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Using Symbolic Execution to Improve the Runtime Management of Spark Applications

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Dedico questa tesi ai miei genitori
A mia moglie Egidia
e ai miei figli Fabio e Anna
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ABSTRACT

THE need to crunch a steadily growing amount of data generated by the modern applications is driving an increasing demand of flexible computing power, often satisfied by cloud computing solutions. Cloud computing revolutionized the way computer infrastructures are abstracted and used by exploiting virtualization and providing an easy access to resources through the Internet [38].

Big data is a research field that deals with ways to analyze and extract information from data sets containing structured and unstructured data whose size is so large that makes the processing of data with traditional databases and applications very difficult or practically impossible. The processing of these data therefore requires the use of distributed frameworks specialized for the parallel execution of programs, such as Apache Hadoop [4] and Apache Spark [8]. These specialized frameworks are used to transform the applications in atomic parts that can be executed in a distributed cluster of physical or virtual machines.

Hadoop uses the Map-Reduce programming model that was firstly introduced by Google [21] and consists of two distinct phases: Map and Reduce. The former processes and *transforms* a block of data to produce key-value pairs (tuples) as intermediate outputs, the latter *aggregates* these tuples into a final output.

A more advanced solution is represented by Apache Spark [8], that allows for faster executions by avoiding or limiting the use of the persistent storage and it provides a more sophisticated programming model based on parallel execution plans (*PEPs*) which are represented as directed acyclic graph (DAG) of phases.

Big data applications pose new challenges in satisfying requirements on the *Quality of Service* (*QoS*) provided to end users. In the context of traditional applications (e.g. web) this problem has often been faced using self-adaptive systems that control runtime *KPIs* (Key Performance Indicators) against changes in the application context and workload.

Compared to traditional applications, where a single execution lasts ten to hundreds of milliseconds, big data applications might require minutes or hours to process large datasets, thus *QoS* must consider

the execution of single runs. Therefore, in this domain the *QoS* is often defined by means of **deadlines**, that are the maximum allowed duration of a single application execution.

The execution time of big data applications depends on many factors such as the amount of computing resources available (cpu's, memory, storage) and the concurrent execution of other applications on the same cluster. Therefore, in the literature one can find several approaches [44, 23, 16] that focus on resource allocation or scheduling techniques in order to reduce deadline violations by using different techniques such as integer linear programming, machine learning and control theory.

All of these approaches use the knowledge of the *PEP* to reason, predict or estimate the application execution time and work under the assumption that the application *PEP* does not change under different input datasets or application parameters. Unfortunately, this is true only if the application code does not contain any conditional branch whose outcome depends on user input values or the result of previous calculations involving input data. Otherwise, different application *PEPs* could be needed to describe all the possible execution flows generated by the combinations of all the different branch outcomes in the application code. Without considering all these *PEPs* the analysis of the application could be significantly unprecise.

xSpark, developed at Politecnico di Milano, is an extension of the Apache Spark framework that offers fine-grained dynamic resource allocation using lightweight containers and control-theoretical planners. It allows users to set application deadlines (which is not possible using Spark) and uses the knowledge of the application *PEP*, retrieved during a profiling phase, to dynamically allocate resources to the application. xSpark does not consider loops or conditional branches in the application code and assumes that the *PEP* is unique.

xSpark_{SEEP}, the solution described in this thesis, extends xSpark capabilities to safely run multi-*PEP* applications, by exploiting symbolic execution. At each decisional branch outcome in the application, *xSpark_{SEEP}* determines which *PEPs* are still valid and prunes the *PEPs* tree, removing the invalid *PEPs*, thus leaving only the valid ones in the *PEPs* tree. A heuristic is used to select the *PEP* to execute among the valid ones, in order to minimize the risk of missing the deadline while maximizing the CPU usage efficiency.

xSpark_{SEEP} is the result of the integration of *SEEP*, a tool exploiting symbolic execution to discover all possible application *PEPs* produced by different inputs and parameters, with a modified

version of xSpark. We tested $xSpark_{SEEP}$ with two applications, Promocalls and Louvain, that uses *GraphX*, a Spark library specialized for graph processing. The evaluation shows that SEEPEP is able to effectively extract all the *PEPs* generated by Spark applications and that $xSpark_{SEEP}$ effectively and efficiently controls the allocation of resources during the execution of PromoCalls and Louvain, keeping the execution times within considered deadlines with significantly smaller errors and consuming a lower amount of resources than the original version of xSpark.

Since the current solution focuses on controlling a single application, a future work could be directed at extending $xSpark_{SEEP}$ to control multiple concurrent applications.

SOMMARIO

Il bisogno di elaborare una quantità sempre crescente di dati generati dalle moderne applicazioni sta guidando una crescente domanda di potenza di calcolo flessibile, spesso soddisfatta dalle soluzioni di cloud computing. Il cloud computing ha rivoluzionato il modo in cui le infrastrutture informatiche vengono astratte e utilizzate sfruttando la virtualizzazione e fornendo un facile accesso alle risorse attraverso Internet [38].

I big data sono un campo di ricerca che si occupa dei modi per analizzare ed estrarre informazioni da set di dati contenenti dati strutturati e non strutturati, la cui dimensione è così grande che ne rende molto difficile o praticamente impossibile l'elaborazione con database e applicazioni tradizionali. L'elaborazione di questi dati richiede quindi l'uso di framework distribuiti specializzati per l'esecuzione parallela di programmi, come Apache Hadoop [4] e Apache Spark [8]. Questi framework specializzati sono utilizzati per trasformare le applicazioni in parti atomiche che possono essere eseguite in un cluster distribuiti di macchine fisiche o virtuali.

Hadoop utilizza il modello di programmazione Map-Reduce che è stato inizialmente introdotto da Google [21] e si compone di due fasi distinte: Map e Reduce.

Il primo processa e *trasforma* un blocco di dati per produrre coppie chiave-valore (tuple) come output intermedi, quest'ultimo *aggrega* queste tuple in un output finale.

Una soluzione più avanzata è rappresentata da Apache Spark [8], che consente esecuzioni più rapide evitando o limitando l'utilizzo dell'archiviazione persistente e fornisce un modello di programmazione più sofisticato basato su piani di esecuzione paralleli (*PEPs*) che sono rappresentati come un grafico aciclico orientato (DAG) delle fasi.

Le applicazioni di big data pongono nuove sfide nel soddisfare i requisiti sulla *Qualità del Servizio* (*QoS*) fornita agli utenti finali. Nel contesto delle applicazioni tradizionali (ad esempio le applicazioni web), questo problema è stato spesso affrontato utilizzando sistemi autoadattativi che controllano *KPIs* (Key Performance Indicators) a runtime rispetto ai cambiamenti nel contesto dell'applicazione e nel carico di lavoro.

Rispetto alle applicazioni tradizionali, dove una singola esecuzione dura da decine a centinaia di millisecondi, le applicazioni di big data potrebbero richiedere minuti o ore per elaborare grandi dataset, quindi il *QoS* deve considerare l'esecuzione di singole esecuzioni. Pertanto, in questo dominio il *QoS* viene spesso definito attraverso la **deadline**, che è la durata massima consentita della singola esecuzione dell'applicazione.

Il tempo di esecuzione delle applicazioni big data dipende da molti fattori come la quantità di risorse di calcolo disponibili (CPU, memoria, storage) e l'esecuzione simultanea di altre applicazioni nello stesso cluster. Pertanto, in letteratura si possono trovare diversi approcci [44, 23, 16] che si concentrano sull'assegnazione delle risorse o sulle tecniche di schedulazione al fine di ridurre le violazioni delle deadline utilizzando diverse tecniche come la programmazione lineare intera, l'apprendimento automatico e la teoria del controllo.

Tutti questi approcci utilizzano la conoscenza del *PEP* per ragionare, prevedere o stimare il tempo di esecuzione dell'applicazione e lavorare partendo dal presupposto che il *PEP* dell'applicazione non cambi a seconda dei diversi dataset di input o parametri dell'applicazione. Sfortunatamente, questo è vero solo se il codice dell'applicazione non contiene alcun branch condizionale il cui risultato dipende dai valori di input dell'utente o dal risultato di calcoli precedenti che coinvolgono dati di input. In caso contrario, potrebbero essere necessari diversi *PEPs* delle applicazioni per descrivere tutti i possibili flussi di esecuzione generati dalle combinazioni dei diversi risultati che derivano dal codice dell'applicazione. Senza considerare tutti questi *PEPs*, l'analisi dell'applicazione potrebbe essere notevolmente imprecisa.

xSpark, sviluppato al Politecnico di Milano, è un'estensione del framework Apache Spark che offre un'allocazione dinamica delle risorse a grana fine utilizzando contenitori leggeri e pianificatori teorici del controllo. Consente agli utenti di impostare le deadline delle applicazioni (cosa non possibile utilizzando Spark) e utilizza la conoscenza del *PEP* dell'applicazione, recuperato durante una fase di profilazione, per allocare dinamicamente le risorse all'applicazione. xSpark non considera loop o branch condizionali nel codice dell'applicazione e presuppone che il *PEP* sia univoco.

xSpark_{SEEP}, la soluzione descritta in questa tesi, estende la capacità di xSpark di eseguire in sicurezza applicazioni multi-*PEP*, sfruttando l'esecuzione simbolica. Ad ogni risultato di un branch decisionale nell'applicazione, *xSpark_{SEEP}* determina quali *PEPs* sono

ancora validi e pota l’albero dei *PEPs*, rimuovendo i *PEPs* non più validi, lasciando così solo quelli validi nell’albero dei *PEPs*. Una euristica viene utilizzata per selezionare il *PEP* da eseguire tra quelli validi, al fine di ridurre al minimo il rischio di oltrepassare la deadline, massimizzando l’efficienza di utilizzo della CPU.

$xSpark_{SEEP}$ è il risultato dell’integrazione di *SEEPEP*, uno strumento che sfrutta l’esecuzione simbolica per scoprire tutti i possibili *PEP* delle applicazioni prodotte da diversi input e parametri, con una versione modificata di *xSpark*.

Abbiamo testato $xSpark_{SEEP}$ con due applicazioni, Promocalls e Louvain, che utilizza *GraphX*, una libreria Spark specializzata per l’elaborazione di grafi.

La valutazione mostra che *SEEPEP* è in grado di estrarre efficacemente tutti i *PEPs* generati dalle applicazioni Spark e che $xSpark_{SEEP}$ controlla in modo efficace ed efficiente l’allocazione delle risorse durante l’esecuzione di *PromoCalls* e *Louvain*, mantenendo i tempi di esecuzione entro scadenze prefissate con errori significativamente minori e consumando una quantità di risorse inferiore rispetto alla versione originale di *xSpark*.

Poiché la soluzione attuale si concentra sul controllo di una singola applicazione, un lavoro futuro potrebbe essere diretto all’estensione di $xSpark_{SEEP}$ per controllare più applicazioni concorrenti.

INTRODUCTION

CLOUD computing has become a widely used form of service oriented computing. It offers the provisioning of infrastructures and software platforms as a service by using virtualization. On-demand resource provisioning, metered usage of resources and pay-per-use, no upfront capital investment, fast time-to-market and risk transfer represent the most interesting features of cloud computing.

The term "big data" is used to describe a research field that deals with ways to analyze and extract information from data sets containing structured and unstructured data whose size is so large that makes their processing very difficult or practically impossible with traditional databases and applications. Data sets can contain a large amount of data that can be structured, semi-structured, like in the self-described XML or JSON documents, or unstructured, like in the logfiles collected mostly by web applications to monitor usage or other user's preferences.

The analysis and processing of big data assets requires the usage of ad-hoc frameworks that are usually deployed on the cloud. The management of these frameworks is a complex task. This thesis tackles the problem of guaranteeing at runtime QoS requirements defined for big data applications, in particular when those are supposed to meet a user-defined constraint over the execution time.

1.1 CONTEXT

Nowadays, every second 2,780,000 emails are exchanged, 3,690 Skype calls are made, 902 Instagram photos are posted, 73,116 Google searches are performed, 1,502 Tumblr posts are created, and 8,411 Tweets are sent [25]. This is only a small fraction of all the data which is continuously collected and analyzed.

Gartner [19] defines big data as data that contains greater variety arriving in increasing volumes and with ever-higher velocity. Other definitions add veracity and value. This is known as the five V's characterizing big data: Volume, Velocity, Variety, Veracity and Value [47].

Volume is important because the amount of data drives both the size of memory infrastructure and the computational effort for their analysis. Big data requires processing of high volumes of low-density, unstructured data. These can be data of unknown value, such as Twitter data feeds, clickstreams on a webpage or a mobile app, or sensor-enabled equipment. In some cases, this might be tens of terabytes of data, sometimes hundreds of petabytes.

Velocity is the fast rate at which data is received and acted upon. Normally, highest velocity data streams are directly stored into memory versus being written to disk. Some internet-enabled smart products operate in real time, or near real time, requiring a very fast evaluation and action.

Variety refers to the many available data types. Traditional data types were structured and are suitable to be stored and managed in a relational database. With the rise of big data, data arrives in an unstructured form. Unstructured and semistructured data types, such as text, audio, and video require an additional preprocessing effort to transform, derive meaning and attach metadata to them.

Value refers to the ability to transform data into business value.

Veracity refers to the quality of data.

By means of hardware virtualization, cloud computing services satisfies all the requested requisites needed to manipulate big data. On demand resource provisioning and redundancy provided by cloud computing also enable big data application high availability, scalability and fault tolerance.

Big data applications are used to transform, aggregate and analyze a large amount of data in an easy and efficient way. These applications are split in atomic parts that can be executed in a distributed cluster of physical or virtual machines by means of specialized frameworks. The limit to the level of parallelism that can be obtain is given by the number of machines and the amount of synchronization needed to keep the data fragments representing the results of intermediate operations synchronized (e.g. aggregations, grouping). This paradigm has been historically represented by the map-reduce programming model firstly introduced by Google [21] and implemented by Apache Hadoop [4]. Nowadays, more advanced solutions are available, such as Apache Spark [8] and Apache Tez [10] that provide a greater flexibility and allow building large-scale data processing applications using a *Directed Acyclic Graph* (DAG) or *Parallel Execution Plan* (PEP) structure to keep track of intermediate results of operations on datasets and determine which parts of the application can be executed in parallel.

The Spark processing platform is very popular [35] and is distinguished by the generality of the solutions and the speed of data processing and sharing. Compared to Hadoop, applications can be run up to 100x faster when operating in memory and up to 10x when operating on disk. Spark is an award-winning platform as the fastest among the open source engines in data sorting operations [31].

Spark embeds fault-tolerance and can run on off-the-shelf hardware. It allows for faster executions by avoiding or limiting the use of the persistent storage and it provides a more sophisticated programming model than the traditional Map-Reduce, based on parallel execution plans (*PEPs*) which are represented as directed acyclic graph (DAG) of phases.

Spark provides a high level API for Java, Python and Scala and a rich set of special purpose software libraries (e.g. machine learning, graph processing). In order to execute big data applications, Spark [50] divides the computation into different phases and split the input dataset into partitions that are stored in a distributed fashion and processed in parallel. It stores in memory the partial results of the operations in order to facilitate its reuse, avoiding recalculations of data sets. The operations performed by Spark on the data can belong to the class of *actions* or the class of the *transformations*. The *actions* return the results of the distributed calculations to the application, while the *transformations* perform the parallel transformation of the data.

Spark operations are gathered in *stages* and the stages are then grouped into *jobs*. A stage is composed by a series of transformations that do not require data shuffling, while a job identifies a set of stages between two actions. To maximize parallel execution, Spark computes a *Parallel Execution Plan (PEP)* for each application job. Inside jobs, each stage is subdivided in *tasks* that are executed in parallel, and multiple stages are also executed in parallel. To support such a high parallelized execution plan, Spark creates a directed acyclic graph structure of the stages in each job, while the composition of all the plans represents the *PEP* of the whole application.

A very important measure related to IT applications is the *Quality of Service* (*QoS* in the reminder of this document).

The meaning of *QoS* referred to big data depends on the type of application. Generally, interactive applications are evaluated based on response time and performance depends on the intensity and variety of incoming requests. Instead, big data applications often perform batch calculations on a large data set, so that *QoS* is relevant for each

single run of the application. In this field, *QoS* is often called *deadline*, i.e. the maximum allowed duration of the execution.

The execution time of Spark applications depends on the amount of resources allocated to the application, thus ensuring that a *QoS* constrained application meets a user-defined deadline is a resource allocation problem. Statically partitioning, i.e. reserving a fixed amount of resources for the whole execution time, is a simple option that is provided by all the cluster managers. A dynamic and workload dependent mechanism to allocate resources to a specific application is available in Spark, and freed-up resources can be returned to the cluster and re-claimed when needed.

In this thesis we focus on *QoS* as a measure of the capability to meet a user-defined deadline when processing big data.

1.2 PROBLEM AND MOTIVATION

In the last years there were developed many methodologies analysis for estimating Spark applications execution times, and consequently perform a tailored resource allocation. Islam et al. [26] propose dSpark, that uses a static model to optimze the resource allocation before the deadline-constrained Spark application is run. Sidhanta et al. [41] propose an optimization model for Spark cluster configuration considering time and cost constraints, not considering at all runtime dynamic resource allocation. Alipourfard et. al [1] compute the best configuration for execution of Spark applications based on generated performance model. Baresi et al. [14, 13] propose xSpark, an extension of Spark exploiting control theory and containers¹, that allows users to constrain deadlines by providing a fine-grained resource allocation and elastically allocating resource at runtime.

The estimation of the application execution time and the dynamic resource allocation have been deeply investigated by the above mentioned researches, however all the proposed approaches is based on the assumption that the application execution is governed by a unique *PEP*, i.e. the plan is defined at the application start time and cannot change during its execution. Applications in the real world, on the other hand, can contain conditional branches and iterative loops in their main code, and therefore a different execution plan is identified by each path corresponding to a specific combination of conditional branches outcomes and result of iterative loops. Therefore, assuming a unique *PEP* strongly impacts the precision of the analysis and severely

¹ <https://www.docker.com>.

limits the accuracy of the prediction. As an example we can take the case of a Spark program that evaluates an intermediate result that is then used to determine the outcome of a conditional expressions of a program branch.

Symbolic execution techniques are exhaustively employed in testing of software programs to help identify unsafe inputs that cause the programs to crash. The use of these techniques to deliver a full coverage of the possible dangerous inputs is severely limited by the exponential growth of the required computational resources as a consequence of *path explosion*. This is due to the need of exploring all the possible execution paths and solve all the related *path conditions* of programs of indefinite complexity, with many iterative loops and/or conditional branches in its code. As a consequence, we can rapidly resort to unsolvability. The work of this thesis relies on a lightweight symbolic execution approach [11] that values the solvability of symbolic evaluation-based tools on an *efficiency* base instead of a *soundness and completeness* – often practically unfeasible – base.

In this thesis we investigate the resource allocation problem when running big data multi-*PEP* applications with deadline-based *QoS* constraints.

The main reason supporting the work in this thesis is the willingness to make a contribution by proposing a solution to the problem of running multi-*PEP*, deadline-based *QoS* constrained Spark applications obeying a user-defined deadline in an efficient way.

1.3 SOLUTION AND CONTRIBUTION

To address the questions raised by the investigation of resource allocation problems related to running big data multi-*PEP* applications with deadline-based *QoS* constraints, we propose a solution that leverages *symbolic execution*.

The solution covered by this thesis exploits a technique called *SEEPEP* (*Symbolic Execution-driven Extraction of Parallel Execution Plans*) that combines lightweight symbolic execution and search-based test generation to deduce the *PEP* corresponding to a specified set of data and input parameters [11]. It creates a model called *PEP** which contains the set of *PEPs* generated by the application, their associated path conditions and profiling data.

The main contribution of this thesis is the integration of *SEEPEP* into an existing solution for the management of the Spark applications called *xSpark* [14, 13].

xSpark is an extension of Spark developed at Politecnico di Milano. It offers fine-grained dynamic resource allocation using lightweight containers and provides the capability to force a user-defined deadline to application runs. xSpark estimates the execution times and allocate resource in order to meet user defined deadlines. A previous work on xSpark has addressed the scheduling problem and established a policy for managing the deadlines when multiple applications run simultaneously on the same hardware.

xSpark leverages metadata provided by an initial profiling to extract the application *PEP* under the assumption that this *PEP* is unique for each set of admissible input data and parameter. At runtime, the *PEP* is used to compute the work done and the amount of work remaining to complete the execution of the application. Since each execution of the same application uses the same *PEP*, we infer that an implicit requirement for any xSpark application is not to contain branches or loops, which might be resolved in different ways at runtime.

To overcome this limitation, we present a new version of xSpark called *xSpark_{SEEP}PEP*. *xSpark_{SEEP}PEP* exploits the knowledge of the *PEP** to refine the runtime resource allocation by using a specialized component that, at each xSpark job boundary, selects the worst-case *PEP* among the *PEPs* that are still valid.

In light of the proposed solution, we have identified the following research questions:

RQ₁ : Can the execution of Spark applications be effectively controlled by *xSpark_{SEEP}PEP*?

RQ₂ : Can the resource allocation capabilities of xSpark be improved, given it used a single, constant *PEP*?

In addition to *xSpark_{SEEP}PEP*, we present a toolchain [49] that automates the usage of *SEEP* to extract the *PEP**, launch the profiling phase and the execution of the application.

RESULTS AND FUTURE WORK

The solution was tested with two applications: *Promocalls*², a paradigmatic example and *Louvain*, a Spark implementation of the Louvain algorithm [15], that we downloaded from a highly rated GitHub repository³. *Louvain* exploits *GraphX*, a Spark graph processing library to

² <https://github.com/seepep/promocalls>

³ <https://github.com/Sotera/spark-distributed-louvain-modularity>

represent large networks of users and analyze communities in these networks.

We evaluated *SEEPEP* by integrating it with xSpark and using it to control the parallel execution of Spark applications *Promocalls* and *Louvain*.

The results of the tests confirm that SEEPEP is able to effectively extract all the *PEPs* generated by Spark applications and that *xSpark_{SEEPEP}* effectively and efficiently controls the allocation of resources during the execution of *PromoCalls* and *Louvain*, keeping the execution times within considered deadlines with significantly smaller errors and consuming a lower amount of resources than the original version of xSpark.

The current solution focuses on controlling a single application. A future work could be directed at extending *xSpark_{SEEPEP}* to control multiple concurrent applications.

2

STATE OF THE ART

THIS chapter contains an overview of the highest level of developments in the information technology fields which represent a solid foundation for the development of this thesis.

2.1 BIG DATA

The term "big data" refers to a research branch that deals with methodologies to analyze and extract information from data sets containing data that can be structured, as in the traditional relational databases, semi-structured, like the self-described XML or JSON documents, or unstructured, as the logfiles collected mostly by web applications to monitor usage or other user's preferences. More properly, we call big data those that cannot be handled using traditional database and software technologies. IDC [24] has predicted that by 2020 one tenth of the world's data will be produced by machines. The organisation forecast that in five years time the amount of connected devices communicating over the internet will reach 32 billion and generate 10% of the world's data. This data is collected and analyzed.

2.1.1 *Batch Processing: Hadoop*

Hadoop [4] uses the Map-Reduce programming model that was firstly introduced by Google [21] and consists of two distinct phases: Map and Reduce.

The former processes and *transforms* a block of data to produce key-value pairs (tuples) as intermediate outputs, the latter *aggregates* these tuples into a final output. There are available MapReduce libraries written in different programming languages.

MapReduce is a programming framework that allows us to perform distributed and parallel processing on large data sets in a distributed environment.¹.

- MapReduce consists of two distinct tasks – Map and Reduce.

¹ Extracted from: <https://www.edureka.co/blog/mapreduce-tutorial/>

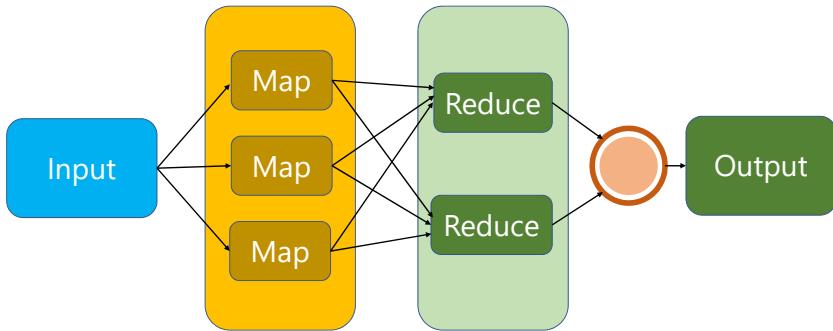


Figure 2.1: Abstract representation of map-reduce paradigm

- As the name MapReduce suggests, reducer phase takes place after mapper phase has been completed.
- So, the first is the map job, where a block of data is read and processed to produce key-value pairs as intermediate outputs.
- The output of a Mapper or map job (key-value pairs) is input to the Reducer.
- The reducer receives the key-value pair from multiple map jobs.
- Then, the reducer aggregates those intermediate data tuples (intermediate key-value pair) into a smaller set of tuples or key-value pairs which is the final output.

Open source implementation of the MapReduce framework, include Apache Hadoop [4]. The MapReduce framework is composed by the following functions:

1. Input Reader
2. Map Function
3. Partition Function
4. Compare Function
5. Reduce Function
6. Output Writer

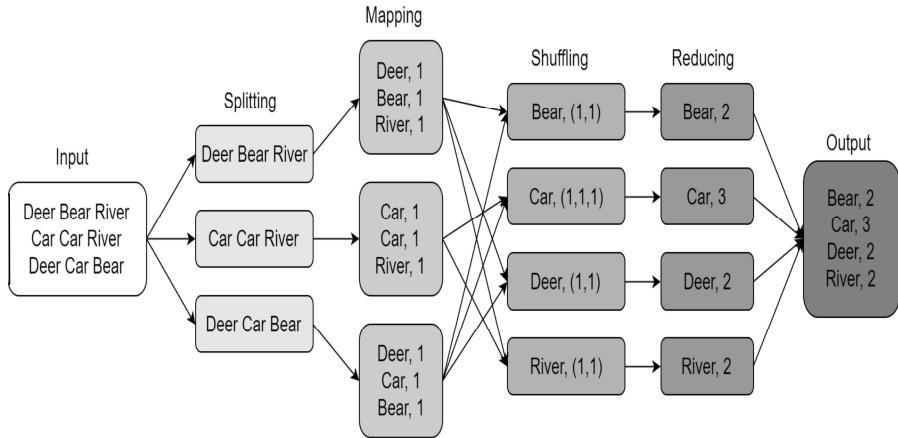


Figure 2.2: Map-Reduce word count job example. Counts the occurrence of each word in input

The Input Reader reads data from mass storage and splits it in many different fragments of fixed size (e.g., 128 MB) and then it distributes them to the servers of the cluster hosting the Map function. It also generates a (key, value) pair. One of the servers of the cluster is elected to be the master, and is in charge of detecting idle slaves and assign them a task, and the others are slaves that are assigned tasks by the master. Each slave running a task reads the content of the input, extracts the (key, value) pairs and send them to the user-defined Map function, that generates (key, value) pairs as output, that are stored in memory and periodically cached on disk. They are also partitioned in sections by the partition function. The addresses of the partitioned sections are sent to the master node which is responsible of rotating the location of the slaves that process the Reduce function. All the pairs are reordered while transitioning between the slave with the Map function and the slave with the Reduce function, in order to group pairs with the same key on the same server. This is the shuffling phase.

Once all the keys that point to the same value are discovered using the compare function, a merge is done. Sorting is useful so that the reducer knows when a new reduce task should start. For each key, the Reduce function defined by the user is applied to the values having the same key, generating one or more output element. The Output Writer writes the results to mass storage.

A sample word count application is shown in figure 2.2. The input is a document containing words, and we have to compute the cardinality

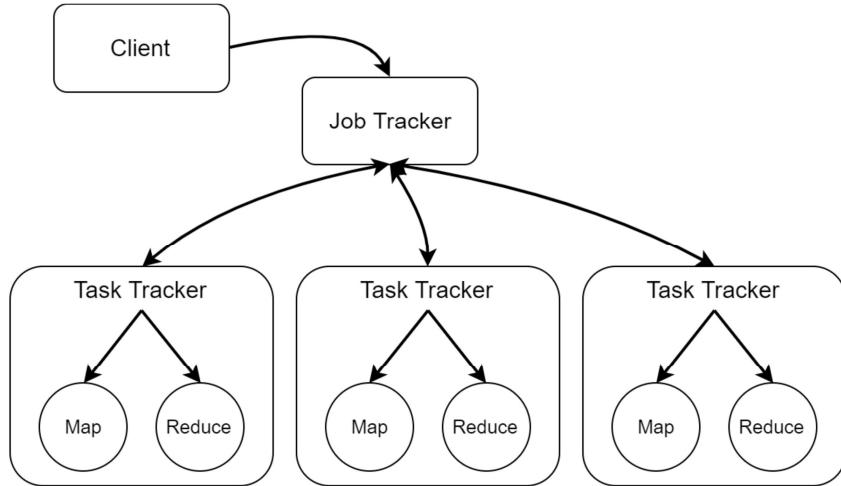


Figure 2.3: Hadoop Map-Reduce Architecture.

of the occurrence of each word in the document. Each Map task is applied to a line of the document, producing pair ('word', 1) for each word. For example if the input line is "Dear Bear River", it is split into ["Dear", "Bear", "River"] and then mapped into [("Dear", 1), ("Bear", 1), ("River", 1)]. After shuffling the results of the Map, the Reduce task receives a word and a list containing as many ones as the cardinality of the word occurrence in the document. The Reduce function will sum the ones in the list and producing as a result the pair ('word', 'count'). For example, a reducer can receive the key "Bear" with list of values (1, 1), this is reduced into ("Bear", 2). Reducers results are then collected and stored to disk.

Apache Hadoop MapReduce cluster has a centralized structure composed by a master Job Tracker (JT) and multiple worker nodes running Task Tracker (TT), as shown in figure 2.3.

JT organizes the job tasks on the slave nodes and continuously polls the Task Trackers by means of heartbeats. Heartbeats retrieve information about the liveliness of the slaves and to inspect the progress of the task executions. If a task execution fails, it is re-executed possibly on a different slave. JT is also the cluster manager, so it checks the eligibility of the submitted MapReduce jobs. TT runs the assigned task and replies to heartbeats in order to affirm their liveliness and update the master about the progress of the assigned tasks.

Apache Hadoop also offers a distributed filesystem that stores data on several machine, providing a high aggregate bandwidth across

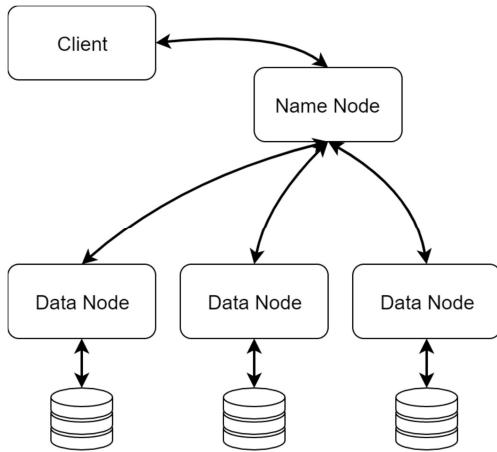


Figure 2.4: HDFS Node Structure.

the cluster. It is called Hadoop Distributed File System (HDFS)². It is highly fault tolerant and designed to run on commodity hardware. HDFS exposes a filesystem namespace and allows user data to be stored in files and retrieved. Clusters are composed by one master and multiple slaves, as shown in figure 2.4.

The master provides a single Name Node (NN), that manages the file system namespace and regulates access to the files by clients. NN executes filesystem operations such as file open, close, rename, and keeps track of the mapping between blocks and Data Node (DN). File stored in HDFS are split into blocks, that are stored in the Data Node (DN). Data Node (DN) represent the slaves, and manage the storage attached to the node they are running on. They serve read and write operation requests from the clients, but also can perform block creation, deletion and replication. Block replication is a way to improve fault tolerance.

2.1.2 Batch Processing: Spark

Apache Spark is an open source framework for distributed computation [8] provides an Application Programming Interface (API) that provides implicit data parallelism and fault tolerance. With respect to the MapReduce paradigm, the in-memory multilevel primitives of Spark allow to have up to 100 times better performance. Spark can

² HDFS Architecture Guide. https://hadoop.apache.org/docs/r1.2.1/hdfs_design.html

run as standalone or on a cluster manager such as Apache Hadoop Yarn or Apache Mesos. It also needs a distributed storage and can natively use HDFS and other solutions.

Spark was designed as a unified engine for distributed data processing. Its programming model extends the MapReduce with a data sharing abstraction called Resilient Distributed Dataset (RDD). This abstraction allows the processing many different workloads, including SQL, streaming, machine learning and graph processing.

The generality of the Spark approach allows an easy development of applications through the use of its API, and an easy combination of processing tasks. Previous distributed frameworks required data to be written to disk before using them in other processes. Spark allows the reuse of the data, often kept in memory.

RDDs are fault-tolerant collections of objects partitioned across the cluster that can be processed in parallel. Users create RDDs by applying "transformation" operations like map, filter and group-by on the input data. RDDs can be backed by a file obtained from an external storage. RDD are evaluated in a lazy mode. This allows the construction of an efficient plan to execute the computation requested by the user.

Every transformation operation returns a new RDD, that represents the result of the computation, however the computation is not executed immediately after the transformation request is encountered, but only when a Spark action is met. When an "action" is requested by the user code, Spark checks the entire graph of the transformation and uses it to create an efficient execution plan. For example, if there are many filters and maps in a row, Spark can merge them together and execute as a single operation.

RDDs also offer an explicit support by default non-persistent data sharing among the computations. This capability is one of the main differences between Spark and the previous models like MapReduce. Data sharing capability allows huge speedups, up to 100 times, in particular when executing interactive queries and iterative algorithms. RDDs can also recover automatically from a failure. Traditionally, fault tolerance in distributed computing was achieved by means of data replication and checkpointing. Spark instead uses a different approach called lineage. Each RDD keeps track of its transformation graph used to generate the RDD and re-executes the transformation operations on the base data to recover every lost partition. Data recovery based on lineage is significantly more efficient than replication in case of

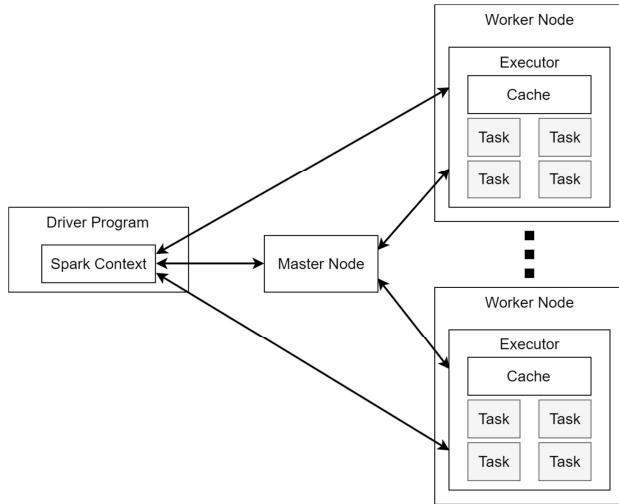


Figure 2.5: Spark Standalone Architecture.

data-intensive workload. In general, recovering lost partitions is faster than re-executing the entire program.

Spark was designed to support different external systems for persistent storage, usually it is used in conjunction with a clustered file system like HDFS. Spark is designed as a storage-system-agnostic engine, to make it easy to run computations against data from different sources.

Different high-level libraries have been developed in order to simplify the creation of programs that can run in Spark framework.

- SQL and DataFrames: support for relational queries, that are the most common data processing paradigm
- Spark Streaming: implements incremental stream processing using a model called "discretized streams", input data is split into micro batches
- GraphX: graph computation interface
- MLlib: machine learning library, more than 50 common algorithms for distributed model training

Spark architecture implements the master/worker paradigm (figure 2.5). A master server accepts data and processing request, splits them into smaller chunks of data and simpler actions that can be executed in parallel by the workers.

A Spark application is executed by a driver program, that makes the user code executable on the computing cluster using a `SparkContext`.

Details for Job 0

Status: SUCCEEDED
 Completed Stages: 2
[Event Timeline](#)
[DAG Visualization](#)

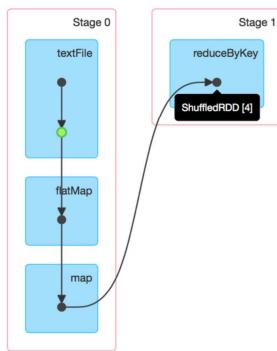


Figure 2.6: Spark DAG Example.

The driver program is responsible for managing the job flow and scheduling tasks that will run on the executors. The `SparkContext` will split the requested operations in tasks the can be scheduled for distributed execution on the workers.

When a `SparkContext` is created, a new Executor process is created on each worker. An executor is a separate Java Virtual Machine (JVM) that runs for the entire lifetime of the Spark application, executes tasks using a thread pool and store data for its Spark application. Communication between the `SparkContext` and the other components is performed using a shared bus.

When an application is submitted to Spark, it is divided in multiple jobs. Jobs are delimited by Spark actions in the application code. Spark actions are those operations that return a value to the driver program after running a computation on the data set.

For each job, a Directed Acyclic Graph (DAG) is created to keep track of the RDDs that are materialized inside the job. DAG nodes represent the RDDs, while arcs represent transformations, that are the operations that create new datasets from existing ones.

The application steps inside a single job are further organized into stages, that are delimited by operations requiring data reshuffling, that will break locality. Spark distinguishes between narrow transformations, that do not reshuffle data (e.g., `map`, `filter`), and wide transformations, that require data reshuffling (e.g., `reduceByKey`).

Stages are also used to produce intermediate result that can be persisted to memory or mass storage to avoid re-computation. When all stages inside a job have been identified, Spark can determine which parallel tasks need to be executed for each stage, and schedule them

Listing 2.1: Spark word count application example.

```

1 sparkContext.textFile("hdfs :/. . . ")
2 .flatMap(line => line.split(" "))
3 .map(word => (word, 1)).reduceByKey(_ + _)
4 .saveAsTextFile("hdfs :/. . . ")

```

for operation on the executors. Spark creates one task for each partition of the RDD received in input by a stage.

Figure 2.6 shows a simple DAG representing the single job of the word count application presented in Listing 2.1 [34]. The image is taken from SparkWeb UI. Through a `textFile` operation, the input file is read from HDFS. Then a `flatMap` operation is applied to split each of the lines of the document into words. Then, a `map` is used to create ('word', 1) pairs. Finally, a `reduceByKey` operation is performed to count the occurrences of each word. The blue boxes represent the Spark operations that the user calls in his code, while the dots represent the RDDs that are created as a result of these operations. Operations are grouped into stages, represented by the boxes with a red border. The job has been divided into two stages because the `reduceByKey` transformation requires the data to be shuffled. The green dot represents a cached RDD, in particular the data read from HDFS has been cached, in this way future computations on this RDD can be done faster since data will be read from memory instead of HDFS. The default deployment of Spark is in standalone mode, that is using its embedded cluster manager.

2.1.3 Stream Processing

Apache Flink [2] is a framework and distributed processing engine for stateful computations over unbounded and bounded data streams. It can run in any commonly used cluster environments, computes at in-memory speed and manages data at any scale.

Flink's architecture can process unbounded and bounded data. Sensors data, server logs or user interactions on a website or mobile application, credit card transactions, all of these data are generated as streams of data.

Data can be processed as unbounded or bounded streams [3].

Unbounded streams have a start but no defined end. They do not terminate and provide data as it is generated. Unbounded streams

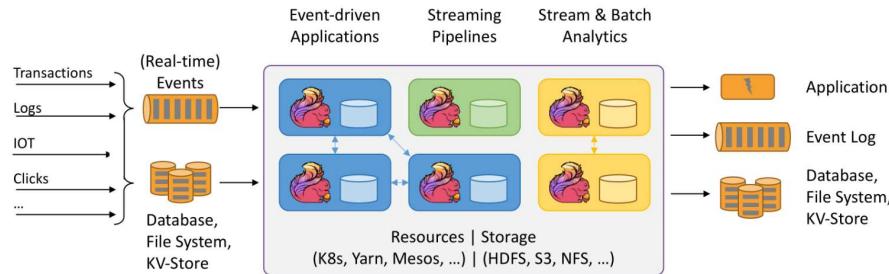


Figure 2.7: Apache Flink® - Stateful Computations over Data Streams.

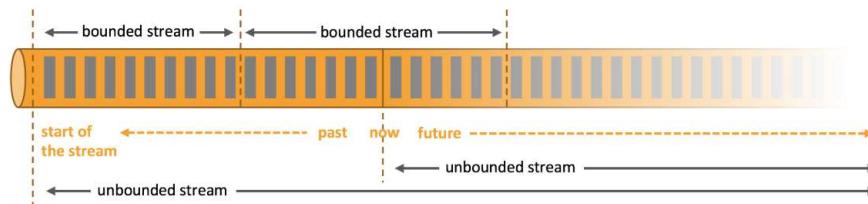


Figure 2.8: Apache Flink® - Bounded & Unbounded Data Streams.

must be continuously processed, i.e., events must be managed right after they have been read.

Bounded streams have a defined start and end. Bounded streams can be processed by reading all data before performing any computations. Ordered reading is not required to process bounded streams because a bounded data set can always be sorted. Processing of bounded streams is also known as batch processing.

Apache Storm [9] is a free and open source distributed realtime computation system. Storm makes it easy to reliably process unbounded streams of data, doing for realtime processing what Hadoop did for batch processing. Storm is simple, can be used with any programming language, and is easy to use.

The Apache Storm architecture is quite similar to that of Hadoop. However there are certain differences which can be better understood by getting a closer look at its cluster in Figure 2.9. There are two types of nodes in Storm cluster similar to Hadoop:

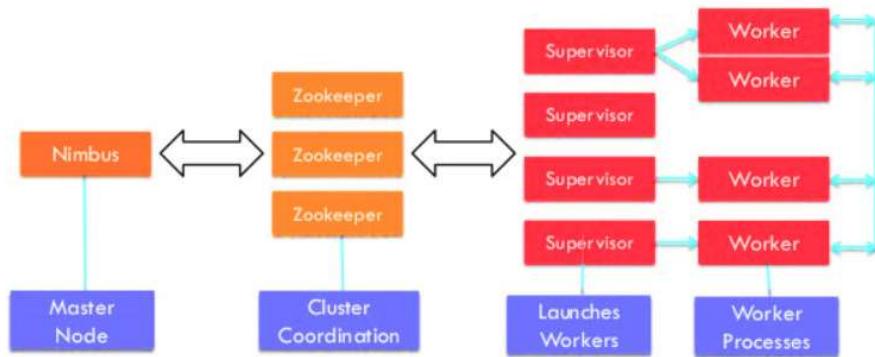


Figure 2.9: Apache Storm.

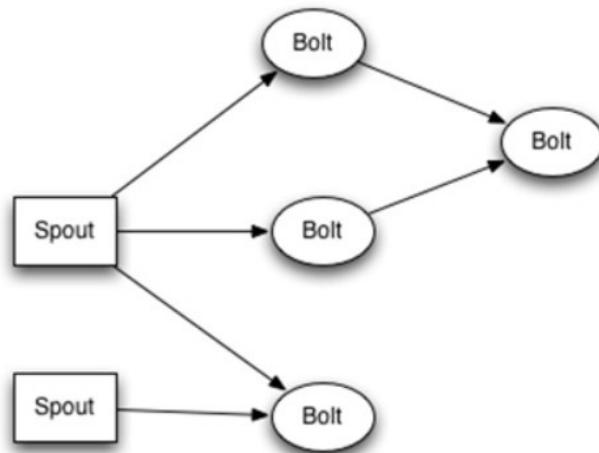


Figure 2.10: Apache Storm Components Abstraction.

- Master node - The master node of Storm runs a daemon called 'Nimbus', which is similar to the 'Job Tracker' of Hadoop cluster. Nimbus is responsible for distributing codes, assigning tasks to machines and monitoring their performance.
- Worker node – Similar to the master node, the worker node also runs a daemon called 'Supervisor' which is able to run one or more worker processes on its node.

There are basically four components which are responsible for performing the tasks(see Figure 2.10):

- Topology – Storm Topology can be described as a network made of **spouts** and **bolts**. It can be compared to the Map and Reduce jobs of Hadoop. Spouts are the data stream source tasks and Bolts are the accrual processing tasks.
- Stream – One of the basic abstractions of the storm architecture is stream which is an unbounded pipeline of tuples.
- Spout – It is the entry point or the source of streams in the topology.
- Bolt - Bolts keep the logic required for processing.

2.2 RUNTIME MANAGEMENT OF BIG DATA APPLICATIONS

Big data applications requires system scalability, fault tolerance and availability [38].

Scalability means the ability to maintain an approximate linear relationship between the size of processed data and the amount of consumed resources.

Fault tolerance is a challenge, especially when systems are complex and involve many networked nodes. By means of hardware virtualization, cloud computing services satisfies all the requested requisites, and the *elasticity* and redundancy it provides also enable big data application high availability, scalability and fault tolerance.

Another very important feature of big data applications is the *Quality of Service* or *QoS*.

QoS definition for IT applications differ by application type. Interactive applications are usually assessed according to response time or throughput, and their fulfillment depends on the intensity and variety of the incoming requests.

Big data applications might require a single batch computation on a very large dataset, thus *QoS* must consider the execution of a single run. In this domain *QoS* is often called *deadline*, or the maximum allowed duration of the computation.

We have mentioned *QoS* as a measure of the capability to meet a user-defined deadline when processing big data. Many factors influence the duration of an application execution, surely resource allocation greatly influences the duration.

The challenges introduced by big data require resilient, flexible and self-adapting software systems [29]. Hence, *autonomic systems* and *self-adaptation* has increasingly captured the attention of researchers

[46]. These systems automatically react to changes in the environment, or in their own state, and change their behaviour to satisfy functional and non-functional requirements. Meeting requirements in complex and variable execution environments is a difficult task that can be tackled at design time or at runtime. At runtime the adaptation is very often obtained by using a well-known process called MAPE [28], a control loop composed of four phases: monitoring, analysis, planning and execution.

One of the challenges that modern software systems face is the provisioning and optimization of resources to meet a varying demand, generated by increasingly common phenomena like fluctuating workloads, unpredictable peaks of traffic and unexpected changes. Service providers cannot disregard these factors if they want to cope with the challenge of satisfying functional and non-functional requirements, usually defined in SLAs (Service Level Agreements). Hence the need arises for an automatic adjustment of system resources allocation to avoid resource saturation and unresponsiveness, users dissatisfaction and unnecessary costs. This paradigm is called elastic resource provisioning [18, 51, 39, 22].

Many approaches about elastic systems and dynamic resource allocation were proposed both in the industry and in academia. In modern technology elasticity is often enabled by cloud computing that gives to an application a theoretical infinite degree of scalability. However considering only resources is rather restrictive because of the many factors that impact application during their runtime life-cycle. In fact Dustdar et al. [18] argue that elastic computing should be designed by considering three dimensions: quality, resources and cost. Quality elasticity considers how quality is affected by a change in resource availability. Instead cost elasticity measures how resource provision is affected when a change in cost happens.

Cloud computing services provide the needed level of fault tolerance and availability required by big data applications. In the remainder of this chapter we present an overview of popular big data frameworks that can leverage cloud computing solutions and how they address elastic resource allocation to satisfy functional and non-functional application requirements. The resulting scenario represent the base for our work, where we will consider quality elasticity and not cost elasticity aspects.

This thesis shows how the application of lightweight symbolic execution techniques to deadline-based *QoS* constrained multi-DAG

big data applications helps reduce the number of deadline violations and allocate resources more efficiently.

2.3 ELASTIC RESOURCE PROVISIONING

The word *elasticity* comes from physics and is defined as the ability of an object or material to resume its normal shape after being stretched or compressed. In computing, elasticity has a similar meaning and is used to characterize *autonomic systems*. Herbst et al. [22] defines elastic provisioning as reported below.

Elasticity is the capability of a system to adapt to workload changes by provisioning or de-provisioning resources automatically such that at each point in time the available resources match the current demand as closely as possible.

A system is in an *under provisioned* state if it allocates less resources than required by the current demand; it is in an *over provisioned* state if allocates more resources than required. Moreover, elasticity is determined by four attributes:

- *Autonomic Scaling*: the adaptation process used to control the system.
- *Elasticity Dimensions*: the set of scaled resources in the adaptation process.
- *Resource Scaling Units*: the minimum amount of allocable resources to each dimension.
- *Scalability Bounds*: the lower and the upper bound on the amount of resources that can be allocated to each dimension.

Additionally, two aspects must be considered in evaluating the elasticity degree of a system: speed and precision.

Speed of scaling up/down: the time it takes to switch from an underprovisioned/overprovisioned state to an optimal or overprovisioned/underprovisioned state respectively.

Precision of scaling: the absolute deviation of the current amount of allocated resources from the actual resource demand.

Scalability and efficiency are terms related to elasticity, nevertheless they differ by the following aspects:

Scalability, although is a prerequisite for elasticity, it does not consider the temporal aspects (how fast and how often) and the granularity of the adaptation actions.

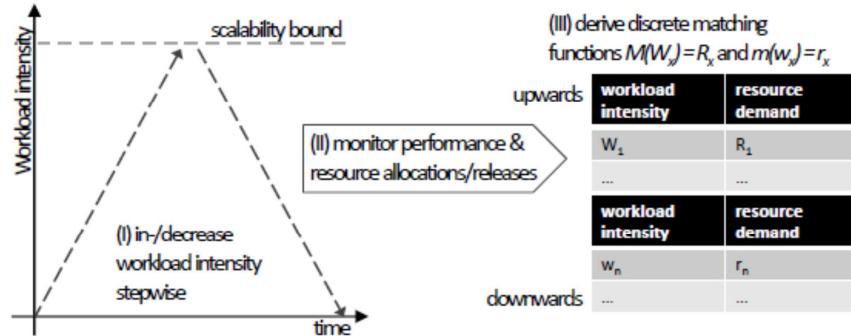


Figure 2.11: Elasticity Matching Function derivation.

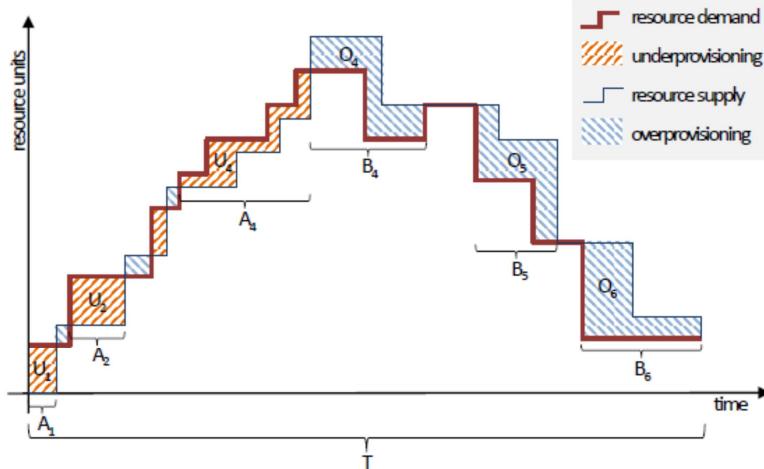


Figure 2.12: Resource Provisioning Chart.

Efficiency, contrary to elasticity, takes in account all the types of resources employed to accomplish a certain amount of work, not only the resources scaled by the adaptation actions.

Elasticity reflects the (theoretical) infinite upper bound on resource scalability in cloud computing and the frictionless resource renting model. Nevertheless elasticity is not just a synonym of resource management. Elasticity is also related to trade off between cost and quality [18]. Cost elasticity describes how resources are managed in response to cost changes, while quality elasticity measures how responsive is the quality to changes in resource utilization.

A *matching function* $m(w) - r$ is a system specific function that gives the minimum quantity of resources r for any given resource type needed to meet the system's performance requirements at a certain

workload intensity. A matching function is required for both up and down scaling directions.

The matching functions can be determined based on measurements, as illustrated in Figure 2.11, by increasing the workload intensity w stepwise, and measuring the resource consumption r , while tracking resource allocation changes. The process is then repeated for decreasing w . After each change in the workload intensity, the system should be given enough time to adapt its resource allocations reaching a stable state for the respective workload intensity. As a rule of thumb, at least two times the technical resource provisioning time is recommended to use as a minimum. As a result of this step, a system specific table is derived that maps workload intensity levels to resource demands, and the other way round, for both scaling directions within the scaling bounds.

An example of how *speed* and *precision* affect resource provisioning is shown in Figure 2.12.

2.4 SPARK RESOURCE PROVISIONING

Spark default deployment mode is standalone, that is using its embedded cluster manager. The cluster manager is responsible for starting the executor processes and set where and when they will run. Using the cluster manager embedded in Spark might be a problem in terms of resource utilization if we want to execute many concurrent distributed applications together with Spark. The use of a single cluster manager for different distributed applications gives a global view on the running applications and which ones are waiting to execute inside the cluster.

Without a single cluster manager, there can be two main approaches to performing resource sharing and allocation:

- allow every application to allocate all the resources in the cluster at the same time: this leads to an unfair situation of resource contention
- split the resource pool into smaller ones, one per application.

With the second approach resource contention are avoided, at the cost of a less efficient utilization of the resources, as some of the applications might request more resources than the ones assigned to their pool, while some others might end up using less resources than the one they have access to. A dynamic approach to resource allocation leads to a better resource utilization. Spark natively supports

the execution on top of Apache Hadoop YARN and Apache Mesos cluster managers. Spark supports the dynamic allocation of executors, also known as elastic scaling. This feature allows addition and removal of Spark executors dynamically to follow the workload demand. In traditional static allocation, a Spark application would allocate CPU and memory upon application start, not caring about the level of resources effectively used later on. Dynamic allocation instead allows the allocation of as much resources as they are necessary, thus avoiding to waste them. The number of running executors follows the workload, in particular idle executors are removed and re-launched when there are tasks waiting to be executed. Dynamic allocation can be activated in Spark settings and should be used in conjunction with the External Shuffle Service. Doing so, data that have been manipulated by an executor will still be available after the executor is removed. Dynamic allocation has two different policy for scaling the executors:

- Scale Up Policy: new executors are requested when there are pending tasks. There is an exponential increase in the number of executors, because the start is conservative, so at the end the application might need a higher number of them
- Scale Down Policy: idle executors are removed after a certain amount of time, and this amount of time is configurable

In order for dynamic allocation to work, it must be configured the initial number of executors that are created when application starts, and the minimum and maximum number of executors that can be reached when scaling down and up respectively. Dynamic allocation is available on all cluster managers currently supported by Spark, including Standalone mode.

2.4.1 *Apache Hadoop Yarn*

Apache Hadoop YARN (acronym of Yet Another Resource Negotiator) is an evolution of the Hadoop computing platform [43]. It separates the functionality of resource management from job scheduling and monitoring. This is done by starting two different types of daemons: a global Resource Manager (RM) and a per-application Application Master (AM).

The data computation framework is made by Resource Manager (RM) and Node Manager (NM) (see Figure 2.13). Resources among all the applications that are running in the system are managed by RM

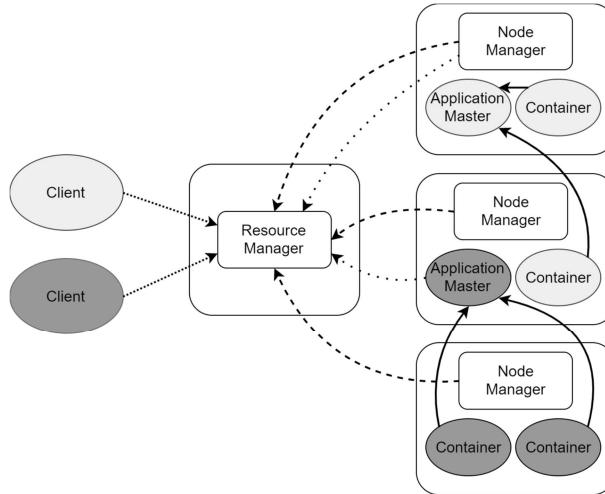


Figure 2.13: Apache Hadoop YARN Architecture.

authority, while NM is the per-machine daemon who manages containers, monitoring and reporting. The per application AM negotiates resources with RM and works with NM to execute and monitor tasks. Resource Manager (RM) is composed by Scheduler and Applications Manager.

2.4.2 Apache Mesos

Apache Mesos [6] is an open-source project used to manage computer clusters. The purpose of Mesos is to share cluster between different computing frameworks, such as Apache Hadoop or Message Passing Interface (MPI) Figure 2.14. The sharing increments the utilization of the cluster and prevents per-framework data replication. Mesos shares resources in a fine-grained way, allowing to achieve data locality. It presents a scheduling mechanism on two layer called resource offers. Mesos decides how many resources to offer to each of the running frameworks, meanwhile they decide how many resources to accept and which computation to execute on the granted resources.

2.4.3 Spark on Yarn

Support for running Spark on YARN was added to Spark in version 0.6.0 and has been improved in subsequent releases [37].

When running on YARN, each Spark executor is run inside a YARN container. Spark supports two different modes to run on YARN, the Yarn-cluster and Yarn-client mode.

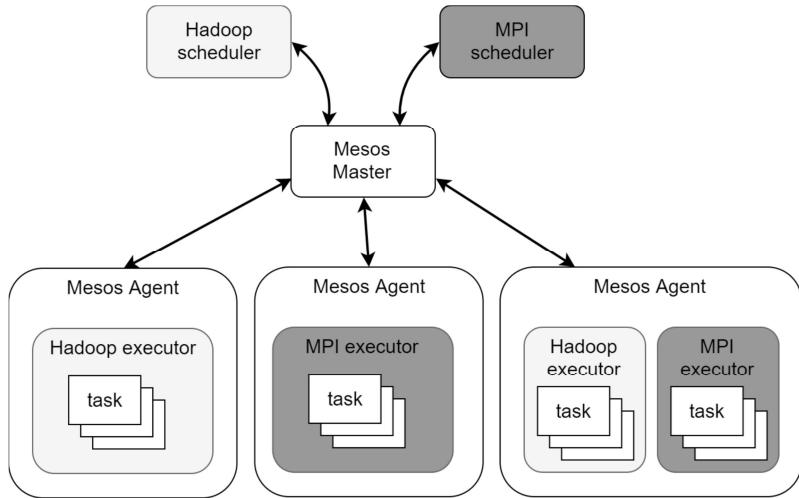


Figure 2.14: Apache Mesos Architecture.

In client mode, as shown in figure 2.16, the driver program is run inside the client process. In this way, the Application Master (AM) that is run in a YARN container is used only to request resources to the Resource Manager (RM). This mode is useful for interactive applications and for debugging purposes, since you can see application output immediately on the client side process. If the client disconnects from the cluster, the Spark application will terminate, this is due to the fact that the driver process resides on the client.

In cluster mode instead, as shown in Figure 2.17, Spark driver program is run inside the AM process managed by YARN. After initializing the application, client can disconnect from the cluster and reconnect later on. This mode makes sense when using Spark on YARN in production jobs.

Running on top of YARN cluster manager has some benefits. First of all YARN allows to dynamically share the cluster resources between the different frameworks that are running together. For example we can run MapReduce jobs after running Spark jobs without the need of changing YARN configurations. Moreover, YARN supports for categorizing, isolating and prioritizing workloads and employs security policies, in this way Spark can use secure authentication between its processes.

When running on YARN, Spark executors and driver program use about 6-10% more memory with respect to the standalone execution, this is due to the fact that this extra amount of off-heap memory is allocated in order to take into account YARN overheads.

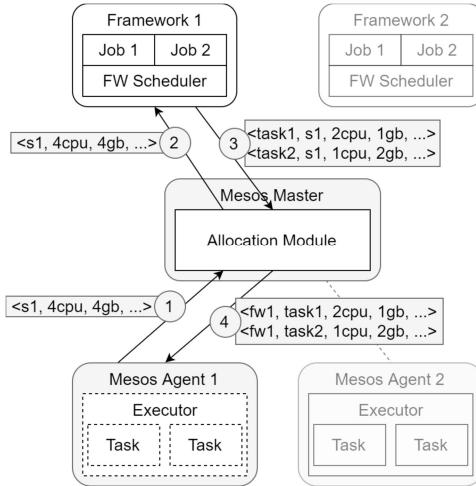


Figure 2.15: Apache Mesos Resource Offer example. 1) Mesos Agent 1 reports free resources to the Allocation Module; 2) Allocation Module offers resources to Framework 1 scheduler; 3) Framework 1 scheduler accepts resources and assign tasks; 4) Allocation Module launches tasks on the executor running in Mesos Agent 1.

2.4.4 Spark on Mesos

Support for running Spark on Mesos was added to Spark in version 1.5. Spark on Mesos can be executed in two different modes: coarse-grained and fine-grained [36]. In coarse-grained mode, as shown in figure 2.18, each Spark application is submitted to Mesos master as a framework and Mesos slaves will run tasks for the Spark framework that are Spark executors. Mesos tasks are launched for each Spark executor and those Mesos tasks stay alive during the lifetime of the application unless we are using dynamic allocation or the executor is killed for various reasons. The advantage of coarse-grained mode is in a much lower task startup overhead, with respect to the other mode, and so it is good for interactive sessions.

The drawback is that we are reserving Mesos resources for the complete duration of the application, unless dynamic allocation is active. Dynamic allocation allows to add and remove executors based on load: i) kill executor when they are idle, ii) add executors when tasks queue up in the scheduler. To use dynamic allocation it is required that the external shuffle service is running on each node.

In fine-grained mode, shown in figure 2.19, Mesos tasks are launched for each Spark task, and those tasks die as soon as Spark tasks are

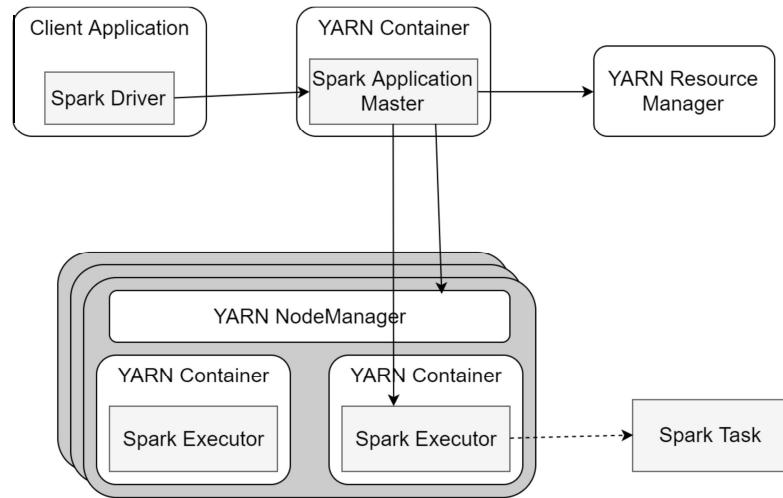


Figure 2.16: Spark on YARN Client Mode.

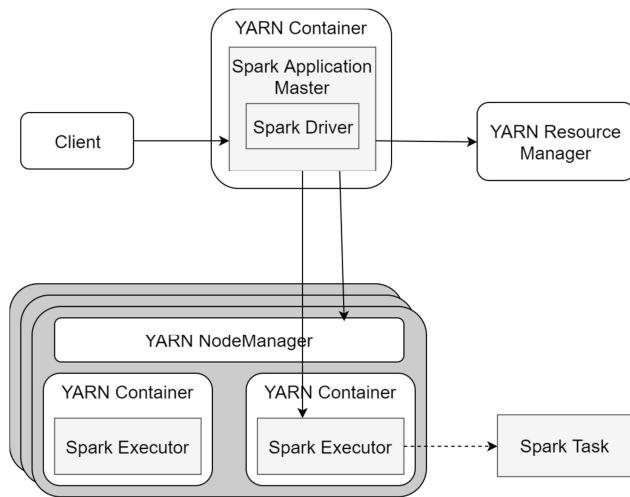


Figure 2.17: Spark on YARN Cluster Mode.

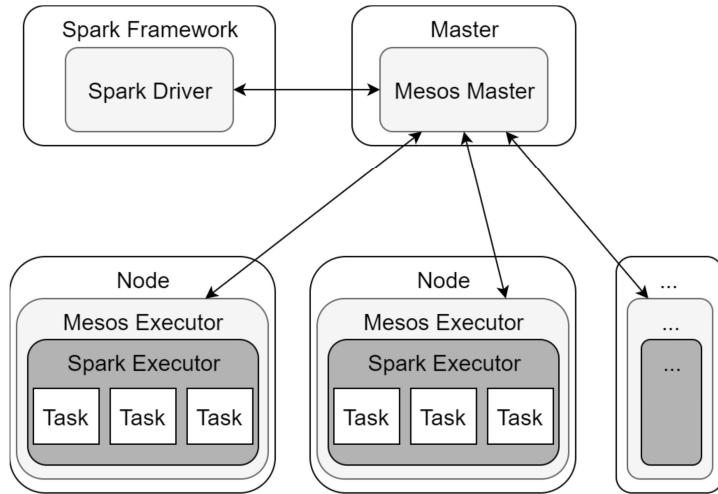


Figure 2.18: Spark on Mesos Coarse Grained Mode.

done. This mode has too much overhead in case that Spark has too many tasks, for example if Spark application has 10,000 tasks, then Spark needs to be installed 10,000 times on Mesos agents. Because of this huge overhead, fine-grained mode has been deprecated since Spark version 2.0.0. This mode allows multiple instances of Spark to share cores at a very fine granularity, but it comes with an additional overhead in launching each task. Thus this mode is inappropriate for low-latency requirements like interactive queries or serving web requests, instead it is fine for batch and relatively static streaming.

Similarly to what happens on YARN, it is possible to run spark in Mesos-client or Mesos-cluster mode. In client mode, the driver process is executed in the client machine that submits the job, so it is required that it stays connected to the cluster for the entire time of the application execution. In cluster mode instead, the driver program is run on a machine of the cluster.

2.5 SYMBOLIC EXECUTION

In computer science, the term symbolic execution refers to a software program analysis technique used to determine which data inputs cause the execution of each part of a program.

In this section we present an overview of *symbolic execution*, taken primarily from a research work of Baldoni et al [12].

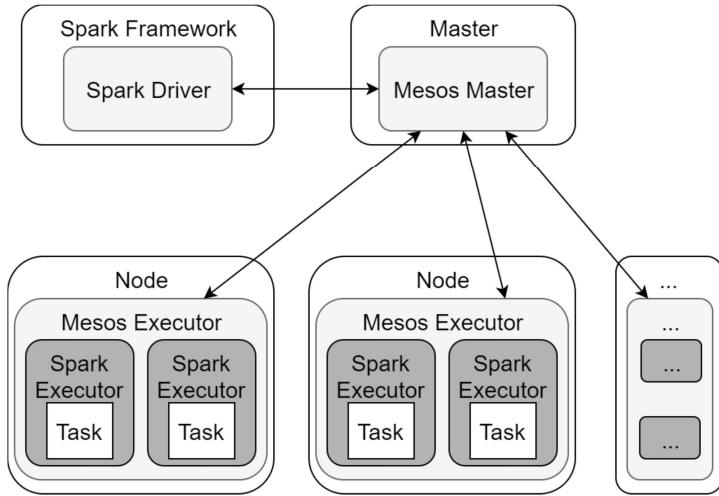


Figure 2.19: Spark on Mesos Fine Grained Mode.

It was introduced in the mid '70s mainly to test whether a software program could violate certain properties, e.g. that no divisions by zero are performed, no null pointers get dereferenced, no access to protected data can happen by unauthorized users, etc. In general, it's not possible to decide every possible program property by means of automated checks, for example we cannot predict the target of an indirect jump. In practice, approximate and heuristic-based analyses are used in many cases.

Software testing is performed to check that certain program properties hold for any possible usage scenario. A viable approach would be to test the program using a wide range of different, possibly random inputs. As the problem may occur only for very specific input values, we need to automate the exploration of the domain of the possible input data.

With symbolic execution many possible execution paths are explored in parallel, without necessarily requiring concrete inputs. The idea is to replace the fully specified input data with symbols, that are their abstract representation, devolving to constraint solvers the construction of actual instances that would cause property violations.

The symbolic execution interpreter walks through all the steps of the program, associating symbolic values to inputs rather than obtaining their actual values, building expressions in terms of those symbols and program variables, and constraints in terms of the symbols corresponding to the possible outcomes of each conditional branch.

```

1. void foo(int a, int b) {
2.     int x = 1, y = 0;
3.     if (a != 0) {
4.         y = 3+x;
5.         if (b == 0)
6.             x = 2*(a+b);
7.     }
8.     assert(x-y != 0);
9. }
```

Figure 2.20: Example: which values of *a* and *b* make the `assert` fail?

When a program is run with a specific set of input data (a concrete execution), a single control flow path is explored. Hence, concrete executions can only under-approximate the analysis of the property of interest. With symbolic execution, multiple paths that a program could take under different inputs can be simultaneously explored. This means that a sound analyses can be done, giving stronger guarantees about the checked property. When a program runs with *symbolic* – rather than concrete – input values, the execution is performed by a *symbolic execution engine*, which builds and updates a structure to hold (i) a first-order Boolean *formula* describing the conditions satisfied by all the traversed branches along that path, and (ii) a *symbolic memory store* mapping variables to symbolic expressions or values, for each path traversed by the control flow. Execution of a branch updates the formula, while assignments update the symbolic store. Finally, a *model checker*, commonly based on a *satisfiability modulo theories* (SMT) solver, is used to verify if the property is violated somewhere along each explored path and if the path itself is concretely feasible, i.e., if any assignment of concrete values to the program’s symbolic arguments exists that satisfies its formula.

EXAMPLE With reference to the C code in Figure 2.20, let’s say we want to discover which of the 2^{32} possible 4-byte inputs make the `assert` at line 8 of function `foo` fail. If we address the problem by running concretely the function `foo` on randomly generated inputs, we will unlikely pick up exactly the assert-failing inputs. Symbolic execution go beyond this limitation by reasoning on *classes of inputs*, rather than single input values, thanks to the evaluation of the code using symbols for its inputs, instead of concrete values,

Going further into details, a symbol α_i is associated to each value that cannot be resolved by a static analysis of the code, e.g. an actual

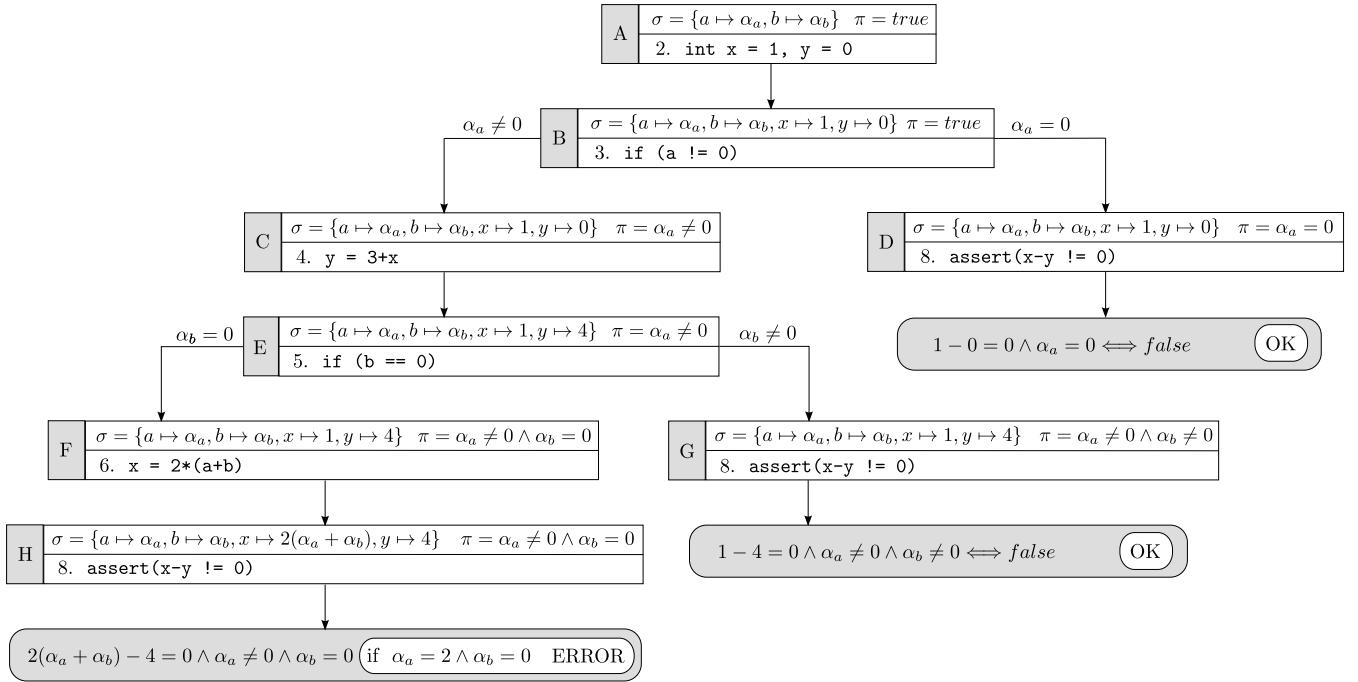
parameter of a function or data read from an input stream. A state (stmt , σ , π) is kept by the symbolic execution engine, where:

- stmt is the next statement to evaluate. At this time, we assume that stmt can be an assignment, a conditional branch, or a jump.
- σ is a *symbolic store* that associates program variables with concrete values of expressions or symbolic values α_i .
- π identifies the *path constraints*, i.e., it is a formula expressing a set of assumptions on the symbols α_i as a result of branches taken in the execution to reach stmt . At the start of the analysis, $\pi = \text{true}$.

Depending on stmt , the symbolic engine changes the state as follows:

- The evaluation of an assignment $x = e$ updates the symbolic store σ by associating x with a new symbolic expression e_s . We express this association with $x \mapsto e_s$, where e_s is obtained by evaluating e in the context of the current execution state and can be any expression involving unary or binary operators over symbols and concrete values.
- The evaluation of a conditional branch `if e then strue else sfalse` affects the path constraints π . The symbolic execution is forked by creating two execution states with path constraints π_{true} and π_{false} , respectively, which correspond to the two branches: $\pi_{\text{true}} = \pi \wedge e_s$ and $\pi_{\text{false}} = \pi \wedge \neg e_s$, where e_s is a symbolic expression obtained by evaluating e . Symbolic execution independently proceeds on both states.
- The evaluation of a jump `goto s` updates the execution state by advancing the symbolic execution to statement s .

Figure 2.21 shows a symbolic execution of function `foo`, that can be adequately represented as a tree. In the initial state (execution state A) the path constraints are true and input arguments a and b are associated with symbolic values. After local variables initialization x and y at line 2, the symbolic store is updated by associating x and y with concrete values 1 and 0, respectively (execution state B). A conditional branch is met in line 3 and the execution is forked: according to which branch is taken, a different statement is evaluated and different assumptions are made on symbol α_a (execution states C and D). In the branch corresponding to $\alpha_a \neq 0$, variable y is assigned to $x + 3$,

**Figure 2.21:** Symbolic execution tree of function *foo* given in Figure 2.20.

Each execution state, labeled with an upper case letter, shows the statement to be executed, the symbolic store σ , and the path constraints π . Leaves are evaluated against the condition in the assert statement. Image courtesy of Association for Computing Machinery [12].

obtaining $y \mapsto 4$ in state E because $x \mapsto 1$ in state C. Arithmetic expression evaluation, generally, change only the symbolic values. When the assert at line 8 is reached by fully expanding every execution state on all branches, we can check which input values for parameters *a* and *b* can make the assert fail. By analyzing execution states {D, G, H}, we can conclude that only H can make $x-y = 0$ true. The path constraints for H at this point implicitly define the set of inputs that are unsafe for *foo*. In particular, any input values such that:

$$2(\alpha_a + \alpha_b) - 4 = 0 \wedge \alpha_a \neq 0 \wedge \alpha_b = 0$$

will make assert fail. An instance of unsafe input parameters can be eventually determined by invoking an *SMT solver* to solve the path constraints, which in this example would yield $a = 2$ and $b = 0$.

The example shown represents a case where symbolic execution can derive *all* the inputs that make the assert fail, by exploring all the possible execution states. With regards to the underpinning theory, exhaustive symbolic execution represents a *sound* and *complete*

methodology for any decidable analysis [12]. Soundness (no false negatives) means that all possible unsafe inputs are guaranteed to be found, while completeness (no false positives) means that input values deemed unsafe are actually unsafe. Exhaustive symbolic execution cannot be easily scalable beyond small-sized applications. In many practical cases, a trade-off between soundness and performance approach is used.

3

XSPARK

THIS chapter illustrates the previous works done on xSpark, that is the base for the developments made and contribution given by this thesis. xSpark is a Spark extension that offers optimized and elastic provisioning of resources in order to meet execution deadlines. This is obtained by using nested control loops. A centralized control loop, implemented on the master node, controls the execution of the different stages of an application; at the same time multiple local loops, one per executor, focus on task execution.

In Figure 3.1 we can see a high level representation of xSpark execution flow. A preliminary Profiling Phase, that is executed once per application, is obtained by executing the application once to obtain information about its runtime execution. The log generated by the application are used to generate its Profiling Data.

In the Execution Phase, we control the application by means of xSpark's control loops. The centralized control loop is represented as a Heuristic Based Planner, which exploits the profiling data, that are used to understand the amount of work that is needed to execute the application. This component uses the provided profiling data to determine the amount of resources to assign to executors for each of the application stages, in order to complete the execution within the given deadline. The local loops instead are represented as control theory controllers. They perform fine-grained tuning of the resources assigned to each of the executors using a control theory based controller. This component is used to counteract the possible imprecision of the estimated needed resources, which may be caused by different factors, such as the available memory, etc.

Usually Spark applications are run multiple times, as they are reusable and long lasting assets. xSpark exploits an initial profiling phase to create an enriched *Directed Acyclic Graph* (DAG) or *Parallel Execution Plan (PEP)* describing the entire application execution flow, by collecting information about all the stages of the application. For each stage, xSpark annotates the DAG with the execution time (stage duration), the number of task processed, the number of input records read, the number of output record written and the nominal rate,

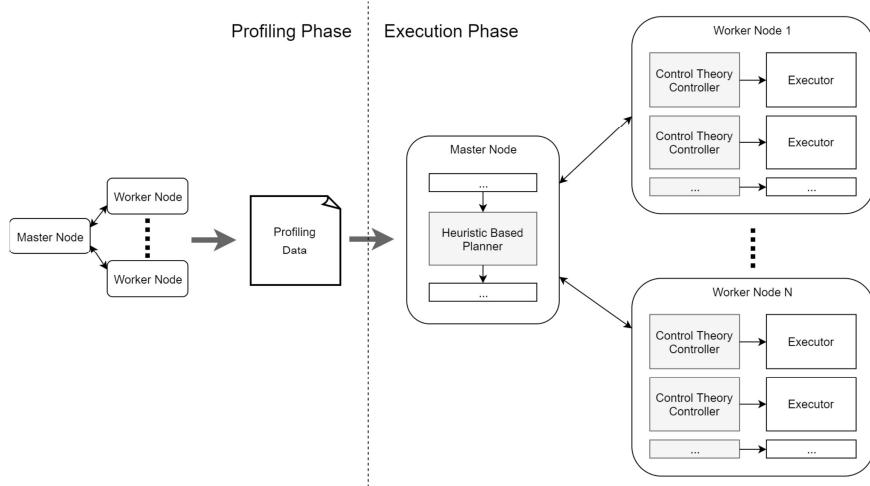


Figure 3.1: High level setup and execution flow of xSpark.

defined as the number of records that a single core processes during one second of execution.

In Figure 3.2 we can see a fragment, relative to stage number zero, of the profiling data of a Louvain application executed in xSpark. The duration field contains the serialized total duration of the tasks in milliseconds.

At runtime, the *PEP* allows the xSpark scheduler function to know how much work was already completed and how much remains to be done. This means that xSpark can only optimize the allocation of the resources if all the executions of the same application use the same *PEP*. This might not always be the case, for example when the code contains branches or loops, because these might need to be resolved in different ways at runtime. If the application *PEP* at runtime differs from the one obtained during the profiling phase, xSpark is not able to estimate the amount of remaining work.

The centralized control loop is activated before the execution of each stage, it uses a heuristic, explained in Section 3.2, in order to assign a deadline to the stage, calculate the amount of CPU cores that are needed to satisfy it, and assign cores to the allocated executors.

The per-stage deadline takes into account the amount of work already completed, the consumed time, and the overall deadline. All the computations done by the heuristic are based on the information stored in the *PEP* and obtained during the profiling phase. Unfortunately many factors can influence the actual performance and invalidate the prediction, such as the amount of records that have been filtered-out, the available memory, the number of used nodes, the storage layer dimension, and so on. It is important to remember

```

1 {
2     "o": {
3         "actual_records_read": 20000000.0,
4         "actual_records_write": 20000000.0,
5         "actualtotalduration": 186000.0,
6         "bytesread": 337777780.0,
7         "byteswrite": 0.0,
8         "cachedRDDs": [
9             5
10        ],
11         "duration": 11000.0,
12         "genstage": false ,
13         "id": 0.0,
14         "io_factor": 1.0,
15         "monocoreduration": 381388.0,
16         "monocoretotalduration": 10127715.0,
17         "name": "mapPartitions at VertexRDD.scala:356",
18         "nominalrate": 52440.03482018312,
19         "nominalrate_bytes": 885653.9272342077,
20         "numtask": 500,
21         "parentsIds": [],
22         "recordsread": 20000000.0,
23         "recordswrite": 0.0,
24         "shufflebytesread": 0.0,
25         "shufflebyteswrite": 114175342.0,
26         "shufflerecordsread": 0.0,
27         "shufflerecordswrite": 2000000.0,
28         "skipped": false ,
29         "t_record_ta_executor": 0.0190694,
30         "totalduration": 207000.0,
31         "weight": 28.777443181222274
32     }
}

```

Figure 3.2: Example of profiling data from application Louvain.

that Spark mostly uses in-memory data, but there are operations like `textFile`, `saveAsTextFile` and `saveAsSequenceFile` that impose restrictive constraints on the storage layer. If not correctly sized, the storage layer might become a bottleneck, causing the throughput to degrade and thus making the provisioning predicted by xSpark incorrect.

Local control loops, explained in Section 3.3, counteract this imprecision by dynamically modifying the amount of CPU cores assigned to the executors during the execution of a stage. This can lead the executor to use more or less resources than the ones previously assigned by the centralized control loop. The local loop controls the progress of a specific executor with respect to the tasks it has assigned.

A control theory algorithm determines the amount of CPU cores that must be allocated to the executor for the next control period, typically one second, and assigns them.

xSpark uses Docker [17] in order to dynamically allocate CPU cores and memory. Memory allocation simply sets an upper bound to the memory that each docker container (executor) can use. CPU cores instead are allocated in a more sophisticated way. Using Linux cgroups, Docker can support CPU shares, reservations and quotas. In particular, xSpark uses CPU quotas. CPU shares are not able to limit the number

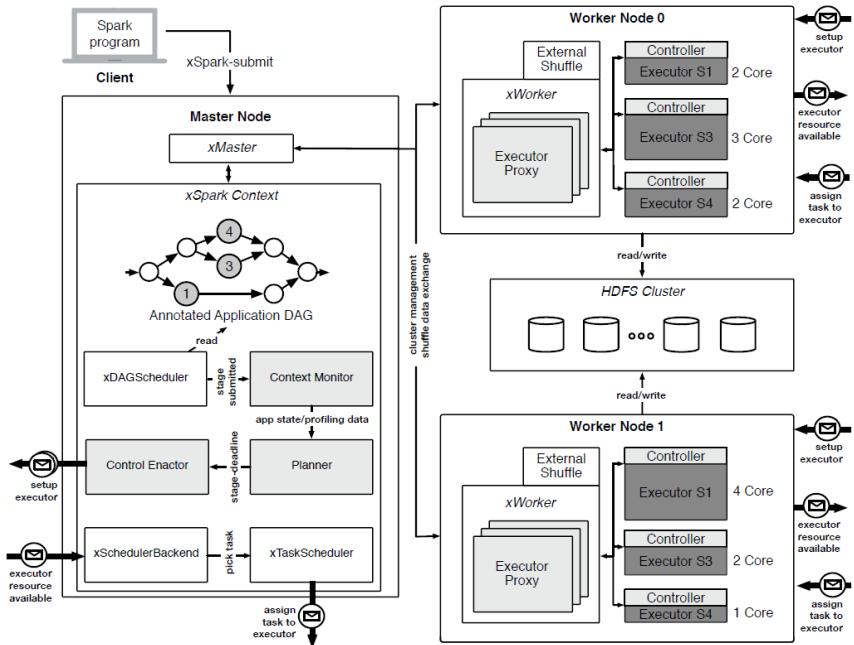


Figure 3.3: Architecture of xSpark. New components are represented in light grey boxes, while those that start with an x are the modified ones. In dark grey are represented the containerized components (the executors).

of CPU cores used by a container in a deterministic way, in particular it is not independent of other processes running on the same machine. CPU reservation instead does not have the fine granularity we are looking for, indeed the allocation would be limited to entire cores. By using CPU quotas instead, we have a reliable and tunable mechanism that provides also fine granularity allocation, in particular it allows xSpark to allocate fractions of cores to the containers (executors), with a precision up to 0.05 cores.

3.1 ARCHITECTURE

To achieve the objectives of xSpark, the architecture and processing model of Spark have been modified. In Figure 3.3 we can see how xSpark architecture differs from Spark. The principal architectural change introduced by xSpark is an increased focus on stages. Instead of considering entire applications, xSpark reasons on per-stage deadlines.

xSpark instantiates an executor per stage per worker, instead of a single executor per worker for all the stages that will be executed. This way the resources that are allocated to a single executor only impact the performance of the stages that are associated with it, this leads to a fine grained control over the different stage, and thus on the entire application. When multiple stages are run in parallel, multiple executors can be running on the same worker node. When a stage is submitted for execution, one executor per worker is created and bound to that stage. This way computation and data are equally spread across the entire cluster.

Thanks to containers, xSpark can isolate the execution of the different executors that are running on the same worker node and achieve quick, fine-grained resource provisioning. On average, containers can be modified in less than one second, allowing a more precise way of allocating cores. Users submit applications and their deadlines to the master node using the submit command. This creates an *xSparkContext* on the master node, containing *axMaster* object that is used to manage the cluster and that knows all the resources that are available on each worker node. A *xSparkContext* is composed by six components:

- *xDagScheduler* schedules the stages according to the application's *PEP*. The submitted stage is enriched with the information obtained during the profiling phase
- *ContextMonitor* monitors the progress of the application, taking into account stage scheduling and completion. It also stores information about the performance of the execution, that will be later used to calculate the deadlines and the resources needed by upcoming stages
- *Planner* is heuristics based and is used to calculate the deadlines and resources associated with a stage
- *ControlEnactor* determines when a stage is ready to be executed, meaning there are enough resources (cores) and sufficient executors are available. It also has the duty of initializing the different executors.
- *xSchedulerBackend* controls the stage execution. In particular it launches new tasks by taking into account the resources availability and registers their completion
- *xTaskScheduler* also controls stage execution, with the goal of allocating tasks to the available cores to optimize data locality.

In general, the closer a data partition required by a task is to the task's executor, the better.

xSpark also modified the worker nodes. Each node contains a *xWorker* that connects to a *xMaster*, generates local controllers for the executors, and controls the evolution of its executor by dynamically scaling their resources. *xWorker* creates an *Executor Proxy* for each of the executors that are running on its node. These proxies are placed between the executors and the *xSchedulerBackend*, and are used to monitor the execution progress of the stage assigned to the executors. It is important to remember that each executor focuses on a single stage at a time. The heuristic calculates how many tasks must be executed by each of the executors of the same stage, the strategy is to have an equal number of tasks assigned to each of the executors. This way the deadline assigned to each of the executors coincides with the deadline of their stage. This allows the different executors of the same stage to not to require synchronization. Native Spark instead requires that executors with free resources spontaneously require new tasks to execute from the master node.

Every *xWorker* uses an External Shuffle Service. Native Spark moves data across the cluster in different ways. If the data is stored on executor's memory, then the executor itself manages the data exchange. If the data is stored on an external storage system (e.g., HDFS cluster), they can be retrieved by using different communication protocols. If the data is stored in the internal storage of a worker node, then the data is managed by the External Shuffle Service. Notice that this is not the default, but xSpark adopts this technique to be able to assign zero CPU cores to an executor, without loosing the ability to read data, since it is effectively not performed by the executor but by the external service.

3.2 HEURISTIC

xSpark uses a heuristic to compute per-stage deadlines and to estimate how many cores must be allocated for a stage to successfully fulfill the deadline. In order to do this, at submission time the user is asked to specify three parameters: i) the application deadline, ii) the cluster size, and iii) the number of cores per worker node. Before executing the application, xSpark performs a feasibility check given the available resources.

When a stage is submitted for execution, its deadline is computed

$$\text{deadline}(\text{sk}) = \frac{\alpha \cdot \text{ApplicationDeadline} - \text{SpentTime}}{\text{weight}(\text{sk})}$$

where SpentTime is the time already spent for execution and α a value between 0 and 1 that xSpark uses to be more conservative with respect to the provided ApplicationDeadline. The weight is computed

$$\begin{cases} w1(\text{sk}) = \#(\text{RemainingStages} + 1) \\ w2(\text{sk}) = \frac{\sum_{i=k}^{k+w1} \text{duration}(s_i)}{\text{duration}(\text{sk})} \\ \text{weight}(\text{sk}) = \beta \cdot w1(\text{sk}) + (1 - \beta) \cdot w2(\text{sk}) \end{cases}$$

where $w1$ is the number of stages still to be scheduled (s included) and $w2$ is the rate between the duration of s and the duration of the remaining stages (s included). xSpark then proceeds to estimate how many cores are needed to execute the stage:

$$\text{estimatedCores}(\text{sk}) = \lceil \frac{\text{inputRecords}(\text{sk})}{\text{deadline}(\text{sk}) \cdot \text{nominalRate}(\text{sk})} \rceil$$

where inputRecords is the number of records that will be processed by sk and nominalRate is the number of records processed by a single core per second in stage sk.

Since xSpark controls the resource allocation of a stage before and during the execution, the maximum amount of allocable cores needs to be greater than the estimated one, in order to be able to accelerate when progressing slower than expected

$$\text{maxAllocableCores}(\text{sk}) = \text{overscale} \cdot \text{estimatedCores}(\text{sk})$$

The final step is to determine the initial number of cores that should be assigned to the different executors, xSpark distributes the cores equally amongst the available workers by creating one executor per stage per worker. In this way, it is guaranteed that executor performances will be equal, and that xSpark can compute the same deadline for all the executors. The initial number of cores per executor is computed as

$$\text{initCorePerExec}(\text{sk}) = \lceil \frac{\text{maxAllocableCores}(\text{sk})}{\text{overscale} \cdot \text{cq} \cdot \text{numExecutors}} \rceil \cdot \text{cq}$$

where numExecutors is the number of executors and cq is the core quantum, a constant that defines the quantization applied to resource allocation, the smaller this value is, the more precise the allocation.

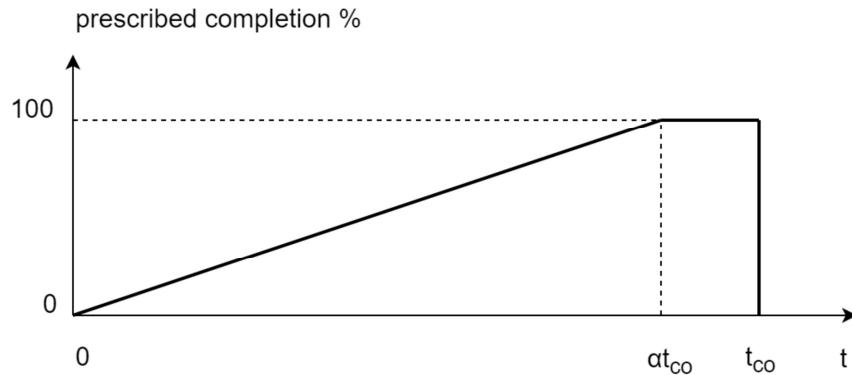


Figure 3.4: Set point generation for an executor controller.

3.3 CONTROLLER

Each containerized executor has an associated local controller, whose goal is to fulfill the per-stage deadline taking into account external disturbances by dynamically allocating CPU cores. The controllers use control theory, with no heuristic involved.

The centralized control loop determines the desired stage duration, the maximum and the initial number of cores that should be assigned to the executors and the number of tasks that must be processed. Local controllers adjust the number of allocated cores, according to the work that has already been accomplished.

Executors that are dedicated to different stages are implicitly independent, and thus their controllers are also independent. The executors that are running in parallel on the same stage must complete the same amount of work (number of tasks) in the same desired time. This means that local controllers are independent and do not need to communicate among themselves. Moreover, the heuristic is relegated outside the local controller, so that it cannot compromise the controller's stability.

In the controller, the progress set point is chosen based on the desired completion time. Its value is received from the centralized control loop. In Figure 3.4 we see the prescribed completion percentage, in particular t_{co} is the desired completion time and $\alpha \in (0, 1]$ is a configuration parameter used to determine how much earlier we are willing to complete the execution with respect to requested deadline. In order to track the set point ramp, we need to use a Proportional plus Integral

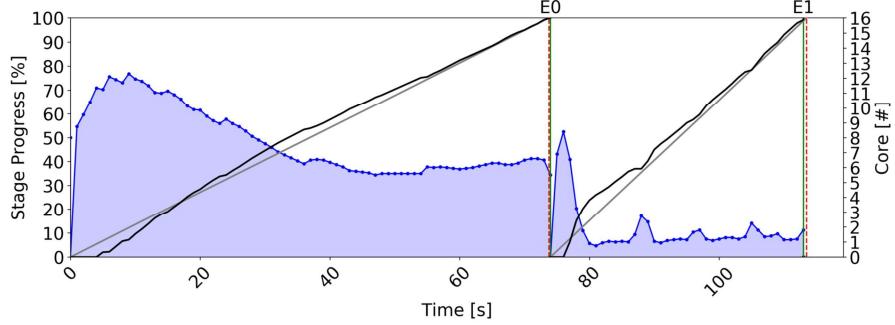


Figure 3.5: CPU cores allocated to the application aggregate-by-key running on a xSpark worker node. The blue line represents the allocated cores over the time, gray and black line are desired and actual progress rate respectively. Green line represents the obtained stage ending, while dashed red line is the desired one.

(PI) controller. As a result, the discrete-time controller in state space form reads:

$$\begin{cases} x_C(k) = x_C(k-1) + (1-a)(a_{\%}^o(k-1) - a_{\%}(k-1)) \\ c(k) = Kx_C(k) + K(a_{\%}^o - a_{\%}(k)) \end{cases}$$

where ($a_{\%}^o$ is the prescribed progress percentage at each k control step and $a_{\%}$ is the accomplished completion percent at each k control step. Notice that it is possible that the controller computes a negative value for $c(k)$, the CPU cores that need to be allocated. To fix this problem $c(k)$ must be clamped between a minimum c_{\min} and a maximum c_{\max} . To maintain consistency, we need to recompute the state $x_C(k)$ as

$$x_C(k) = \frac{c(k)}{K} - a_{\%}^o(k) + a_{\%}(k)$$

In Figure 3.5 the cores allocated to an application executor running on a worker node are shown. The running application is *aggregatebykey* and is composed by two stages. The black line represents the progress of the stage, meanwhile the gray one is the desired progress rate. The goal of the controller is to reduce the error, i.e., the distance between the two lines. We want the black line to follow as much as possible the gray line.

PROBLEM STATEMENT AND SOLUTION OVERVIEW

BIG data applications are widely used in the industry and research fields. Specialized distributed frameworks are used to execute these applications on clusters of computers, very often made by cloud computing resources, like virtual machines and virtual storage. Apache Spark is probably the most popular big data processing framework. Spark organizes computations in directed acyclic graphs (DAGs) or *Parallel Execution Plans (PEPs)* and its declarative API offers the capability to make transformations to datasets and return results to the client program, usually a standard Java, Python or Scala application.

In order to execute programs, Spark starts by defining jobs, that are identified by the actions in the code, and stages inside jobs, that are delimited by operations requiring data shuffling (i.e., moved across executors). Shuffling operations break data locality. Spark distinguishes between narrow and wide transformations specifically to minimize data locality breaches; the former do not shuffle data (e.g., map, filter, etc.), while the latter do (e.g., reduceByKey, etc.).

Spark identifies all the operations that are ready to be executed, up to the first action, and materializes them in a *PEP* represented as a directed acyclic graph. The *PEP* is not the control-flow graph of the job's code. It does not contain branches and loops since they were already resolved during the execution of the driver program. The *PEP* defines the execution order among stages, and defines the extent to which stages can be executed in parallel.

For each job, Spark computes a *PEP* to maximize the parallelism while executing an application. Stage are always executed in parallel, and also many different stages can be in execution at the same time. Spark materializes *PEPs* as directed acyclic graphs of stages for this purpose, while the complete *PEP* of an application is made by joining *PEPs* of its jobs to form a sequence of *PEPs*. A Spark application is usually composed by several jobs executed using a LIFO queue, therefore the *PEP* of a Spark application is composed by the sequence of the *PEPs* generated by the application jobs (an action corresponds to a job).

In fact, Spark does not "compile" the code of the driver program to generate the application *PEP*, instead it incrementally generates it as soon as an action is reached.

4.1 PROBLEM STATEMENT

The literature contains several works exploring adaptation capabilities, formal guarantees or response time estimation for Spark applications based on their *PEP*-based structure [26, 14, 13], assuming that the *PEP* of the application does not change with respect to different data input or parameters. However, the *PEP* uniqueness assumption does not hold if conditional branches or loops are present in the control flow of the client program.

This is particularly relevant in Spark because of the possibility of evaluating partial results through actions. In fact, these values can be used in the code as part of conditional expressions that can create branches in the control flow graph. In this cases the conditional branches govern the final structure of the *PEP* and also the operations that form a stage while loops influence the number of repetition of either transformations, stages or actions.

Many of the research approaches [20, 41, 26, 30] use the execution graph to establish the amount of work to be done, the degree of parallelism, duration and other specific elements of the application. In all these approaches the assumption that the graph does not change is always taken for granted, since many loops and conditional branches are embedded in the code (eg Filter, Map). As mentioned earlier in this document, this condition is not verified when the code contains explicit loop and conditional statements.

As an example, let's take a simple application made by the concatenation of two jobs: the first gets some records from an input file and filters them according to certain criteria, then the second one sorts the records and returns the first x records. We could think of executing the second job only if the number of the filtered records c , (i.e. the output of the first job), is greater than zero.

The execution graph would then be composed by two jobs if $c \geq 0$ and contain only the first job if $c < 0$. This example shows how partial results (c) returned to the driver program by Spark actions can be evaluated in conditional expressions that decide the outcome of conditional statements like loops or branches, thus materializing different execution graphs.

To bypass this problem, xSpark and many other approaches [41, 26] leverage an initial profiling phase to retrieve the execution graph and collect performance data. Considering again the simple example used above, running a profiling phase on it would return the execution graph generated by the input data fed to the application. However, there is no way to adapt the execution to the actual situation, in case the actual data drives the execution to walk through a different execution path than the one used to profile the application.

In the end, the quality of the results is impacted. Consider that, even if a conservative approach were used by retrieving the worst-case execution graph (i.e., the graph corresponding to the two jobs in the previous example), this would result in an over-allocation of resources and/or over-estimation of the execution time. Conversely, if we adopted the best case (one job), we would forecast too few resources and a too short execution time.

```

1 from pyspark import SparkContext
2 def run(numIterations, threshold):
3     sc = SparkContext('local', 'example')
4     x = sc.textFile(...).map(...).groupBy(...)
5         .map(...).aggregate(...)
6     y = sc.textFile(...).map(...).groupBy(...)
7         .map(...).aggregate(...)
8     if x > threshold and y > threshold:
9         for i in range(numIterations):
10             z = sc.parallelize(...).map(...).sort(...).take(10)
11     if x > y:
12         w = sc.parallelize(...).map(...).filter(...).count()

```

Figure 4.1: Example Spark application with conditional branches and loops.

User parameters or local variables can also affect the execution graph, so they must be considered in a sound analysis. For example, Figure 4.1 shows the code of application that has two input parameters *numIterations* and *threshold*. Its execution graph depends on both the user parameters and the input dataset. The first two *aggregate* jobs¹ are always executed (line 4 and 6) and the results are assigned to variables *x* and *y*, respectively. Line 8 checks if both variables are greater than *threshold*. If this is the case, a *take* job (line 10) is repeated *numIterations* times (*for* loop). Finally, if *x* > *y* (line 11) *count* (line 12) is executed.

Four possible execution graphs (Figure 4.2) correspond to the code in Figure 4.1. They are: i) the two cascaded *aggregates* (case where

¹ In Spark *aggregateByKey* is a transformation while *aggregate* is an action.

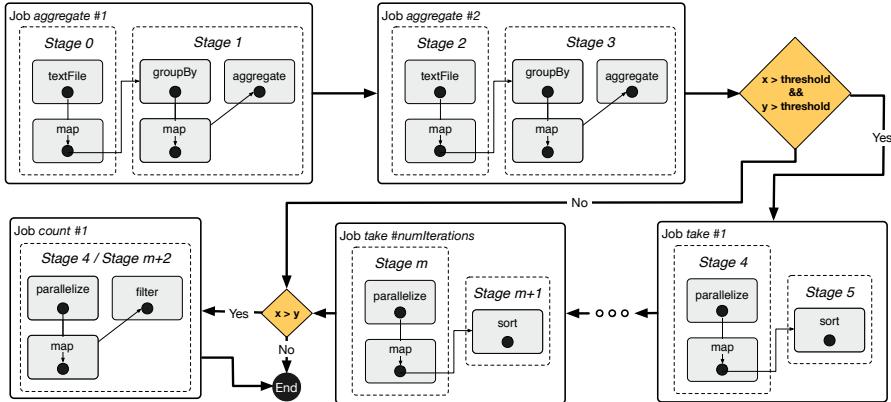


Figure 4.2: The four *PEPs* of the application of Figure 4.1.

the two conditional statements are both false) ii) the two cascaded *aggregates* and *take* repeated $numIterations$ times (case where the first conditional statement is true and the second is false) iii) the two cascaded *aggregates* and *count* (case where the second conditional statement is true and the first is false), and iv) the concatenation of the two *aggregates*, *take* repeated $numIterations$ times, and *count* (if both conditional statements are true) [11].

4.2 SOLUTION OVERVIEW

This section contains a functional level description of the proposed solution, of its components and their interactions to make the solution work.

Our solution is based on xSpark, a modified version of Apache Spark, developed at Politecnico di Milano [14, 13], that has demonstrated the capability to execute deadline-constrained single-*PEP* applications by using resources more efficiently than Spark would do in running the same applications. xSpark is able to use less resources than native Spark and can complete executions with less than 1% error in terms of set deadlines.

This thesis presents *xSpark_{SEEPPEP}*, a toolchain providing the capability to manage the efficient execution of deadline-based QoS constrained multi-*PEP* Spark applications.

xSpark_{SEEPPEP} is the result of the integration of *SEEPPEP* [11], a tool exploiting symbolic execution techniques to generate the path condition associated to each possible *PEPs* produced by different inputs and parameters, with a modified version of xSpark.

SEEPEP uses the algorithm shown in Figure 4.3 to symbolically analyze the paths of the target driver program, and returns the path condition computed for each path. It is composed by the: i) application of a lightweight symbolic execution of the Spark application driver program to derive a representative set of the control-flow paths execution conditions in the program, ii) use of these execution conditions with a search-based test generation algorithm, to compute sample input datasets that make each path to execute, iii) execution of the target application with these datasets as input, to profile the *PEP* generated by each path, and synthesize the *PEP** accordingly, iv) generation of an artifact called *GuardEvaluator* that returns the feasible *PEPs* given a partial set of concrete values of the symbolic variables.

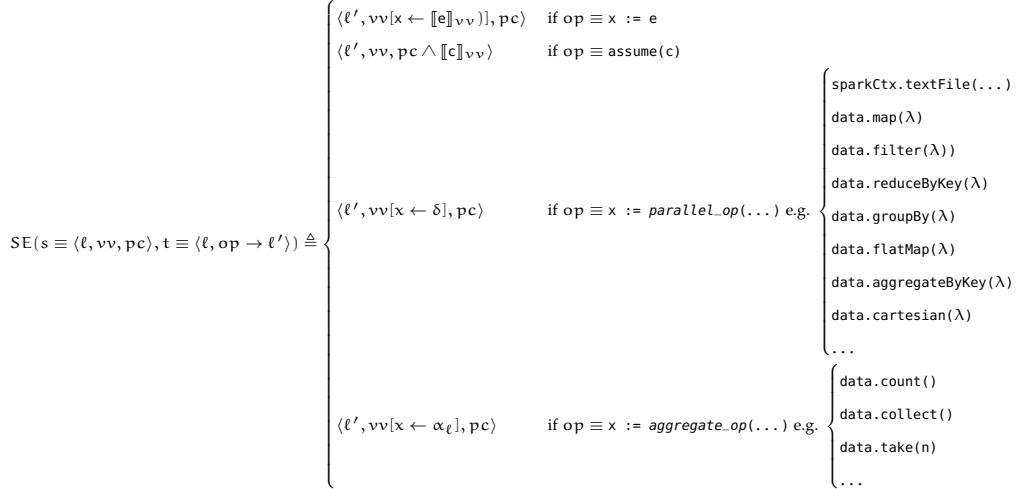
Moreover, $xSpark_{SEEPEP}$ generates a launcher with a synthesized dataset for each *PEP* and an artifact to retrieve the feasible *PEPs* given a set of symbolic variables resolved to a value. Finally, we integrated this approach with xSpark, an extension of Spark that can control the duration of Spark applications according to specified deadlines through dynamic resource allocation.

We take advantage of the information in the *PEP** extracted with SEEPEP to extend xSpark with the capability of tuning its adaptation strategy according to the worst-case behaviour of the application. At runtime, our extended version of xSpark uses the *GuardEvaluator* to refine the control policy by recomputing the worst-case estimation every time the current worst-case refers to a program path for which the execution condition stored in the *PEP** becomes unsatisfiable.

The evaluation shows that SEEPEP is able to effectively extract all the *PEPs* generated by Spark applications and that xSpark reduces the number of deadline violation thanks to the presented integration.

4.2.1 $xSpark_{SEEPEP}$

In this section we describe how *SEEPEP* is integrated with xSpark to form a tool-chain called $xSpark_{SEEPEP}$. The path conditions associated with each *PEP* of the application are produced by *SEEPEP*, along with a set of input data test cases for each *PEP* for executing the profiling, and a *GuardEvaluator* that xSpark uses to select the most appropriate *PEP* at runtime. The function of the *GuardEvaluator* is to always return the *PEPs* whose associated path conditions still hold true. *GuardEvaluator* is called at each execution step (xSpark job boundary),

**Figure 4.3:** Symbolic execution algorithm of SEEPEP.

The main elements of the tool-chain are represented in Figure 4.4. We use it to explain the profile and control phases of the example application of Figure 4.2 (*app*, hereafter). As a first step, *SEEPEP* generates the n (in general) launchers, which activate the four (n) *PEPs* of the program, and an application specific *GuardEvaluator*.

xSparkSEEPEP then associates each *PEP* to its path condition, and uses the generated launchers to generate the profiling data for each *PEP*. It then synthesizes the *PEP** for the application and stores it in the component *PEP* Store* on the Spark master node. Finally the generated *GuardEvaluator*, is also stored in the master node (component *GuardEvaluator Store*). *GuardEvaluator* implements a common interface that is dynamically instantiated and used (without a static import) inside the modified *xSpark* code. At this point, *app* can be executed and controlled by *xSpark*.

xSpark component *SparkSubmit* has been modified to store the values of the application run command parameters, as they can be associated to symbols and define a path condition. A symbol is identified by application name, action name, line of code in the driver program, and a counter to take in account multiple executions of the same line of code (i.e., loops or recursive functions).

At runtime, everytime the result of an action is computed and returned to the driver program, our modified version of the *RDD API* notifies component *PEPSelector* that a new result is available. This component is in charge of selecting the *PEP* and its profiling data then used by *Application Level Controller* to compute the local deadlines for the next stages and thus to provision resources. *PEPSelector* saves

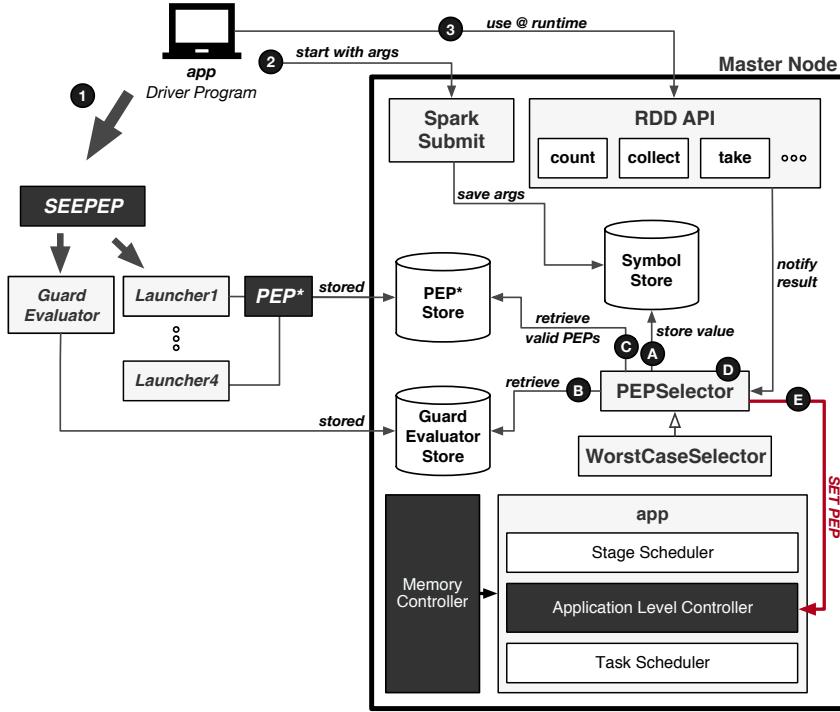


Figure 4.4: *xSpark_{SEEPEP}*

computed results into component *Symbol Store*, retrieves an instance of the dedicated *GuardEvaluator*, and feeds it with all the symbols resolved by the aforementioned results. *GuardEvaluator* [11] returns the list of *PEP* whose path conditions still hold.

At the beginning of the execution of function *run* of app, there are four valid *PEPs*, since neither *x* nor *y* have been assigned a concrete value. The job at line 4 produces the value of *x* and if the value is less than or equal to threshold, the if statement of line 8 is skipped. Even if the value of *y* is still unknown, *GuardEvaluator* only returns two *PEPs*, that are the only two *PEPs* whose path conditions are still verified. All the path conditions that depends on the expression *x > threshold*) are excluded. Since the *PEP* is constantly updated, xSpark becomes aware of the progress in the execution, and can use this information to adjust the provisioning of resources.

The computation of the next *PEP* to use is made by the component *PEPSelector* that receives all the valid *PEPs*. In order to minimize deadline violations, the current selection criteria reflects a conservative approach and always returns the worst-case *PEP*, corresponding to the *PEP* with the highest number of remaining stages to be executed. However, this selection criteria can be customized by the user, for

example if the performance indicator to be optimized does not require a strict deadline, and the used resources must be minimized, a plan corresponding to an average case could be selected instead of the worst-case.

5

IMPLEMENTATION

IN this chapter we show the implementation details of *xSpark_{SEEP}*, which consists of the modifications to existing xSpark component, new components added to xSpark, *SEEP* concrete application *launchers* and the *Python tool* embedded in *xSpark_{SEEP}* that was used to launch the experiments that generated the results for the evaluation of the solution.

5.1 OVERVIEW

Figure 5.1 shows a simplified overview of the components of the solution. New components are highlighted with a yellow dotted-pattern background, modified components are highlighted with a grey background.

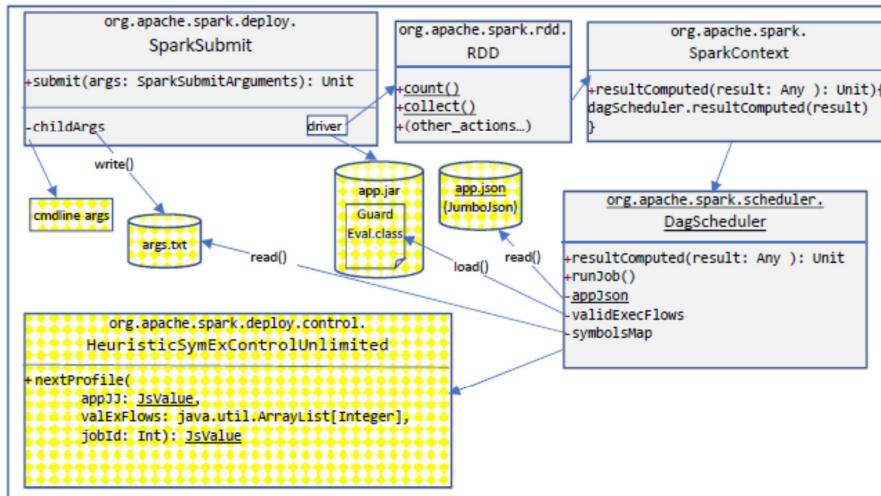


Figure 5.1: Simplified solution components overview.

5.1.1 *Background: Current xSpark Heuristic*

xSpark uses a heuristic to compute per-stage deadlines and to estimate how many cores must be allocated for a stage to successfully fulfill the deadline. See Section 3.2 for an exhaustive description of its functionality.

5.1.2 *Current xSpark Scheduling Limitation*

At runtime, an annotated DAG or *Parallel Execution Plan*, (from here onwards *PEP*) allows the xSpark scheduler function to comprehend how much work has already been completed and how much work still needs to be done. This means that xSpark can only optimize the allocation of the resources if the execution of all jobs of the application use the same *PEP*. This might not always be the case, for example when the code contains branches or loops, because these might need to be resolved in different ways at runtime. This is a severe limitation of the xSpark capability to manage real-world applications.

5.2 IMPLEMENTATION SCOPE AND OBJECTIVE

The present work, by addressing the xSpark limitation explained above, aims at extending the scope of applicability of xSpark, enhancing it with the capability to manage the case of applications that can potentially generate, at runtime, a different *PEP* at each execution. The code in this kind of applications includes conditional branches or iterative loops whose outcomes can only be resolved at runtime because they depend on user input values or results from previous computations that cannot be predicted or folded to constant values by the compiler.

5.2.1 *Symbolic Execution*

Executing a program symbolically means to simultaneously explore multiple paths that a program could take under different inputs. The key idea is to allow a program to take on symbolic – rather than concrete – input values. Execution is performed by a symbolic execution engine, which maintains for each explored control flow path: (i) a first-order Boolean formula that describes the conditions satisfied by the branches taken along that path, and (ii) a symbolic memory store that maps variables to symbolic expressions or values.

When a conditional branch is met, both sides of the branch are executed. Branch execution updates the formula, while assignments update the symbolic store. A symbolic execution tree is generated with an execution state associated with each node, containing the statement to be executed, the symbolic store, and the path conditions (a formula that expresses a set of assumptions on the symbols). The leaves of the tree identify the end of the computations, and tracing back from each leaf up to the root of the tree allows us to reconstruct, in reverse order, all the possible execution paths of the program. Our implementation exploits the functionality provided by *GuardEvaluator*, an extension to Spark applications explained in Section 5.6, which is generated by an external implementation of a lightweight symbolic execution algorithm.

5.2.2 $xSpark_{SEEP}$ vs. $xSpark$

The first important difference between $xSpark_{SEEP}$ and $xSpark$ is in the profiling of the applications. $xSpark$ requires the generation of a single *PEP* profile per application, while $xSpark_{SEEP}$ requires a family of *PEP* profiles, one for each possible execution path, each of them associated to a unique set of "Path Conditions". Profile information is collected in special JSON files, called "JSON profiles". Listing 5.1 shows an example of a JSON profile.

Listing 5.1: Example of JSON profile.

```

1 {
2     "o": {
3         "RDDIds": {
4             "o": {
5                 "callsite": "textFile at PromoCalls.java:34",
6                 "name": "hdfs://10.0.0.4:9000//user/ubuntu/
7                     last24HoursLocalCalls.txt"
8             },
9             "i": {
10                 "callsite": "textFile at PromoCalls.java:34",
11                 "name": "hdfs://10.0.0.4:9000//user/ubuntu/
12                     last24HoursLocalCalls.txt"
13             }
14         },
15         "actual_records_read": 597900000.0,
16         "actual_records_write": 597900000.0,
17         "actualtotalduration": 43000.0,
18         "bytesread": 55618499408.0,

```

```

17     "byteswrite": 0.0,
18     "cachedRDDs": [],
19     "duration": 17000.0,
20     "genstage": false,
21     "id": 0.0,
22     "io_factor": 1.0,
23     "jobs": {
24       "0": {
25         "id-symb": "count_PromoCalls.java:34_0",
26         "stages": [
27           0
28         ]
29       },
30       "1": {
31         "id-symb": "count_PromoCalls.java:42_0",
32         "stages": [
33           1
34         ]
35       },
36       "2": {
37         "id-symb": "count_PromoCalls.java:45_0",
38         "stages": [
39           2
40         ]
41       }
42     },
43     "monocoreduration": 705582.0,
44     "monocoretotalduration": 2170942.0,
45     "name": "count at PromoCalls.java:34",
46     "nominalrate": 847385.562556868,
47     "nominalrate_bytes": 78826414.8008311,
48     "numtask": 500,
49     "parentsIds": [],
50     "recordsread": 597900000.0,
51     "recordswrite": 0.0,
52     "shufflebytesread": 0.0,
53     "shufflebyteswrite": 0.0,
54     "shufflerecordsread": 0.0,
55     "shufflerecordswrite": 0.0,
56     "skipped": false,
57     "t_record_ta_executor": 0.0011801003512293025,
58     "totalduration": 43000.0,
59     "weight": 3.0384051747351832
60   },
61   "1": {
62     "RDDIds": {
63       "2": {

```

```
64      "callsite": "textFile at PromoCalls.java:35",
65      "name": "hdfs://10.0.0.4:9000//user/ubuntu/
66          last24HoursLocalCalls.txt"
67  },
68  "3": {
69      "callsite": "textFile at PromoCalls.java:35",
70      "name": "hdfs://10.0.0.4:9000//user/ubuntu/
71          last24HoursLocalCalls.txt"
72  },
73  "4": {
74      "callsite": "filter at PromoCalls.java:36",
75      "name": "MapPartitionsRDD"
76  },
77  },
78  "actual_records_read": 597900000.0,
79  "actual_records_write": 597900000.0,
80  "bytesread": 55618499408.0,
81  "byteswrite": 0.0,
82  "cachedRDDs": [],
83  "duration": 13000.0,
84  "genstage": false,
85  "id": 1.0,
86  "io_factor": 1.0,
87  "monocoreduration": 737425.0,
88  "name": "count at PromoCalls.java:42",
89  "nominalrate": 810794.3180662441,
90  "nominalrate_bytes": 75422584.54486898,
91  "numtask": 500,
92  "parentsIds": [],
93  "recordsread": 597900000.0,
94  "recordswrite": 0.0,
95  "shufflebytesread": 0.0,
96  "shufflebyteswrite": 0.0,
97  "shufflerecordsread": 0.0,
98  "shufflerecordswrite": 0.0,
99  "skipped": false,
100 "t_record_ta_executor": 0.001233358421140659,
101 "weight": 1.9935654473336273
102 },
103 "2": {
104     "RDDIds": {
105         "5": {
106             "callsite": "textFile at PromoCalls.java:44",
107             "name": "hdfs://10.0.0.4:9000//user/ubuntu/
108                 last24HoursAbroadCalls.txt"
109         },
110         "6": {
```

```

108     "callsite": "textFile at PromoCalls.java:44",
109     "name": "hdfs://10.0.0.4:9000//user/ubuntu/
110         last24HoursAbroadCalls.txt"
111   },
112   "7": {
113     "callsite": "filter at PromoCalls.java:45",
114     "name": "MapPartitionsRDD"
115   }
116   },
117   "actual_records_read": 597900000.0,
118   "actual_records_write": 597900000.0,
119   "bytesread": 55618499408.0,
120   "byteswrite": 0.0,
121   "cachedRDDs": [],
122   "duration": 13000.0,
123   "genstage": false,
124   "id": 2.0,
125   "io_factor": 1.0,
126   "monocoreduration": 727935.0,
127   "name": "count at PromoCalls.java:45",
128   "nominalrate": 821364.5449112902,
129   "nominalrate_bytes": 76405859.60010166,
130   "numtask": 500,
131   "parentsIds": [],
132   "recordsread": 597900000.0,
133   "recordswrite": 0.0,
134   "shufflebytesread": 0.0,
135   "shufflebyteswrite": 0.0,
136   "shufflerecordsread": 0.0,
137   "shufflerecordswrite": 0.0,
138   "skipped": false,
139   "t_record_ta_executor": 0.001217486201705971,
140   "weight": 1.0
141 }
}

```

The profiling information for a *xSpark_{SEEP}* application is obtained by combining the JSON profiles, obtained by driving the application with different sets of input data so to drive the execution of all the possible execution paths, into a JSON file that we will call with a jargon “JumboJSON”, as shown in Figure 5.2. Furthermore, each single json profile is enhanced with information about the jobs composing the application, as shown in Figure 5.3.

Inside *xSpark_{SEEP}* is kept a symbolic memory store that maps symbolic values (or symbols) to actual values. To this structure, initially empty, a new entry is added every time a symbolic value gets assigned

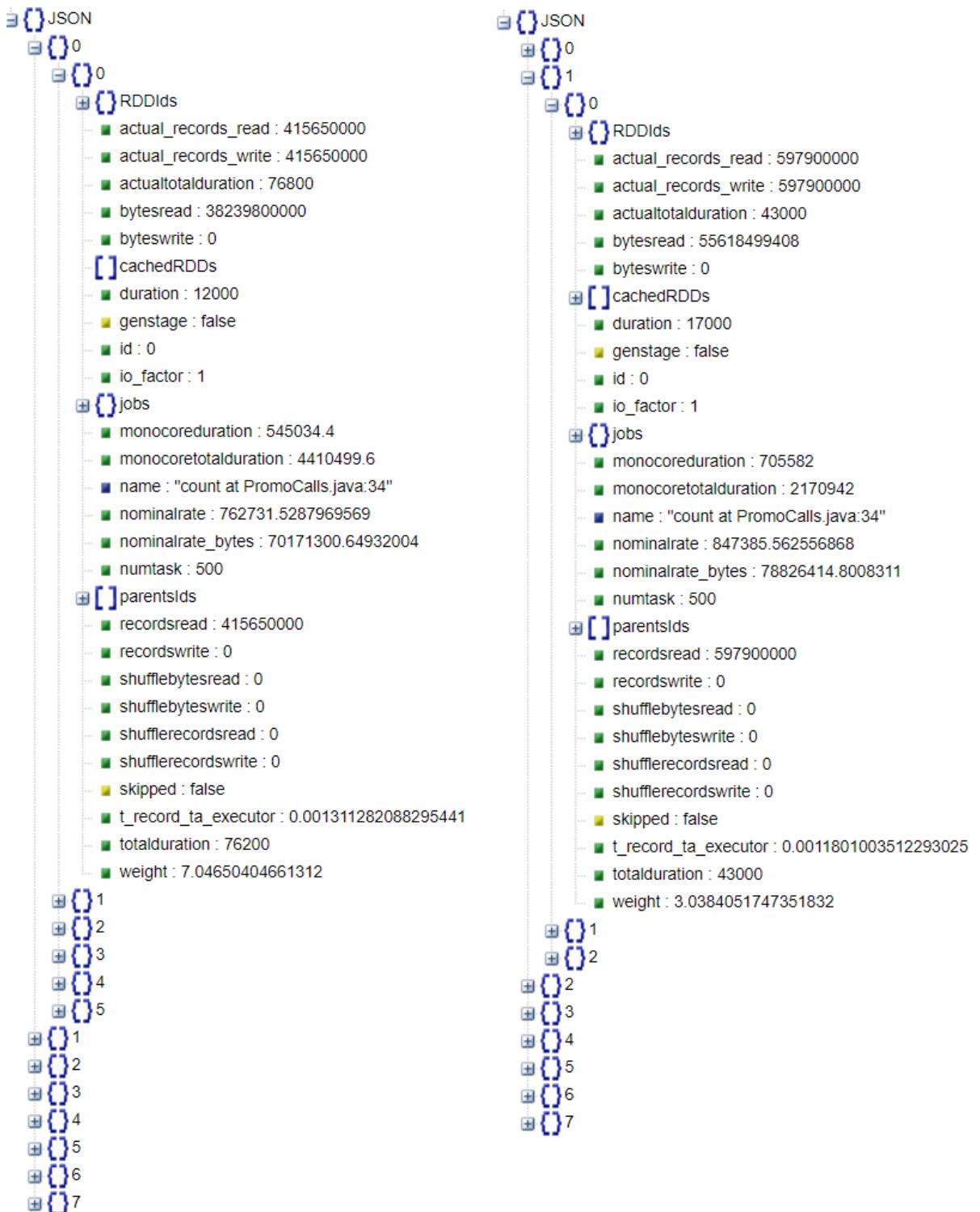


Figure 5.2: Structure of profile JumboJSON. Each profile is identified by its profile id's "0", "1", ..., "7" and, in general, is characterized by its own number of stages and key values. Left and right images show the same JumboJSON profile where profile "0" (left) and profile "1" (right) are expanded, to show their difference in terms of number of stages (6 stages for profile 0 and 3 for profile 1) and totalduration (76,200 ms for profile 0 ms and 43,000 ms for profile 1).

```

1 {
2   "o": {
3     "o": {
4       "jobs": {
5         "o": {
6           "id-symb": "count_PromoCalls.java:34_o",
7           "stages": [
8             0
9           ]
10        },
11        "1": {
12          "id-symb": "count_PromoCalls.java:42_o",
13          "stages": [
14            1
15          ]
16        },
17        "2": {
18          "id-symb": "count_PromoCalls.java:45_o",
19          "stages": [
20            2
21          ]
22        },
23        "3": {
24          "id-symb": "count_PromoCalls.java:51_o",
25          "stages": [
26            3
27          ]
28        },
29        "4": {
30          "id-symb": "count_PromoCalls.java:52_o",
31          "stages": [
32            4
33          ]
34        },
35        "5": {
36          "id-symb": "count_PromoCalls.java:68_o",
37          "stages": [
38            5
39          ]
40        }
41      },
42      ...
43    },
44    ...
45 }

```

Figure 5.3: Information about jobs in json DAG profile.

a concrete value. Each entry is a key-value pair containing the symbol as key and the assigned value as value. The convention adopted for naming the symbols is the following:

- **Commandline arguments:** prefix “arg_” followed by an integer reflecting the position of the argument on the commandline. For example: “arg_o”, “arg_1” etc...
- **Program variables:** Spark action name followed by “_”, followed by program name followed by “：“, followed by the program line number where the action is called, followed by “_”, followed by an integer representing the number of times the action in the same line of code is being repeated. For example: “count_PromoCalls.java:34_2”

Table 5.1: Example of Symbolic Memory Store contents.

Entry#	Key	Value
0	arg_0	100
1	arg_1	200
2	arg_2	300
3	count_PromoCalls.java:42_0	2350
4	count_PromoCalls.java:45_0	1920
5	count_PromoCalls.java:45_1	3800

Table 5.1 shows an example of symbolic memory store contents during the execution of the application, run with three commandline arguments having value “100”, “200”, “300” and two Spark actions already executed, of which the second was executed twice.

The application is also required to implement the *GuardEvaluator* functionality (explained in Section 5.6) by providing a Java class implementing a method called evaluateGuards that receives in input a Map of a symbolic memory store (as the one described above) and returns a list of the profile id’s whose *PEPs* are still executable (i.e. they contain execution paths whose Path Conditions are satisfiable).

5.2.3 A new Heuristic

xSparkSEEP implements *HeuristicSymExControlUnlimited*, a new heuristic that extends *HeuristicControlUnlimited*. The class diagram with the relationships between the heuristic classes is shown in Figure 5.4. A new method, *nextProfile*, is implemented by the new heuristic. It takes the following input parameters:

- 1) a json containing the application profiles obtained by the concrete execution of every possible execution path of the application;
- 2) a list of the profile id’s that are still satisfiable;
- 3) the id of the job being submitted;

and returns the json of the application profile to be used during the execution of the next job. Keeping in mind that the scheduler uses the *HeuristicSymExControlUnlimited* to estimate how many cores are needed to execute the stage, given the application deadline and the parameters in the application profile, we expect the new heuristic

to choose the profile so as not to jeopardize the controller's ability to meet the deadline. This can be achieved by choosing a profile that will lead to not underestimate the cores needed to execute the remaining stages. All the following parameters seem to be good proxies for estimating the remaining computing effort:

- 1) Number of remaining stages to be executed
- 2) Sum of duration of remaining stages to be executed
- 3) Weighted combination of 1 and 2 above

The above parameters can be calculated using the data inside the application json profile. Current implementation of the heuristic uses proxy #1 (number of remaining stages to be executed). It calculates the value for each of the satisfiable profiles, and then selects the profile associated to the maximum value of the proxy. This way, we supply the "worst case" profile to the heuristic, so that the stage deadline is not overestimated and consequently the number of cores to be assigned for the next stage execution is not underestimated.

5.3 APPLICATION PARAMETERS

As explained in Chapter 4, the application parameters can be part of a path condition as they could have been associated to a symbol by the symbolic executor part of *SEEPEP*. Hence, we have introduced in xSpark a mechanism to intercept and store these application parameters in the *xSpark_{SEEPEP} Symbol Store*, as shown in Figure 4.4. Listing 5.2 shows part of the code of method *submit* of xSpark class *SparkSubmit*, that was modified in order to read the values of the application's runtime arguments passed via the Spark *submit* command and write them as separate lines to textfile *args.txt*. This file is a component of the *PEP* Store*. Records from this file are read by xSpark at a later stage, when lazily executing the application by means of job scheduling.

5.4 APPLICATION PROFILING

As shown in Figure 4.4, for each set of input parameters identified by *SEEPEP* a *Launcher* is generated. A *Launcher* is a Java class which contains the command to run the application with a specific set of arguments, which is in a 1:1 relationship with the application parameters of the corresponding *PEP*. An example of Launcher class is shown in Listing 5.3.

Listing 5.2: Changes to SparkSubmit method "submit".

```

1 private def submit(args: SparkSubmitArguments): Unit = {
2   val (childArgs, childClasspath, sysProps, childMainClass) =
3     prepareSubmitEnvironment(args)
4   val argsFile = sys.env.getOrElse("SPARK_HOME", ".") + "/conf/
5   args.txt"
6   val bw = new BufferedWriter(new FileWriter(argsFile))
7   if (childArgs.size > 0) {
8     bw.write(childArgs(0) + "\n")
9     bw.write(args.primaryResource + "\n")
10    for (i <- 1 to childArgs.size - 1) {
11      bw.write(childArgs(i)+"\n")
12    }
13  }
14  bw.close()
15  ...

```

A *Profiling* (see Figure 3.1) of the application is done by running it with each *Launcher*'s set of arguments. Each profiling run generates the corresponding *PEP* in a specialized JSON file. At the end of this process, all the generated *PEPs* are packaged into another JSON file, in jargon called *JumboJSON*, to form the *PEP**. All the generated JSON files are then stored along with the *PEP** in the *PEP* Store* on the *Spark Master* server.

Listing 5.3: Example of Launcher Code .

```

1 package it.polimi.deepse.dagsymb.launchers;/*
2  * This file was automatically generated by EvoSuite
3  * Wed May 16 13:17:45 GMT 2018
4  */
5 import it.polimi.deepse.dagsymb.examples.PromoCalls;
6 import it.polimi.deepse.dagsymb.examples.UserCallDB;
7 public class Launcher0 {
8   /*Test case number: 0
9    * 1 covered goal:
10   * Goal 1. com.xspark.varyingdag.examples.calls.PromoCalls.
11     run_driver(IJJI)V: path condition EvoSuiteWrapper_0_0 (id
12     = 0)
13   */
14   public static void main(String[] args) {
15     int threshold = 2772;
16     long minLocalLongCalls = 2772;
17     long minAbroadLongCalls = 1397;

```

```

15     int pastMonths = 0;
16     int last24HLocalCallsLength = 0;
17     int last24HLocalCallsSize = 0;
18     int last24HAbroadCallsLength = 3361;
19     int last24HAbroadCallsSize = 2794; // 1397 * 2
20     int MonthCallsLength = 2990;
21     int MonthCallsSize = 3000;
22     int num_partitions = 500;
23     PromoCalls promoCalls0 = new PromoCalls();
24     boolean genData = false;
25     String appName = "";
26     if (args[12] != null && args[12].startsWith("-g")) genData
27         = true;
28     if (args[13] != null && !args[13].startsWith("-")) appName
29         = args[12];
30     promoCalls0.run(threshold, minLocalLongCalls,
31                     minAbroadLongCalls, pastMonths,
32                     last24HLocalCallsLength, last24HLocalCallsSize,
33                     last24HAbroadCallsLength, last24HAbroadCallsSize,
                         MonthCallsLength, MonthCallsSize, num_partitions,
                         genData, appName);
32 }
33 }
```

5.5 PEP*

The previous version of xSpark required a single *PEP* to be present in the *PEP* Store*, so we had to modify the xSpark class *DAGScheduler* to take in account that the data in the *JumboJSON file* now contains all the *PEPs*. To maintain backwards compatibility, a new variable was introduced, *JumboJson*, to hold the contents of the *PEP* Store*. The modified code is in charge of checking the *heuristic type* in the *SparkContext* instance *sc*, to understand if it should expect the contents of the *PEP* Store* to be a single *PEP* or a whole set of *PEPs* representing a *PEP**. The heuristic type is initialized with the value of the key *spark.control.heuristic* specified in the xSpark configuration file *spark-defaults.conf*.

5.6 GUARDEVALUATOR

With the term *GuardEvaluator* we collectively refer to the interface class *IGuardEvaluator* and its implementation class defining the *evaluateGuards* method, that is in charge of returning the list of

Listing 5.4: Changes to class DAGScheduler.scala - reading PEPs.

```

1 val jsonFile = sys.env.getOrElse("SPARK_HOME", ".") +
2   "/conf/" + sc.appName + ".json"
3
4 val appJumboJson = if (Files.exists(Paths.get(jsonFile))) {
5   io.Source.fromFile(jsonFile).mkString.parseJson
6 } else null
7
8 var appJson = if (appJumboJson != null && heuristicType > 2)
9   heuristic.nextProfile(appJumboJson)
10 else appJumboJson

```

Listing 5.5: Interface class IGuardEvaluator.

```

1 package it.polimi.deepse.dagsymb.examples;
2 import java.util.List;
3 import java.util.Map;
4
5 public interface IGuardEvaluator {
6
7   public List<Integer> evaluateGuards(Map<String, Object>
8     knownValues);
9 }

```

valid profiles (*PEPs*) when it is called with the `HashMap` of the known symbols and their values. The code of the `IGuardEvaluator` interface is shown in Listing 5.5, while Listing 5.6 shows an example of an implementation class and its method `evaluateGuards` for a specific application.

Listing 5.6: Class `GuardEvaluatorPromoCallsFile`, implementing the `IGuardEvaluator` interface.

```

1 package it.polimi.deepse.dagsymb.examples;
2 import java.util.ArrayList;
3 import java.util.List;
4 import java.util.Map;
5 public class GuardEvaluatorPromoCallsFile implements
6   IGuardEvaluator {
7   private List<Integer> satisfiableGuards;
8   @Override

```

```
8 public List<Integer> evaluateGuards(Map<String, Object>
9     knownValues) {
10    satisfiableGuards = new ArrayList<>();
11    extractValues(knownValues);
12    evaluateActualGuards();
13    return satisfiableGuards;
14 }
15 private void evaluateActualGuards() {
16     //path condition evaluation
17     if (
18         ( !arg0_known || arg0 > 100 ) &&
19         ( !arg3_known || arg3 >= 0 ) &&
20         ( !arg3_known || arg3 <= 2 ) &&
21         ( !count_PromoCalls_java_42_0_known || !arg1_known || count_PromoCalls_java_42_0 - arg1 <= 0 ) &&
22         ( !arg2_known || !count_PromoCalls_java_45_0_known || count_PromoCalls_java_45_0 - arg2 > 0 ) &&
23         true) {
24         satisfiableGuards.add(0);
25     }
26     if (
27         ( !arg0_known || arg0 > 100 ) &&
28         ( !arg3_known || arg3 >= 0 ) &&
29         ( !arg3_known || arg3 <= 2 ) &&
30         ( !count_PromoCalls_java_42_0_known || !arg1_known || count_PromoCalls_java_42_0 - arg1 <= 0 ) &&
31         ( !arg2_known || !count_PromoCalls_java_45_0_known || count_PromoCalls_java_45_0 - arg2 <= 0) &&
32         true) {
33         satisfiableGuards.add(1);
34     }
35     if (
36         ( !arg0_known || arg0 > 100 ) &&
37         ( !arg3_known || arg3 >= 0 ) &&
38         ( !arg3_known || arg3 <= 2 ) &&
39         ( !count_PromoCalls_java_42_0_known || !arg1_known || count_PromoCalls_java_42_0 - arg1 > 0 ) &&
40         ( !arg3_known || 1 > arg3 ) &&
41         ( !arg2_known || !count_PromoCalls_java_45_0_known || count_PromoCalls_java_45_0 - arg2 > 0 ) &&
42         true) {
43         satisfiableGuards.add(2);
44     }
45     if (
46         ( !arg0_known || arg0 > 100 ) &&
47         ( !arg3_known || arg3 >= 0 ) &&
48         ( !arg3_known || arg3 <= 2 ) &&
```

```

48      ( !count_PromoCalls_java_42_0_known || !arg1_known || 
49          count_PromoCalls_java_42_0 - arg1 > 0 ) &&
50      ( !arg3_known || 1 > arg3 ) &&
51      ( !arg2_known || !count_PromoCalls_java_45_0_known || 
52          count_PromoCalls_java_45_0 - arg2 <= 0) &&
53      true) {
54          satisfiableGuards.add(3);
55      }
56      if (
57          ( !arg0_known || arg0 > 100 ) &&
58          ( !arg3_known || arg3 >= 0 ) &&
59          ( !arg3_known || arg3 <= 2 ) &&
60          ( !count_PromoCalls_java_42_0_known || !arg1_known || 
61              count_PromoCalls_java_42_0 - arg1 > 0 ) &&
62          ( !arg3_known || 1 <= arg3 ) &&
63          ( !arg3_known || 2 > arg3 ) &&
64          ( !arg2_known || !count_PromoCalls_java_45_0_known || 
65              count_PromoCalls_java_45_0 - arg2 > 0 ) &&
66          true) {
67              satisfiableGuards.add(4);
68          }
69          if (
70              ( !arg0_known || arg0 > 100 ) &&
71              ( !arg3_known || arg3 >= 0 ) &&
72              ( !arg3_known || arg3 <= 2 ) &&
73              ( !count_PromoCalls_java_42_0_known || !arg1_known || 
74                  count_PromoCalls_java_42_0 - arg1 > 0 ) &&
75              ( !arg3_known || 1 <= arg3 ) &&
76              ( !arg3_known || 2 > arg3 ) &&
77              ( !arg2_known || !count_PromoCalls_java_45_0_known || 
78                  count_PromoCalls_java_45_0 - arg2 <= 0) &&
79              true) {
80                  satisfiableGuards.add(5);
81              }
82              if (
83                  ( !arg0_known || arg0 > 100 ) &&
84                  ( !arg3_known || arg3 >= 0 ) &&
85                  ( !arg3_known || arg3 <= 2 ) &&
86                  ( !count_PromoCalls_java_42_0_known || !arg1_known || 

```

```

87     if (
88         ( !arg0_known || arg0 > 100 ) &&
89         ( !arg3_known || arg3 >= 0 ) &&
90         ( !arg3_known || arg3 <= 2 ) &&
91         ( !count_PromoCalls_java_42_0_known || !arg1_known || 
92             count_PromoCalls_java_42_0 - arg1 > 0 ) &&
93         ( !arg3_known || 1 <= arg3 ) &&
94         ( !arg3_known || 2 <= arg3 ) &&
95         ( !arg2_known || !count_PromoCalls_java_45_0_known || 
96             count_PromoCalls_java_45_0 - arg2 <= 0 ) &&
97         true) {
98     satisfiableGuards.add(7);
99 }
100 private boolean arg0_known; private Integer arg0;
101 private boolean count_PromoCalls_java_42_0_known; private
102     Long count_PromoCalls_java_42_0;
103 private boolean arg2_known; private Long arg2;
104 private boolean arg1_known; private Long arg1;
105 private boolean count_PromoCalls_java_45_0_known; private
106     Long count_PromoCalls_java_45_0;
107 private boolean arg3_known; private Integer arg3;
108 private void extractValues(Map<String, Object> knownValues) {
109     arg0_known = (knownValues.get("argo") != null);
110     arg0 = arg0_known ? Integer.parseInt((String) knownValues
111         .get("argo")) : null;
112     count_PromoCalls_java_42_0_known = (knownValues.get(""
113         count_PromoCalls.java:42_0") != null);
114     count_PromoCalls_java_42_0 =
115         count_PromoCalls_java_42_0_known ? (Long) knownValues
116             .get("count_PromoCalls.java:42_0") : null;
117     arg2_known = (knownValues.get("arg2") != null);
118     arg2 = arg2_known ? Long.parseLong((String) knownValues.
119         get("arg2")) : null;
120     arg1_known = (knownValues.get("arg1") != null);
121     arg1 = arg1_known ? Long.parseLong((String) knownValues.
122         get("arg1")) : null;
123     count_PromoCalls_java_45_0_known = (knownValues.get(""
124         count_PromoCalls.java:45_0") != null);
125     count_PromoCalls_java_45_0 =
126         count_PromoCalls_java_45_0_known ? (Long) knownValues
127             .get("count_PromoCalls.java:45_0") : null;
128     arg3_known = (knownValues.get("arg3") != null);
129     arg3 = arg3_known ? Integer.parseInt((String) knownValues
130         .get("arg3")) : null;
131 }
132 }
```

The application is in charge of providing the *GuardEvaluator* as a java class, implementing the interface *IGuardEvaluator*, and packaged inside the jar of the application. This class is loaded dynamically at runtime by the new code added for this purpose to the xSpark class *DAGScheduler* and shown in Listing 5.7.

Listing 5.7: Changes to class DAGScheduler.scala - Loading GuardEvaluator.

```

1 var guardEvalObj: Any = null
2 var guardEvalMethod: java.lang.reflect.Method = null
3 if (heuristicType > 2) {
4     /*
5      * DB - DagSymb enhancements
6      * The following variables are needed to load the
7      * GuardEvaluator class from the application jar
8      */
9     val jarfile = new File(appJar)
10    val classLoader = new URLClassLoader(Array(jarfile.toURI.toURL)
11        )
12    val guardEvalClass = classLoader.loadClass(guardEvalClassname)
13    val guardEvalConstructor = guardEvalClass.getConstructor()
14    guardEvalObj = guardEvalConstructor.newInstance()
15    val methods = guardEvalClass.getDeclaredMethods()
16    for (m <- methods) {
17        m.getName match {
18            case "evaluateGuards" => guardEvalMethod = m
19            case _ =>
20        }
21    } else {
22        guardEvalObj = new core/src/main/scala/org/apache/spark.
23                      scheduler.GuardEvaluator
24    }

```

5.7 SYMBOL STORE

In order to take advantage of the symbolic execution, we need to maintain an updated *Symbol Store* containing all the symbols that can be part of a path condition and their associated determinations (assigned values). We added the code into the xSpark class *DAGScheduler* to abstractly represent the *Symbol Store* as a *HashMap[String, Any]*. Each entry of this *HashMap* stores a *known symbol* name and its value. By *known symbol* we mean a symbol that has been associated to a value

during the concrete execution of program code. Given this definition, at the very beginning of the computation the only known symbols are the runtime arguments passed to the application. We added to the xSpark class `DAGScheduler` the code to read the arguments and their values and create the corresponding *Symbol Store* entries. The code is shown in Listing 5.8, where we can notice that the first two arguments loaded when `var iter` is set to negative values (`-2` and `-1`) are respectively the *GuardEvaluator* class name and the application jar name, that are not symbols. They are not kept in the Symbol Store, instead they are used to initialize the variables `guardEvalClassname` and `appJar` which will be needed in a later step of the execution to identify the location and dynamically load the class implementing the *GuardEvaluator* function.

Listing 5.8: Changes to class `DAGScheduler.scala` - Initializing Symbol Store.

```

1 var symbolsMap = new java.util.HashMap[String, Any]()
2 var symbolName: String = ""
3 var guardEvalClassname: String = ""
4 var appJar: String = ""
5 val argsFile = sys.env.getOrElse("SPARK_HOME", ".") +
6   "/conf/args.txt"
7 var iter: Int = -2
8 if (Files.exists(Paths.get(argsFile))) {
9   for (line <- Source.fromFile(argsFile).getLines) {
10     iter match {
11       case -2 => guardEvalClassname = line
12       case -1 => appJar = line.split(":")(1)
13       case _   => symbolsMap.put("arg" + iter, line)
14     }
15     iter += 1
16   }
17 ...

```

5.8 HEURISTIC

The heuristic used by xSpark is determined by the value of configuration parameter `spark.control.heuristic` and is an implementation of the class `HeuristicBase`, whose class diagram is shown in Figure 5.4. In Listing 5.9, we can see that the heuristic `HeuristicControl` is used by default, but other heuristics can be selected. `HeuristicFixed` and `HeuristicControlUnlimited` were already available in xSpark, while

we implemented a new heuristic **HeuristicSymExControlUnlimited** to exploit *Symbolic Execution*.

Listing 5.9: Changes to class ControlEventListener.scala - selecting the heuristic.

```

1 val heuristicType = conf.getInt("spark.control.heuristic", 0)
2 val heuristic: HeuristicBase =
3   if (heuristicType == 1 &&
4       conf.contains("spark.control.stagecores") &&
5       conf.contains("spark.control.stagedeadlines") &&
6       conf.contains("spark.control.stage"))
7     new HeuristicFixed(conf)
8   else if (heuristicType == 2)
9     new HeuristicControlUnlimited(conf)
10  else if (heuristicType == 3)
11    new HeuristicSymExControlUnlimited(conf)
12  else
13    new HeuristicControl(conf)

```

`HeuristicSymExControlUnlimited` extends `HeuristicControlUnlimited` by adding the implementation of a new method, `nextProfile`, taking parameters `appJson`, the JumboJSON containing the PEP* representation and `valExFlows`, a list containing the id's of the valid application profiles, (i.e. the list of the *PEPs* whose path conditions still hold true), and returns the *PEP* of the profile to be used during the executing of the next scheduled job. Class `HeuristicSymExControlUnlimited` implementation code is shown in Listing 5.10. The *PEP* selection performed by method `nextProfile` is made by choosing the "*worst case*" among the valid *PEPs*, that is the *PEP* with the maximum number of stages still to be executed, as we want to be conservative and minimize the deadline violations. If we wanted to optimize another performance indicator, like minimum resource utilization in absence of strict deadline commitment, we could choose the profile with an average number of remaining stages to be executed.

STAGE DEADLINE ADJUSTMENT As it was explained in Section 3.2, when a stage is submitted for execution, the heuristic calculates its stage deadline `deadline(sk)` based on the `ApplicationDeadline`, the `SpentTime`, which is the sum of the durations of the stages already executed, and the stage weight `weight(sk)`. Our solution implies that we select potentially a new *PEP* at each new job execution boundary. This means that we have to face a situation where heuristic calculates the new stage deadline using the value of `SpentTime`

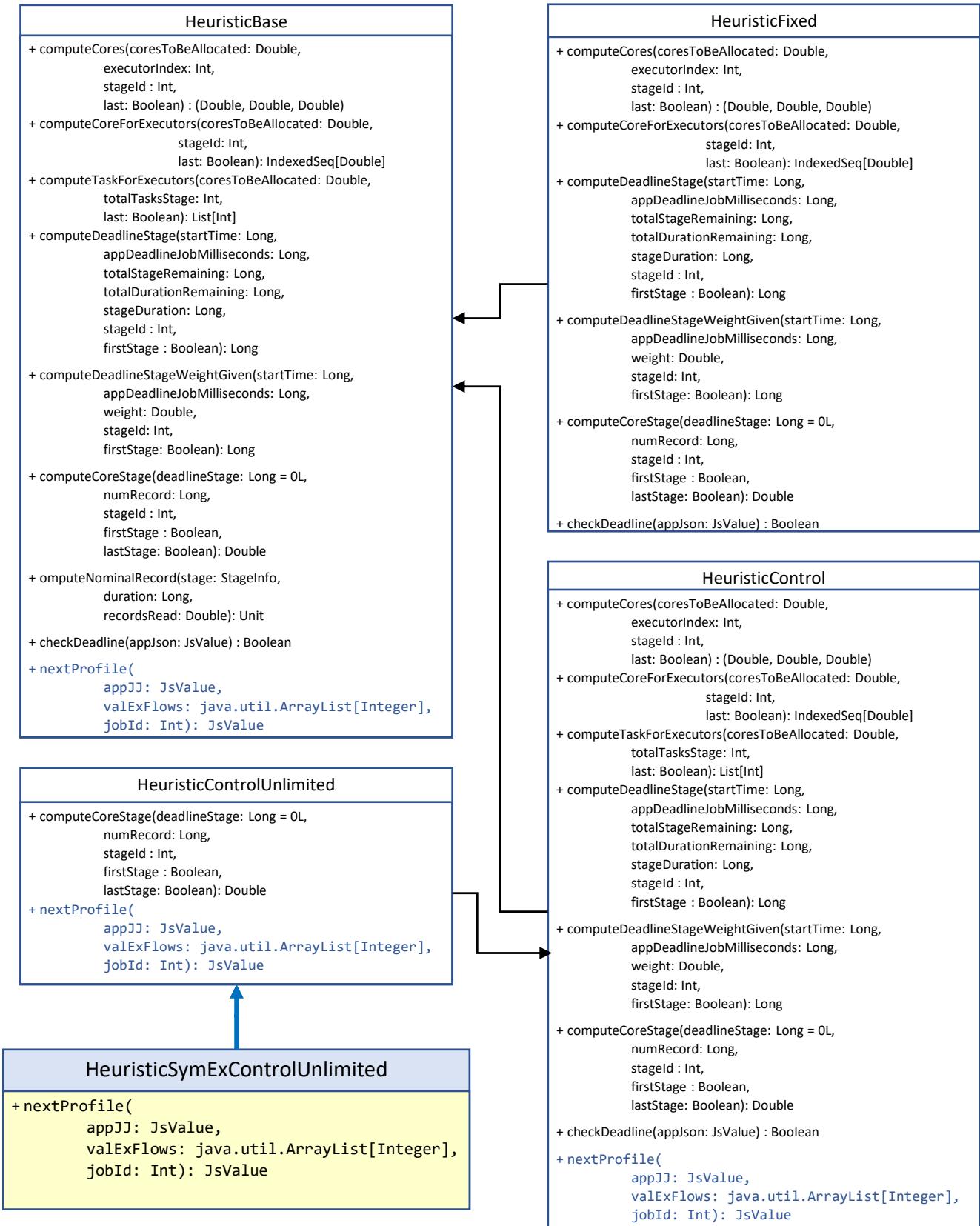


Figure 5.4: Class diagram of Heuristic related classes.

Listing 5.10: Class HeuristicSymExControlUnlimited.scala implementation.

```

1 class HeuristicSymExControlUnlimited(conf: SparkConf)
2     extends HeuristicControlUnlimited(conf) {
3     override def nextProfile(appJJ: JsValue,
4         valExFlows: java.util.ArrayList[Integer] = null,
5         jobId: Int = 0): JsValue = {
6         var setP = appJJ.asJsObject.fields
7         val stageId = if (valExFlows != null)
8             setP(valExFlows.get(0).toString()).asJsObject.fields("o")
9                 .asJsObject.fields("jobs")
10                .asJsObject.fields(jobId.toString())
11                .asJsObject.fields("stages")
12                .convertTo[List[Int]].sortWith((x, y) => x < y).apply(0)
13         if (valExFlows != null)
14             setP = setP.filter(
15                 {case (k, v) => valExFlows.exists(x => x == k.toInt)})
16         var wCaseProfId = setP.toList.map({ case (k, profile) => {
17             val numStage = profile.asJsObject.fields.filter(
18                 {case (k, stage) => {
19                     !stage.asJsObject.fields("skipped")
20                         .convertTo[Boolean]}})
21             .size()
22             (k, numStage)}}).reduce({ (x, y) => {
23                 if (x._2 > y._2) x else y
24             }})._1;
25         setP(wCaseProfId)
26     }
27 }
```

that is calculated from the *PEP* used to execute the previous stages and the value of `weighth(sk)` that is calculated from the newly selected *PEP*. This is incorrect, since the new *PEP*, in general, has its own number of stages and stage durations. We fixed it by changing the way `SpentTime` is calculated by the following changes to the xSpark code: i) *case* class `SparkStageWeightSubmitted` in class `SparkListener.scala` shown in Listing 5.11, where optional formal parameter `executedstagesduration` is added to the *case* class declaration ii) class method `submitMissingTasks` of class `DAGScheduler.scala` shown in Listing 5.12, where the variable `executedstagesduration` is initialized with the cumulated duration of the executed stages from the selected *PEP* and passed as a parameter to the `SparkStageWeightSubmitted` and iii) method `onStageWeightSubmitted` in class `ControlEventListener.scala`

shown in Listing 5.13, where `stageSubmitted.executedstagesduration` is used to calculate the value of the variable `totaldurationremaining`.

Listing 5.11: Changes to case class `SparkStageWeightSubmitted` of class `SparkListener.scala`

```

1 @DeveloperApi
2 case class SparkStageWeightSubmitted
3 (stageInfo: StageInfo, properties: Properties = null, weight:
4   Long, duration: Long,
5   totalduration: Long, parentsIds: List[Int],
6   nominalrate: Double, genstage: Boolean, stageIds: List[String],
7   executedstagesduration: Long = 0L)
8   extends SparkListenerEvent

```

Listing 5.12: Changes to method `submitMissingTasks` of class `DAGScheduler.scala`

```

1 private[spark] class DAGScheduler(
2   ...
3   private def submitMissingTasks(stage: Stage, jobId: Int) {
4     ...
5     if (tasks.nonEmpty) {
6       ...
7       if (appJson != null) {
8         val stageJson = appJson.asJsObject.fields(stage.id.
9           toString)
10        val submittedStageId = stage.id
11        var stageId = stage.id
12        // Adding resilience in case of profile does not match no
13        . stages
14        val highestStageIdInProfile = appJson.asJsObject.fields.
15          keys.size - 1
16        if (stage.id > highestStageIdInProfile) {
17          stageId = highestStageIdInProfile
18          logInfo(s"Submitted Stage ID not contained in appJSON
19            profile. Submitted Stage ID: $submittedStageId,
20            " +
21            s"Highest Stage ID in appJSON profile:
22              $highestStageIdInProfile" )
23        }
24        val stageJson = appJson.asJsObject.fields(stageId.
25          toString)
26        val totalduration = appJson.asJsObject.fields("o").
27          asJsObject.fields("totalduration").convertTo[Long]
28        val duration = stageJson.asJsObject.fields("duration").
29          convertTo[Long]

```

```
21     val weight = stageJson.asJsObject.fields("weight").  
22         convertTo[Long]  
23     val stageJsonIds = appJson.asJsObject.fields.keys.toList.  
24         filter(id =>  
25             appJson.asJsObject.fields(id).asJsObject.fields("nominalrate").convertTo[Double] != 0.0)  
26     val executedstagesduration = appJson.asJsObject.fields.  
27         filter(stage =>  
28             stage._1.toInt <  
29                 stageId)  
30             .foldLeft(0L){ (acc, elem) =>  
31                 acc + elem._2.asJsObject  
32                     .fields("duration").  
33                     convertTo[Long] }  
34     listenerBus.post(SparkStageWeightSubmitted(stage.  
35         latestInfo, properties,  
36         weight,  
37         duration,  
38         totalduration,  
39         stageJson.asJsObject.fields("parentsIds").convertTo[  
40             List[Int]],  
41         stageJson.asJsObject.fields("nominalrate").convertTo[  
42             Double],  
43         stageJson.asJsObject.fields("genstage").convertTo[  
44             Boolean],  
45         stageJsonIds))  
46     stageJsonIds,  
47     executedstagesduration))  
48 }  
49 else {  
50     logError("NO JSON FOR APP: " + jsonFile)  
51     ...  
52 }
```

Listing 5.13: Changes to method `onStageWeightSubmitted` of class `ControlEventListener.scala`

```
1 class ControlEventListener(conf: SparkConf) extends
2   JobProgressListener(conf) with Logging {
3   var totalDurationRemaining = -1L
4   var totalStageRemaining = -1L
5   var previous_profile_totalStages = 0L
6   var previous_profile_totalDuration = 0L
7   ...
8   override def onStageWeightSubmitted
9   (stageSubmitted: SparkStageWeightSubmitted): Unit =
```

```

10     val genstage = if (firstStageId != -1) 1 else 0
11     stageIdToParentsIds(stage.stageId) = stageSubmitted.
12         parentsIds
13
14     if (totalDurationRemaining == -1L) {
15         totalDurationRemaining = stageSubmitted.totalDuration
16         previous_profile_totalDuration = totalDurationRemaining
17     } else {
18         totalDurationRemaining = stageSubmitted.totalDuration -
19             stageSubmitted.executedStagesDuration
20     }
21     if (totalStageRemaining == -1L) {
22         totalStageRemaining = stageSubmitted.stageIds.size - 1 +
23             genstage
24         previous_profile_totalStages = totalStageRemaining
25     } else {
26         totalStageRemaining += stageSubmitted.stageIds.size - 1 +
27             genstage - previous_profile_totalStages
28     }
29     stageIdToDuration(stage.stageId) = stageSubmitted.duration
30 ...
31     previous_profile_totalDuration = stageSubmitted.totalDuration
32     previous_profile_totalStages = stageSubmitted.stageIds.size -
33         1 + genstage
34 }
35 ...
36 }
```

STAGE CARDINALITY MISMATCH ADJUSTMENT As it will be presented in Chapter 6 dedicated to the evaluation of the solution, we have to be able to run the applications under xSpark configured to use heuristic HeuristicControlUnlimited and providing a single *PEP* corresponding to the best case (i.e. lowest number of stages) and the worst case (i.e. highest number of stages). These test settings are necessary to compare the performance of xSpark with and without *Symbolic Execution* capabilities, however this situation leads to the problem that we call *Stage Cardinality Mismatch*. It happens when the number of stages of the application does not match the number of stages in the *PEP*. We can have two cases: the *PEP* contains more stages than the application or, vice-versa, the *PEP* contains less stages than the application. In the former case there are no problems, and xSpark terminates correctly the execution of the application, while in the latter case xSpark tries to retrieve information from the *PEP* about a non-existent stage and it terminates the execution of the application in

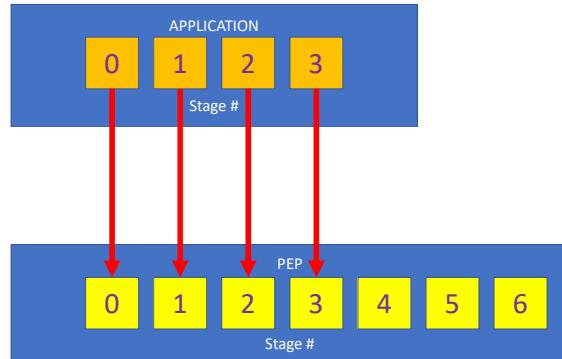


Figure 5.5: Stage Cardinality Mismatch - Acceptable situation.

error. To avoid this unwanted situation, we have changed the code in method `submitMissingTasks` of class `DAGScheduler.scala` shown in Listing 5.12, where we added the variable `highestStageIdInProfile` that is initialized with the cardinality of the stages in the *PEP* and its value assigned to the variable `stageId` if the id of the requested stage is higher than `highestStageIdInProfile`. This creates the effect called *stage id extension* depicted in Figure 5.6.

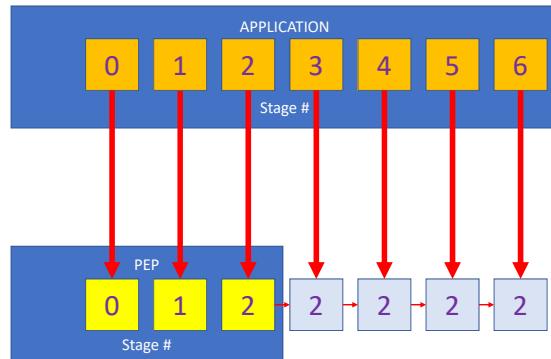


Figure 5.6: Stage Cardinality Mismatch - stage id extension.

5.9 SYMBOLS

As mentioned in Section 5.7, we have to update the Symbol Store everytime a variable associated to a symbol is evaluated by the concrete execution of the application. We adopted the convention to identify a symbol by the string `arg_n` if it refers to a runtime application argument, where n is the position of the argument (e.g. `arg_0`), or

by a string obtained by concatenating its *CallSite* and *IterationNumber* separated by an underscore character “_”, where *Call Site* is a string obtained by concatenating *SparkActionName*, *ApplicationClassName*, *SourceLanguageName:SourceLineNumber* separated by an underscore character “_”, and *IterationNumber* is an integer starting from 0 and incremented everytime a call is originated by the same *CallSite*. i.e. the same line of code is re-executed (e.g. due to iterative loops). Examples of formal symbol names are shown in Figure 5.7.

```
arg_0
count_PromoCalls.java:45_2
```

Figure 5.7: Example of symbol formal names.

As stated above, a symbol, if not associated to an application runtime argument, is identified by its *CallSite*. This means that to identify the symbols we have to intercept calls coming from their *CallSite*. Since the values associated to a symbol can only be changed by xSpark *actions* which delimit jobs, we added code to the method `runJob` of class `DAGScheduler` to extract the *CallSite*, generate a symbol and push it in the *Symbol Store* everytime the method `runJob` is called. The code is shown in Listing 5.14.

Listing 5.14: Changes to class `DAGScheduler.scala` - method `runJob`.

```
1 var symbolMap = HashMap[String, Int]()
2 var symbolName: String = ""
3 def runJob[T, U](
4   rdd: RDD[T],
5   func: (TaskContext, Iterator[T]) => U,
6   partitions: Seq[Int],
7   callSite: CallSite,
8   resultHandler: (Int, U) => Unit,
9   properties: Properties): Unit = {
10   val actionCallSite = callSite.shortForm.replace(" at ", "_")
11   symbolName = actionCallSite + "_" + symbolMap.getOrDefault(
12     actionCallSite, 0).toString()
13   symbolMap.put(symbolName, null)
14   symbolMap(actionCallSite) += 1
15 }
```

The variable `actionCallSite` is initialized using the value of the `callSite` parameter. An auxilliary structure, the `HashMap[String, Int]` `symbolMap` keeps track of every `actionCallSite` and counts how many

times each of them has called the method `runJob`. The value of the count determines the suffix of each symbol. Symbols are initially assigned a null value, and stay in the symbol store waiting to be assigned the result of the *action* originated from the `actionCallSite`.

This task is performed by the new method `resultComputed`, that was added to the xSpark class `DAGScheduler`. `resultComputed` is called by the homonymous method, added to the class `SparkContext`, that passes to it the computed result of the action received from an *action* method in the class `RDD`. Lastly, we have indeed modified the methods that execute the *actions* in the `RDD` xSpark class by inserting a call to the method `resultComputed` of the `SparkContext` instance `sc` and passing to it the computed result of the action.

Updating the value of *symbols* in the *Symbol Store* is not the only task fulfilled by the `resultComputed` method of class `DAGScheduler`. It also executes the method stored in the variable `guardEvalMethod` with the map of the known *symbols* getting in return the variable `new_validExecFlows` containing the list of valid profiles. It is also in charge of selecting the profile `appJson` to be used to run the next job. It fulfills this task by calling the method `nextProfile` of the `HeuristicSymExControlUnlimited` instance `heuristic` and passing to it the list of valid profiles. In returns, it gets the json profile to be used in the next job to be run, stored in the variable `appJson`.

The new and modified methods are shown in Listings 5.15, 5.16, 5.17.

Listing 5.15: Changes to class `DAGScheduler.scala` - new method `resultComputed`.

```

1 private[scheduler] def numTotalJobs: Int = nextJobId.get()
2
3 def resultComputed(result: Any ): Unit = {
4     if (heuristicType > 2) {
5         symbolsMap(symbolName) = result
6         val resultType = ClassTag(result.getClass)
7         var new_validExecFlows = guardEvalMethod.invoke(guardEvalObj,
8             symbolsMap).asInstanceOf[java.util.ArrayList[Integer]]
9         if (new_validExecFlows.size() > 0)
10            validExecFlows = new_validExecFlows
11        else
12            println("Warning! GuardEvaluator returned an empty set of
13                profile ids")
13        val highestJobId: Int =
14            if (validExecFlows != null) {
```

```

15     appJumboJson.asJsObject.fields(validExecFlows.get(0) .
16         .toString())
17         .asJsObject.fields("o").asJsObject.fields("jobs")
18         .asJsObject.fields.keys.max.toInt}
19     else 0
20     appJson = if (numTotalJobs <= highestJobId) {
21         heuristic.nextProfile(appJumboJson,
22             validExecFlows, nextJobId.get())}
23     else appJson

```

Listing 5.16: Changes to class SparkContext.scala - new method resultComputed.

```

1 def resultComputed(result: Any ): Unit = {
2     dagScheduler.resultComputed(result)
3 }

```

Listing 5.17: Changes to class RDD.scala - modified methods count, collect and reduce.

```

1 def count(): Long = {
2     val res = sc.runJob(this, Utils.getIteratorSize _).sum
3     sc.resultComputed(res)
4     res
5 }
6
7 def collect(): Array[T] = withScope {
8     val results = sc.runJob(this, (iter:Iterator[T]) => iter.toArray)
9     val res = Array.concat(results: _*)
10    sc.resultComputed(res)
11    res
12 }
13
14 def reduce(f: (T, T) => T): T = withScope {
15     val cleanF = sc.clean(f)
16     val reducePartition: Iterator[T] => Option[T] = iter => {
17         if (iter.hasNext) {
18             Some(iter.reduceLeft(cleanF))
19         } else {
20             None
21         }
22     }

```

```

23 var jobResult: Option[T] = None
24 val mergeResult = (index: Int, taskResult: Option[T]) => {
25   if (taskResult.isDefined) {
26     jobResult = jobResult match {
27       case Some(value) => Some(f(value, taskResult.get))
28       case None => taskResult
29     }
30   }
31 }
32 sc.runJob(this, reducePartition, mergeResult)
33 jobResult.getOrElse(throw new UnsupportedOperationException(
34   "empty collection"))
35 val res = jobResult.getOrElse(throw new
36   UnsupportedOperationException("empty collection"))
37 sc.resultComputed(res)
38 res
39 }
```

5.10 INTERCEPTING ACTIONS RESULTS

Jobs in xSpark are delimited by *actions* (e.g. *count()*, *collect()* etc...) and are composed by a number of stages, that reflect the *transformations* operated on data. Data are abstracted by Resilient Distributed Datasets (*RDDs*) classes, which contains specialized methods implementing the actions that are in charge of calling the method *runJob* of the *SparkContext* instance *sc*. As we have seen in Section 5.9, the result of a Spark *action* is associated to a symbol through its *CallSite*. Hence, we have changed the code of the methods implementing the *actions* in the xSpark class *RDD* to store the result of the action in the local variable *res*, which is passed as a parameter in the call to the *resultComputed* method of the active *SparkContext* instance *sc*. The process to update the *xSpark_{SEEP} Symbol Store* with the result of the action, which is associated to a unique symbol, is explained in Section 5.9.

5.11 PYTHON TOOL

xSpark-dagsymb is the name of the Python tool, which is part of the *xSpark_{SEEP}* solution that exploits symbolic execution techniques to safely run multi-dag applications in xSpark ¹. It combines two distinct functionalities, application profiling and application execution, which are part of *xSpark_{SEEP}* application lifecycle, in one integrated tool.

¹ <https://github.com/gioenn/xSpark-dagsymb.git>

The tool is composed by ten principal modules: **xSpark_dagsymb.py**, **launch.py**, **run.py**, **log.py**, **plot.py**, **metrics.py**, **configure.py**, **processing.py**, **average_runs.py**, **process_on_server.py**, in addition to the configuration files **credentials.json**, **setup.json**, **control.json**.

5.11.1 Core Functionality

The **launch.py** module manages the startup of spot request instances on *Amazon EC2* or virtual machines on *Microsoft Azure* and waits until the instances are created and are reachable from the network via their public ip's. Subsequently the **run.py** module receives as input the instances on which to configure the cluster (*HDFS* or *Spark*), configures and runs the applications to be executed and waits for the applications to complete. The module **log.py** downloads and saves the logs created by the applications run. The **plot.py** and **metrics.py** modules respectively generate charts and calculate metrics. The **process_on_server.py** module can be called to remotely execute the log analysis, charts generation and metrics calculation on the xSpark master server, and download the results to the client. This option is very useful to speed-up the processing especially in case of sizeable logfiles.

5.11.2 Cloud Environment Configuration

The Cloud environment must be properly initialized in order to allow **xSpark-dagsymb** to access and modify resources in the cloud. We will present the procedure to setup the cloud environment on Microsoft Azure [32]:

Azure Follow the instructions to create an identity called **service principal**² and assign to it all the required permissions:

- 1) Check that your account has the **required permissions**³ to create an identity.
- 2) Create an **Azure Active Directory application**

² <https://docs.microsoft.com/en-us/azure/azure-resource-manager/resource-group-create-service-principal-portal>

³ <https://docs.microsoft.com/en-us/azure/azure-resource-manager/resource-group-create-service-principal-portal?view=azure-cli-latest#required-permissions>

- 3) Get the *Application ID* and an *Authentication Key*⁴. The *Application ID* and *Authentication Key* values replace respectively the <AZ-APP-ID> and the <AZ-SECRET> values in the credentials.json file described in the next paragraph.

5.11.3 Tool Configuration

The **configure.py** module contains the Config class (shown in Listing 5.18) used to instantiate configuration objects that are initialized with default values. The **credentials.json** file, shown in Figure 5.8, contains *Amazon EC2* and/or *Microsoft Azure* credential information. The **setup.json** contains cloud environment and *Amazon EC2* and/or *Microsoft Azure* image parameters. The **control.json** file contains xSpark controller configuration parameters. Information in the **credentials.json**, **setup.json** and **control.json** files are used to customize the configuration object used by other modules during the application execution.

Listing 5.18: Fragment of configuration class Config.

```

1 class Config(object):
2     """
3         Configuration class for xSpark-dagsymb
4     """
5     class Heuristic(Enum):
6         CONTROL = 0
7         FIXED = 1
8         CONTROL_UNLIMITED = 2
9         SYMEX_CONTROL_UNLIMITED = 3
10
11    REGION = ""           #"""Region of AWS to use"""
12    PROVIDER = ""        #"""Provider to be used"""
13    AZ_KEY_NAME = ""     #""" name of Azure private key """
14    AZ_PUB_KEY_PATH = "" #""" path of Azure public key """
15    AZ_PRV_KEY_PATH = "" #""" path of Azure private key """
16    AWS_ACCESS_ID = ""   #""" Azure access id """
17    AWS_SECRET_KEY = ""  #""" Azure secret key """
18    AZ_APPLICATION_ID = "" #""" Azure application id """
19    AZ_SECRET = ""       #""" Azure secret """
20    AZ_SUBSCRIPTION_ID = "" #""" Azure subscription id """
21    AZ_TENANT_ID = ""     #""" Azure tenant id """

```

⁴ <https://docs.microsoft.com/en-us/azure/azure-resource-manager/resource-group-create-service-principal-portal?view=azure-cli-latest#get-application-id-and-authentication-key>

```

22     ...
23     HEURISTIC = Heuristic.SYMEX_CONTROL_UNLIMITED
24     ...
25     def __init__(self):
26         self.config_credentials("credentials.json")
27         self.config_setup("setup.json")
28         self.config_control("control.json")
29         self.update_config_parms(self)
30     ...
31     def config_experiment(self, filepath, cfg):
32         ...
33     def config_setup(self, filepath):
34         ...
35 config_instance = Config()

```

AWS and/or MS-Azure Credentials: Open the *credentials_template.json* file and add the credentials for *xSpark-dagsymb* (see instructions below to retrieve missing credentials):

```

1 {
2     "AzTenantId": "",
3     "AzSubscriptionId": "",
4     "AzApplicationId": "",
5     "AzSecret": "",
6     "AzPubKeyPath": "",
7     "AzPrvKeyPath": "",
8     "AwsAccessId": "",
9     "AwsSecretId": "",
10    "KeyPairPath": ""
11 }

```

Figure 5.8: Credential template file.

Save the file as *credentials.json*.

How to retrieve your Azure credentials (using the Azure Command Line Interface):

Install the **Azure CLI**⁵. Launch the following command from a console terminal:

```
$ az login
```

Note, we have launched a browser for you to login. For old experience with device code, use "az login --use-device-code"

⁵ <https://docs.microsoft.com/it-it/cli/azure/install-azure-cli?view=azure-cli-latest>

A browser authentication windows is open to allow you to login to the Azure portal. If login is successful, you should get an output similar to the following:

```
You have logged in. Now let us find all the subscriptions to which you have access...
```

```
[  
  {  
    "cloudName": "AzureCloud",  
    "id": "< AZ-SUBSCRIPTION-ID >",  
    "isDefault": true,  
    "name": "Microsoft Azure Sponsorship xx",  
    "state": "Enabled",  
    "tenantId": "< AZ-TENANT-ID >",  
    "user": {  
      "name": "*your_username*",  
      "type": "user"  
    }  
  }  
]
```

< AZ-SUBSCRIPTION-ID > and < AZ-TENANT-ID > parameters should be replaced by the actual values from the *credentials.json* file.

Launch the following command from a console terminal to create the private and public RSA cryptography keys:

```
$ ssh-keygen -t rsa
```

Save the generated files in your favorite folder and replace the values < AZ-PUB-KEY-PATH > and < AZ-PRV-KEY-PATH > in the *credentials.json* file respectively with the fully qualified file name of the public and the private keys.

Setup the xSpark and the Virtual Machine Cloud environment: edit the *setup.json* file to set the values to your need. An example using Microsoft Azure VM Cloud Service is shown in Figure 5.9.

5.11.4 Application Profiling: PEP and PEP* generation

Profiling is the first logical phase of the *xSpark_{SEEPEP}* application life-cycle. *xSpark_{SEEPEP}* allows to obtain the PEP* of an application. This can be obtained by launching the profiling command **profile_symex**

```

1  {
2      "Provider": "AZURE",
3      "VM": {
4          "Core": 16,
5          "Memory": "100G"
6      },
7      "ProcessOnServer": false,
8      "InstallPython3": false,
9      "Azure": {
10          "ResourceGroup": "xspark-davide",
11          "SecurityGroup": "cspark-securitygroup2",
12          "StorageAccount": {
13              "Sku": "standard_lrs",
14              "Kind": "storage",
15              "Name": "xsparkstoragedavide"
16          },
17          "Subnet": "default",
18          "NodeSize": "Standard_D14_v2_Promo",
19          "Network": "cspark-vnet2",
20          "Location": "centralus",
21          "NodeImage": {
22              "BlobContainer": "vhdx",
23              "StorageAccount": "xsparkstoragedavide",
24              "Name": "vm3-os.vhd"
25          }
26      },
27      "Spark": {
28          "ExternalShuffle": "true",
29          "Home": "/opt/spark/",
30          "LocalityWaitRack": 0,
31          "CpuTask": 1,
32          "LocalityWaitProcess": 1,
33          "LocalityWait": 0,
34          "LocalityWaitNode": 0
35      },
36      "xSpark": {
37          "Home": "/usr/local/spark/"
38      },
39      "SparkSeq": {
40          "Home": "/opt/spark-seq/"
41      }
42  }

```

Figure 5.9: Example - setup.py file.

followed by the list of experiment files initialized with the input data set identified by the *SEEPEP launchers* and specifying the number n of iterations the single experiment should be repeated.

In profiling mode, experiments are run using the “vanilla” Spark version. Then the **processing.py** module is called to analyze the logs and create the “application profile”, that is a JSON file containing the annotated DAG (*PEP*) of the executed stages plus additional information intended to be used by the controller in the execution phase.

For each experiment the **average_runs.py** module is called to create a JSON profile called $\langle appname \rangle.json$ containing the average values of the n *PEPs* obtained by iterating the n times.

When all the experiments have produced their averaged *PEP*, a JSON file also called *JumboJSON* containing the *PEP** is created by

collecting the averaged *PEPs*. Finally, the *PEP** file and all the *PEPs* are uploaded to the *xSpark* configuration directory of the *xSpark* master server. For example, the command

```
$ python3 xSpark_dagsymb profile_symex -r 5
exp_Louvain_1.json exp_Louvain_2.json
exp_Louvain_3.json
```

runs the profiling of application *Louvain* using launchers data sets 1, 2 and 3 and generating *PEP* files *Louvain_1.json*, *Louvain_2.json*, *Louvain_3.json* and *PEP** file *Louvain.json*.

5.11.5 Application Execution

Applications are executed using *xSpark* , and require the application profile *<appname>.json* to be present in the *xSpark* configuration directory. The name of the application and the experiment parameters are inserted into a JSON format “experiment files” and passed as commandline arguments to the *submit_symex* command. As an example, an experiment files for *CallsExample* and one for *Louvain* are shown here below:

```
CallsExample experiment file example:
{
    "Deadline": 91200,
    "AppName": "CallsExample-6",
    "MetaProfileName": "CallsExample",
    "AppJar": "dagsymb/target/dagsymb-1.0-jar-with-dependencies.jar",
    "AppClass": "it.polimi.deepse.dagsymb.launchers.Launcher",
    "GuardEvaluatorClass": "it.polimi.deepse.dagsymb.examples
                            .GuardEvaluatorPromoCallsFile",
    "NumPartitions": 500,
    "AppConf": {
        "0": {"Name": "threshold", "Value" : 10060000},
        "1": {"Name": "minLocalLongCalls", "Value" : 10060000},
        "2": {"Name": "minAbroadLongCalls", "Value" : 10060000},
        "3": {"Name": "pastMonths", "Value" : 2},
        "4": {"Name": "last24HLocalCallsLength", "Value" : 16100000},
        "5": {"Name": "last24HLocalCallsSize", "Value" : 16140000},
        "6": {"Name": "last24HAbroadCallsLength", "Value" : 20030000},
        "7": {"Name": "last24HAbroadCallsSize", "Value" : 20030000},
```

```

    "8": {"Name": "MonthCallsLength", "Value" : 29900000},
    "9": {"Name": "MonthCallsSize", "Value" : 30000000}
}
}

Louvain experiment file example:
{
  "Deadline": 287040,
  "AppName": "Louvain-2",
  "MetaProfileName": "Louvain",
  "AppRepo": "https://github.com/gioenn/louvain-modularity-spark.git",
  "AppBranch": "master",
  "AppJar": "louvain/target/louvainspark-1.0-SNAPSHOT-jar-with-
              dependencies.jar",
  "AppClass": "it.polimi.dagsymb.launchers.LouvainLauncher",
  "GuardEvaluatorClass": "it.polimi.dagsymb.GuardEvaluatorLouvain",
  "NumPartitions": 500,
  "DataMultiplier" : 1,
  "DeadlineMultiplier" : 1,
  "AppConf": {
    "0": {"Name": "inputFile", "Value" : "/louvain_2.txt"},
    "1": {"Name": "outputFile", "Value" : "/louvain_2-out"},
    "2": {"Name": "parallelism", "Value" : 500},
    "3": {"Name": "minimumCompressionProgress",
           "Value" : -2147483648},
    "4": {"Name": "progressCounter", "Value" : 2},
    "5": {"Name": "delimiter", "Value" : ","},
    "6": {"Name": "size", "Value" : 9999970},
    "7": {"Name": "id1", "Value" : 0},
    "8": {"Name": "id2", "Value" : 1}
  }
}

```

Many files are downloaded from the xSpark Master and Slaves containing application log information and system resources utilization, that are processed to create resource utilization reports and statistics and a series of charts about the application progress, the worker progress, including application and stages deadlines, actual execution times and cpu utilization. One of the features that was added by this work is the creation of Matlab interactive and zoomable charts that allow an accurate evaluation of the details of the data shown on the charts. Examples of Matlab charts, contained in the Matlab executable

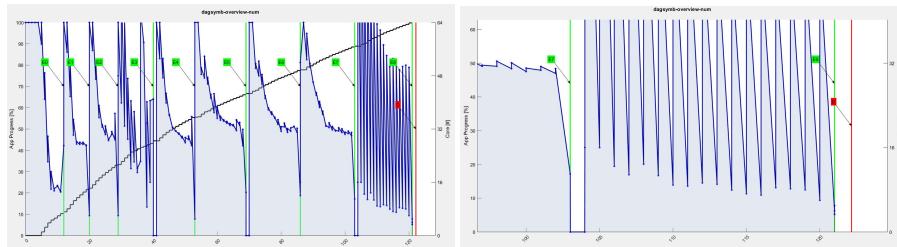


Figure 5.10: Example - Application Matlab Chart.

Figure 5.11: Example - Zoomed Application Matlab Chart.

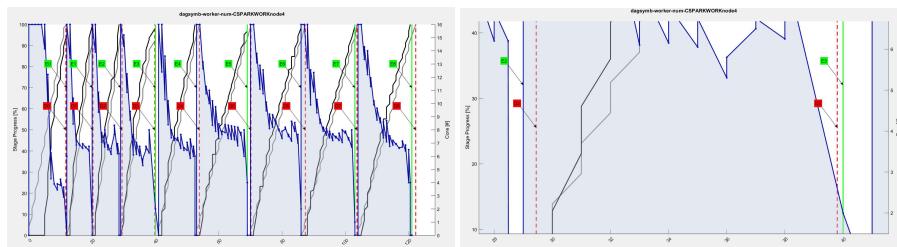


Figure 5.12: Example - Worker Matlab Chart.

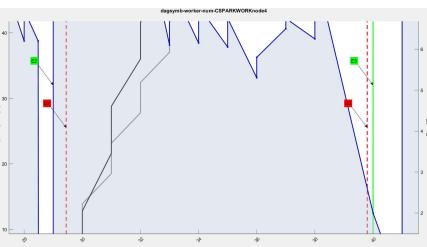


Figure 5.13: Example - Zoomed Worker Matlab Chart.

file charts.m are shown in Figure 5.10, Figure 5.11, Figure 5.12, Figure 5.13

5.11.6 Download & Requirements

```
$ git clone https://github.com/gioenn/xSpark-dagsymb.git
$ cd xSpark-dagsymb
$ pip3 install -r requirements.txt"
```

5.11.7 xSpark-dagsymb commands

xSpark-dagsymb run command syntax:

```
$ cd xSpark-dagsymb
$ python3 xSpark_dagsymb.py *command [*args]*
```

command [*args] syntax:

```
[setup | reboot | terminate | log | check |
```

```
profile_symex | submit_symex | launch_exp] [*args*]
```

where *args* is a set of command-specific arguments list or options.

***setup* command syntax:**

```
setup [hdfs | spark | all | generic]
      {[-n | --num-instances] *numinstances*}
      {[ -y | --assume-yes]}
```

where *numinstances* is the number of nodes to add to the specified cluster (default is 5), *-y* or *--assume-yes* option sets default affirmative answer to interactive confirmation requests.

***reboot* command syntax:**

```
reboot [hdfs | spark | all | generic]
```

reboots all nodes in the specified cluster.

***terminate* command syntax:**

```
terminate [hdfs | spark | all | generic]
```

deletes (destroys) all nodes and their connected resources in the specified cluster.

***check* command syntax:**

```
check [hdfs | spark | all | generic]
```

checks the status of all nodes in the specified cluster.

***profile_symex* command syntax:**

```
profile_symex [*exp_file_paths*] {[ -r | --num-runs] *numruns*}
              {[ -R | --reuse-dataset]}
              {[ -q | --spark-seq]}
```

where *exp_file_paths* is a non-empty space separated list of experiment file paths, *numruns* is the number of times to repeat the profiling for each experiment file (default is 1), *-R* or *--reuse-dataset* option instructs xSpark to reuse (not to delete) application data in hdfs master node, *-q* or *--spark-seq* option instructs xSpark to use Spark data sequencing home directory.

***submit_symex* command syntax:**

```
submit_symex [*exp_file_paths*] {[[-r | --num-runs] *numruns*]
{[-R | --reuse-dataset]}
```

where **exp_file_paths** is a non-empty space separated list of experiment file paths, **numruns** is an integer specifying the number of times to repeat the profiling for each experiment file (default is 1), *-R* or *--reuse-dataset* option instructs xSpark to reuse (not to delete) application data in hdfs master node.

5.11.8 Example: Profile and Test CallsExample

- 1) Create the credential.json file as instructed above.
- 2) Configure the setup.json file as instructed above.
- 3) Configure the control.json file as instructed above.
- 4) Create and initialize a hdfs cluster with 5 nodes:

```
$ python3 xSpark_dagsymb.py setup hdfs -n 5
```

- 5) Create and initialize a spark cluster with 5 nodes:

```
$ python3 xSpark_dagsymb.py setup spark -n 5
```

- 6) Create *CallsExample_1.json* *CallsExample_2.json* file with the following contents:

CallsExample_1.json:

```
{
    "Deadline": 150000,
    "AppName": "CallsExample-1",
    "MetaProfileName": "CallsExample",
    "AppJar": "dagsymb/target/dagsymb-1.0-jar-with-dependencies.jar",
    "AppClass": "it.polimi.deepse.dagsymb.launchers.Launcher",
    "GuardEvaluatorClass": "it.polimi.deepse.dagsymb.examples.
                                GuardEvaluatorPromoCallsFile",
    "NumPartitions": 500,
    "DataMultiplier" : 1,
    "DeadlineMultiplier" : 1,
    "AppConf": {
```

```

        "0": {"Name": "threshold", "Value" : 1994},
        "1": {"Name": "minLocalLongCalls", "Value" : 1994},
        "2": {"Name": "minAbroadLongCalls", "Value" : 1994},
        "3": {"Name": "pastMonths", "Value" : 0},
        "4": {"Name": "last24HLocalCallsLength", "Value" : 1993},
        "5": {"Name": "last24HLocalCallsSize", "Value" : 1993},
        "6": {"Name": "last24HAbroadCallsLength", "Value" : 1993},
        "7": {"Name": "last24HAbroadCallsSize", "Value" : 1993},
        "8": {"Name": "MonthCallsLength", "Value" : 2990},
        "9": {"Name": "MonthCallsSize", "Value" : 3000}
    }
}

```

CallsExample_2.json:

```
{
    "Deadline": 150000,
    "AppName": "CallsExample-2",
    "MetaProfileName": "CallsExample",
    "AppJar": "dagsymb/target/dagsymb-1.0-jar-with-dependencies.jar",
    "AppClass": "it.polimi.deepse.dagsymb.launchers.Launcher",
    "GuardEvaluatorClass": "it.polimi.deepse.dagsymb.examples.
                                GuardEvaluatorPromoCallsFile",
    "NumPartitions": 500,
    "DataMultiplier" : 1,
    "DeadlineMultiplier" : 1,
    "AppConf": {
        "0": {"Name": "threshold", "Value" : 2600},
        "1": {"Name": "minLocalLongCalls", "Value" : 2600},
        "2": {"Name": "minAbroadLongCalls", "Value" : 2600},
        "3": {"Name": "pastMonths", "Value" : 0},
        "4": {"Name": "last24HLocalCallsLength", "Value" : 2635},
        "5": {"Name": "last24HLocalCallsSize", "Value" : 2635},
        "6": {"Name": "last24HAbroadCallsLength", "Value" : 2635},
        "7": {"Name": "last24HAbroadCallsSize", "Value" : 2635},
        "8": {"Name": "MonthCallsLength", "Value" : 2990},
        "9": {"Name": "MonthCallsSize", "Value" : 3000}
    }
}
```

- 7) Run the Profiling with 5 iterations:

```
$ python3 xSpark_dagsymb.py profile_symex -r 5
```

```
CallsExample_1.json CallsExample_2.json
```

Run the Application Test with 5 iterations:

```
$ python3 xSpark_dagsymb.py submit_symex -r 5  
CallsExample_1.json CallsExample_2.json
```


6

EVALUATION

IN this chapter we describe the experiments we have performed to evaluate the feasibility and quality of the solution and to address the research questions identified in Section 1.3. The evaluation took place by using *xSpark_{SEEPEP}*, which is the integration of *SEEPEP* with xSpark, to control the parallel execution of the Spark applications.

6.1 TEST ENVIRONMENT

The test environment was built on Virtual Machines (from here onward VMs) of type *Standard_D14_v2* [45] provided by Microsoft Azure [33], each of them equipped with 16 CPUs, 112 GiB of memory, 800 GiB of local SSD memory and 6000 Mbps of network bandwidth. This type of VM is optimized for memory usage, with a high memory/core ratio. The os and software packages installed on these VMs are: Canonical Ubuntu Server 14.04.5-LTS [42], Oracle Java 8 [27], Apache Hadoop 2.7.2 [5], Apache Spark 2.0.2 [7] and xSpark. All VM software is stored in a 200 GiB virtual hard drive maintained in the persistent layer of an Azure Blob Storage [24]. The VMs are organized in clusters composed of 5 VMs running HDFS (storing the input datasets) and 5 hosting Apache Spark and xSpark (5 for old xSpark and 5 for xSpark + *SEEPEP*). The Spark cluster runs Spark application either under Spark with the default configuration or under xSpark + *SEEPEP* or xSpark with the configuration parameters shown in Figure 6.1 or in Figure 6.2 respectively.

6.2 TESTED APPLICATIONS

We performed the experiments with two applications: PromoCalls and Louvain. PromoCalls is an example application¹. It resembles a batch application from a telecommunications company that calculates promotional discounts based on the number of daily domestic and foreign calls (calls longer than a parametric threshold) made by customers. If a customer makes more than min_1 local long calls or

¹ <https://github.com/seepep/promocalls>

```

1 {
2   "Alpha": 1.0,
3   "Beta": 0.3,
4   "OverScale": 2,
5   "K": 50,
6   "Ti": 12000,
7   "Tsample": 500,
8   "Heuristic": "SYMEX_CONTROL_UNLIMITED",
9   "CoreQuantum": 0.05,
10  "CoreMin": 0,
11  "CpuPeriod": 100000
12 }

```

Figure 6.1: control.json xSpark_{SEEPEP} configuration parameters.

```

1 {
2   "Alpha": 1.0,
3   "Beta": 0.3,
4   "OverScale": 2,
5   "K": 50,
6   "Ti": 12000,
7   "Tsample": 500,
8   "Heuristic": "CONTROL_UNLIMITED",
9   "CoreQuantum": 0.05,
10  "CoreMin": 0,
11  "CpuPeriod": 100000
12 }

```

Figure 6.2: control.json xSpark configuration parameters.

more than \min_a abroad long calls (or both) in a day, she may receive discounts on the calls made in that day, in the last m months, or in the current month. Only some or all of the discounts may be applied to the customer depending on the possible combinations of the trigger conditions. PromoCalls uses Spark to efficiently analyze the data of all calls and calculate the applicable discounts. PromoCalls was used as a reference application during the development of SEEPEP and for a preliminary assessment of the accuracy of the technique used.

Instead, to evaluate our approach to a real world application, we selected Louvain, a Spark implementation of the Louvain algorithm [15] that we downloaded from a highly ranked GitHub repository². Louvain uses *GraphX*, a Spark library specialized for graph processing, suitable for representing large user networks and analyzing communities belonging to these networks.

6.3 EXPERIMENTS

The experiments were performed on each of the applications subjected to the tests following the procedure described below, which consists of three distinct phases:

- 1 Execution of *SEEPEP* to obtain the path conditions and generate the launchers corresponding to each identified path.
- 2 Profiling the application subject to the test with the launchers generated and obtaining the plans for each path.
- 3 Use of tool to control the execution of the application by feeding it with input data sets larger by one order of magnitude compared to those used to generate the launchers.

² <https://github.com/Sotera/spark-distributed-louvain-modularity>

We have generated at least one large data set for each profiled path. We also set a reasonable deadline, that is 20% longer than the minimum deadline, measured by running the application on Spark configured to use all the resources available on the clusters, and with the same data sets used in the experiments .

The datasets were randomly generated using *SEEPEP*.

The comparison of *xSpark_{SEEPEP}* with the original xSpark version has been done, for each application under test, identifying the best and worst cases, i.e. the paths with the lowest and highest number of stages³. In this way, we have quantified the error that xSpark can generate due to the fact that it ignores which plan was used in the profiling phase.

6.3.1 Results

Results produced by *xSpark_{SEEPEP}* for PromoCalls and Louvain tools, up to the profiling phase, are shown in Tables 6.1 and 6.2. Column Path lists the paths found by *SEEPEP*: 8 unique paths were discovered in both cases.

Column Found shows whether or not *SEEPEP* succeeded in generating a test case (and thus a corresponding profiling launcher) for the identified paths: it was successful in generating test cases for all path of PromoCalls, instead it was able to identify 6 out of 8 possible paths of Louvain⁴. As a matter of fact, we currently have no clue if Louvain can execute these program paths or not.

Column Jobs and column Stages report the number of jobs and stages collected when profiling the launchers with xSpark, which range between 3 and 9 jobs, 3 and 9 stages for Promocalls, and 11 and 17 jobs, 73 and 364 stages for Louvain, respectively. These data are not available for the two paths of Louvain for which *SEEPEP* did not generate a launcher. We marked with • and † the paths corresponding to the best and worst case, respectively, of each application in both tables.

The effectiveness of *xSpark_{SEEPEP}* to control the execution of the tested applications, whose inputs were fed with large datasets, is measured by the results of our experiments that are summarized in

³ In case two paths have the same number of stages, we chose the path with the shortest/longest execution time respectively for the best/worst case.

⁴ The two paths of Louvain for which *SEEPEP* was not successful in identifying a corresponding test case were manually inspected. In any case, the proof that either these paths are infeasible, or an input datasets can be identified that exercise these paths, is missing.

Path	Found	#Jobs	#Stages
0	Yes	6	6
1*	Yes	3	3
2	Yes	7	7
3	Yes	6	6
4	Yes	8	8
5	Yes	7	7
6†	Yes	9	9
7	Yes	8	8

Table 6.1: PromoCalls paths.

Path	Found	#Jobs	#Stages
0	Yes	11	149
1	Yes	17	364
2†	Yes	17	364
3	Yes	11	149
4	No	-	-
5	No	-	-
6	Yes	17	364
7*	Yes	8	73

Table 6.2: Louvain paths.

Tables 6.3 and 6.4. These tables also include the results obtained with the original version of xSpark, tuned on the worst and best case datasets mentioned above, and allow us to compare $xSpark_{SEEP}$ against xSpark. The meaning of each column of the tables is explained here below.

For each profiled path P_i , column Experiment indicates the data obtained with $xSpark_{SEEP}$ ($xSpark_s$), and xSpark configured with the worst-case dataset ($xSpark_w$) and with the best-case dataset ($xSpark_b$), respectively. In column deadline we show the set deadline in seconds. In column exec_time the actual execution time of the application is reported in seconds, as the average of 5 iterations of the experiments (for a total of 120 executions of PromoCalls (8 paths \times 5 repetitions \times 3 modes) and 90 executions of Louvain). In column violation we show the deadline violations (i.e., $exec_time > deadline$). The error is quantified in column error, defined as:

$$\text{error} = \frac{|deadline - exec_time|}{deadline} \cdot 100\%$$

that is, the percentage change vs. the deadline of the distance between the actual execution time and the deadline itself. In general the smaller error, the more efficient is the resource allocation, provided that the deadline is not violated, since less resources were used to meet the goal. On the other hand, if the deadline is violated, to smaller errors correspond shorter delays. Note that if the deadline were to be considered strict, the penalty for a violation would be considered of

Experiment	deadline[s]	exec_time[s]	violation	error	core_alloc[core/s]	penalty
xSpark _s	91.4	90.3	No	1.2%	41.3	—
P ₀ xSpark _w	91.4	88.0	No	3.8%	53.0	28.3%
xSpark _b	91.4	143.0	Yes	56.4%	30.6	∞
xSpark _s	56.4	46.0	No	18.4%	56.2	—
P ₁ xSpark _w	56.4	45.3	No	19.6%	56.5	0.5%
xSpark _b	56.4	55.3	No	1.9%	38.2	-33.6%
xSpark _s	107.8	106.3	No	1.3%	39.2	—
P ₂ xSpark _w	107.8	104.0	N	3.5%	52.1	32.9%
xSpark _b	107.8	175.0	Yes	62.4%	29.0	∞
xSpark _s	87.5	86.0	No	1.7%	42.4	—
P ₃ xSpark _w	87.5	83.0	No	5.1%	53.5	26.2%
xSpark _b	87.5	138.0	Yes	57.8%	30.1	∞
xSpark _s	147.6	146.0	No	1.1%	37.0	—
P ₄ xSpark _w	147.6	130.0	No	11.9%	51.4	38.9%
xSpark _b	147.6	228.0	Yes	54.5%	28.4	∞
xSpark _s	77.0	75.3	No	2.2%	41.0	—
P ₅ xSpark _w	77.0	70.0	No	9.1%	53.7	30.9%
xSpark _b	77.0	122.0	Yes	58.4%	29.7	∞
xSpark _s	122.2	120.3	No	1.5%	39.2	—
P ₆ xSpark _w	122.2	120.7	No	1.2%	43.6	11.3%
xSpark _b	122.2	204.0	Yes	67.0%	27.9	∞
xSpark _s	112.1	110.7	No	1.3%	39.2	—
P ₇ xSpark _w	112.1	100.0	No	10.8%	53.0	35.2%
xSpark _b	112.1	180.0	Yes	60.6%	28.8	∞

Table 6.3: Results for PromoCalls

Experiment	deadline [s]	exec_time [s]	violation	error	core_alloc [$\frac{\text{core}}{\text{s}}$]	penalty
xSpark _s	184.3	180.1	No	2.3%	35.9	—
P ₀ xSpark _w	184.3	142.0	No	23.0%	46.1	28.4%
xSpark _b	184.3	222.3	Yes	20.6%	15.2	∞
xSpark _s	228.0	227.0	No	0.4%	32.3	—
P ₁ xSpark _w	228.0	222.0	No	2.6%	33.2	2.8%
xSpark _b	228.0	329.3	Yes	44.4%	7.4	∞
xSpark _s	292.8	290.7	No	0.7%	32.3	—
P ₂ xSpark _w	292.8	289.0	No	1.3%	32.5	0.5%
xSpark _b	292.8	429.0	Yes	46.5%	7.0	∞
xSpark _s	228.7	226.0	No	1.2%	35.5	—
P ₃ xSpark _w	228.7	211.3	No	7.6%	41.4	16.6%
xSpark _b	228.7	292.0	Yes	27.7%	16.0	∞
xSpark _s	163.0	159.4	No	2.2%	38.4	—
P ₆ xSpark _w	163.0	158.0	No	3.0%	39.8	3.8%
xSpark _b	163.0	242.0	Yes	48.5%	8.5	∞
xSpark _s	156.0	139.0	No	10.9%	33.2	—
P ₇ xSpark _w	156.0	131.5	No	15.7%	43.6	31.4%
xSpark _b	156.0	152.7	No	2.1%	30.9	-7.0%

Table 6.4: Results for Louvain

infinite value [40]. In column `core_alloc` we show the average core allocation during the execution, that is defined as:

$$\text{core_alloc} = \frac{\sum_{s=0}^{\text{exec_time}} \text{coresAllocatedAtSecond}(s)}{\text{exec_time}}$$

We remark that the maximum value of `core_alloc` is 64 core/second since 64 is the number of cores provided by the cluster used for these experiments.

In the last column `penalty` we quantify the performance of $x\text{Spark}_{\text{SEEP}}_{\text{PEP}}$ compared to xSpark when executing the same experiment: `penalty` is defined as:

$$\text{penalty} = \begin{cases} \frac{\text{ru}_{\text{WORST}} - \text{ru}_{\text{BEST}}}{\text{ru}_{\text{SEEP}}_{\text{PEP}}} \cdot 100\%, & \text{if violation} = \text{No} \\ \infty, & \text{if violation} = \text{Yes} \end{cases}$$

Remarkably in our experiments, $x\text{Spark}_{\text{SEEP}}_{\text{PEP}}$ never violated the deadline, hence `penalty` measures the amount of resources that either $x\text{Spark}_w$ or $x\text{Spark}_b$ have used with respect to $x\text{Spark}_{\text{SEEP}}_{\text{PEP}}$. E.g. a penalty of 30% means that xSpark used 30% more resources than $x\text{Spark}_{\text{SEEP}}_{\text{PEP}}$. Instead, a negative penalty means that xSpark used less resources than $x\text{Spark}_{\text{SEEP}}_{\text{PEP}}$. Lastly, when the deadline is violated by either $x\text{Spark}_w$ or $x\text{Spark}_b$, we consider `penalty` to be infinite [40].

As evidenced by the data in Tables 6.3 and 6.4, $x\text{Spark}_b$ violated the deadline in 7 out of 8 paths in the experiments with `PromoCalls`, and 5 out of 6 paths in the experiments with `Louvain`. This is due to the optimistic, yet wrong, estimations made in the profiling phase. To explain this behaviour, we have to consider that, for `PromoCalls`, $x\text{Spark}_b$ computes the local deadlines and the resource allocation as if the *PEP* always consisted of 3 stages. As a consequence, in all the experiments but P_1 (which is the actual best-case path) xSpark under allocates resources, resulting in the execution time eventually exceeding the deadline by as much as 51.9%. We measured the highest error displacement, equals to 67.0%, with the worst-case path P_6 where xSpark faces the widest gap between the profiling estimations and the actual runtime workload.

In the same tables we can appreciate that $x\text{Spark}_w$ does not violate any deadline, on the contrary it causes the earlier termination of the applications in most of the cases, with an error between 1.2% and 19.6% in the case of `PromoCalls`, and between 1.3% and 23% in the case of `Louvain`. This behaviour depends on the pessimistic, yet wrong, estimations made in the profiling phase, that mistakenly consider the

worst-case path of the applications to represent all the possible paths. When considering paths P_1 , P_4 , P_5 and P_7 of PromoCalls, and P_0 , P_3 and P_7 of Louvain, the error is greater than 7%, leading to significantly sub-optimal resource allocations.

Remarkably, and on the contrary, $xSpark_{SEEP}$ does not violate any deadline and successfully provides an efficient resource allocation. The average error measured in our experiments is equal to 3.6% for PromoCalls, where for $xSpark_b$ and $xSpark_w$ is 52.4% and 8.1%, respectively, and equal to 2.9% for Louvain, where $xSpark_b$ and $xSpark_w$ have an average error of 31.6% and 8.9%, respectively.

The data in columns `core_alloc` confirm that $xSpark_{SEEP}$ outperforms the performance of $xSpark_b$ and $xSpark_w$. $xSpark_b$ underestimates allocated resources so as to make $xSpark$ violate the deadlines in all experiments, except for path P_1 in PromoCalls and path P_7 in Louvain (the best cases). In the latter two cases, profiled data match the runtime workload, leading $xSpark_b$ to outperform both $xSpark_w$ and $xSpark_{SEEP}$, and minimizes the error and used resources.

$xSpark_{SEEP}$ allocates an average of 25.5% fewer resources in PromoCalls, and 13.9% in Louvain, with respect to $xSpark_w$.

From the results of our experiments we can evince a positive answer to both research questions RQ₁ and RQ₂, because $xSpark_{SEEP}$ effectively and efficiently controls the allocation of resources during the execution of PromoCalls and Louvain, keeping the execution times within considered deadlines with significantly smaller errors and consuming a lower amount of resources than the original version of $xSpark$.

6.4 THREATS TO VALIDITY

We came up with a considerable trial effort, which has led us to perform a total of 226 experiments on two different applications: a paradigmatic example and a real-world application taken from GitHub. We have shown that *SEEPEP* was able to find a test-case for 14 out 16 of the application paths statically identified with symbolic execution, and demonstrated how $xSpark$ could take advantage from the integration with *SEEPEP*. In this section, we highlight the threats that may constrain the validity of our current results [48]:

Internal Threats. The test cases generated by *SEEPEP* have been slightly modified to increase the size of the datasets (without breaking the path conditions) for the execution of the experiments. This was done to ensure that we could test the desired paths and reliably obtain

different repetitions of the experiments. However, data sets were not created in a totally random way. For this reason, we have preliminary executed some experiments with completely randomly created data sets and have obtained a similar result to the one presented. A broader set of experiments could be done to address this aspect as a matter for future developments.

External Threats. A limit to the generality of the experiments and of the solutions tested may derive from the assumption underlying the choice of the Spark applications that we have considered. We have chosen two applications: one that uses Spark's core transformations and one that uses the *GraphX* entry for graph analysis. To increase the degree of generality of evaluations, an extension of the number and variety of Spark applications is desirable, taking into consideration different types, such as those that exploit machine learning solutions and use SQL.

The experiments demonstrate the validity of our idea, namely that the knowledge of the different *PEPs* generated by the Spark applications helps to analyze and control their performance and execution time. Furthermore, we show that an approach based simply on knowledge of the worst case may be sufficient to limit the number of deadline violations, but is significantly less efficient than the one we obtain with our solution. The results obtained are statistically robust and they show only a small variance.

CONCLUSION

IN the previous chapters we have presented the work done in order to support deadline-based *QoS* constrained multi-*PEP* Spark applications, i.e. applications whose execution flow cannot be represented with a single *Parallel Execution Plan* (*PEP*), and whose actual execution flow is only known at runtime.

This chapter summarizes the conclusion of our work and the future works to improve the solution by extending the field of applicability and optimizing each individual components, to obtain a more complete and efficient solution.

The contribution provided by this thesis consists of the design and the development of *xSpark_{SEEP}PEP*, a solution composed by

- 1 – the integration in xSpark of additional features that exploit the knowledge of the execution plans to manage the allocation of resources at runtime to help achieve the goal of maintaining the execution time of the application within a deadline specified by the user, and
- 2 – the development of a *Python tool* to automate the entire testing lifecycle, including the application profiling, the test execution and reporting of test results.

The results of the evaluation show that *xSpark_{SEEP}PEP* meets all the expectations identified by the research questions formulated in Section [1.3](#), as it misses fewer deadlines and allocate resources more efficiently than xSpark.

Since the current solution focuses on controlling a single application, a future work could be directed at extending *xSpark_{SEEP}PEP* to control multiple concurrent applications.

BIBLIOGRAPHY

- [1] Omid Alipourfard, Hongqiang Harry Liu, Jianshu Chen, Shivaram Venkataraman, Minlan Yu, and Ming Zhang. "CherryPick: Adaptively Unearthing the Best Cloud Configurations for Big Data Analytics." In: *14th Symposium on Networked Systems Design and Implementation*). USENIX Association, 2017 (cit. on p. 4).
- [2] *Apache Flink*. 2019 (cit. on p. 17).
- [3] *Apache Flink Architecture*. 2019 (cit. on p. 17).
- [4] *Apache Hadoop*. 2019 (cit. on pp. xiii, xvii, 2, 9, 10).
- [5] *Apache Hadoop*. <http://hadoop.apache.org>. 2019 (cit. on p. 97).
- [6] *Apache Mesos*. <https://mesos.apache.org>. 2017 (cit. on p. 26).
- [7] *Apache Spark*. <http://spark.apache.org>. 2017 (cit. on p. 97).
- [8] *Apache Spark*. 2019 (cit. on pp. xiii, xvii, 2, 13).
- [9] *Apache Storm*. 2019 (cit. on p. 18).
- [10] *Apache Tez*. 2019 (cit. on p. 2).
- [11] Anonymous Author(s). "Symbolic Execution-driven Extraction of the Parallel Execution Plans of Spark Applications." In: *Proceedings of The 27th ACM Joint European Software Engineering Conference and Symposium on the Foundations of Software Engineering (ESEC/FSE 2019)*. (2019), pp. 1–11 (cit. on pp. 5, 50, 53).
- [12] Roberto Baldoni, Emilio Coppa, Daniele Cono D'Elia, Camil Demetrescu, and Irene Finocchi. "A Survey of Symbolic Execution Techniques." In: *ACM Comput. Surv.* 51.3 (May 2018), 50:1–50:39. ISSN: 0360-0300 (cit. on pp. 30, 34, 35).
- [13] L. Baresi and G. Quattrocchi. "Towards Vertically Scalable Spark Applications." In: *Proc. of Euro-Par 2018: Parallel Processing Workshops*. Springer, 2018 (cit. on pp. 4, 5, 48, 50).
- [14] L. Baresi, S. Guinea, A. Leva, and G. Quattrocchi. *Fine-grained Dynamic Resource Allocation for Big-Data Applications*. Tech. rep. 2018 (cit. on pp. 4, 5, 48, 50).
- [15] Vincent D Blondel, Jean-Loup Guillaume, Renaud Lambiotte, and Etienne Lefebvre. "Fast Unfolding of Communities in Large Networks." In: *Journal of statistical mechanics: theory and experiment* (2008) (cit. on pp. 6, 98).

- [16] D. Cheng, J. Rao, C. Jiang, and X. Zhou. "Resource and Deadline-Aware Job Scheduling in Dynamic Hadoop Clusters." In: *Parallel and Distributed Processing Symposium (IPDPS), 2015 IEEE International*. Institute of Electrical and Electronics Engineers (IEEE), 2015 (cit. on pp. [xiv](#), [xviii](#)).
- [17] *Docker Documentation*. 2019 (cit. on p. [39](#)).
- [18] Schahram Dustdar, Yike Guo, Benjamin Satzger, and Hong-Linh Truong. "Principles of Elastic Processes." In: *IEEE Internet Computing* 15.5 (2011), pp. 66–71 (cit. on pp. [21](#), [23](#)).
- [19] *Gartner*. <https://www.gartner.com/en>. 2019 (cit. on p. [1](#)).
- [20] Giovanni Paolo Gibilisco et al. "Stage Aware Performance Modeling of DAG Based in Memory Analytic Platforms." In: *Proc. of IEEE 9th International Conference on Cloud Computing*. IEEE. 2016 (cit. on p. [48](#)).
- [21] *Google Map-Reduce*. 2019 (cit. on pp. [xiii](#), [xvii](#), [2](#), [9](#)).
- [22] Nikolas Roman Herbst, Samuel Kounev, and Ralf H Reussner. "Elasticity in Cloud Computing: What It Is, and What It Is Not." In: *ICAC*. 2013 (cit. on pp. [21](#), [22](#)).
- [23] Benjamin Hindman, Andy Konwinski, Matei Zaharia, Ali Ghodsi, Anthony D. Joseph, Randy Katz, Scott Shenker, and Ion Stoica. "Mesos: A Platform for Fine-grained Resource Sharing in the Data Center." In: *Proc. of the 8th USENIX Conference on Networked Systems Design and Implementation*. NSDI. USENIX, 2011 (cit. on pp. [xiv](#), [xviii](#)).
- [24] *IDC*. 2019 (cit. on p. [9](#)).
- [25] *Internet Live Statistics*. 2019 (cit. on p. [1](#)).
- [26] M. Islam et al. "dSpark: Deadline-based Resource Allocation for Big Data Applications in Apache Spark." In: *Proc. of the 13th IEEE International Conference on eScience*. 2017 (cit. on pp. [4](#), [48](#), [49](#)).
- [27] *Java 8*. <http://www.oracle.com/technetwork/java/javase/overview/java8-2100321.html..> 2019 (cit. on p. [97](#)).
- [28] Jeffrey O Kephart and David M Chess. "The Vision of Autonomic Computing." In: *Computer* 36 (2003) (cit. on p. [21](#)).

- [29] Rogério de Lemos, Holger Giese, Hausi A. Müller, Mary Shaw, Jesper Andersson, Marin Litoiu, Bradley Schmerl, Gabriel Tamura, Norha M. Villegas, Thomas Vogel, Danny Weyns, Luciano Baresi, Basil Becker, Nelly Bencomo, Yuriy Brun, Bojan Cukic, Ron Desmarais, Schahram Dustdar, Gregor Engels, Kurt Geihs, Karl M. Göschka, Alessandra Gorla, Vincenzo Grassi, Paola Inverardi, Gabor Karsai, Jeff Kramer, Antónia Lopes, Jeff Magee, Sam Malek, Serge Mankovskii, Raffaela Mirandola, John Mylopoulos, Oscar Nierstrasz, Mauro Pezzè, Christian Prehofer, Wilhelm Schäfer, Rick Schlichting, Dennis B. Smith, João Pedro Sousa, Ladan Tahvildari, Kenny Wong, and Jochen Wuttke. "Software Engineering for Self-Adaptive Systems: A Second Research Roadmap." In: *Software Engineering for Self-Adaptive Systems II: International Seminar, Dagstuhl Castle, Germany, October 24-29, 2010 Revised Selected and Invited Papers*. Ed. by Rogério de Lemos, Holger Giese, Hausi A. Müller, and Mary Shaw. Springer Berlin Heidelberg, 2013 (cit. on p. 20).
- [30] Francesco Marconi, Giovanni Quattrocchi, Luciano Baresi, Marcello Bersani, and Matteo Rossi. "On the Timed Analysis of Big-Data Applications." In: *Proc. of the 10th NASA Formal Methods Symposium*. Springer, 2018 (cit. on p. 48).
- [31] Patrick Wendell et al Matei Zaharia Reynold S Xin. "Apache Spark: A unified engine for big data processing." In: *Communications of the ACM* 59 (Nov. 2016), pp. 56–65 (cit. on p. 3).
- [32] Micorosft Azure. <https://azure.microsoft.com/en-us/>. 2019 (cit. on p. 84).
- [33] Micorosft Azure Virtual Machines. <https://azure.microsoft.com/en-us/services/virtual-machines/>. 2019 (cit. on p. 97).
- [34] Andrew Or. *Understanding your Apache Spark Application Through Visualization*. 2019 (cit. on p. 17).
- [35] Poornima Purohit, DR Apoorva, and et al PV Lathashree. "Big data analytics in the cloud: Spark on Hadoop vs MPI/OpenMP on Beowulf." In: *Procedia Computer Science* 53 (Dec. 2015), pp. 121–130 (cit. on p. 3).
- [36] *Running Spark on Mesos*. 2019 (cit. on p. 28).
- [37] *Running Spark on YARN*. 2019 (cit. on p. 26).

- [38] Mythreyee S, Poornima Purohit, Apoorva D.R., Harshitha R, and Lathashree P.V. "A Study on Use of Big Data in Cloud Computing Environment." In: *International Journal of Advance Research, Ideas and Innovations in Technology* 3 (2017), pp. 1312–1318 (cit. on pp. [xiii](#), [xvii](#), [20](#)).
- [39] Anuj Sehgal, Vladislav Perelman, Siarhei Kuryla, and Jürgen Schönwälder. "Management of Resource Constrained Devices in the Internet of Things." In: *Communications Magazine, IEEE* 50 (2012) (cit. on p. [21](#)).
- [40] Kang G Shin and Parameswaran Ramanathan. "Real-time Computing: A New Discipline of Computer Science and Engineering." In: *Proceedings of the IEEE* 82 (1994) (cit. on p. [103](#)).
- [41] S. Sidhanta, W. Golab, and S. Mukhopadhyay. "OptEx: A Deadline-Aware Cost Optimization Model for Spark." In: *16th IEEE/ACM International Symposium on Cluster, Cloud and Grid Computing*. 2016 (cit. on pp. [4](#), [48](#), [49](#)).
- [42] *Ubuntu 14.04.5 LTS (Trusty Tahr)*. <http://releases.ubuntu.com/14.04/>. 2019 (cit. on p. [97](#)).
- [43] Vinod Kumar Vavilapalli, Arun C. Murthy, Chris Douglas, Sharad Agarwal, Mahadev Konar, Robert Evans, Thomas Graves, Jason Lowe, Hitesh Shah, Siddharth Seth, Bikas Saha, Carlo Curino, Owen O'Malley, Sanjay Radia, Benjamin Reed, and Eric Baldeschwieler. "Apache Hadoop YARN: Yet Another Resource Negotiator." In: *Proceedings of the 4th Annual Symposium on Cloud Computing*. SOCC '13. Santa Clara, California: ACM, 2013, 5:1–5:16. ISBN: 978-1-4503-2428-1 (cit. on p. [25](#)).
- [44] Abhishek Verma, Ludmila Cherkasova, and Roy H. Campbell. "ARIA: Automatic Resource Inference and Allocation for Mapreduce Environments." In: *Proc. of the 8th ACM International Conference on Autonomic Computing*. ACM, 2011 (cit. on pp. [xiv](#), [xviii](#)).
- [45] *Virtual machine sizes for Azure Cloud services*. <https://docs.microsoft.com/en-us/azure/cloud-services/cloudservices-sizes-specs#dv2-series>. 2019 (cit. on p. [97](#)).
- [46] Danny Weyns, M. Usman Iftikhar, Sam Malek, and Jesper Andersson. "Claims and Supporting Evidence for Self-adaptive Systems: A Literature Study." In: *Proc. of the 7th International Symposium on Software Engineering for Adaptive and Self-Managing Systems*. SEAMS '12. Zurich, Switzerland: IEEE Press, 2012. ISBN: 978-1-4673-1787-0 (cit. on p. [21](#)).

- [47] *What is Big Data.* <https://www.oracle.com/big-data/guide/what-is-big-data.html>. 2019 (cit. on p. 1).
- [48] Claes Wohlin et al. “Empirical Research Methods in Web and Software Engineering.” In: *Web Engineering* (2006) (cit. on p. 104).
- [49] *xSparkDagsymb.* 2019 (cit. on p. 6).
- [50] Matei Zaharia, Dhruba Borthakur, Joydeep Sen Sarma, Khaled Elmeleegy, Scott Shenker, and Ion Stoica. “Delay Scheduling: A Simple Technique for Achieving Locality and Fairness in Cluster Scheduling.” In: *Proc. of the 5th European Conference on Computer Systems*. EuroSys ’10. Paris, France: ACM, 2010. ISBN: 978-1-60558-577-2 (cit. on p. 3).
- [51] Qi Zhang, Lu Cheng, and Raouf Boutaba. “Cloud computing: State of the Art and Research Challenges.” In: *Journal of internet services and applications* 1 (2010) (cit. on p. 21).