Infrastructure-Aware Functional Testing of MapReduce programs

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Abstract—**Programs that process a large volume of data generally run in a distributed and parallel architecture, such as the programs implemented in the processing model MapReduce. In these programs, developers can abstract the infrastructure where the program will run and focus on the functional issues. However, the infrastructure configuration and its state cause different parallel executions of the program and some could derive in functional faults which are hard to reveal. In general, the infrastructure that executes the program is not considered during the testing, because the tests usually contain few input data and then the parallelization is not necessary. In this paper a testing technique is proposed to generate different infrastructure configurations for a given test input data, and then the program is executed in these configurations in order to reveal functional faults. This testing technique is automatized by using a test engine and applied in a case study. As a result, several infrastructure configurations are automatically generated and executed for a test case revealing a functional fault that is then fixed by the developer.**

Keywords— Software testing, MapReduce programs, Big Data Engineering, Hadoop

I. INTRODUCTION

The new trends in massive data processing have brought to light several technologies and processing models in the field called *Big Data Engineering* [1]. Among them, *MapReduce* [2] can be highlighted as it permits the analysis of large data based on the "divide and conquer" principle. These programs run two phases in a distributed infrastructure: the *Mapper* phase divides the problem into several subproblems, and then the *Reducer* phase solves each subproblem. Usually, *MapReduce* programs run on several computers with heterogeneous resources and features. This complex infrastructure is managed by a framework, such as *Hadoop* [3] which stands out due to its wide use in the industry [4].

From the developer point of view, a *MapReduce* program can be implemented only with *Mapper* and *Reducer*, without any consideration about the infrastructure. Then the framework that manages the infrastructure is also responsible to automatically deploy and run the program over several computers and lead the data processing between the input and output. Among others, the framework divides the input into several subsets of data, then processes each one in parallel and re-runs some parts of the program if necessary.

Despite the fact the program can be implemented abstracting the infrastructure, the developer needs to consider how the infrastructure configuration could affect the program functionality. A previous work [5] detects and classifies several faults that depend on how the infrastructure configuration affects the program execution and produces different output. These faults are often masked during the test execution because the tests usually run over an infrastructure configuration without considering the different situations that could occur in production, as for example different parallelism levels or the infrastructure failures [6]. On the other hand, if the tests are executed in an environment similar to the production, some faults may not be detected because it is common that the test inputs contain few data, which means that *Hadoop* does not parallelize the program execution. There are some tools to enable the simulation for some of these situations (for example computer and net failures) [7, 8, 9], but it is difficult to design, generate and execute the tests in a deterministic way because there are a lot of elements that need fine grained simulation, including the infrastructure and framework.

The main contribution of this paper is a technique that can be used to generate automatically the different infrastructure configurations for a *MapReduce* application. The goal is to execute test cases with these configurations in order to reveal functional faults. Given a test input data, the configurations are obtained based on the different executions that can happen in production. Then each one of the configurations is executed in the test environment in order to detect functional faults of the program that may occur in production. The contributions of this work are:

1. A combinatorial technique to generate the different infrastructure configurations, taking into account characteristics related to the *MapReduce* processing and the test input data.

2. Automatic support by means of a test engine based on MRUnit [10] that allows the execution of the infrastructure configurations, together with the evaluation to detect failures.

The rest of the paper is organized as follows. In Section II the principles of the *MapReduce* paradigm are introduced. The generation of the different configurations, the execution and the automatization of the tests are defined in Section III. In Section IV it is applied to a case study. In Section V the related work about software testing in *MapReduce* paradigm is presented. The paper ends with conclusions and future work in Section VI.

II. MAPREDUCE PARADIGM

The *MapReduce* program processes high quantities of data in a distributed infrastructure. The developer implements two functionalities: *Mapper* task that splits the problem into several subproblems and *Reducer* task that solves these subproblems. The final output is obtained from the deployment and the execution over a distributed infrastructure of several instances of *Mapper* and *Reducer*, also called tasks. The deployment and execution are automatically carried out by *Hadoop* or another framework. First, several *Mapper* tasks analyse in parallel a subset of input data and determine which subproblems these data need. When the execution of all *Mappers* are finished, several *Reducers* are also executed in parallel in order to solve the subproblems. Internally *MapReduce* handles <key, value> pairs, where the key is the subproblem identifier and the value contains the information to solve it.

To illustrate *MapReduce* let us suppose a program that computes the average temperature per year from historical data about temperatures. This program solves one subproblem for each year, so the identifier or key is the year. The *Mapper* task receives a subset of temperature data and emits <year, temperature of this year> pairs. Then *Hadoop* aggregates all values per key. Therefore, the *Reducer* tasks receive subproblems like <year, [all temperatures of this year]>, that is all temperatures grouped per year. Finally, the *Reducer* calculates the average temperature. For example, in Fig. 1 an execution of the program considering the input is detailed: year 2000 with 3°, 2002 with 4°, 2000 with 1°, and 2001 with 5°. The first two inputs are analysed in one *Mapper* task and the remainder in another task. Then the temperatures are grouped per year and sent to the *Reducer* tasks. The first *Reducer* receives all the temperatures for the years 2000 and 2002, and the other task for the year 2001. Finally, each *Reducer* emits the average temperature of the analysed subproblems: 2° in the year 2000, 4° in 2002 and 5° in 2001. This program with the same input could be executed in another way by the framework, for example with three *Mappers* and three *Reducers*. Regardless of how the framework runs the program, it should generate the expected output.

Additionally, to optimize the program, a *Combiner* functionality can be implemented. This task is run after the
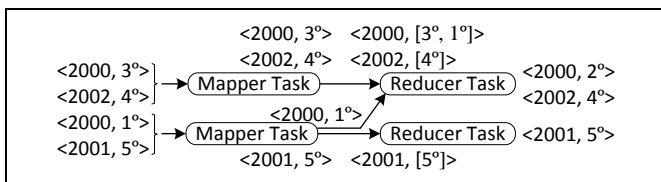
Mapper and the goal is to remove the irrelevant <key, value> pairs to solve the subproblem. In *MapReduce* there are also other implementations such as for example Partitioner that decides for each <key, value> pair which *Reducer* analyses it, Sort that sorts the <key, value> pairs, and Group that aggregates the values of each key before the *Reducer*.

The wrong implementation of these functionalities could cause a failure in one of the different ways in which *Hadoop* can run the program. These faults are difficult to detect during testing because the test cases usually contain few input data. In this way it is not necessary to split the inputs and therefore the execution is over one *Mapper*, one *Combiner* and one *Reducer* [2].

III. GENERATION AND EXECUTION OF TESTS

The generation of the infrastructure configurations for the tests are defined in Section A, and a framework to execute the tests in Section B.

A. Generation of the test scenarios

To illustrate how the infrastructure configuration affects the program output, suppose that the example of Section II is extended with a *Combiner* in order to decrease the data and improve the performance. The *Combiner* receives several temperatures and then they are replaced by their average in the *Combiner* output. In this case, the program does not admit a *Combiner* because all the temperatures are needed to obtain the total average temperature. The error of adding the *Combiner* in order to optimize the program injects a functional fault in the program. Fig. 2 represents three possible executions of this program that could occur in production considering the different infrastructure configurations and the same input (year 1999 with temperatures 4°, 2° and 3°).

The first configuration consists of one *Mapper*, one *Combiner* and one *Reducer* that produces the expected output. The second configuration also generates the expected output executing one *Mapper* that processes the temperatures 4° and 2°, another *Mapper* for 3°, two *Combiner*, and finally one *Reducer*. The third configuration also executes two *Mapper*, two *Combiner* and one *Reducer*, but produces an unexpected output because the first *Mapper* processes 4° and the second *Mapper* the temperatures 2° and 3°. Then one of the *Combiner* tasks calculates the average of 4°, and the other *Combiner* of 2° and 3°. The *Reducer* receives the previous averages (4° and
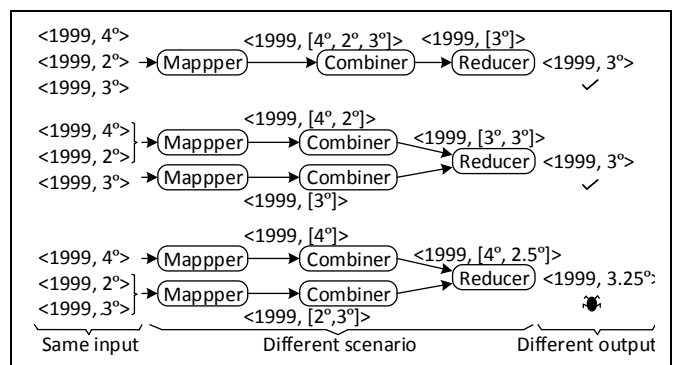
Fig. 1. Program that calculates the average temperature per year

Fig. 2. Different infrastructure configurations for a program that calculates the average temperature per year with Combiner task

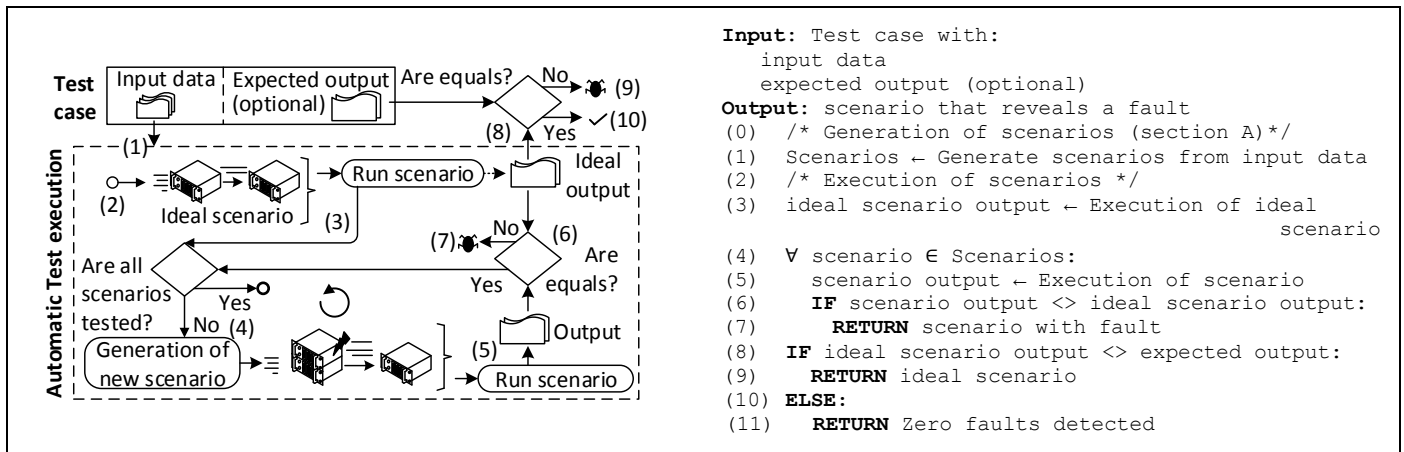Fig. 3. a) General famework of test execution

```
Input: Test case with:
   input data
   expected output (optional)
Output: scenario that reveals a fault
(0)   /* Generation of scenarios (section A)*/
(1)   Scenarios ← Generate scenarios from input data
(2)   /* Execution of scenarios */
(3)   ideal scenario output ← Execution of ideal
                                      scenario
(4)   ∀ scenario ∈ Scenarios:
(5)     scenario output ← Execution of scenario
(6)     IF scenario output <> ideal scenario output:
(7)        RETURN scenario with fault
(8)   IF ideal scenario output <> expected output:
(9)      RETURN ideal scenario
(10)  ELSE:
(11)     RETURN Zero faults detected
```

b) Algorithm for test generation and execution of test scenarios

2.5º), and calculates the total average in the year. This configuration produces 3.25º as output instead of the 3º of the expected output. The program has a functional fault only detected in the third configuration. The failure is produced whenever this infrastructure configuration is executed, regardless of the computer failures, slow net or others. This fault is difficult to reveal because the test case needs to be executed in the infrastructure configuration that detect it, and in a completely controlled way.

Given a test input data, the goal is to generate the different infrastructure configurations, also called in this context *scenarios*. For this purpose, the technique proposed considers how the *MapReduce* program can execute these input data in production. First, the program runs the *Mappers*, then over their outputs the *Combiners* and finally the *Reducers*. The execution can be carried out over a different number of computers and therefore the *Mapper-Combiner-Reducer* can analyse a different subset of data in each execution. In order to generate each one of the *scenarios*, a combinatorial technique [11] is proposed to combine the values of the different parameters that can modify the execution of the *MapReduce* program. In this work the following parameters are considered based on previous work [5] that classifies different types of faults of the *MapReduce* applications:

- *Mapper* parameters: (1) Number of *Mapper* tasks, (2) Inputs processed per each *Mapper*, and (3) Data processing order of the inputs, that is, which data are processed before other data in the *Mapper* and which data are processed after.

- *Combiner* parameters for each *Mapper* output: (1) Number of *Combiner* tasks, and (2) Inputs processed per each *Combiner*.

- *Reducer* parameters: (1) Number of *Reducer* tasks, and (2) Inputs processed per each *Reducer*.

The different *scenarios* are obtained through the combination of all values that can take the above parameters and applying the constraints imposed by the sequential execution of *MapReduce*. The constraints considered in this paper are the following:

1. The values/combinations of the *Mapper* parameters depend on the input data because it is not possible more tasks than data. For example, if there are three data items in the input, the maximum number of *Mappers* is three.

2. The values/combinations of the *Combiner* parameters depend on the output of the *Mapper* tasks.

3. The values/combinations of the *Reducer* parameters depend on the output of the *Mapper-Combiner* tasks and another functionality executed by *Hadoop* before *Reducer* tasks. This other functionality is called Shuffle and for each <key, value> pair determines the *Reducer* task that requires these data, then sorts all the data and aggregates by key.

To illustrate how the parameters are combined and how the constraints are applied, suppose the program of Fig. 2. The input of this program contains three data items, and these data constrain the values that the *Mapper* parameters can take because the maximum number of *Mapper* tasks is three (one *Mapper* per each <key, value> pair). The first *scenario* is generated with one *Mapper*, one *Combiner* and one *Reducer*. For the second *scenario* the parameter "Number of *Mapper* tasks" is modified to 2, where the first *Mapper* analyses two <key, value> pairs, and the second processes one pair. The third *scenario* maintains the parameter "Number of *Mapper* tasks" at 2, but modifies the parameter "Inputs processed per each *Mapper*", so the first *Mapper* analyses one <key, value> pair and the other *Mapper* processes two pairs. The *scenarios* are generated by the modification of the values in the parameters in this way and considering the constraints.

B. Execution of the test scenarios

The previous section proposes a technique to generate *scenarios* that represent different infrastructure configurations according to the characteristics of the *MapReduce* processing. Fig. 3 describes a framework to execute systematically the tests with the *scenarios* generated by the technique of the previous section.

The framework takes as input a test case that contains the input data and optionally the expected output. The test input data can be obtained with a generic testing technique or one

specifically designed for *MapReduce*, such as MRFlow [12]. Then, the *ideal scenario* is generated (1) and executed (2, 3). This is the *scenario* formed by one *Mapper*, one *Combiner* and one *Reducer* which is the usual configuration executed in testing. Next, new *scenarios* are iteratively generated (4) and executed (5) through the technique of the previous section. The output of each *scenario* is checked against the output of the *ideal scenario* (6), revealing a fault if the outputs are not equivalent (7). Finally, if the test case contains the expected output, the output of *ideal scenario* is also checked against the expected output (8), detecting a fault when both are not equivalent (9, 10).

Given a test case, the *scenarios* are generated according to the previous section, then they are iteratively executed and evaluated following the pseudocode of Fig. 3. For example, Fig. 2 contains the generation and execution of a program that calculates the average temperature per year in three *scenarios* considering the same test input: year 1999 with temperatures 4º, 2º and 3º. The first execution is the *ideal scenario* with one *Mapper*, one *Combiner* and one *Reducer*, that produces 3º as output. Then the second scenario is executed and also produces 3º. Finally, a third *scenario* is executed and produces 3.25º as output, this temperature is not equivalent to the 3º of the *ideal scenario* output. Consequently, a functional fault is revealed without any knowledge of the expected output of the test case.

This approach is automatized by means of a test engine based on MRUnit library [10]. This library is used to execute each *scenario*. In MRUnit the test cases are executed in the *ideal scenario*, but this library is extended to generate other *scenarios* and enable parallelism supporting the execution of several *Mapper*, *Combiner* and *Reducer* tasks.

IV. CASE STUDY

In order to evaluate the proposed approach, we use as case study the *MapReduce* program described in I8K|DQ-BigData framework [13]. This program measures the quality of the data exchanged between organizations according to part 140 of the ISO/TS 8000 [14]. The program receives (1) the data exchanged in a row-column fashion, together with (2) a set of mandatory columns that should contain data and (3) a percentage threshold that divides the data quality of each row in two parts: the first part is maximum if all mandatory columns contain data and zero otherwise, and the second part of the data quality is calculated as the percentage of the non-mandatory columns that contain data. The output of the program is the data quality of each row, and the average of all rows.

Over the previous program, a test case is obtained using a specific *MapReduce* testing technique based on data flow [5]. The test input data and the expected output of the test case contain two rows represented in Table I. Row 1 contains two columns (Name and City), and only one column has data, so the data quality is 50%. Row 2 contains data in all columns, so the data quality is 100%. The total quality is 75%, which is the average of both rows.

The procedure described in Section III is applied on the previous program using the previous test case as input. As a result, a fault is detected and reported to the developer. This failure occurs when the rows are processed in different *Mappers* and only the first *Mapper* receives the information related to the mandatory columns and the data quality threshold, because *Hadoop* splits the input data into several subsets. Without this information, the *Mapper* cannot calculate the data quality and does not emit any output. The bottom of Fig. 4 represents the *scenario* that produces the failure. There are two *Mappers* that process different rows. The first *Mapper* receives the data quality threshold (value of 50%), the mandatory column ("Name") and the two columns of row 1 with only data in one column, so the *Mapper* emits 50% as data quality of row 1. The second *Mapper* processes only row 2, but no other information about the mandatory columns or data quality threshold, so this *Mapper* cannot emit any output. Then the *Reducer* receives only the data quality of row 1 and emits an incorrect output of the average data quality.

This fault is difficult to detect because it implies the parallel and controlled execution of the program. Moreover, this fault is not revealed by the execution of the test case in the following environments: (a) *Hadoop* cluster in production with 4 computers, *Hadoop* in local mode (simple version of *Hadoop* with one computer), and (c) MRUnit unit testing library. These environments do not detect the fault because they only execute one *scenario* that masks the fault. Normally these environments run the program in the *ideal scenario* that is formed by one *Mapper*, one *Combiner* and one *Reducer*, and then the fault is masked due to a lack of parallelism.

The test engine proposed in this paper executes the test case in the different *scenarios* that can occur in production with large data and infrastructure failures. In contrast with the other

TABLE I.   TEST CASE OF THE I8K|DQ-BIGDATA PROGRAM

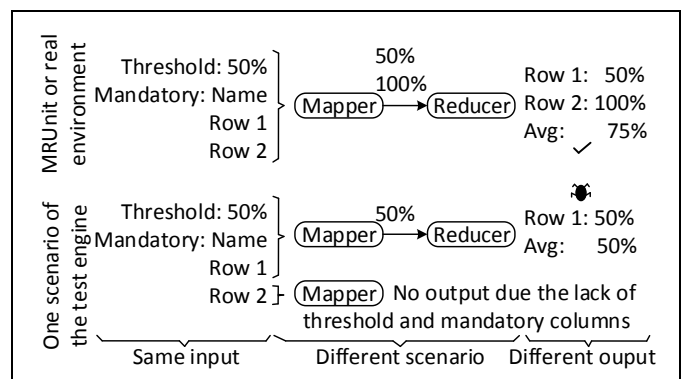| Input		Excepted output	
Data quality threshold: 50%			
Mandatory columns: "Name"			
Row 1	Name: Alice	50%	75% (average)
	City: (no data)		
Row 2	Name: Bob	100%	
	City: Vienna		

Fig. 4.   Execution of the test case in different scenarios

environments, the test engine proposed does not need the expected output to detect faults. For example, in this case study the fault is revealed automatically because the outputs of the different *scenarios* are not equivalent to each other. The execution of some *scenarios* obtains an average quality of 75%, whereas the execution of other *scenarios* obtains 50%. These outputs are not equivalent, and the test engine detects automatically a fault despite the unknown expected output.

After the detection and report of the fault during the test phase, the developer fixed the program and then the test case passed.

V. RELATED WORK

Despite the testing challenges of the *Big Data* applications [15, 16] and the progresses in the testing techniques [17], little effort is focused on testing the *MapReduce* programs [18], one of the principal paradigms of *Big Data* [19]. A study of Kavulya et al. [20] analyses several *MapReduce* programs and 3% of them do not finish, while another study by Ren et al. [21] places the number between 1.38% and 33.11%.

Many of the works about testing of the *MapReduce* programs focus on performance and to a lesser degree functionality. A testing approach for *Big Data* is proposed by Gudipati et al. [22] specifying several processes, one of which is about *MapReduce* validation. In this process Camargo et al. [23] and Morán et al. [5] identify and classify several functional faults. Some of these faults are specific of the *MapReduce* paradigm and they are not easy to detect because they depend on the program execution over the infrastructure. One common type of fault is produced when the data should reach the *Reducer* in a specific order, but the parallel execution causes these data to arrive disordered. This fault was analysed by Csallner et al. [24] and Chen et al. [25] using some testing techniques based on symbolic execution and model checking. In contrast to the previous works, the approach of this paper is not focused on the detection of only one type of fault, it can also detect other *MapReduce* specific faults. To do this, the test input data is executed over different infrastructure configurations that could lead to failures.

Several research lines suggest injecting infrastructure failures [26, 27] during the testing, and several tools support their injection [7, 8, 9]. For example, the work by Marynowski et al. [28] allows the creation of test cases specifying which computers fail and when. One possible problem is that some specific *MapReduce* faults could not be detected by infrastructure failures, but require full control of *Hadoop* and the infrastructure. In this paper, the different ways in which *Hadoop* could run the program are automatically generated from the functional point of view, regardless of the infrastructure failures and *Hadoop* optimizations.

Furthermore, there are other approaches oriented to obtain the test input data of *MapReduce* programs, such as [12] that employs data flow testing and [29] based on a bacteriological algorithm. In this paper, given a test input data, several configurations are generated and then executed in order to reveal functional faults. The test input data could be obtained with the previous testing techniques.

The functional tests can be executed directly in the production cluster or in one computer with *Hadoop*. Herriot [30] can be used to execute the tests in a cluster while providing access to their components supporting, among others, the injection of faults. Another option is to simulate a cluster in memory with the MiniClusters libraries [31]. In the unit testing, JUnit [32] could be used together with mock tools, or directly by MRUnit library [10] adapted to the *MapReduce* paradigm. These test engines only execute one infrastructure configuration and usually without parallelization. In this paper a test engine is implemented by an MRUnit extension that automatically generates and executes the different infrastructure configurations that could occur in production.

VI. CONCLUSIONS

A testing technique for the *MapReduce* programs is introduced and automatized in this paper as a test engine that reproduces the different infrastructure configurations for a given test case. Automatically and without an expected output, the test engine can detect functional faults specific to the *MapReduce* paradigm that are in general difficult to detect in the test/production environments. This approach is applied in a real program using a test case with few data. As a result, a functional fault is revealed allowing the developer to fix the program.

In order to improve the generation of the infrastructure configurations, as part of the future we plan to extend the technique to select efficiently the configurations that are more likely to detect faults. The current approach is *off-line* because the tests are not carried out when the program is in production. As future work we plan to extend the approach to *on-line* testing, in order to monitor the functionality with the real data when the program is executed in production and detect the faults automatically.

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