Symbolic Execution of Higher-order Functions in Big Data Systems

Symbolische Ausführung von Funktionen höherer Ordnung in Big Data Systemen
Master-Thesis von Omar A. Erminy Ugueto
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Abstract

Informationen zu Inhalten der Zusammenfassung entnehmen Sie bitte Kapitel 6.1 des Skripts zur Veranstaltung *Wissenschaftliches Arbeiten und Schreiben für Maschinenbau-Studierende*.

Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like "Huardest gefburn"? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

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Contents

1 Introduction

1.1 Problem Statement

This study aims to identify if *symbolic execution techniques can be used in the context of big data frameworks to generate reduced input data sets that enforce full path coverage*.

The following research questions are relevant for this study:

1. Is symbolic execution a suitable technique for analyzing programs in the context of Spark applications.

2. What are the particular characteristics associated with the symbolic execution of a Spark program.

3. Is there a symbolic execution framework that can be adapted to perform symbolic executions of Spark programs.

4. If it exists, what are the advantages and disadvantages of such a framework in the context of Spark applications.

1.2 Contributions

This work introduces *JPF-SymSpark*, a symbolic execution framework for Apache Spark programs built as an extension of Java PathFinder (JPF). The main goal of *JPF-SymSpark* is to generate reduced input datasets that offer full path coverage of the analyzed program. Such datasets can have several uses in the development process of a Spark application, for example, the generation of input data for unit tests.

The tool is able to symbolically execute Spark programs that handle primitive data types and Strings as their input datasets. It is also capable of chaining multiple Spark operations during a symbolic execution; providing the mechanisms for a complete analysis of a program instead of a method-by-method approach. This reasoning over the inter-relation of Spark operations and the data flow among them is the most useful contribution of this work. To our knowledge, there has not been any study over the application of symbolic execution in big data frameworks.

JPF-SymSpark is built on top of Symbolic PathFinder (SPF), a symbolic execution extension of JPF for general Java programs. During the development of the tool, SPF presented unexpected behaviors when analyzing some programs. Most of these abnormal results were caused by common programming practices in Spark applications, for example, the use of anonymous classes and lambda expressions to represent the

parameter functions passed to many of Spark's operations. The SPF extension was modified accordingly in order to cope with these scenarios. The modifications SPF are:

- Detection of synthetic bridge methods
- Consistent ordering of String path conditions
- Improvements to the visitor pattern in the symbolic constraints

Some of these modifications were included in a patch ans submitted to the SPF administrator for revision. However, to the date this document was published they have not been included in the official source code.

A detailed explanation about the modifications can be found in appendix A.

2 Related Work

This chapter provides an overview to the main concepts and technologies related to our study; it aims to provide sufficient background information to fully understand the upcoming chapters. The reader is encouraged to skip this chapter if she is familiar with the concepts explained next. Section 2.1 introduces *Apache Spark* as the big data framework under study. Next, section 2.2 presents two program analysis techniques: explicit state model checking, and symbolic execution. Finally, section 2.3 gives an introduction to Java PathFinder (JPF) and its symbolic execution module.

2.1 Apache Spark

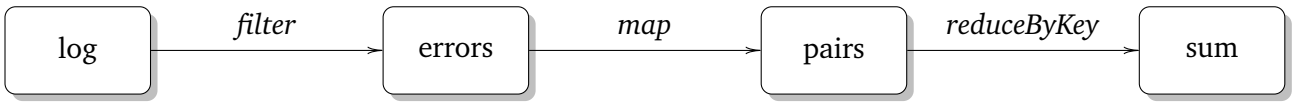
Spark is a distributed data processing framework that was first introduced in 2012 [53]. Similar to other systems, such as MapReduce [14] and Dryad [21], it aims to provide a clean and flexible abstraction to distributed computations on large datasets. However, Spark offers two advantages in comparison to such systems: It makes use of a shared memory abstraction that improves performance by avoiding persisting intermediate sets. It also maintains an efficient fault-tolerance mechanism, based on tracking coarse-grained operations, that can recover lost tasks with minimal impact.

The working units in Spark are called *Resilient Distributed Datasets*, better known as RDDs. These units represent an immutable partitioned collection of elements in a distributed memory space. RDDs can only be created through a set of deterministic operations, known as *transformations* (e.g., *map*, *filter* and *join*), that can be applied to both, raw data or other RDDs. Transformations are not evaluated immediately, instead Spark keeps track of all the transformations applied to each RDD in a program so it can optimize their subsequent processing. Additionally, RDDs can be made persistent into storage or can be operated to produce a value. This kind of operations are known as *actions* (e.g., *count*, *reduce* and *save*), and they are the ones that trigger the processing of RDDs.

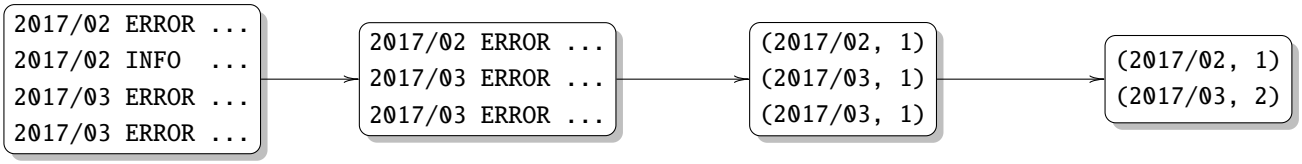
To interact with the RDD abstraction, Spark provides several APIs for different programming languages such as Java, Scala, Python and recently R [45]. Listing 2.1 presents a simple Spark program written with the Scala API, that processes log files in the search for errors. The operation in line 1 creates the first RDD from a log file, whose origin could be a local file or a partitioned file in a distributed file system such as

```
1 val log = spark.textFile("*file*")
2 val errors = log.filter(_.contains("ERROR"))
3   .map(error => (error.split('\t')(0),1))
4   .reduceByKey(_+_)
5 errors.save()
```

Listing 2.1: Entries in a log file are filtered, grouped and counted based on a common property. Finally the result is saved to persistent storage.



(a) Lineage of the program shown in listing 2.1. After each transformation, a new node in the lineage tree is created.



(b) Sample execution of the program shown in listing 2.1. If a task failed, Spark is capable to recalculate only the missing portions by retracing the operations in the lineage that led to the missing data.

Figure 2.1: Lineage and execution of the Spark program shown in listing 2.1. The lineage is independent from the association of an RDD to a variable; for example, the RDD resulting from the filter transformation is not assigned to a variable, however it is a node in the lineage tree.

Hadoop Distributed File System (HDFS) [49]. Spark converts each line in the file to a *String* element in the newly created RDD. In lines 2 to 4, a chain of transformations is applied to the RDD: First, elements not containing the text "ERROR" are filtered. Next, the remaining elements are transformed to tuples consisting of a certain property (e.g., a time stamp; assumed to be the first information in a log entry) and the number 1. Finally, the tuples are grouped and counted based on the chosen property. Line 5 represents the action applied to the RDD, in this case, saving it to persistent storage.

During the execution of a program, Spark does not generate imperatively new data collections for every transformation it finds. Instead, it constructs new RDDs attached with the operation that has to be applied to each element. The resulting RDD is a sequence of operations starting from the source dataset, whose semantics depends on the nature of each transformation involved. It is not until an action is found that the target RDD is resolved and the whole sequence of transformations actually operates the data.

Delaying the resolution of RDDs in this way allows Spark to improve the distribution of operations in a clustered dataset, taking advantage of properties like data locality. Moreover, the trace of operations that produced a certain element in an RDD, known as *lineage*, enables Spark to recover failed tasks only recalling to the necessary data elements that reproduce the lost portion. Figure 2.1a depicts the resulting lineage of the program explained in listing 2.1 and figure 2.1b shows a sample execution of the same program.

Most of the operations in Spark are higher-order functions, this means they accept one or more functions as parameters. For example, the *filter* transformation requires a function that takes an element of the RDD and evaluates to a boolean value. These user-defined functions work as closures by scoping their environment even if it contains references to variables outside itself; this enables Spark to ensure consistency when applying such functions in parallel nodes. The use of higher-order functions serve as a flexible mechanism to adapt Spark's computation model to different tasks.

The inherent capacity of Spark to operate in a distributed memory space makes it well-suited for two

particular scenarios: iterative algorithms and interactive querying. The former, which are commonplace among machine learning algorithms, leverages on the reuse of datasets and avoids having to perform costly I/O operations for every iteration. The latter, allows data mining techniques to synthesize queries faster by keeping working data at hand.

Spark is part of the Apache Software Foundation and it is offered as an open-source software [50, 4]. Several purpose-specific libraries are built on top of Spark, as is the case of: MLlib for machine learning [28], GraphX for graph computations [51], Spark Streaming for stream processing [54], and Spark SQL, an SQL-like interface for structured querying in Spark [5].

In 2014, Spark reported the fastest Daytona GraySort as defined by the Sort Benchmark committee, and later in 2016, Spark was part of the technology stack that claimed the most resource-efficient Daytona CloudSort as defined by the same committee [40, 52, 48]. Overall, Spark offers a better performance in comparison to other data processing frameworks.

2.2 Program Analysis

Ensuring the quality and correctness of programs is a key aspect of the software development process. A wide variety of techniques are used to achieve this purpose, among which software testing is one of the most common. However, testing techniques are not always suitable; in particular, they are not effective detecting the causes of spurious failures that occur only under conditions that are hard to control or replicate (e.g., race conditions). Program analysis techniques result in a better approach in those scenarios because they reason about a model representing the system under test, thus, scoping down the program only to the relevant pieces that are used to verify a desired property.

In general, a model is an abstraction that preserves some selected attributes of an object or concept. They are used in many disciplines as mechanisms to improve communication and support decision making. Models that represent the execution of a program have to discard the unnecessary aspects of it while still preserving the capacity of explaining the potentially infinite execution states in a finite, compact, meaningful, and general view [32].

Programs can be modeled as a series of *states* that can be reached after certain actions occur, for instance, an action can be thought as the execution of code statements. In consequence, the *behavior* of a program can be defined as a sequence of states (or *path*) ranging from the beginning of the execution to its termination.

Control Flow Graphs (CFGs) are one example of such models, where nodes represent program statements and directed edges define the control flow relationship between them [1]. Listing 2.2 and figure 2.2 show a simple linear search algorithm and its corresponding Control Flow Graph respectively. CFGs serve as a starting point for different types of analyses, for example, data flow analysis where each node is augmented with information related to data accesses in order to verify that a variable is always initialized before is read.

Models like CFGs are useful when reasoning about properties related to the structure of the system under

```java
public static int search(int[] a, int elem) {
  for(int i = 0; i < a.length; i++) {
    if(a[i] == elem) {
      return i;
    }
  }
  return -1;
}
```

Listing 2.2: Linear search algorithm written in Java to illustrate the creation of a Control Flow Graph. If the element is contained in the array, the corresponding index is returned, otherwise a -1 is returned.

test. However, analyses of this kind often over-approximate on their conclusions given that they lack the means for conclusively asserting properties that depend on the execution of the program. In contrast, *explicit state model checking* and *symbolic execution* techniques reason about the properties of a program when this is being executed. The following sections discuss these two concepts in more detail.

2.2.1 Explicit State Model Checking

This technique, also known as Finite State Verification, consists of systematically exploring the potentially huge state space of a program in order to understand all possible executions. States are determined, for example, by all the possible values a variable or an expression can take during the execution of the system under test or by all possible interleavings that can result from the execution of a concurrent program.

As can be expected, the number of states for non-trivial programs grow exponentially; what is known as *state space explosion* problem. This condition poses several limitations to the practical use of the technique given that computational resources are quickly exhausted and timeliness conclusions are not feasible. Hence, the challenge relies on the reduction of the state space of the execution while still maintaining a full semantic correspondence between the model and the program, at least in terms of the property that is validated.

Strategies to make the state space smaller are frequently used when generating and exploring a model as an effort to make the technique applicable. For example, *Partial Order Reduction* is a strategy that aims to reduce the number of states to be explored by detecting when transitions resulting from concurrent operations result in equivalent states, making it necessary to explore such path only once.

Nonetheless, explicit state model checking proves itself useful because of its capacity to easily detect faults that would have been challenging, if not impossible, to notice with traditional software testing techniques. In particular, they result useful for discovering faults that would occur rarely under very specific conditions that cannot be generalized. They are commonly used to validate critical and concurrent systems, and are often combined with other testing techniques.

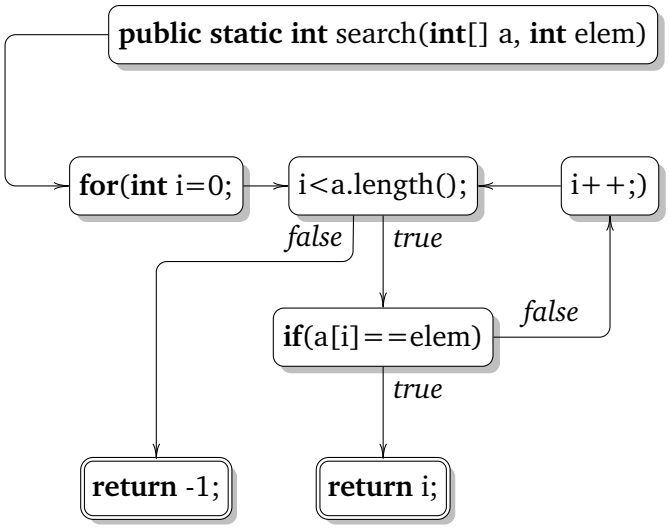


Figure 2.2: Control Flow Graph corresponding to the linear search algorithm shown in listing 2.2. The entry node is the signature of the method, while end nodes, represented with a double frame, contain the return statements that put at end to the execution. The *for* loop instruction was split into its composing statements to better display how the control flow work for this instruction.

2.2.2 Symbolic Execution

The first discussions of symbolic execution date several decades back [20, 25]. The idea consists of executing a program using a set of "symbolic" input parameters in order to build logical predicates that characterize all possible executions. This symbolic parameters can be thought as mathematical variables, in contrast to what would be a concrete value. Throughout the execution, the symbolic values are operated, which generates more complex symbolic expressions. Moreover, control flow statements define logical predicates that could depend on symbolic expressions, bridging the representation of the program from its operational view to a series of logical expressions.

Conditional statements are trivial to evaluate when tracing the execution of a program with a concrete value; the branching conditions are simply evaluated and a path is chosen to proceed with the execution. However, if the branch condition depends on symbolic values, both paths corresponding to the *true* and *false* evaluation respectively are an option, hence, the execution continues to be traced through both branches. As a result, each execution path of the program is characterized by a sequence of predicates and how they were evaluated; also known as path condition.

A path condition is satisfiable if there exists a group of concrete input values that makes its logical predicate hold, which means that these values can steer the execution of the program through that path. Whereas, if the path condition cannot be satisfied then it will be impossible for any concrete execution to follow that path, rendering the path infeasible. Interestingly enough, each satisfiable path condition represents an equivalence class of concrete input values. Figure 2.3 shows the symbolic execution tree of the program in listing 2.3.

Symbolic execution could be combined with pre-conditions, post-conditions, loop invariants and, in general, any assertion at any given point in the source code. Comparing path conditions against these vali-

```
1 public void trivial(boolean a, int b, boolean c) {
2   int x = 0, y = 0, z = b + 1;
3   if (a) { x = -1; }
4   if (z > 5) {
5     if (!a && c) { y = -1; }
6   }
7   assert x + y != 0;
8 }
```

Listing 2.3: Trivial program to illustrate how symbolic execution works.

dations help reasoning about the status of the execution, in particular when detecting faulty programs. Moreover, loop invariants are helpful when executing loops symbolically, given that in most cases loops lead to unbounded chains of logical predicates due to the inability to evaluate the stopping condition concretely.

To determine if a path condition is satisfiable, symbolic execution tools make use of constraint solvers and theorem provers. Though having improved considerably in recent years, solvers and provers still represent the main bottlenecks for the application of symbolic execution in large scale programs [9].

Although full verification based on symbolic execution might be unfeasible, reduced domains and specific validations could benefit from its principles. For example, there are several applications for symbolic execution in program analysis; the most common are input data generation [10], test case generation [8, 11, 17, 46] and static detection of errors [7, 44], among many others [12, 39].

2.3 Java PathFinder

Developed at NASA's Ames Research Center [31], Java PathFinder (JPF) is an execution environment for verification and analysis of Java bytecode programs [47, 23]. Since its publication in the year 2000 [19], JPF has evolved from being a model translator to a fully fledged, highly customizable virtual machine capable of controlling and augmenting the execution of a program.

Java is a widely known, general-purpose programming language with strong roots on concurrency support and object-oriented principles [18]. Programs written in Java are compiled to the standardized instruction set of the Java Virtual Machine (JVM), known as Java bytecode. This process makes Java programs portable between architectures implementing the JVM specification. A JVM implementation serves as an interpreter of Java bytecode and allows the optimization and execution of the program tailored for the host platform [26].

JPF focuses on Java mainly for three reasons: its wide adoption as a modern programming language, its simplicity in comparison to other high profile languages, and the flexibility in terms of bytecode analysis; potentially enabling the verification of any other language capable of being compiled into Java bytecode. Moreover, the non-trivial nature of concurrent programs makes them difficult to construct and debug. A

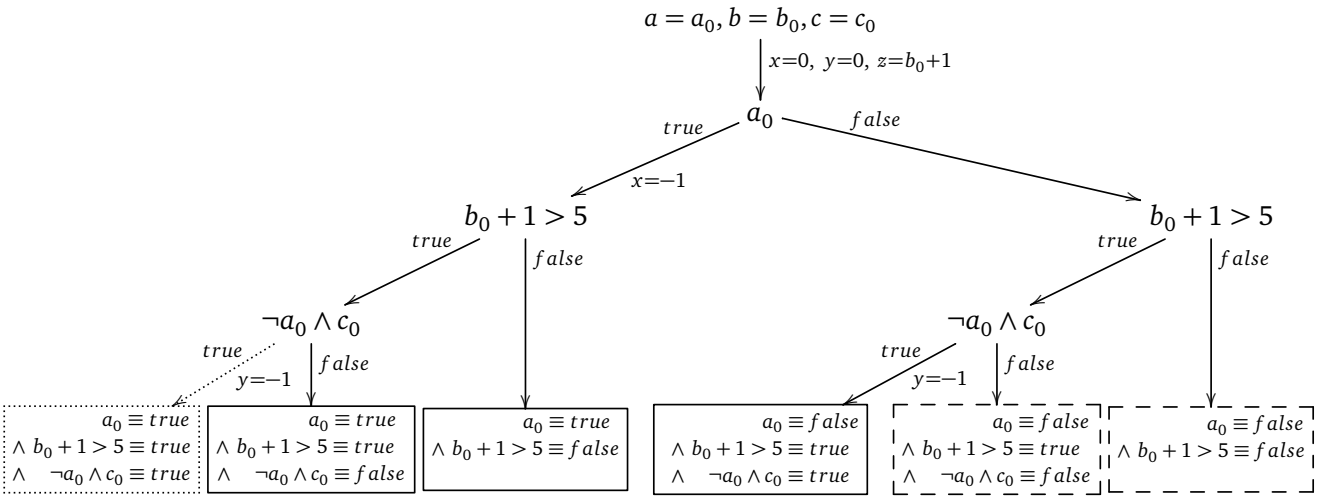


Figure 2.3: Symbolic execution tree of the program presented in listing 2.3. The root node represents the input parameters as symbolic values while the intermediate nodes illustrate the control flow of the program evaluated on these symbolic values wherever possible.Each intermediate node branches into two options, each corresponding to the predicate evaluating to *true* or *false* respectively. Also, each branch is labeled with the statements executed following one of the evaluations. More importantly, the leaves collect the predicates that form the path condition for that particular execution. The left most leave in the dotted frame contains an unfeasible path condition given that the predicate cannot be satisfied. Moreover, the path conditions in the dashed frames define executions that will fail the assertion of line 7.

model checker with the capacity of validating concurrent Java programs is crucial for ensuring correctness of mission-critical software, such as the likes required by NASA.

In its core, JPF is a Java Virtual Machine implemented in Java itself, comprised of several extensible components that dictate the verification strategy to be followed. The fact that JPF is written in Java means that it is executed on a canonical JVM; in other words, a JVM on top of a JVM.

The default mode of operation of JPF is *explicit state model checking*. This means that JPF keeps track of the execution status of a program, commonly referred to as a state, to check for violations of predefined properties. A state is characterized by three aspects: the information of existing threads, the contents of the heap, and the sequence of previous states that led to the current execution point (also known as path). A change in any of the aforementioned aspects represents a transition to a new state. Additionally, JPF associates complementary information to a state (e.g., range of possible values that trigger transitions), in order to reduce the total number of states to be explored. Termination is ensured by avoiding revisiting states.

Figure 2.4 portrays the components that participate in a verification process using JPF. The program under test is loaded into JPF's core, where its instructions are executed one by one until an execution choice is found. At this point, JPF records the current state and attempts to resume execution, exploring all possible scenarios based on the choice criteria. Once a chosen path has been completely explored, JPF

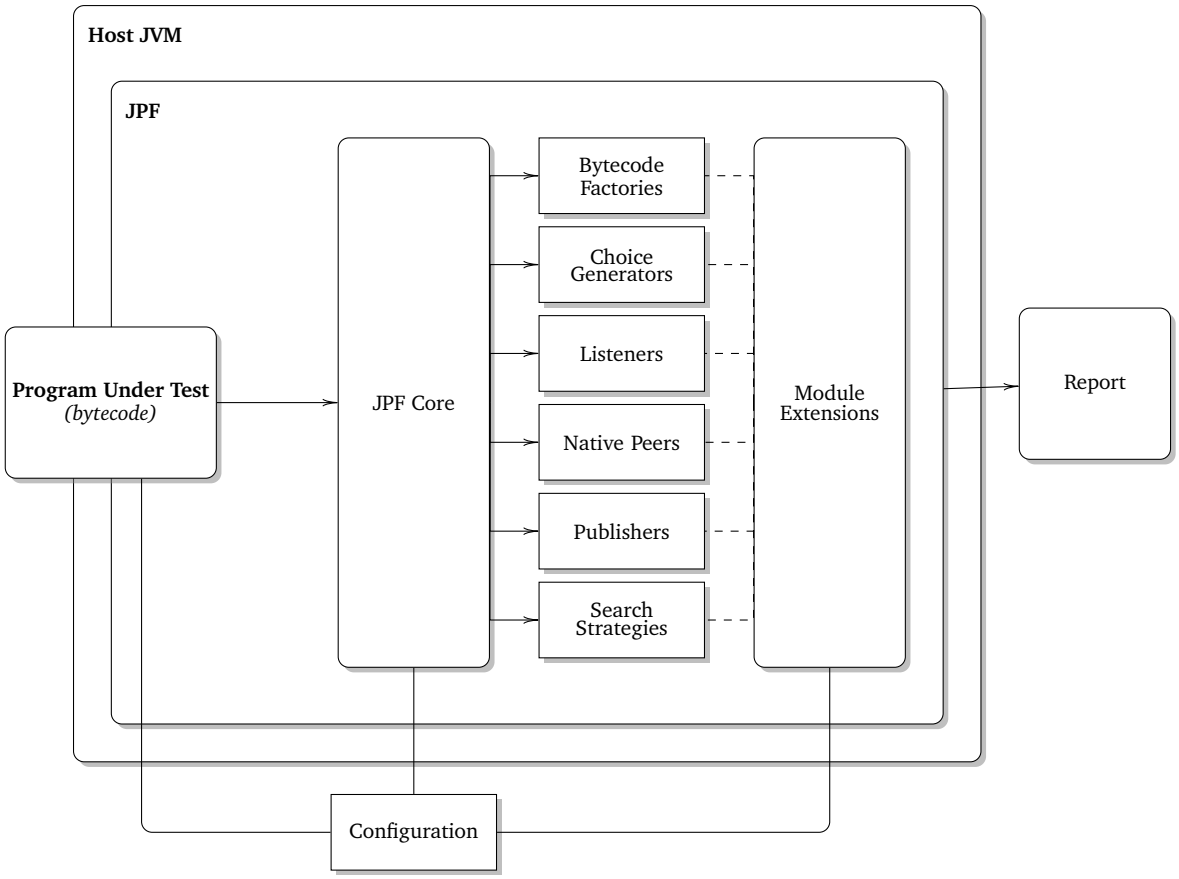


Figure 2.4: JPF Components and workflow. The program under test, taken as bytecode, is loaded into the JPF Virtual Machine which is un turn executed on top of the host JVM. Libraries used in the program under test need to be visible to the core in order to be able to execute the program correctly. Note that the core is comprised by several components in charge of directing the execution of the analysis. The behavior of this components could be extended by including modules. The final output is a report in its general sense; this could range from simple console output to automatic test generation. Moreover, several configuration inputs dictate how the participants proceed through their execution.

backtracks to a recorded state in order to explore a new path.

Listing 2.4 introduces an example that illustrates better how JPF works. The program analyzed represents a trivial division of two random values. However, the problem relies on the fact that, under some specific values, the operation could yield invalid. Problems like this, where computations depend on random and unbounded values, are common sources of bugs in real software and, in many cases, are difficult to identify. With the right configuration, JPF could detect this kind of problems by exploring the range of possible values that a random integer could take. Lines 6 and 7 indicate that random values have been generated; at this point JPF could start exploring all different possible combinations spanning the domain of all integer values that can be represented, but clearly this would imply an enormous number of combinations that would result in a state space explosion. To avoid this, a choice generator is registered, defining a minimal range of integers that could actually occur in an execution; in this case ranging from 0 to the parameter passed to the *nextInt* function. Consequently, a combination that triggers the invalid

```java
import java.util.Random;

public class RandomExample {
  public static void main(String[] args) {
    Random random = new Random();
    int a = random.nextInt(2);
    int b = random.nextInt(3);
    int c = a/(b+a-2);
  }
}
```

Listing 2.4: The use of random values could lead to unexpected behavior. In this case, a division by zero could occur if certain combinations of random values are used. (Example taken from [31])

operation is found promptly and reported back to the user. Figure 2.5 depicts how JPF explores the state space in order to validate the program.

A key aspect of JPF was to make it extensible and customizable. Following a modular design, users of the tool are capable of tuning JPF up to the needs of a wide variety of analyses and verifications. Its main components are:

- **Bytecode Factories**: Define the semantics of the instructions executed by JPF's virtual machine. Modifications to the bytecode factory define de execution model of the analyzed program (e.g., operations on symbolic values).

- **Choice Generators**: A set of possible choices must be provided in order to explore different behaviors of the system under test (e.g., a range of integer values for validation of random input). This aspect is critical reduce the number of states explored during a validation, hence scoping the reach of an analysis.

- **Listeners**: Serve as monitoring points for interacting with the execution of JPF. Listeners react to particular events triggered during the execution of an analysis, providing the right environment for the assertion of different properties.

- **Native Peers**: In some cases, a system under test will contain calls that are irrelevant to the analysis carried out (e.g., calling external libraries) or will execute native instructions that cannot be interpreted by JPF. For these cases, native peers provide a mechanism for modeling the behavior of such situations and efficiently delegating their execution to the host virtual machine.

- **Publishers**: Report the outcome of an analysis. Whether a property was violated or the system under test was explored satisfactorily, publishers provide the information that makes the analysis valuable.

- **Search Strategies**: Indicate how the state space of the system under test is to be explored. In other

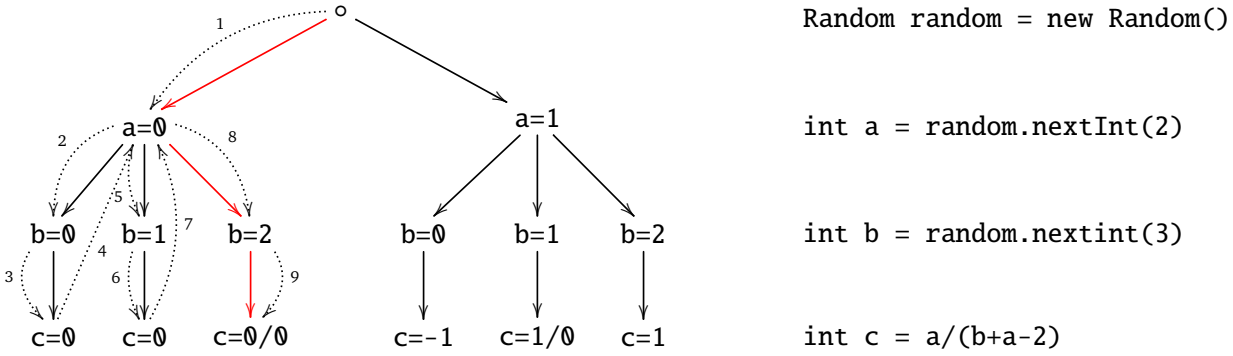


Figure 2.5: State space exploration of the program shown in listing 2.4. JPF starts checking the state space whenever the the conditions that trigger the property to be validated are found; in this case, using random values. The `nextInt` instruction causes JPF to register a *Choice Generator* and start exploring the state space of the possible options. The dashed edges represent the search strategy used to explore the state space; in this case depth-first search. If a given execution path gets to an end and no unexpected behavior is found, JPF backtracks to the latest instruction where a *Choice Generator* was registered and tries a different value. The red arrows point to an execution that triggers an error. Whenever an error is found JPF halts the validation and reports its findings.

words, the search strategy tells JPF when to move forward and generate a new state or when to backtrack to a previously known state in order to try a different choice. Search strategies can be customized to guide the exploration of the state space to areas of interests where the analysis is most likely to detect an anomaly.

Although *explicit state model checking* is JPF's default mode of operation, by no means is the only one. Different kinds of formal methods can be used or implemented through modules, which are sensible extensions to JPF's core that accomplish a particular task. The modules range from different execution models to the validation of specific properties not included previously in the core. Some examples are: JPF-Racefinder, an extension for precisely detecting data races, and Symbolic PathFinder (SPF), which gives support to the *symbolic state model checking* operation mode. The latter of these examples is explained further in the next section.

2.3.1 Symbolic PathFinder

As one of the earliest extension modules, Symbolic PathFinder (SPF) integrates symbolic execution principles into JPF. Although it has undergone several modifications throughout the years [24, 35, 2], its current mode of operation consists of replacing the concrete execution semantics of the default JPF model checker with a corresponding symbolic interpretation [34]. In recent years SPF has had some improvements, primarily supporting Java 1.7 and better detection of unfeasible paths [27].

The introduction of symbolic semantics is achieved through the use of the *SymbolicInstructionFactory* class;

an extension to the default bytecode instruction set that interacts with symbolic values and expressions. For example, operating two symbolic integers using the *IADD* bytecode instruction results in the creation of a symbolic expression that represents the sum of those integers. Furthermore, symbolic values and expressions are assigned to variables and fields, instead of the corresponding concrete representation that would result from a normal execution.

SPF supports symbolic operations on several primitive types: booleans, integers and doubles, as well as on complex data structures. Nevertheless, only limited support to symbolic *String* operations is offered in the latest SPF version.

The interpretation of branching instructions is a key point of symbolic execution because it determines how the subsequent paths ought to be explored. SPF process branches by generating a special choice generator called *PCChoiceGenerator* every time a conditional instruction is found. The choices registered by the choice generator correspond to the evaluation of the predicate and its negation respectively, where each choice is linked with a path condition reflecting how the predicate was evaluated. SPF takes advantage of JPF's model checking framework to explore the symbolic state space by considering only the registered choices at branching instructions.

SPF checks the satisfiability of path conditions using third-party constraint solvers like Choco [33], CORAL [41], and CVC3 [6]. Most of these solvers are geared towards solving complex numerical constraints, while solving structural constraints (like *String* predicates) are limited at best or incompatible at worst. If a path condition is unsatisfiable, SPF backtracks to the latest branching point and tries out a different choice.

Listeners are used to gather information during the evaluation of path conditions. Publishers make use of this information to present it to the user in different ways: One common case is to partition the input data in the different equivalence classes, while other is the automatic generation of unit tests. Using symbolic execution to automatically generate a test suite with path coverage is a research topic explored in several studies [36, 46, 17].

Configuration files are used to indicate which methods should be executed symbolically and also specify which their parameters are to be considered as symbolic or concrete values. By combining symbolic and concrete values during the execution of a method marked to be symbolically executed, SPF provides the framework for concolic execution [16].

3 Symbolic Execution of Spark Programs

To provide a flexible programming paradigm for big data processing, Spark's main API exposes methods that act as higher order functions. Particularly, these methods receive user defined functions as input parameters that dictate how certain operations will be carried out. However, the passed functions always have to comply to some conditions imposed by the method, for example, the function passed to a *filter* transformation must be defined over the data type of the target RDD and must return a *boolean* value.

The use of functions as parameters in Spark operations has an impact on the control flow of the program. Not only the particular Spark operation defines how the program will behave, but also the passed functions could potentially introduce control flow statements like conditionals or loops. Moreover, the control flow behavior of the Spark operations themselves is mostly static (e.g., the iterative and cumulative nature of a *reduce* action), whereas the diverse range of variation introduced by a user defined function is practically unbounded.

For this reason, in the context of program analysis in general and to our particular scope of symbolic execution, both the nature of the Spark operations and the peculiarities of the user defined functions on each program are necessary components that have to be studied together in order to provide a reasonable conclusion.

The following sections describe the conceptual process of a symbolic execution carried out on a Spark program, as well as a detailed explanation of our proposed implementation.

3.1 Conceptual Process

A Spark program consists of a chain of transformations on one or more RDDs that finally conclude with an action applied on them. RDDs are manipulated through an API that provides the general guidelines on how the data collection is to be processed without falling into the specifics. For example, the *filter* transformation indicate that only the elements matching a given filtering condition would be selected, without specifying exactly what is the condition to be evaluated. A similar approach is followed by most of the actions and transformations in Spark.

The precise behavior of most actions and transformations is defined by the programmer. Given that most of Spark's actions and transformations are higher order functions, the programmers define a custom function that fulfills the contract of the specific operation. For example, again the *filter* transformation expects as a parameter a function that takes an element of the same type as the type of the elements in the collection handled by the RDD and returns a boolean value. When the *filter* transformation is later invoked, it calls the passed function with each element in the RDD and, depending on the output, it decides if the value is filtered or not.

Having this in mind, the symbolic execution of an isolated Spark operation depends solely on the behavior of the function passed by the user. However, when analyzing a whole program, special considerations

for every particular operation must be taken into account. These considerations are different in nature but mostly refer to how output values are percolated to the subsequent operations in order to ensure the correct analysis of the next functions.

The whole process could be summarized in the following three steps:

1. Identify the Spark operation

2. Carry out the symbolic execution of the passed function

3. Take special considerations based on the executed Spark operation

Following these three steps, the symbolic execution of a Spark program, using SPF as the underlying analysis framework, is represented by the state diagram depicted in 3.1. Here we consider how a black-box analysis should proceed in order to reason about the execution flow of a Spark program and the control flow instruction that might occur in it.

The starting point of the analysis consists in detecting that a Spark operation of interest is being executed; relevant operations can be defined by the user beforehand. Once this has happened, the next step is to prepare for the exact operation that was detected, for example, indicating what function was passed to the detected operation and prepare the SPF analysis to consider its input parameters as symbolic values. Generally, these two steps occur simultaneously but given their semantic differences in the process, it was important to highlight them as different states of the analysis.

The real analysis begins once the passed function is invoked. The process is split in three stages: *pre-process*, *analysis* and *post-process*. During the *pre-process* stage, we must ensure that the parameters passed to the function are correctly instantiated; for example, if a *map* and a *filter* transformations took place in that order, we must ensure that the input symbolic expression passed to the function executed by the *filter* is the output of the function invoked by the *map* transformation. This guarantees a coherent inter-methodical analysis. The subsequent stage is the core analysis, which proceeds in the same way as an analysis of a regular method in SPF would do. Lastly, during the *post-process* stage the framework makes all the necessary preparations to be able to continue the symbolic execution of subsequent Spark operations.

Once the analysis of a Spark operation is done, the framework continues to explore the program. This can lead to the detection of another relevant Spark operation. Finally, once the execution has finished, JPF will backtrack to any decision points defined by the *Choice Generators*. These points always take place inside one of the functions passed to any Spark operations; this is why the framework has to re-establish a strategy corresponding the Spark operation containing the invoked function. The analysis continues as usual once the strategy has been re-established. After all choices have been explored the execution terminates and the analysis provides an output.

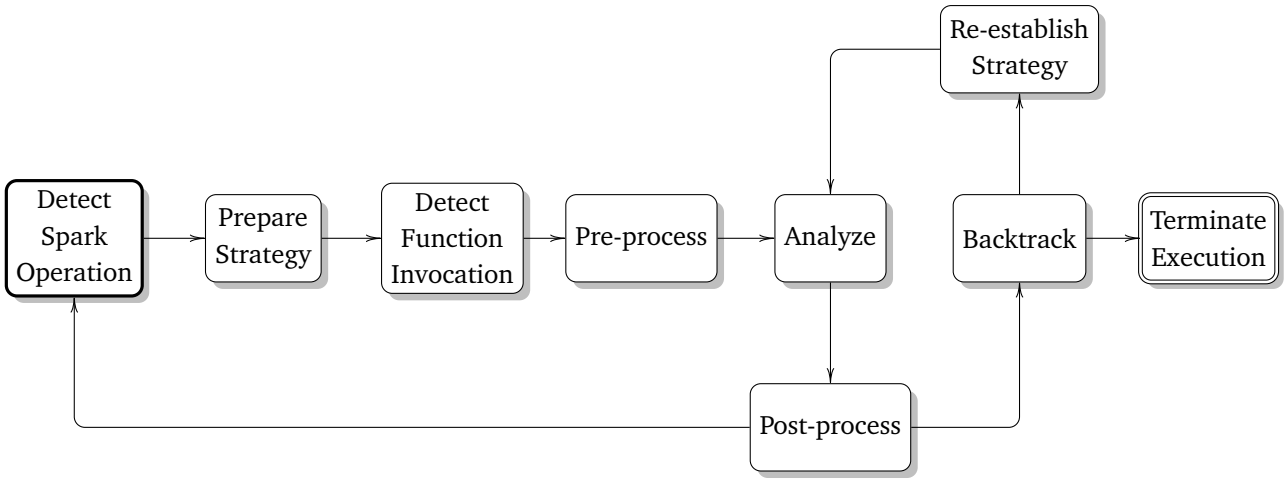


Figure 3.1: State diagram of the symbolic execution process of Spark programs.

3.2 A Concrete Example

The trivial example presented in listing 3.1 depicts a simple Spark program with no purpose in itself. However, this simple example allows us to explain better how the analysis will be carried out. The relevant Spark operations in this example are the *map* and *filter* transformations in lines 10 and 14 respectively. All other operations related to Spark are not relevant.

The first operation detected during the analysis is the *map* transformation in line 10. At this point, the analysis opts for a "map" strategy and prepares itself for the imminent invocation of the function passed to the *map*. Fro convenience, all the functions in this example are depicted as lambda functions although anonymous or named classes would work as well. Once the function is invoked, the framework proceeds with the pre-processing stage, however, because no previous operations were executed, the initial input for the function is a trivial symbolic reference (V_0).

During the symbolic execution of the function we find that there is a branching instruction in line 11. This represents a decision point and, for this reason, a *choice generator* is registered with two options: one where V_0 is greater than one and another where it is less than or equals to one. The control flow continues with one of the paths and stores the other for a later exploration. Given the nature of the *map* transformation, the input parameter might suffer a certain transformation which, in turn, is the returned value as it is shown in line 12. During the post-processing of the operation, the symbolic expression $V_0 + 2$ is then set to be the input value of the immediate Spark operation, which in this case is a *filter*. The *filter* transformation is processed in a similar fashion except that in this case the input value used in its function is instantiated to whatever output generated the *map* transformation.

The function passed to the *filter* transformation returns a boolean that depends on the symbolic input value. Given the nature of this kind of instruction, SPF registers a *choice genertor* in order to explore the possible outcomes of evaluating the boolean condition. Again, one of the paths is chosen and the analysis continues. At this point there are no more relevant Spark operations and the execution comes to an end, thus, triggering a backtrack to the last unexplored path. Finally, the analysis continues until there are no more unexplored paths left.

```
1  SparkConf conf = new SparkConf()
2  .setAppName("Example")
3  .setMaster("local");
4
5  JavaSparkContext spark = new JavaSparkContext(conf);
6
7  List<Integer> numberList = Arrays.asList(1,2,3);
8  JavaRDD<Integer> numbers = spark.parallelize(numberList);
9
10 numbers.map(v1 -> {
11   if(v1 > 1) return v1;
12   else return v1+2;
13 })
14 .filter(v2 -> v2 > 2);
15
16 spark.stop();
17 spark.close();
```

Listing 3.1: Trivial example to illustrate the symbolic execution of spark programs. The program itself has no real purpose other than to serve as a good scenario to demonstrate inter and intra procedural conditions of the analysis.

To further illustrate the example, figure 3.2 shows the symbolic execution tree of the program. One interesting aspect to note is that the results of the *map* are percolated to the subsequent Spark operations; such is the case of the rightmost subtree in the symbolic execution tree.

When observed in this way, the analysis of the program turns out to be similar to the sequential execution of the respective input functions of each of the Spark operations in the program. However, this is not always the case given that some operations have particular semantic implications, for example, *flatMap* produces multiple symbolic output, hence, making it impossible to simply connect the function passed to a *flatMap* as it is, to any following operation.

After the analysis is done, the module can solve the resulting path conditions and obtain a representative value in the range to produce a reduced input data set that is able to offer full path coverage of the program.

3.3 JPF-SymSpark

JPF-SymSpark is a JPF module whose goal is to coordinate the symbolic execution of Apache Spark programs to produce a reduced input dataset that ensures full path coverage on a regular execution. It builds on top of SPF to delegate the handling of symbolic expressions while it focus on how to interconnect Spark's transformations and actions in order to reason coherently over the execution flow of the program. This section describes the general structure and technical aspects of the *JPF-SymSpark* module. The work presented here is based on the logical processes defined in the previous section.

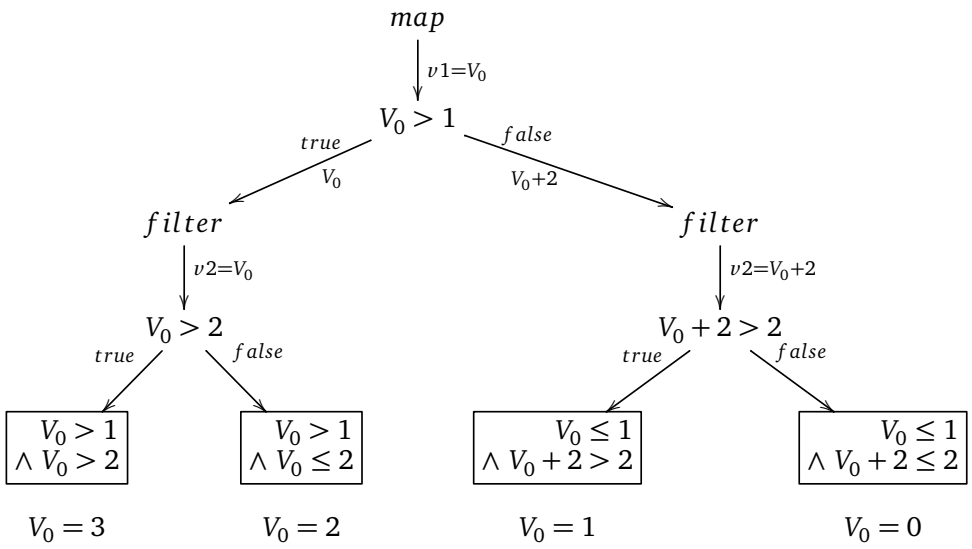


Figure 3.2: Symbolic execution tree corresponding to the Spark program shown in listing 3.1. The input set $\{3, 2, 1, 0\}$ represents a minimal input set that would explore all feasible paths in the program.

The main JPF extension points used in the module are:

- **Bytecode Factory**: Implemented in the *SparkSymbolicInstructionFactory* class, this bytecode instruction factory is in charge of detecting relevant Spark instructions.

- **Listeners**: The main listener is the *SparkMethodListener* class. After the bytecode instruction factory, the listener provides the main interaction point with the analyzed program. In our case, the listener aims to orchestrate the correct symbolic execution of a sequence of Spark operations.

- **Publishers**: The *SparkMethodListener* class also works as a publisher (these two responsibilities are often held together by the same class). The class produces a reduced input dataset obtained after selecting concrete values that satisfy the path conditions.

- **Choice Generators**: In some cases, additional choice generators must be registered in order to correctly reproduce the behavior of some of the Spark operations. Such is the case of the *SparkMultipleOutputChoiceGenerator* class, which is used when analyzing a *flatMap* transformation, given that it can potentially produce multiple outputs.

Additionally, the module also introduces the following control components that play an important role during the analysis:

- **Validators**: This are abstractions that encapsulate the necessary validations to determine if an executed instruction is a Spark operation or an invocation of the user-defined function. As for the case of the Java platform, the validator is implemented in the *JavaSparkValidator* class.

- **Method Strategies**: Each Spark operation follows a different strategy depending on how they deal with their input and output parameters. One example of a method strategy can be found in the *FilterStrategy* class.

- **Method Coordinator**: The coordinator is in charge of selecting the adequate strategy based on the Spark operation currently being executed. It maintains a general view of the whole analysis. The method coordinator is implemented in the *MethodSequenceCoordinator* class.

- **Dummy Spark Library**: The regular Spark library undergoes several unnecessary workload that is not relevant to the symbolic execution. Instead of it, a dummy Spark library was implemented and included as one of the dependencies of the module to relieve the analysis of the irrelevant load.

The following sections explain in more detail the different components that conform the module and what role do they play in the whole analysis.

3.3.1 Spark Library and JPF

When executing an analysis using JPF, the whole program is run under an instrumented JVM that keeps track of the execution state of the program. JPF considers every program statement executed, even if it is executed by third-party libraries or dependencies indirectly invoked in the system under test. These libraries must be included in the JPF's classpath (which is a different classpath than the normal Java classpath of the system under test) if they are executed, because if not, JPF will fail indicating that it is not able to find certain references during execution.

On the other hand, Spark, as many other modern applications, depends on a constantly growing number of external libraries. To execute an analysis on a Spark program with JPF one could include all this libraries and dependencies in the the JPF's classpath and let tool handle all the invocations internally. However, this approach has several problems: First, the execution of more statements increases the workload and state space of JPF. Second, some of Spark's operations handle native calls that, for example, deal with the way tasks are placed in the OS; JPF does not handle such native operations by default, which leads to the need of creating surrogate peers that mock the behavior of such calls. Lastly and more importantly, most of these operations are called in methods that are unrelated to the actions and transformations that are relevant to the symbolic execution, leading to an unnecessary overhead that does not provide any benefit.

Because of all these reasons, including the Spark library and all its dependencies was not a reasonable approach. Instead, we decided mock up the Spark library, in order to mimic some of the classes that participate in a Spark program. The idea is to minimize the number of external dependencies and native calls while at the same time replacing the implementations of methods irrelevant to the analyses with simplified versions of themselves. Listing 3.2 is an example of how a class that is irrelevant to the analysis is simplified. In the regular Spark library the *JavaSparkContext* class triggers a lot of heavy processes, like initializing the whole Spark framework; now it is just reduced to empty or simple code blocks.

However, some of the methods invoked by the Spark library are relevant to the analysis. Such is the case

```java
import java.util.Arrays;
import java.util.List;
import org.apache.spark.SparkConf;

public class JavaSparkContext {
  public JavaSparkContext(SparkConf conf){}
  public void stop() {}
  public void close() {}
  public <T> JavaRDD<T> parallelize(List<T> list) {
    return new JavaRDD<T>(list);
  }
  public JavaRDD<String> textFile(String file) {
    return new JavaRDD<String>(Arrays.asList(""));
  }
}
```

Listing 3.2: Mocked version of the *JavaSparkContext* class. The methods are as simple as they could be while still maintaining the contract of the original class. Note that the classes *SparkConf* and *JavaRDD* are also mocked.

of the methods defined in the *JavaRDD* class and the rest of the classes in the RDD family. These methods include operations like *filter*, *map* and *reduce*, that make use of the functions passed by the programmers. In these cases, it is extremely relevant that the passed function is invoked inside these methods so the analysis can be triggered following the usual SPF approach. Listing 3.3 shows an example of the mocked *filter* method of the *JavaRDD* class. The function passed to the *filter* method is invoked with the first element of the RDD only and the returned value is the current RDD itself given that it does not affect the end result when using symbolic input parameters.

```java
public JavaRDD<T> filter(Function<T,Boolean> f) {
  try {
    f.call(list_t.get(0));
  } catch (Exception e) {
    e.printStackTrace();
  }
  return this;
}
```

Listing 3.3: Mocked filter method in the JavaRDD class. The function passed to the method is invoked. Note that the *Function* interface is also mocked.

The surrogate Spark library is already included into the dependencies of the *JPF-SymSpark* module. Nevertheless, the implementation is not extensive, which might require further expansion as the different cases and programs require. Moreover, the library is bound to version 2.0.2 of the original Spark library, which poses a drawback in terms of consistency if the core behavior of Spark changes in future versions. More about this drawback can be found in section 4.1.

Having effectively discarded irrelevant portions of the system under test by the means of the mocked up library, it is simpler to identify the relevant Spark operations that have an impact on the analysis.

3.3.2 Instruction Factory

The first step for carrying out the analysis is to identify when a Spark operation is being executed. Given that all relevant operations in the concrete *JavaRDD* class are implemented as non-static methods, the bytecode instruction of interest is *invokevirtual*. This instruction is in charge of dispatching Java methods, unless they are interface methods, static methods or some other special cases (*invokeinterface*, *invokestatic* and *invokespecial* are used respectively) [26].

For this purpose, we implemented the *SparkSymbolicInstructionFactory* class; which extends from the *SymbolicInstructionFactory* class defined in the SPF module. The goal of this class is to solely intercept calls to the *invokevirtual* bytecode instruction and validate if they intend to dispatch one of the Spark operations relevant to the analysis.

Just to illustrate this situation better in the case of the Java implementation, let us assume that the *filter* transformation is being called on an existing RDD such as

```
rdd.filter(...)
```

then, the corresponding bytecode will look like the following

```
invokevirtual PATH/JavaRDD.filter:(PATH/Function;)PATH/JavaRDD;
```

with "PATH" representing the full package path where the classes or interfaces are located. The rest of the instruction represents the method name and the method descriptor; sufficient information for identifying the relevant operations. The function parameter was intentionally omitted because, although the passed parameter must implement the *Function* interface, this can be done in several ways; being the two most common ways lambda expressions and anonymous classes. At this point, neither of this two approaches represent a difference when detecting the Spark operation, however, it will require special attention later on when detecting the invocation of the passed function.

The instruction factory that we implemented, makes use of a validator, which is in charge of detecting the concrete method and class names that are particular for each Spark implementation. At the moment we only support the Java implementation, although the framework is flexible to support additional validators, for example, one that could detect the Scala implementation of Spark.

Moreover, the user must define in a configuration file the method names of the operations of interest (e.g., map, filter) in order to indicate this type of methods should be analyzed. The method names must be defined in a `.jpf` file, in a similar fashion as SPF, under the key `spark.methods`; in the case of having multiple methods of interest, they most be separated with a semicolon.

Once the method has been detected, the instruction factory issues a custom `INVOKEVIRTUAL` instruction to the JPF core. This instruction indicates what should the JPF virtual machine do when the method of

interest is executed. In our case, we need to prepare for the subsequent execution of the function passed as a parameter to the Spark operation. To do this, we manipulate the JPF configuration programatically in order to take advantage of the configuration properties used by SPF to define which methods are supposed to be analyzed by the symbolic engine.

Again, let us assume this time that the *filter* method above was executed in a class defined in a class named `Main` (fully described in `com.test.Main`). Then, after detecting the *filter* transformation, the configuration will contain one of the following entries in the `symbolic.method` key:

```
symbolic.method=...;com.test.Main$1.call(sym)                    (1)
```

or

```
symbolic.method=...;com.test.Main.lambda$main$0(sym) (java compiler)
symbolic.method=...;com.test.Main.lambda$0(sym) (eclipse compiler)   (2)
```

depending if the passed function was implemented as an anonymous class or a lambda expression.

The "`$1`" in (1) points to the first anonymous class created inside `com.test.Main` (the qualified path for an anonymous class is always separated by a "`$`" sign). The number is monotonically increasing according to how many anonymous classes have been created up to that point. It is important to note that the method *call* indicated here corresponds to the implementation of the method *call* defined in the *Function* interface.

In the case of (2), the method indicated corresponds to a static method defined by the Java compiler whenever a lambda expression is found. This method will invoke afterwards an anonymous class created on the fly which implements the *call* method of the *Function* interface. It is sufficient to indicate the first static method with the symbolic parameter given that it only forwards the execution to the *call* method in the anonymous class. This solution came as a workaround for detecting lambda expressions, given that SPF does not provide any mechanism on its own to clearly specify the analysis of such methods. Same as in the case of anonymous classes, the number accompanying the method is monotonically increasing and depends on how many lambda expressions have been created thus far.

It will be relevant later on, that the method marked to be symbolically executed by (1) will be invoked using `invokevirtual`, while the one defined by (2) will be invoked using `invokestatic`. This will require the handling of the input and output parameters in a different way.

The dynamic manipulation of the configuration properties makes it easier for the user to specify which methods are to be symbolically executed. Defining the methods before hand, as in the regular SPF approach, proves to be cumbersome, given that the method names corresponding to anonymous classes or lambda expressions are often elusive and even difficult to track.

For further information on how anonymous functions and lambda expressions are compiled and represented in Java bytecode please refer to the Java Language Specification [18].

3.3.3 Spark Listener and Method Sequence Coordinator

The overall process of the *JPF-SymSpark* module is implemented by the *SparkMethodListener* and the *MethodSequenceCoordinator*. The listener acts as a stateless interpreter of the analysis' progress while the coordinator behaves as a stateful control node that provides coherence to the whole process. Both entities work together closely, being the listener just an entry point that dispatches actions to the coordinator based on a selected few relevant events.

Spark Method Listener

The Spark method listener extends the *PropertyListenerAdapter* which already provides entry points to all the events exposed by JPF. The relevant events in our case are:

- **instructionExecuted**: Which is triggered every time an instruction is executed. When this event is triggered, the listener forwards the executed instruction to the coordinator in order to validate if it is a relevant instruction for the analysis.

- **methodExited**: Which is triggered every time a method finishes its execution. In this case, if the method is related to Spark, the listener indicates to the coordinator that it should prepare to percolate the output to possible subsequent Spark methods.

- **stateAdvanced** Which every time the internal state of JPF advances. This is only relevant to identify that an end state has been reached, in which case the listener indicates to the coordinator that a full path has been explored.

- **stateBacktracked**: Which is triggered every time the execution reached an end state but there were already choice generators registered with unexplored options. The state is always backtracked to the latest point where a choice generator was registered. In this case, the listener instructs the coordinator to obtain a solution to the symbolic input value if the state backtracked to a different alternative of the path condition.

Additionally to these events, the *SparkMethodListener* also implements the *PublisherExtension* interface which allows it to act as a publisher as well. The combination of a listener and a publisher is a common practice among the JPF modules, given it is convenient to collect information worth to be published during the different events tracked by the listener. As a publisher, when the whole analysis is done, the different sample values that satisfied the path conditions that were collected by the coordinator are displayed in the console as a single input dataset.

Method Sequence Coordinator

The *MethodSequenceCoordinator* class was created as a stateful control structure used to keep track of the progress and results of the analysis. Although it is heavily influenced by the events detected in the listener, the idea was to keep it detached to the event-flow responsibilities of the listener, focusing only on the module's process state.

The goal of the coordinator is to switch to the adequate strategy based on the Spark operations. The different strategies actually do the heavy-lifting in the analysis, and are in charge of handling the behavior of each particular operation correctly. More on the strategies can be found in section 3.3.4.

The main actions of the coordinator are:

- **detectSparkInstruction**: This action determines whether the executed instruction is a Spark operation or the respective invocation if its parameter function. In the case of being a Spark operation, the coordinator selects the adequate strategy matching the operation. Otherwise, if it detect the invocation of the parameter function, then it indicates to the currently active strategy to execute the pre-processing phase.

- **percolateToNextMethod**: In this case, the coordinator instructs the active strategy to execute its post-processing phase. In general, all post-processing activities deal with the inter-connection of Spark operations, this is, dealing with output parameters and the interruption of the control flow, among others.

- **processSolution**: Arguably the most important action of the coordinator. This action is invoked anytime JPF backtracks to a previous state. In the case the state is backtracked to a point where a different path most be taken in a branching condition, that means that the other path has been completely explored. Being this the case, the current path condition is obtained from the choice generator and passed to the solver to determine if it is feasible or not; in the positive case, a sample value of the symbolic input is added to the solution list, otherwise an unfeasible path is reported.

The diagram shown in 3.3 shows at which point during the execution of the program under test will the listener events be triggered. The *instructionExecuted* event gets triggered on every instruction, however, the depicted points only refer to those instructions that are relevant to the analysis and will cause a respective action in the coordinator; the namely instructions correspond to the invocation of a Spark operation or its respective parameter function. Likewise, the *methodExecuted* action is only relevant when the Spark operation or the parameter function finish. The *stateBacktracked* is indicated to occur at a later point, usually at the end of the program although the backtrack process can be forced without necessarily having reached this point.

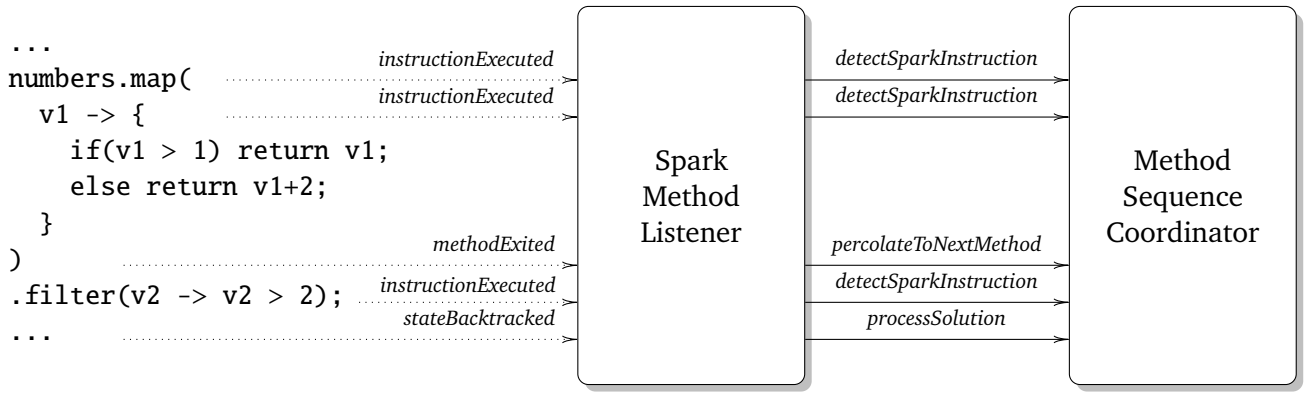


Figure 3.3: Execution flow of the Spark method listener and the coordinator when analyzing the sample program shown in listing 3.1. The exact point on which the listener events are triggered actually depends on precise bytecode instructions; this diagram provides an approximation to where this instructions occur in the source code.

3.3.4 Method Strategies

The method strategies specify the concrete behavior of the analysis for each relevant Spark operation. They implement how the analysis is to be carried out, particularly during the pre-processing and post-processing phases. Additionally, they maintain a reference to the input and output values of the operation.

The supported Spark operations are: *filter*, *map*, *reduce* and *flatMap*.

This section explains what particular conditions apply to each strategy and how are they carried out through the analysis.

filter

The purpose of the *filter* transformation is to produce a new RDD containing only the elements that satisfy a given predicate. The predicate is passed to the transformation in the form of a boolean function that is invoked for each element of the RDD. Because of this reason, the *filter* transformation itself always imply at least two possible execution paths, one for those who satisfy the predicate and one for those who do not. Figure 3.4 depicts the symbolic execution of a *filter* transformation according to the filter strategy.

Pre-processing

During the pre-processing phase, the filter strategy only checks for the invocation of the parameter function and validates if it is coming from an `invokevirtual` or an `invokestatic` bytecode instruction. If it is coming from an `invokevirtual` (the function was implemented as an anonymous class), the strategy manipulates the stack frame of the current invocation and replaces the element in the second position with the symbolic expression passed by the coordinator. This element corresponds to the input parameter of the passed function (i.e., an element of the RDD). The replacement of the second element is necessary because, if this is not done, SPF will call the function with a new symbolic expression instead, breaking

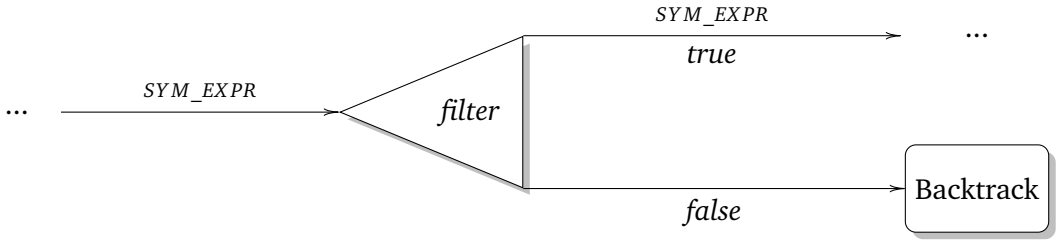


Figure 3.4: Diagram of the *filter* strategy. The input parameter is initialized to the symbolic expression percolated by the previous Spark operation if there is any, otherwise a new symbolic expression is used instead. Filter transformations always produce at least two branches, one that satisfy the predicate and one that does not. In the case of the branch that does not satisfy it, the execution is terminated and an immediate backtrack is triggered. The output of the transformation is always the same input symbolic expression disregarding the path taken.

the continuity of the analysis. The reason the second element is the one replaced instead of the first is that, in the stack frame of an `invokevirtual` instruction, the first position contains a reference of the invoking object instead (i.e., a reference to `this`). On the contrary, if the invocation of the function comes from a `invokestatic` instruction (the function was implemented as a lambda expression), then the first element is replaced in the stack frame because `invokestatic` instructions do not have references to invoking object itself.

Given that the *filter* transformation always imply a fork in the control flow, it is most likely that a choice generator was registered by SPF during the execution of the method in order to explore the possible paths. Needless to mention, this only occurs if the symbolic expression passed to the function participates in any of the conditional operations, otherwise, no choice generator is registered; then again, this scenario is irrelevant given that it means that the filter does not act upon the values of the RDD.

Post-processing

On the post-processing phase, the strategy checks if the exited method is actually the *filter* transformation and proceeds to obtain the last registered choice generator. As explained above, this choice generator will always be a path condition choice generator registered by SPF. Then the strategy proceeds to validate is the path currently executing corresponds to the negative evaluation of the predicate, in which case the execution of the thread is abruptly interrupted and a backtrack action is forced. The reason for this relies in the fact that exploring a path with a negative filter condition is not relevant given that this path will never be executed in a Spark program. However, by forcing the backtrack action, the analysis is guided to find a solution that satisfy that path, which ends in a value that does not pass the filter (necessary for full path coverage).

The symbolic input of a *filter* transformation does not suffer any permanent modification during its execution. For this reason, the output of the *filter* transformation is the same input value passed to the function during the pre-processing phase.

map

The *map* transformation constructs a new RDD containing the result of applying the parameter function to each element of the initial RDD. Normally, the input value passed to the parameter function is used in the operation that produces the output value, hence making the output be a derivation of the input value. Considering this rationale in the context of a symbolic execution, the output of the parameter function passed to a *map* transformation is defined in terms of the input symbolic expression. Figure 3.5 depicts the symbolic execution of a *map* transformation according to the map strategy.

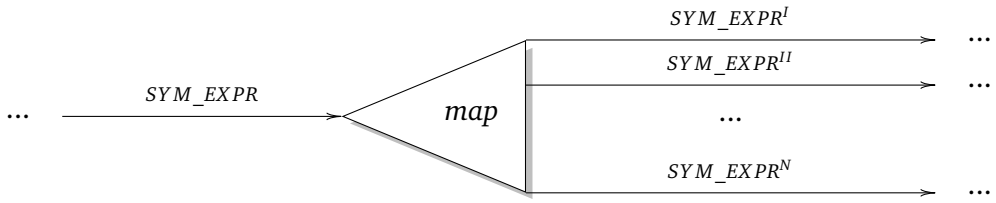


Figure 3.5: Diagram of the *map* strategy. The input parameter is initialized to the symbolic expression percolated by the previous Spark operation if there is any, otherwise a new symbolic expression is used instead. The output value percolated to the following functions is a new symbolic expression derived from any operations applied on the symbolic input. Map transformations do not necessarily have a branching condition, however, in the case there are, it is most likely that the output value will be different.

Pre-processing

The pre-processing phase is identical to the pre-processing phase of the filter strategy. The handling of the input parameters of the passed function is carried out in the same way given that, in both cases, the passed functions have the same number of input parameters, hence their stack frame behaves the same.

Post-processing

In the post-processing phase, the map strategy waits until the passed function finishes its execution. This is done by checking if the exited method matches the full descriptor of the *call* method in either the anonymous class or lambda expression that represents the passed function. Once it detects the right exited method then it stores its output value in an attribute of the strategy. This value will be used the next time strategies are switched and it will be used as the input value of the next Spark operation.

A *map* transformation does not have a branching condition necessarily; it might be the case that the RDD is just manipulated and an output value returned. However, even in this case, the transformation of the symbolic input needs to be tracked in order to percolate it to the next Spark operation. Chaining output and input values between Spark operations is of utmost importance in order to build precise path conditions that faithfully represent the control flow of the program.

In the case the *map* transformation incurs in any branching condition, then SPF will register the respective choice generators and all the options will be explored accordingly. Such a case leads to potentially different outputs depending on which path was taken.

reduce

The *reduce* action produces a single output value resulting from the combination of all the elements in the RDD. The combination is defined in the function passed to action, which has to fulfill the properties of being commutative and associative. The function passed to the action implements the *Function2* interface, whose main difference is that it takes two input parameters: the first is the accumulated value of the operation so far, and the second represents one element in the RDD. The behavior of a *reduce* action resembles to a full scan over the elements of the RDD, carrying always the accumulated value iteration over iteration.

Reduce actions can be analyzed following two different strategies: one where the accumulated parameter of the function is not considered as a symbolic variable and another where it is. The strategy discussed next refers to the former; the latter is explained in the subsequent section. The user indicates which mode to use by specifying it in the configuration file.

Pre-processing

This strategy considers the input parameter corresponding to a single element in the RDD as the percolated symbolic expression, however, the parameter corresponding to the accumulated value of the reduce action is considered as a concrete input.

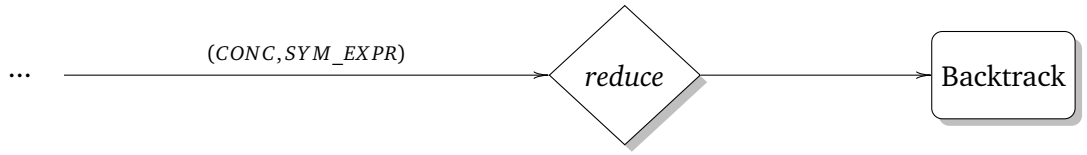
The analysis takes advantage of the concolic operational mode of SPF by defining the method to be inspected with the first parameter as a concrete input (achieved by using the “con” keyword instead of “sym” in the fully qualified method name). Afterwards, in a similar fashion as in the filter and map strategies, the second or third element in the stack frame is replaced with the percolated symbolic expression (depending if the instruction is `invokevirtual` or `invokestatic`). Figure 3.6a illustrates this mode.

Post-processing

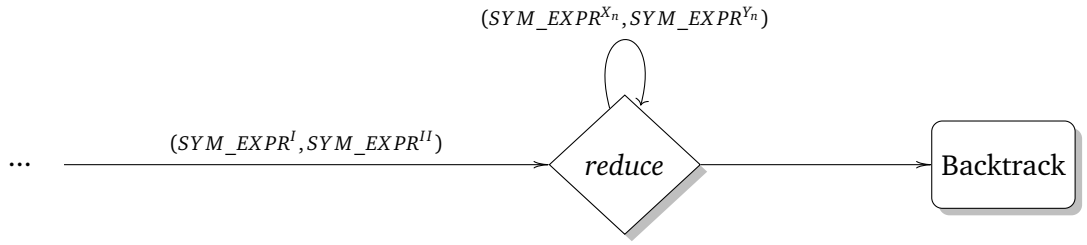
Independently of the output of the *reduce* action, the post-processing phase of the reduce strategy always triggers a termination of the current execution thread and a backtrack. This is because of the nature of Spark actions which indicate the culmination of the processing of an RDD. However, during the analysis of the reduce action, there might be branching operations executed on the single parameter, which will cause SPF to register a choice generator and explore all the possible paths. Ultimately, all these paths will lead to a backtrack after the end of the *reduce* action.

iterativeReduce

The second strategy that can be used when analyzing *reduce* actions considers both parameters of the passed function as symbolic. The direct consequence of this consideration is that the symbolic engine has to reason now over a variable that represents an accumulated value resulting from the application of the passed function several times. Given that the numbers of elements in the RDD is irrelevant for the sake of the analysis, the uses has to specify how many iterations of the *reduce* action will be carried out in oder to



(a) Reduce strategy with the accumulated value taken as a concrete input.



(b) Reduce strategy with the accumulated value taken as a symbolic input. The value n represents a given iteration.

Figure 3.6: Diagrams of the *reduce* Strategy. The two modes of execution are shown here. The first considers the accumulated input parameter as concrete, this translates to only considering branching operations applied on single elements of the RDD. The other mode considers the accumulated to be a symbolic input as well and iterates over the operation a fixed number of times. A backtrack is always triggered after a reduce action.

ensure termination. However, path explosion can occur easily given that each iteration makes the number of reachable states grow exponentially.

The complexity of this strategy is noticeable in comparison to the other strategies. The expected output dataset now becomes a family of datasets corresponding to the number of elements indicated to be in the RDD. The path conditions take into consideration multiple symbolic variables that have to comply with all the transformations and constraints collected so far.

Pre-processing

As mentioned before, this strategy considers both parameters of the function passed to the *reduce* action as symbolic variables. Once the *reduce* actions is detected, a new choice generator called *SparkIterativeChoiceGenerator* is registered. This choice generator is used to keep a reference of the number of times the function has to be executed and it also keeps track of the output of each the iterations; it is not used as a value provider in a direct sense rather as a placeholder to keep track of the iterative execution. The current path condition, if any, is also kept in the choice generator along with the single symbolic variable used so far. This values will serve as a template for creating new symbolic variables that comply to the conditions found so far.

Once the execution of the *call* method is detected, the strategy follows one of two approaches: If there are no accumulated values registered in the choice generator then a new symbolic expression is created taking into consideration the base structure of the percolated expression. This new expression is used as

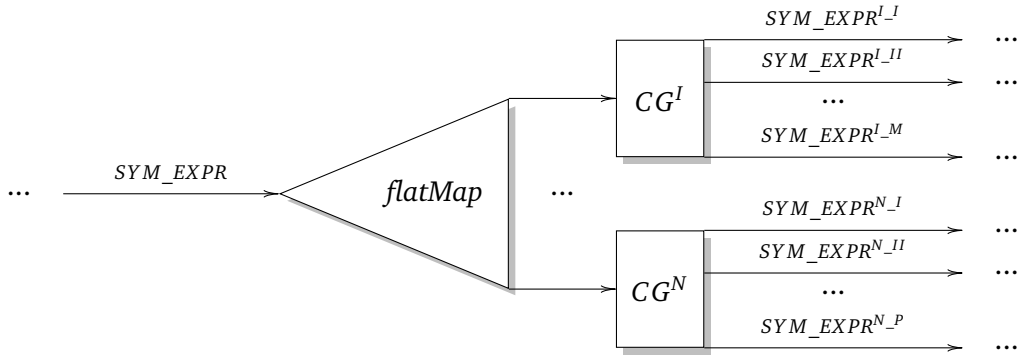


Figure 3.7: Diagram of the *flatMap* strategy. The input parameter is initialized to the symbolic expression percolated by the previous Spark operation if there is any, otherwise a new symbolic expression is used instead. The output value percolated to the following functions is taken from a special choice generator registered when the *flatMap* transformation has finished executing. The choice generator contains all the different elements contained in the collection. Every path taken during the *flatMap* transformation registers a new choice generator with all possible values returned in that particular path.

the first accumulated value while the percolated expression is used as the single input value. On the other case, an output value (representing the result of a previous iteration) is taken from the choice generator and set as the accumulated value while a new symbolic expression is produced and set as the regular single input value of the function. Figure 3.6b illustrates this mode.

As a technical note, symbolic expressions and path conditions are implemented in SPF following the *visitor* design pattern [15]. New visitors were implemented in order to create copies of existing expressions and conditions among others.

Post-processing

Once the *call* method finishes execution the current path condition is extended by enforcing the same initial constraints on the newly generated expressions for this iteration. Additionally, any constraints accumulated from a previous iteration must also be included in the current path condition. This has to be done at this point because JPF is not really executing an iteration, instead the iteration is simulated with the *SparkIterativeChoiceGenerator*, which will cause the path conditions to be solved after the method and the engine to backtrack to the latest point (most likely the point where the *SparkIterativeChoiceGenerator* was registered), hence missing interconnection between the iterations. Including this conditions ensure that the right path in the symbolic execution tree is taken.

Lastly, the output expression of the method is stored in the the choice generator along with the current path condition. This will serve as an input for a subsequent iteration in case the maximum number of iterations has not been reached yet.

flatMap

The *flatMap* transformation behaves similarly to the *map* action, the only difference is that the function passed to the *flatMap* has a collection of elements as an output value instead of a single element. These elements could have undergone different transformations even though they are returned in the same collection. One example of this behavior can be seen in listing 3.4. Here, two different iterable collections are returned, one contains two elements resulting from two different manipulations of the initial input, while the second contains only one element with another manipulation different from the other two. Figure 3.7 depicts the symbolic execution of a *flatMap* transformation according to the flatMap strategy; it shows how each path taken inside the passed function ends up in the registration of a new choice generator whose options are the possible symbolic expressions in the returned collection.

```
1 numbers.flatMap(t -> {
2 if(t > 2) return Arrays.asList(t*2, t*3).iterator();
3 else return Arrays.asList(t*4).iterator();
4 });
```

Listing 3.4: A trivial example of the *flatMap* transformation. It shows how the returned iterable can have elements that have undergone different transformations.

Pre-processing

The pre-processing phase is identical to the pre-processing phase of the filter and map strategies. Again, the handling of the input parameters of the passed function is carried out in the same way because the passed functions have the same number of input parameters, hence their stack frame behaves the same. However, the function passed to a *flatMap* transformation implements the `FlatMapFunction` interface, which differentiates from the `Function` interface used by the other two transformation by returning an the iterator of a collection instead.

Post-processing

The post-processing phase of this strategy behaves quite differently from all the other strategies so far. The idea would be to obtain all the different symbolic expressions inside the iterable object returned by the function and use each of them to feed subsequent Spark operations. However, the problem here lies in the change of the cardinality of the possible outcomes; so far we have had always the scenario of one input producing exactly one output, but now one input could potentially imply several output.

For this purpose, the strategy relies on how the mocked up *flatMap* transformation is implemented in `JavaRDD` class. In this implementation, the returned iterable is completely traversed using the *next* method, forcing the execution to bring each element of the collection into the stack frame of the *flatMap* method. This implementation does not deviate starkly from the original *flatMap* operation given that in the case of the regular Spark library, the whole iterator is explored to build a new RDD.

Considering how the implementation behaves, the post-processing phase waits until the passed function

exits and then checks for an `invokevirtual` instruction invoking the *next* method. Once detected, the respective value is taken from the stack frame and added to a list of output values in the strategy. This list is filled up with every element in the iterator.

Lastly, when the *flatMap* transformation exits, the strategy register a new custom-made choice generator whose possible values are the collected output values. Registering a choice generator a this point ensures that, after backtracking, a new option from the collection will be chosen exactly at the end of the *flatMap* transformation. The selected value will be used as input of any subsequent Spark operations and the analysis will continue accordingly.

The choice generator used in this scenario is called `SparkMultipleOutputChoiceGenerator`; it extends the `IntIntervalGenerator` of the JPF core. It contains a list of symbolic expressions representing the different manipulations of the input value and uses the integer range to select one of this options every time a backtrack occurs. The range is defined between zero and the size of the list minus one.

4 Evaluation

4.1 Limitations

The processing logic of *JPF-SymSpark* focuses on programs that were written complying to version 2.0.2 of the Apache Spark library. It might be the case that previous or future libraries of the tool are still compatible, however, any change in the classes mocked up by the surrogate Spark library included in the module might render those programs incompatible. Users are encouraged to modify the surrogate library to match another official Spark library as long as the semantics are preserved.

Analyses using *JPF-SymSpark* are expected to be run on portions of Spark code that contain a series operations applied to a single RDD. Including several RDDs in an execution could provide an invalid outcome. This point is suggested in section 5.1 as one of the possible future extensions of the tool.

Furthermore, there were several concealed, or at least not evident, aspects of SPF that arose during the implementation of *JPF-SymSpark*. These aspects represented major obstacles in the development process and had an impact on the scope of the developed tool. We consider relevant to indicate these pitfalls as part of the evaluation in order to guide future research initiatives on the field and also to improve the knowledge base when assessing SPF in the research context. The intent of these remarks is not to diminish SPF in any sense, on the contrary, it aims to guide future researchers to the weak spots that require more attention.

The most relevant impediment is the limited support of symbolic String operations. Although it has been a work in progress since 2012 [38, 37], there are still some key String operations that are not yet supported by SPF. For example, the *split* operation, which is commonly used in Spark programs, is not supported and if included in an analysis it halts the verification and crashes JPF. Additionally, constraints that combine conditions on the String structure and its length are not solved correctly, bypassing any restrictions set on the size of the String.

Moreover, specialized String constraint solvers are claimed to be supported, however, in practice this is no longer the case. This situation not only applies to String solvers but also to other third-party solvers specialized in more complex numerical constraints. The problem is that the implemented interfaces that communicate with the constraint solvers are outdated given that they were implemented initially based on now obsolete versions of the tools. Some solvers like CVC3 [6] are still compatible (although the newer libraries must be included), while others like Z3 [13] are no longer compatible.

Another relevant obstacle in the context of Spark applications is the limited support of symbolic data structures, sometimes also referred to as symbolic heap or symbolic objects [34]. Although supported, symbolic data structures often generate errors if used in the regular way inside Spark transformations and actions. The lack of an interface when dealing with symbolic objects makes it difficult to build extensions on top of it.

Some obstacles were bested by means of a workaround. Such is the case of the lack of support of lambda expressions as target methods to be analyzed by SPF. As noted in a series of posts exchanged between the author and Kasper Luckow (SPF and JDart contributor) in the official JPF forum, the workaround consists in referring to the static methods in the anonymous classes that are generated as a consequence of the compilation of the lambda expression. This solution is further explained in section 1.2.

With a few exceptions, the JPF and SPF communities are relatively silent and the tools seems to be lacking enthusiasts. This plays a big role when trying to extend the current tools; software communities in other open-source projects have a more structured communication mechanism and a clear list of new features and bugs where the collaborators can easily share information.

Lastly, one of the aspects that resulted to be the most cumbersome was the poor quality of the SPF's source code. Frequent redundancy (for example, the *IFInstrSymbHelper* class), immense amounts of commented code, even in a way that seemed to be used as a communication platform among developers, and the general lack of coding style made the extension of the tool more troublesome than what it should have been. On top of this, new revisions are seldom uploaded and when they are, they often include a huge number of undocumented changes that are not clearly specified in the revision notes. This makes it particularly hard when tracking differences between the documentation and the current software.

5 Conclusion

5.1 Future Work

The next points represent some improvements and extensions to Symbolic PathFinder and *JPF-SymSpark* that would broaden the scope of programs the tools can analyze.

Symbolic execution of data structures

As mentioned in section 4.1, the limited support of symbolic data structures on SPF affected greatly the scope of *JPF-SymSpark*. The use of data structures in Spark programs is a common practice as it is in object-oriented programming languages. Improving SPF to provide better mechanisms to handle and manipulate symbolic data structures would be the first step to eventually analyzing Spark operations defined over data structures.

This will prove particularly useful in the many cases where RDDs are defined over tuples, and the many pair-oriented operations that are characteristic for this kind of structures. One example of a frequently used operations is the *reduceByKey* transformation, that takes pairs matching the same key and applies a reduce function to them.

Support more Spark operations

Giving support to additional Spark operations would improve the usability of the tool. Most of the operations that are not supported yet are implemented over RDDs of *Pair* or other data structures, hence, in order to support these operations it is necessary to provide support to symbolic data structures first. However, once this occurs, the processing logic of many of these operations resembles to many of the already implemented strategies.

Nevertheless, transformations like *join*, *union*, and *intersection* would require new processing strategies given that these transformations work over two potentially symbolic RDDs, something the we do not contemplate in this work.

Provide a Java annotation for analyzing single methods

The initial approach of this work is to provide a blackbox analysis on Spark programs. Any guidance on how the analyses should proceed are communicated via the configuration properties that are defined beforehand for each analysis. However, in some cases it could prove useful to provide the means to indicate in the source code which particular Spark operations should be considered in an analysis.

JPF offers a mechanism to introduce information relevant to an analysis directly in the source code of the program being analyzed through customized Java annotations. A new Java annotation can be created to mark which Spark operations ought to be symbolically executed. Moreover, complementary information

about the data being processed could be provided, for example a pre-condition that could be appended to any path condition found during the analysis. Although this will shift the tool to a whitebox approach, it will offer more flexibility for the users.

Support Scala

Scala is a functional programming language that also adopts many object-oriented concepts [42]. The Spark library was originally written in Scala, only offering support to other programming languages like Java and Python later on. For this reason, Scala is the default language of choice when writing Spark programs.

By design, Scala is compiled to the Java Virtual Machine in order to take advantage of the portability and the long-time tested stability of Java. Given that Scala works on the same set of bytecode instructions, it would be possible to use JPF (and by extension SPF as well) to analyze Scala. However, there is no official documentation about JPF supporting Scala, although it is often a topic of conversation in the official JPF community. Being able to analyze Spark programs written in Scala will improve greatly the scope of the tool, although it would prove to be a daunting task. It will require first to ensure compatibility with JPF and SPF, to later create the necessary mechanisms that would allow *JPF-SymSpark* to support such programs.

A Appendix - Contributions and Collaborations to SPF

This appendix explains in detail all the modifications done to the Symbolic PathFinder (SPF) extension that were necessary in order to be able to execute Apache Spark programs symbolically. This modifications were submitted as a patch for the SPF project to Corina Păsăreanu, lead developer and repository administrator of SPF. The changes are under revision and could be included in future releases. The modifications are:

- Detection of synthetic bridge methods
- Consistent ordering of String path conditions
- Improvements to the visitor pattern in the symbolic constraints

A.1 Detection of Synthetic Bridge Methods

The *synthetic* modifier is a compiler-only modifier that marks a certain method or class included in the compiled bytecode that was not part of the original source code. Basically it refers to any construct introduced by the compiler. There are several reasons to include a synthetic constructs in the bytecode, for example, dynamic proxy classes or references in switch statements.

Likewise, the *bridge* modifier is a compiler-only modifier that is used to mark a method that simply delegates its invocation to another method, hence serving as a bridge. For example, bridge methods are necessary when implementing generic interfaces. After type erasure, the signatures of the concrete methods implementing an interface defined over a generic type will no longer match with the methods in interface itself; the methods in the interface will be defined over the *Object* class or the closest class in the hierarchy if the generic type was covariant or countervariant, while the methods in the class implementing the interface will be defined over the concrete type used in the implementation. This problem is solved by introducing bridge methods in the concrete implementation of the interface that match the signatures of the methods in the interface. These methods simply perform a cast in the parameters defined over the generic type and forward the call to the correct method. By definition, bridge methods are always synthetic given that they are constructs introduced by the compiler.

Listing A.1 shows an example where this can be appreciated. This example was chosen because of its resemblance to the way Spark operations are implemented. On line 2 an internal interface is defined over a generic type *T*. On line 5 the *sampleMethod* is defined which takes an implementation of the aforementioned interface over the concrete *Interger* type. This method invokes the *call* method of the parameter interface with a concrete value. In lines 9 to 13 the interface is implemented over the *Integer* type as an anonymous class and it is passed directly to an invocation of the *sampleMethod* method. The code presented in the example is correct and it compiles without problems. However, it requires the inclusion of a *synthetic bridge* methods that fills the gap for those methods that don not match the signatures after type erasure. Listing A.2 shows how the program in listing A.1 would look after type

```
1  public class SymbolicGenericTest {
2    interface SampleInterface<T> {
3      public T call(T param);
4    }
5    public static Integer
         sampleMethod(SampleInterface<Integer> a) {
6      return a.call(2);
7    }
8    public static void main(String[] args){
9      sampleMethod(new SampleInterface<Integer>() {
10       @Override
11       public Integer call(Integer param) {
12         return param+1;
13       }
14     });
15   }
16 }
```

Listing A.1: Example of a program where a symbolic bridge method will be added after commpilation. The *SampleInterface* is programmed as an interface over a generic type. Anytime this interface is implemented with a concrete type, an intermediate bridge method is created to cast the invocation of the method in the most generic type to the type specified in the concrete implemention.

erasure.

Although the program shown in listing A.2 is not a valid Java program, it serves to illustrate the purpose of a *synthetic bridge* method after type erasure occurs during the compilation phase. Line 2 shows the definition of the internal interface but this time the generic type has been replaced by the closest class higher in the hierarchy; the *Object* class. Moreover, the method *sampleMethod* defined in line 5 it does not assume that the passed object is an implementation of the interface over the *Integer* type and, because of this, it requires both its return value and the parameters to be casted to the corresponding types matching the signature of the interface and the return type of the method itself. Lastly, lines 9 to 16 contain the implementation of the interface, however, the overridden method works now as a bridge method between the concrete implementation of type *Integer*.

This kind of code is common among Spark programs to specify the functions passed to the actions and transformations. Most of Spark operations depend on functions that are defined based on several functional generic interfaces, for example, the *Function* interface used in the *filter* transformation and the *Function2* interface used in the *reduce* action. Disregarding whether this functions are implemented as anonymous classes or lambda expression, the existence of symbolic bridge methods will always be present as a consequence of type erasure.

```
1  public class SymbolicGenericTest {
2    interface SampleInterface {
3      public Object call(Object param);
4    }
5    public static Integer sampleMethod(SampleInterface a) {
6      return (Integer)a.call((Object)2);
7    }
8    public static void main(String[] args){
9      sampleMethod(new SampleInterface() {
10       @Override
11       public synthetic bridge Object call(Object param) {
12         return (Object)call((Integer)param);
13       }
14       public Integer call(Integer param) {
15         return param+1;
16       }
17     });
18   }
19 }
```

Listing A.2: This is the same sample program shown in listing A.1 but showing how it would look after type erasure. This sample, although not a compiling Java program, illustrates the necessity of *synthetic bridge* methods to ensure correct inheritance after type erasure.

Let us assume that we would like use SPF to carry out a symbolic execution of the method *call*. Then, the *symbolic.method* property in the *.jpf* file should point to:

```
symbolic.method= SymbolicGenericTest$1.call(sym)
```

The relevant method invocation in the analysis would be the one defined over the *Integer* type which is the one that actually has an implementation. However, the *symbolic.method* property does not provide any information about the types of the symbolic parameters; it might try to analyze a method matching the method name and class but defined over the *Object* class, as well as one defined over the *Integer* type.

This occurs in line 6 of listing A.1 when the method *call* is invoked. This line triggers an `INVOKEINTERFACE` instruction that attempts to invoke the *synthetic bridge call* method. At this point, SPF detects a method invocation that matches the specified property and attempts to set the symbolic variables. Nevertheless, under this circumstances SPF always stopped the analysis and aborted the execution due to an unhandled exception relative to empty method arguments.

Considering that *synthetic bridge* methods should not be relevant to any symbolic execution and having detected that the faulty behavior only occurred when *synthetic bridge* methods were found, we resolved that only methods who did not contain the *synthetic* nor *bridge* modifiers should be considered as valid targets for the analysis.

For this purpose a new validation was included in the *BytecodeUtils* class of SPF. This validations consists

of comparing the modifiers of the invoked method an determining if they contain the *0x0040* and *0x1000* values as specified in the official specification of the JVM [26]. After implementing the change, the symbolic execution of methods in this scenario worked as expected.

A.2 Order of String Path Conditions

This change is rather simple. It aims to maintain consistency on the way regular path conditions and String path condition explore their options. Although we consider that both path conditions should be refactored in order to respond to a common API, a temporary solution to this problem was more efficient in terms of time and resources.

The basic idea behind of this modification was to switch the ways string path conditions were explored; the path that evaluated to *false* first followed by the path that evaluated to *true*. This was helpful when dealing with some strategies, for example in the case of the filter strategy (see figure 3.4) where the negative branch triggers a immediate break in the state transition. If this change had not been included, a verbose check would have been necessary on every instance were a path condition would have been processed.

A.3 Improving the Visitor Pattern in the Symbolic Constraints

SPF implements both symbolic constraints and symbolic expressions following the visitor pattern [15]. Symbolic expressions are used to represent any transformation of a symbolic value during the execution. They contain a left operand, a right operand, and an operator; the operands have to be also symbolic expressions as well. When a visitor is used to explore the data structure, first the current element is visited and then the left and right operands are visited respectively.

On the other hand, symbolic constraints are used to represent boolean expressions evaluated on symbolic values. Constraints are used to produce path conditions, which in turn are later parsed and passed to the solvers to determine their satisfiability. On the contrary to what it could be expected, symbolic constraints were not implemented in the same way as the symbolic expression. They contain also a left and right operand, and an operator but, additionally they maintain and reference to a chained constraint kept in an attribute called *and*.

The implementation of the visitor pattern in the case of the constraints was forwarded to the left and right operands but not to the following constraints referenced by the *and* attribute. This resulted in incomplete visits, not being able to explore completely all the constraints in a path condition. This was particularly necessary in the case of the iterative reduce strategy (see figure3.6b), when the path condition prior to the *reduce* method was cloned to match the new symbolic variable generated each iteration.

The modification in this case was trivial. If the *and* attribute of the constraint was not null then it would accept a visitor prior to the left and right operands. This behaves similar to a depth-first search.

B Appendix - Installation and Use

This appendix aims to serve as a checklist for installing *JPF-SymSpark*, as well as a brief guide on how to use the module in combination with JPF. There are two installation approaches:

- Docker approach (preferred)
- Manual approach

B.1 Docker approach

Docker is a widely supported platform for the creation and maintenance of virtual containers [30]. It is designed to provide self-contained, portable environments that are ideal for distributing software with a fixed set of dependencies.

For this reason, we provide the description of a Docker container that prepares an environment with all the dependencies and configurations required by *JPF-SymSpark*. This installation method is the preferred approach given its simplicity and tested behavior. The following instructions guide the process for creating the Docker container; Docker is assumed to be installed already.

1. Clone the *JPF-SymSpark* repository

   ```
   git clone https://github.com/omrsin/jpf-symbc.git
   ```

2. Go to the root directory of the project and build the container

   ```
   docker build -t jpf-symspark .
   ```

3. Once the container has been successfully built, run a container shell

   ```
   docker run -it jpf-symspark
   ```

4. Inside the container, the installation of the module can be validated by running

   ```
   cd jpf-symspark/src/examples/de/tudarmstadt/thesis/symspark/examples/java/applied/
   jpf WordCountExample.jpf
   ```

The output should display the outcome of the analysis run on the WordCountExample.java program.

The created container could serve as a template for any future projects that aim to execute analyses on Spark programs.

B.2 Manual approach

This section lists all the dependencies and configuration requirements that are needed to execute JPF and *JPF-SymSpark* correctly. By no means it should be considered as an extensive guide that works under all platforms; the described approach will only be focused on explaining the steps used in the environment where to project was developed. The following steps should be executed in an Ubuntu 16.04 Desktop OS [43] with at least 2 gigabytes of memory.

Prerequisites

The following dependencies need to be installed first:

- **Java**: Preferably the oracle distribution. The version used was *1.8.0_111*.
- **Mercurial**: Used by JPF as a version control tool [29]. Can be installed with the regular package manager. The version used was *3.7.3*.
- **Apache Ant**: Build tool for Java [3]. Can be installed with the regular package manager. The version used was *1.9.6*.
- **JUnit**: Framework for unit testing in Java [22]. Can be downloaded from the official website and placed in a know directory.The version used was *4.12*.

jpf-core

This is the main module of JPF. In addition to the following installation steps, always check the official installation instructions because the repositories could have been moved.

1. Clone the project *jpf-core* from the official repository

   ```
   hg clone http://babelfish.arc.nasa.gov/hg/jpf/jpf-core
   ```

2. Create the *site.properties* file as suggested in the official JPF site. Make sure to be pointing the jpf-core property to the directory where the project was cloned. Additionally, be sure to remove or comment the other references to modules in the example *.properties* file provided.

3. In order to be able to build the project, JUnit libraries need to be in the classpath. The ant script requires the JUNIT_HOME directory to be specified. This could be done by creating the JUNIT_HOME environment variable and placing it in the path. However, the *build.xml* file of the *jpf-core* project could be modified by replacing the value property *junit.home* with the value of the directory where the JUnit library was placed. This option is more convenient because it avoids polluting the classpath with variables that might potentially generate conflicts with other programs.

4. Finally, build the *jpf-core* project. Go to the directory where it is located and execute

   ```
   ant test
   ```

5. In order to test if the build was successful, go to the jpf-core directory and execute

   ```
   java -jar build/RunJPF.jar src/examples/Racer.jpf
   ```

   JPF should run a basic model checking analysis on the Racer example.

jpf-symbc

This is the symbolic execution module built on top of JPF known as SPF or Symbolic Pathfinder. In addition to the following installation steps, always check the official installation instructions. The version used in this project is a modified version of the module. At the moment of this publication, the repository of this customized version might not be public yet.

1. Clone the project *jpf-symbc* from our hosted repository on the same root directory where *jpf-core* was cloned

   ```
   git clone https://github.com/omrsin/jpf-symbc.git
   ```

2. Update the *site.properties* file as suggested in the official JPF site. Every time a new module is downloaded this file must be updated. Make sure to be pointing the *jpf-symbc* property to the directory where the project was cloned.

3. Set the JUNIT_HOME environment variable or update the *build.xml* file of the project in a similar fashion as explained for *jpf-core*.

4. Build the *jpf-symbc* project. Go to the directory where it is located and execute

   ```
   ant test
   ```

   If the test target generates errors then executing `ant build` would be sufficient (considering no build errors were found). With this, SPF should be available.

jpf-symspark

This is the module that we developed based on SPF. It provides the mechanisms to carry out symbolic executions of Spark programs. The installation steps follow the same pattern as in the case of *jpf-symbc*.

1. Clone the *jpf-symspark* project from our hosted repository on the same root directory where *jpf-core* and *jpf-symbc* were cloned

   ```
   https://github.com/omrsin/jpf-symspark.git
   ```

2. Update the *site.properties* file as suggested in the official JPF site. Every time a new module is downloaded this file must be updated. Make sure to be pointing the *jpf-symspark* property to the directory where the project was cloned.

3. Build the *jpf-symspark* project. Go to the directory where it is located and execute

   ```
   ant build
   ```

4. In order to test if the build was successful, go to the jpf-symspark directory and execute

   ```
   java -jar build/RunJPF.jar \\
   src/examples/de/tudarmstadt/thesis/symspark/examples/java/applied/WordCountExample.jpf
   ```

   This will execute an analysis on an example program and produce a reduced input dataset that explores all possible paths.

It is recommended to install the *eclipse-jpf* plug-in for the Eclipse IDE. This tool enables the IDE to carry out analyses as specified in the *.jpf* files. To install it simply follow the instructions as described in the official JPF website.

B.3 Usage

The *JPF-SymSpark* module is used in a similar way as SPF. However, some additional properties were added to the *.properties* file of the module or must be included in the *.jpf* file used for a particular analysis in order execute correctly.

The properties used are:

- **spark.methods**: Used to indicate which spark operations are to be analyzed by the module. Every time a Spark operation with this name is found in the program it will be executed symbolically. This option replaces the use of the *symbolic.method* property used by SPF given that the target methods to be analyzed will be set dynamically during the analysis based on the spark operations defined. The values supported for this property are: *filter*, *map*, *reduce* and *flatMap*; multiple values must be separated with a semicolon.

- **spark.reduce.iterations**: Used to indicate how many iterations of a reduce action will be analyzed. The value must be greater than 0. This option is only relevant if the reduce action was included among the methods to be analyzed in the *spark.methods* property.

- **listener**: Defines the listener to be used during the analysis. By default, the module uses the *SparkMethodListener* as defined in its *.properties* file.

```
1  @using=jpf-symspark
2
3  jpf-spark.package_path=
       de.tudarmstadt.thesis.symspark.examples.java.applied
4
5  target=${jpf-spark.package_path}.WordCountExample
6  target.args=input,output
7
8  symbolic.dp=choco
9  symbolic.string_dp=automata
10
11 spark.methods=filter
```

Listing B.1: Sample *.jpf* file of the *JPF-SymSpark* module corresponding to the WordCountExmaple.java program.

- **jvm.insn_factory.class**: This property is used to specify the instruction factory used by the module. By default, the module uses the *SparkSymbolicInstructionFactory* as defined in the *.properties* file.

Other SPF specific properties are still supported. Listing B.1 shows the *.jpf* file used in the *WordCountExample* analysis. The property *jpf-spark.package_path* defined in line 3 is just a shorthand for the full path where the target file is found; it is not mandatory for any analysis as long as the target is defined correctly. Additionally, line 11 defines which methods are to be analyzed; in this case just the *filter* transformation is relevant for the analysis.

The analysis can be run by means of the previously mentioned Eclipse plug-in or by execution through the command line as shown in the installation steps. Additional examples can be found in the *examples* directory of the *JPF-SymSpark* module.

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