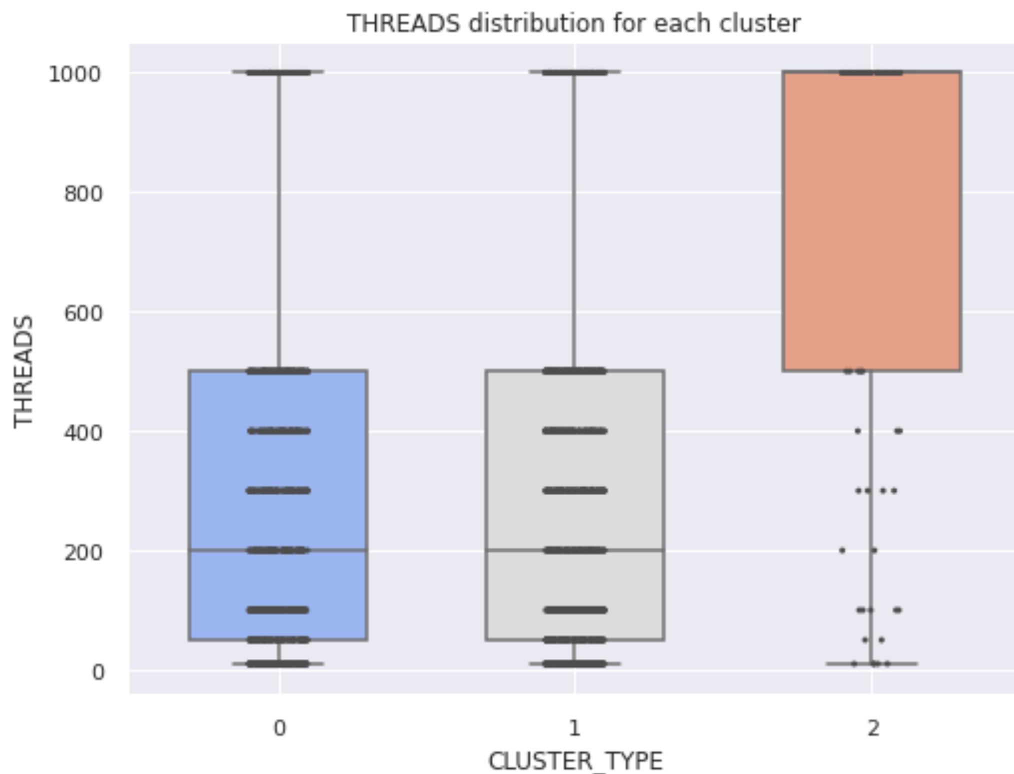


Figure 6.1: Observing Threads distribution using box plot visualization for each cluster

the situation that cluster 0, which is the fault type 1 (high hold time), has the sleep times distribution higher than the other two clusters. Moreover, from Figure 6.2 it is also visible that cluster 1 has the sleep times distribution, which is lower compared to the other two clusters.

Although we expected two clusters from our dataset, either cluster representing high hold time fault or high-frequency requests fault, methods for validating the optimal number of clusters show three. Now, we assume cluster 1 in our dataset is probably represents the low contention cluster as the sleep times distribution is lower compared to other two. It also proves that the low contention cluster gains the lower sleep time distribution compared to both fault type 1 and fault type 2.

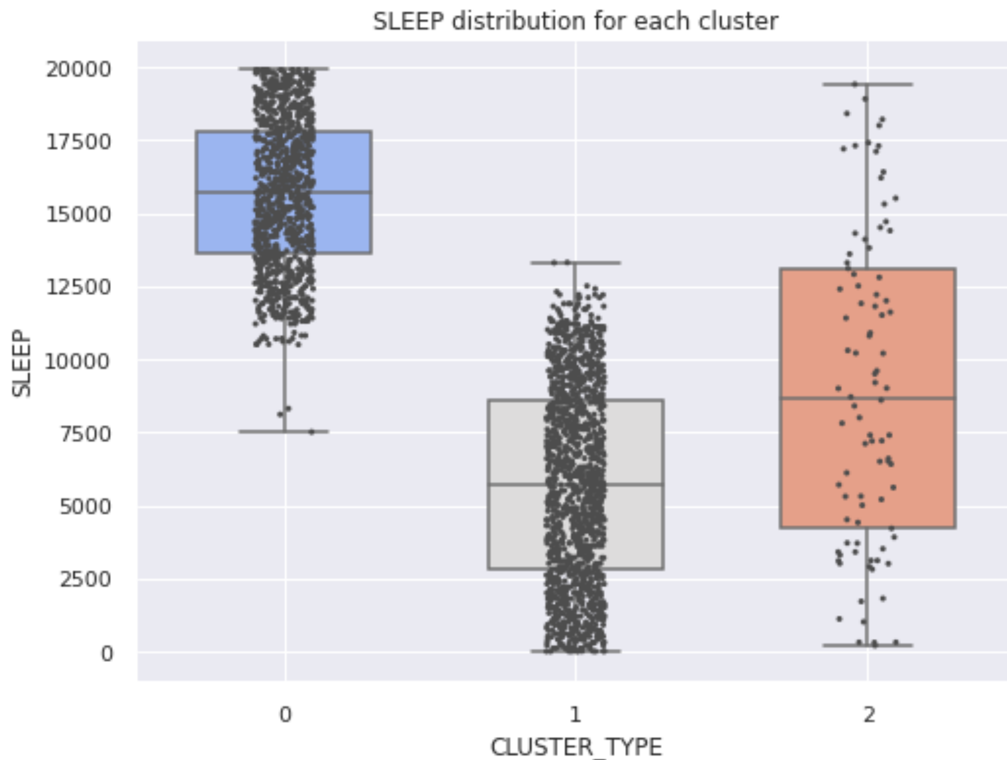


Figure 6.2: Observing Sleep distribution using box plot visualization for each cluster

6.3 Observing Features : An Advanced Analysis

Analyzing the features and exploring dominant features for each cluster is always recommended for our work, as our investigation regarding feature exploring is still in progress. However, in order to explore dominant features for each class, we take the assistance of this box plot visualization method where it presents the distribution of a particular feature against the clusters. The plotted features against the clusters are scaled values, and they are scaled leveraging Python package **Standard Scaler**. The different plotting of the features are listed below:

6.3.1 Observing GETS:

GETS feature of JLM represents the total number of successful lock acquisitions. Therefore, it is pretty straightforward that the low contention cluster should gain the high range of GETS values compared to the other two clusters, and it is also visible in the Figure 6.3. However, from the figure it is also visible that the GETS distribution for cluster 2 overlaps with cluster 1. The GETS distribution figure proves that the high hold time cluster negatively correlates to the GETS value. If the lock is acquired and spent for a long time, then the other threads wait to acquire it, and as a result, acquisition decreases.

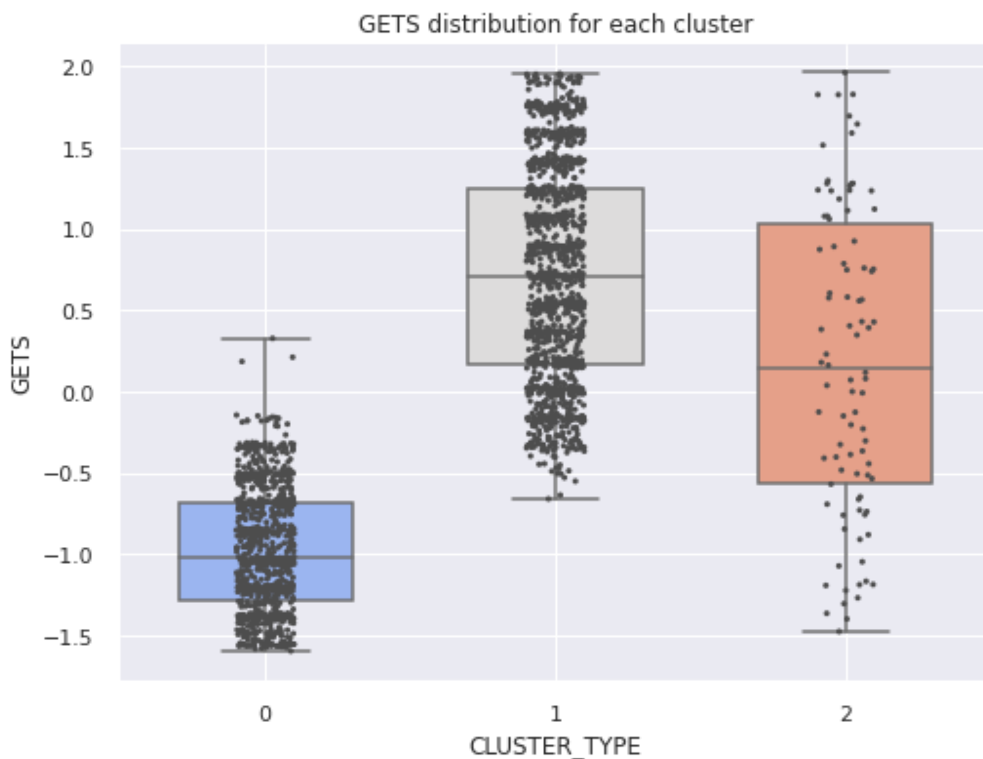


Figure 6.3: Observing GETS feature distribution using box plot visualization for each cluster

6.3.2 Observing Spin Features:

Expectation regarding JLM's spin-related features such as TIER2 and TIER3 is that they should experience high counts when multiple threads sends requests simultaneously. Therefore, based on the experiment the fault type 2 should gain the high counts in JLM's spin-related features. Plotting the spin-related counts in box plot, it reveals that the cluster 2 has the high counts both for TIER2 and TIER3 indicating the frequent access bottleneck. Hence, these TIER2 and TIER3 counts can be the distinguishing factor for fault type 2 performance issue. Both box plot of TIER2 and TIER3 are shown in Figure 6.4 and Figure 6.5.

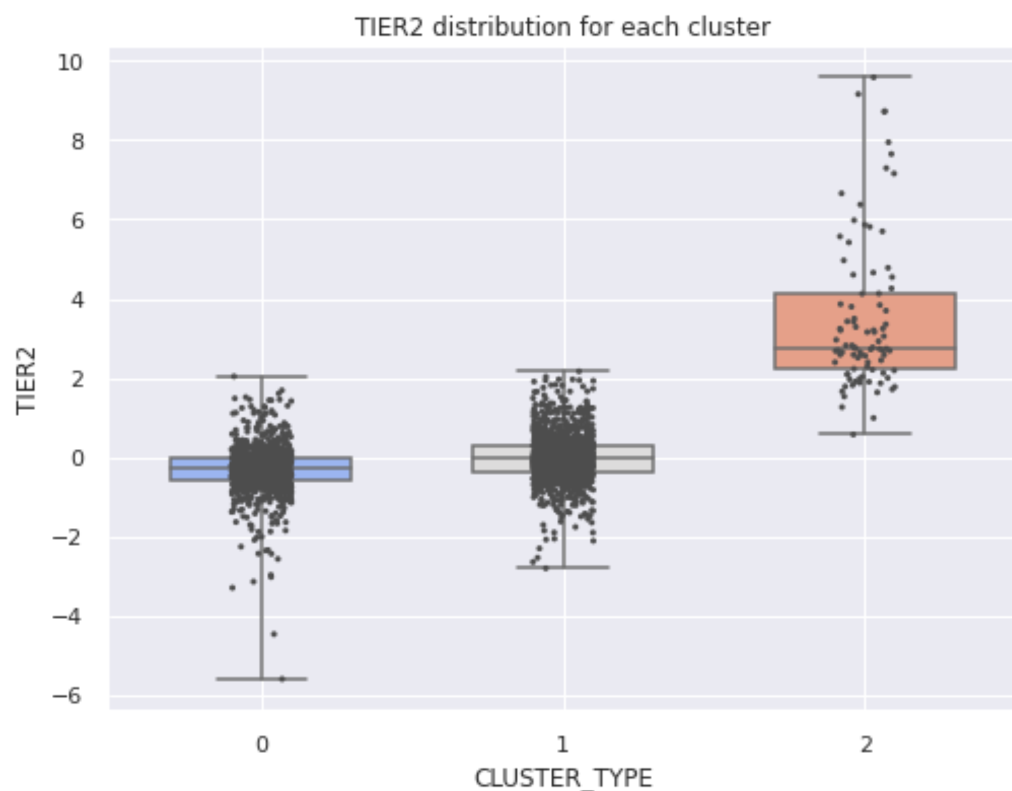


Figure 6.4: Observing TIER2 feature distribution using box plot visualization for each cluster

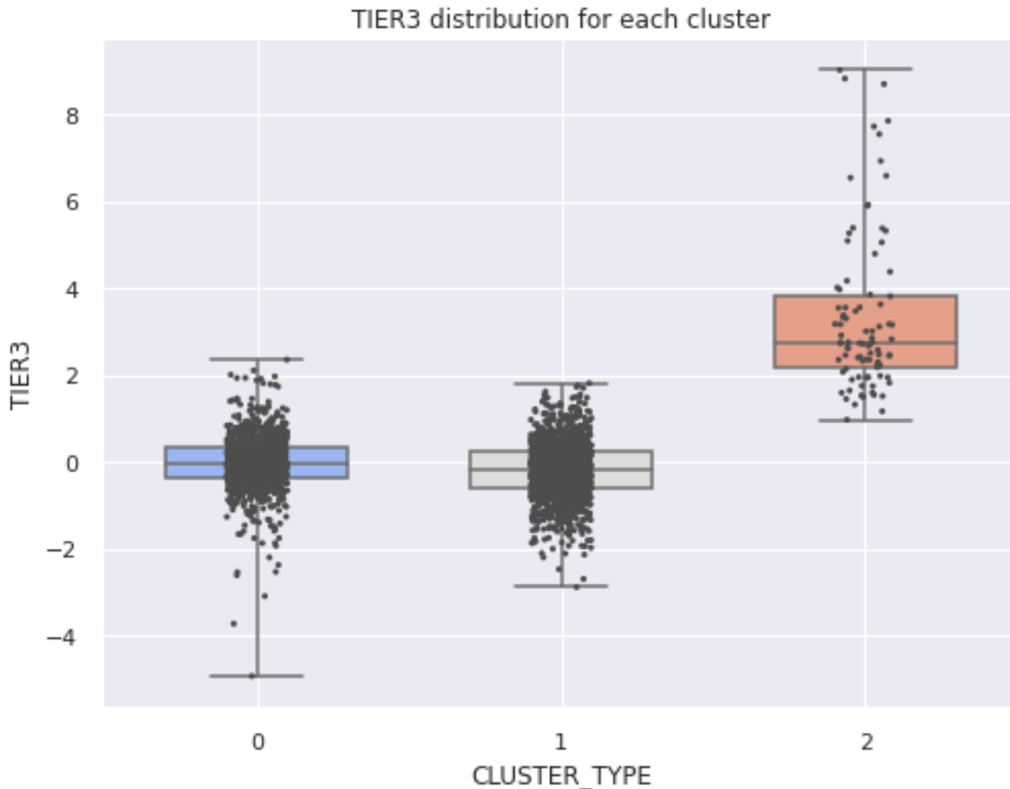


Figure 6.5: Observing TIER3 feature distribution using box plot visualization for each cluster

6.3.3 Observing AVER_HTM:

JLM Feature AVER_HTM represents the average hold time and negatively correlated to the GETS value we obtain from heatmap analysis. The expectation is, in case of high hold time this feature increases in counts and which is what we observe in the AVER_HTM distribution box plot. Accordingly the low contention gains lower counts and fault type two is relatively higher than the low contention. The box plot of AVER_HTM feature is shown in Figure 6.6.

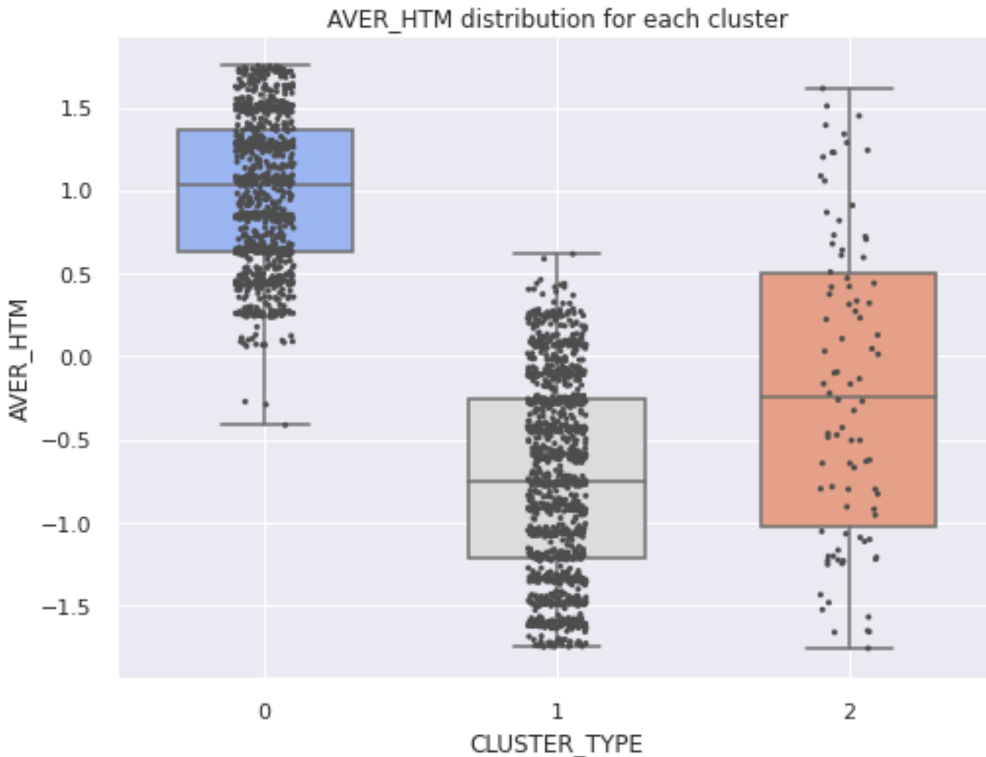


Figure 6.6: Observing AVER_HTM feature distribution using box plot visualization for each cluster

6.3.4 Observing The Other Features:

Although plotting the other features come from the perf data such as RAW_SPIN_LOCK or CTX_SWITCH and DELAY_MWAITX mainly do not assist us in distinguishing the fault types explicitly, and their distribution overlap more, but the feature RAW_SPIN_LOCK is positively correlated to spin-related features, hence the cluster 2 (frequent access fault) has relatively higher counts than the other two. The box plot of RAW_SPIN_LOCK is shown in Figure 6.7. Kernel symbol CTX_SWITCH happens more when there are more threads compete each other to acquire the lock and therefore it slightly increases for cluster 2 again. See the box plot for CTX_SWITCH in Figure 6.8. However, the feature DELAY_MWAITX is kernel symbol represents monitor wait sample counts, showing less range in here for high hold time faults but during experiment our analysis observe that it increases tremendously when critical section is held for more than equal to one millisecond. The feature SLOW fails to present any interesting characteristics in our experiment. The box plot of features DELAY_MWAITX and SLOW are shown in Figure **??** and Figure 6.10 respectively.

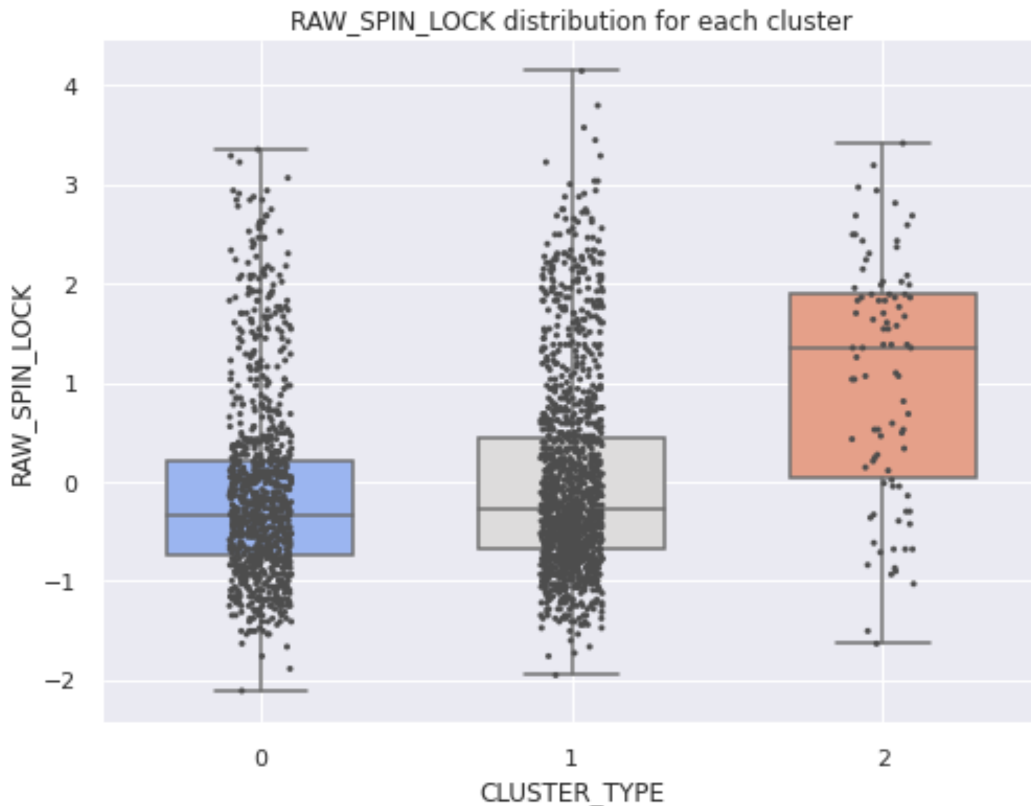


Figure 6.7: Observing RAW_SPIN_LOCK feature distribution using box plot visualization for each cluster

After analyzing the plotting of all of those graphs we can conclude the followings:

- “Less Contention” has the low spinning counts as well as low hold times but the lock acquisition is higher.
- “Contention Fault 1” has low spinning counts but high in hold times.
- “Contention Fault 2” has high spinning counts but low in hold times.

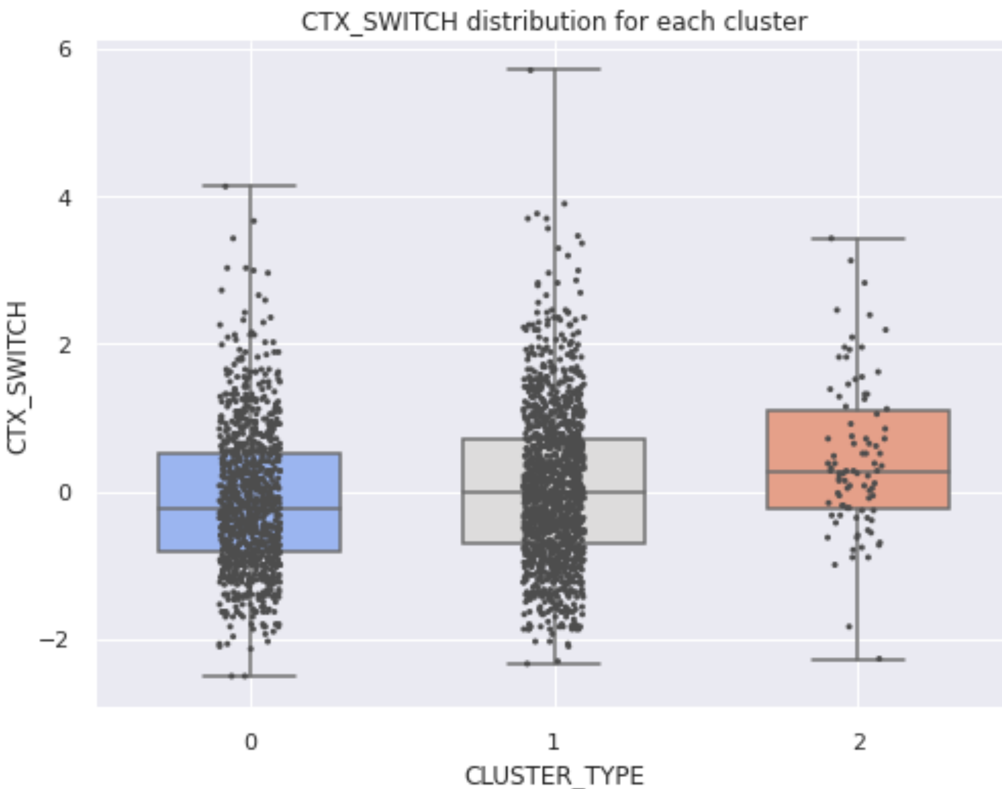


Figure 6.8: Observing CTX_SWTICH feature distribution using box plot visualization for each cluster

6.4 Dominant Features : Importance to The Developers

At the end of this analysis, it is important to know why the dominant features are crucial to the developers and performance engineers. A clustering technique helps construct some groups out of the dataset where the actual labels for the groups are unknown. In order to label these clusters, the dominant features play a significant role here. If a data point has a high hold time, then it definitely falls under fault type 1. Again if the data point has high counts on spin-related counts (TIER2 and TIER3) then it falls under fault type 2. In this case, A threshold value is needed to consider the high hold time or high spin counts. However, in order to obtain and reveal the threshold value of high hold-time or high spin counts, one can train a decision tree model using the KMeans-extracted

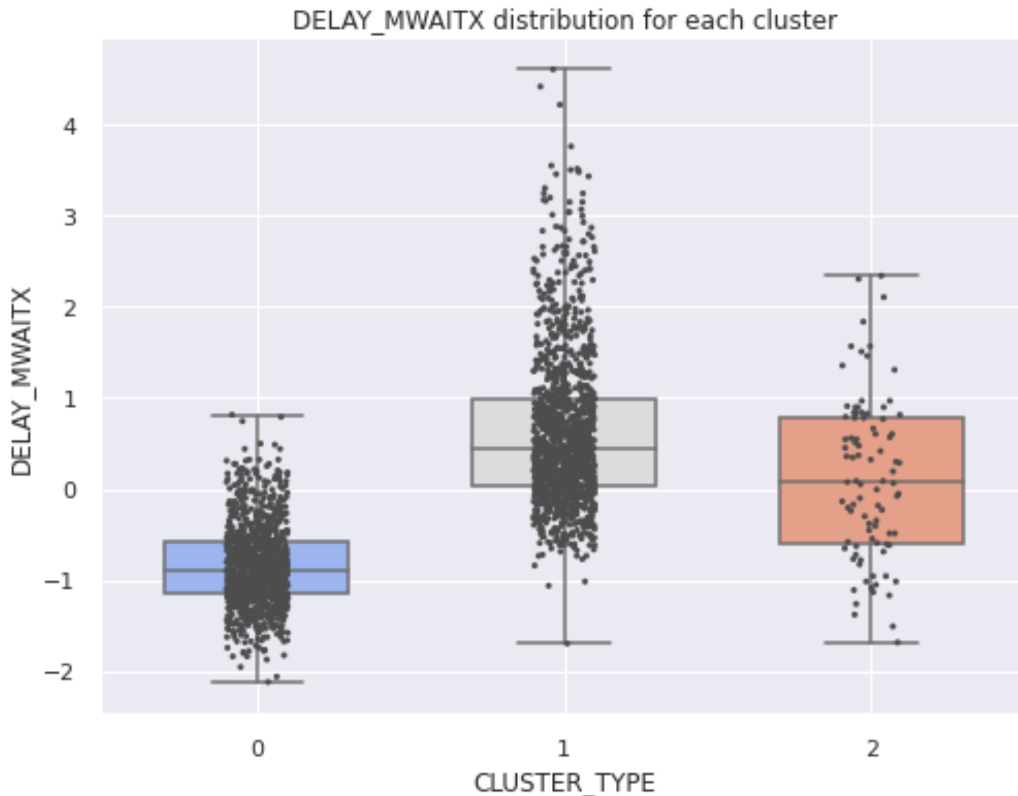


Figure 6.9: Observing DELAY_MWAITX feature distribution using box plot visualization for each cluster

labeled data. Once the decision tree publishes the threshold value, a new data point can be compared and put into its actual label.

Based on the labeling, it is also possible to throw some recommendations by our approach. In case of the high hold time situation, our approach should recommend that the lock consume more than expected time and be reduced by optimizing some unnecessary computations inside it. On the other hand, in case of high-frequency access by the threads, our approach should notify about reducing lock access by separating the shared resources into multiple locks (lock splitting) or making the shared resources more granular during reading and writing.

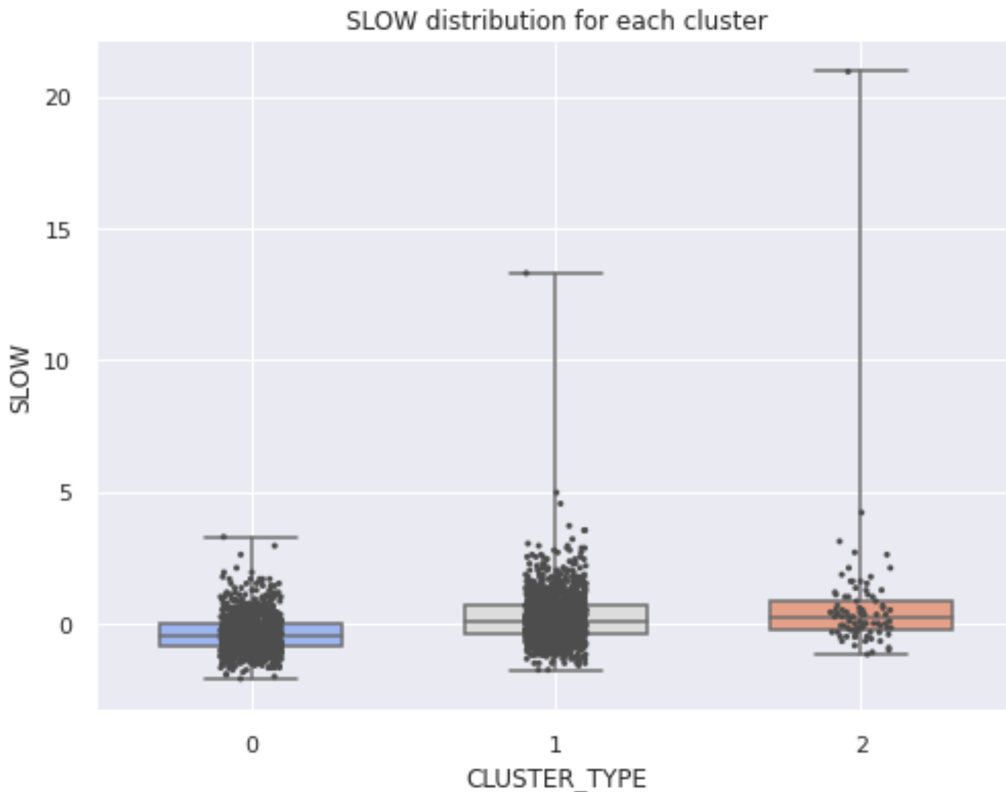


Figure 6.10: Observing SLOW feature distribution using box plot visualization for each cluster

6.5 SUMMARY

When Radial Visualization fails to reveal the crucial feature, an advanced analysis with box plotting comes with great help to reveal the important features for each cluster. In this chapter, we try to present that some features are dominant for each cluster, such as, when it is a high hold time issue, then AVER_HTM will be higher than any other clusters present in the dataset. When AVER_HTM feature increases, then lock acquisition metrics (e.g., GETS) decrease in number. Features related to spin counts (e.g., TIER2, TIER3) are dominant features for high-frequency access problem. Lastly, we manage to show that, low contention cluster has high lock acquisition counts, which is the GETS feature. These features for each cluster are essential to the developers and the performance engineers to understand the actual issue and what type of solution they should apply to reduce the contention.

Chapter 7

CONCLUSIONS

7.1 OVERVIEW

In this research we try to prove a hypothesis that lock contention fault types could be classified through run-time traces via the training of an unsupervised classifier. It is possible, because the fault types leave out some patterns in the run-time logs when different types of contention occurs. Initially we studied the java intrinsic lock and the locking mechanism. Our empirical study shows that, according to Brian Goetz, lock contention performance bottlenecks are primarily caused by two reasons, first, threads hold the critical section more than expected time period, and second, threads access the critical section more frequently. Issues with these bottlenecks cannot be expressed as bug, because bug produces faulty results whereas performance bottlenecks reduce application performance or in other words application entire throughput. Later our study moved forward with learning more about the tools named JLM that IBM uses for their internal use to profile java applications' health. We carefully studied the JLM data and the java inflated monitors which was essential for our study. Understanding the JLM tool and its log assisted accelerate our work. Not only JLM but the perf trace is also equally essential to identify the lock contention faults and classify them. Our research shows that when contention faults occur the perf trace experiences with some common symbols and our analysis carefully studied them as well.

However, our experiment started with creating example code to simulate lock contention faults. In order to prove that, besides the two primary fault types we could experience more types and for that we simulate another class which is the low contention type. We did exercise our code in a controlled environment so that we can control threads and sleep time inside the critical section simulating different execution times.

We built a parser that parses the JLM and perf data from the raw JLM and perf log. After collecting the data from both JLM and perf we merged them into single file and applied heatmap to perform the initial data preprocessing that helps us reducing some less necessary features from the dataset. At our final stage we applied Principal Component Analysis to reduce the dimentionality into two final dimension. We applied the KMeans using the PCA extracted data-frame and found that the data forms some clusters based on the dominant behaviors of the features. Clusters show that one group is the fault type one, spent too much time inside the critical section, one group is low contention and another is with the high spin counts represents the fault type two where threads have too much access requests to the locked resource.

Later on we evaluate our model using train test split and k-fold cross validation method and they show some accuracy around 94%.

7.2 Research Questions

This research intend to classify lock contention fault types and deliver a method that helps identify faults with ease. However, our study answers some primary questions regarding contention classification using the clustering ML approach.

1. **How is this method good enough over traditional approaches?** To answer this question, it is worth mentioning an approach that IBM's performance engineers follow. The "Health Center" is a monitoring tool that helps performance engineers to identify and locate performance-related faults due to locking in a java application. Although this tool delivers

its job quite well, it needs some manual intervention and manual analysis. To detect locking bottlenecks, engineers follow the steps below:

Let us consider an application that creates a locking problem, but we do not know if it is related to contention. The first step would be to check the *perf* profile and then the JLM stat.

- **STEP 1 (Check *perf* profile)**:
  - Run *perf* record and check the profile data.
  - Check how much time is spent on which known routines related locking issue.
  - If the locking related routines are prominent, then it is worth spending time to debug JLM data.
- **STEP 2 (Check JLM stat)**:
  - Check for java application-related monitors under ”Java Inflated Monitors” section.
  - Check if the AVER_HTM is high in counts, definitely it is a problem with holding the lock more time than expected.
  - Check if the GETS or lock acquisition degree related counts such as TIER2, TIER3 is high in number, then the issue is an increase in the requests for the lock monitor.

After identifying the issue, they usually go back to the code-base and resolve the problem based on the decision from the *perf* and JLM analysis. In our approach, this much effort will be lessened once we will able to classify the contention faults.

2. **Why ML is needed for this type of work?** Lock contention performance-related data is numeric and such high range of numbers are often impossible to digest easily by the engineers. In our opinion, ML approach helps to visualize the fault types and translate the necessary guidance to the developers.

7.3 Limitations of our approach

The very first limitation of our approach is the lack of a proper dataset. Due to the lack of an available dataset, it is pretty hard to train and then run an unsupervised ML algorithm and acquire the expected clusters of fault types. We tried to generate some synthetic data by running an example concurrent code. However, we do believe, our dataset can be extended by exercising some concurrent example code with faults in them. It needs an exploration of example codes in open source repositories such as GitHub. Therefore, another problem we experienced is lack of concurrent example codes in the outside. Moreover, there are not so many real world java application exist with faults in them we can use them as benchmark application. Our second limitation of the approach is the logs we collect which might be in some cases incompatible to other types of operating systems. Our approach collects logs from kernel which is a Linux-based and some operating systems does not share the same kernel. Therefore collecting features could be a problem in other types of OS(s). And finally the last limitation of our approach is the JVM we choose. JLM is compatible with OpenJ9 and incompatible to other JVM(s) such as HotSpot. Therefore, our approach might be vulnerable to these situations. However, even though we continued our experiment with synthetic data, from the JLM and *perf* performance data and observing their behavior, it can be assumed that the faults can be classified to help the developers with proper recommendations.

7.4 Future work

In the future, our plan is to collect concurrent codes with faults as many as we can. By exercising the codes we will collect necessary JLM and *perf* data and create a proper dataset. Therefore it can be used as a iconic dataset for identifying or classifying the contention-related faults. Moreover, we believe, through our research it is also possible to extract some other types of faults those are currently unknown. And therefore our research has another potential work to label the different fault types and we also have a plan for that. Additionally, we will try to collect real-world example java application with faults in them so that those can be used for benchmark as well as performance evaluation. We strongly believe, our final training corpus will have a significant contribution to the research community who work with contention related faults identification and classification process through ML approach

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Appendices

Listing 3 Bash script algorithm to run Sync Task Example code, collect JLM and perf data and store them

```bash
#!/bin/bash
javac -sourcepath ${BENCH_CLASS_DIR} ${BENCH_CLASS_DIR}/${BENCH_CLASS}.java

java -Xjit:perfTool -agentlib:jprof -classpath ${BENCH_CLASS_DIR} \
    ${BENCH_CLASS} ${THREADS} ${SLEEP_TIME} &> /dev/null &

# Capture pid of java program
PID_JAVA=`ps aux | grep 'agentlib:jprof' | grep -v grep | awk '{print $2}'`

if [[ "" !=  "$PID_JAVA" ]]
then
 # Record JLM data
 rtdriver -a 127.0.0.1 -c jlmstart 10 -c jlmdump 10 -c jlmstop &

 # Record perf data
 sleep 10
 perf record -p $PID_JAVA -g &

 sleep 10
 PID_PERF_REC=`ps aux | grep 'perf record' | grep -v grep | awk '{print $2}'`

 kill -SIGINT $PID_PERF_REC
else
  echo "java pid process not found!"
fi

# Kill the java program
kill -9 $PID_JAVA

# Convert raw perf.data to human-readable perf.log file
perf script -G -F comm,tid,ip,sym,dso | ./perf-hottest sym > perf.log

# Store the raw perf and JLM log
mv perf.log ./{DESIRED_PATH}/perf.log
mv jlm.xxx ./{DESIRED_PATH}/jlm.log
```

Listing 4 Bash script algorithm to run test multiple times varying thread number and sleep time

```
#!/bin/bash
for THREADS in {10,50,100,200,300,400,500,1000}
do
  TRIALS=200
  DELAY=10
  DELAY_TYPE='ns'
  for ((i = 0; i < $TRIALS; i++))
  do
    ./collect-log.sh /log_saving_path/ /class_path/ JavaMainClass \
        ${THREADS} ${DELAY} ${DELAY_TYPE}
    DELAY=$[$DELAY + 100]
  done
done
```