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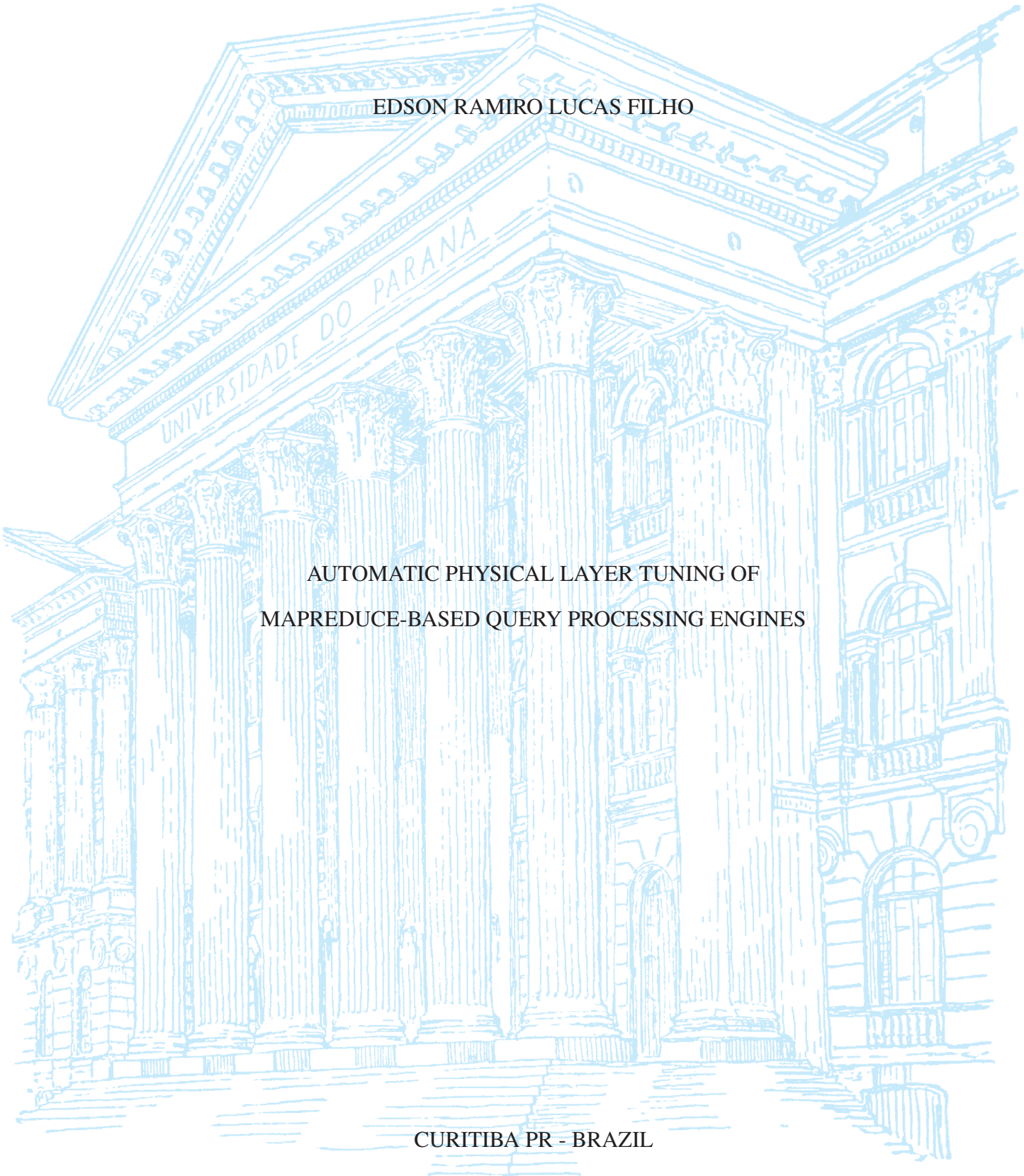


# AUTOMATIC PHYSICAL LAYER TUNING OF MAPREDUCE-BASED QUERY PROCESSING ENGINES

CURITIBA PR - BRAZIL

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EDSON RAMIRO LUCAS FILHO

# AUTOMATIC PHYSICAL LAYER TUNING OF MAPREDUCE-BASED QUERY PROCESSING ENGINES

Tese apresentada como requisito parcial à obtenção do grau de Doutor em Ciência da Computação no Programa de Pós-Graduação em Informática, Setor de Ciências Exatas, da Universidade Federal do Paraná.

Área de concentração: *Ciência da Computação*.

Orientador: Eduardo Cunha de Almeida.

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Os membros da Banca Examinadora designada pelo Colegiado do Programa de Pós-Graduação em INFORMÁTICA da Universidade Federal do Paraná foram convocados para realizar a arguição da tese de Doutorado de **EDSON RAMIRO LUCAS FILHO** intitulada: **Automatic Physical Layer Tuning of MapReduce-based Query Processing Engines**, sob orientação do Prof. Dr. EDUARDO CUNHA DE ALMEIDA, que após terem inquirido o aluno e realizada a avaliação do trabalho, são de parecer pela sua APROVAÇÃO no rito de defesa.

A outorga do título de doutor está sujeita à homologação pelo colegiado, ao atendimento de todas as indicações e correções solicitadas pela banca e ao pleno atendimento das demandas regimentais do Programa de Pós-Graduação.

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*to my wife Alessa*

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*Futuro intangível, impossível, irreal*
*Atrevi-me a sonhar*
*E não por minha força*
*Aqueles sofismas fez desmantelar*
*E o irreal, impossível e intangível*
*Deus fez-me abundar*

*E nesse ímpeto caminho eu*
*Para conhecer um outro eu*
*Sonhado não por mim, mas por Deus*
*Cujos pensamentos são maiores do que os meus*
*Quais os meus não conseguem alcançar*

# RESUMO

A crescente necessidade de processar grandes quantidades de dados semi-estruturados e não-estruturados levou ao desenvolvimento de mecanismos de processamento especializados como o MapReduce. O MapReduce é um modelo de programação projetado para processar grandes quantidades de dados semiestruturados de maneira distribuída e paralela. Os sistemas SQL-on-Hadoop são interfaces SQL construídas sobre os mecanismos de processamento baseados em MapReduce para consultar grandes quantidades de dados semi-estruturados. No entanto, o número de máquinas, o número de sistemas na pilha de software e os mecanismos de controle fornecidos pelos mecanismos do MapReduce aumentam a complexidade e os custos operacionais de um cluster SQL-on-Hadoop. O aumento do desempenho dos motores de processamento MapReduce é um fator chave que pode ser alcançado delegando a quantidade certa de recursos físicos para suas tarefas. No entanto, usuários e até administradores especializados lutam para entender e ajustar as tarefas MapReduce para obter um desempenho melhor. A falta de conhecimento para ajustar as tarefas MapReduce deu origem a uma linha de pesquisa bem-sucedida sobre o ajuste automático dos parâmetros do MapReduce, originando vários Orientadores de Ajuste. No entanto, o problema de ajustar automaticamente as consultas SQL-no-Hadoop permanece amplamente inexplorado, pois a abordagem atual da aplicação dos Orientadores de Ajuste projetados para MapReduce em consultas SQL-on-Hadoop acarreta em vários problemas. Por exemplo, o processador de consultas do Hive, um sistema SQL-on-Hadoop popular, traduz consultas HiveQL em grafos de tarefas MapReduce, e seria fácil supor que, ajustando as configurações do motor de processamento MapReduce, as consultas HiveQL também se beneficiariam. Entretanto, essa suposição não se aplica quando os Orientadores de Ajuste existentes são aplicados ingenuamente às consultas HiveQL devido a arquitetura do Hive, Hadoop e dos Orientadores de Ajuste. Nesta tese tratamos da questão de como ajustar corretamente as consultas SQL-no-Hadoop. Por “corretamente”, entendemos que, ao ajustar as configurações das consultas SQL-no-Hadoop, a geração das configurações deve considerar várias características que

estão presentes apenas em tarefas geradas pelos sistemas SQL-no-Hadoop. Essas características incluem: (i) no caso de consultas individuais, todas as tarefas MapReduce que constituem o plano de consulta desta consulta são executadas com configurações idênticas. (ii) apesar da busca e geração das configurações de ajuste serem realizadas para cada tarefa MapReduce, apenas uma configuração de ajuste é selecionada e aplicada à consulta e as demais configurações de ajuste são simplesmente descartadas. (iii) Os Orientadores de Ajuste do Hadoop tratam as funções do MapReduce como caixas-pretas e fazem suposições de modelagem simplificadoras que podem valer para tarefas clássicas do MapReduce (Sort, Grep), mas não são verdadeiras para consultas do tipo SQL como o HiveQL, onde as tarefas contêm vários operadores de álgebra relacional como junções e agregadores. Estendemos o processador de consultas do Hive para ajustar as consultas SQL-no-Hadoop. Esta extensão compreende uma abordagem chamada de ajuste não-uniforme que permite que os sistemas SQL-on-Hadoop tenham um controle mais refinado da configuração das consultas, onde cada tarefa MapReduce recebe uma configuração especializada. Apresentamos um modelo conceitual, chamado assinatura de código, que usa informações estáticas disponíveis antes da execução de cada tafera para mapear tarefas que tenham padrões de consumo de recursos similares. Também apresentamos um cache que armazena configurações de ajuste, geradas por algum Orientadore de Ajuste, e as recicla entre tarefas que possuem consumo de recursos semelhantes. Nossa extensão funciona em conjunto como uma solução única para o ajuste automático de consultas SQL-no-Hadoop. Para validar nossa solução, realizamos um estudo experimental focado no Hive executando sobre o Hadoop porque (i) O Hive é um bom representante dos sistemas SQL-on-Hadoop nativos (como o System-R fez para os sistemas de bancos de dados relacionais); (ii) o Hive e o Hadoop são altamente populares para processamento analítico; e (iii) O ajuste de parâmetros do Hadoop foi estudado extensivamente nos últimos anos. Para preencher o cache de ajuste, empregamos o Starfish, o primeiro Orientador de Ajuste baseado em custo que encontra configurações (quase) ótimas e é o único Orientador de Ajuste disponível ao público para fins de pesquisa acadêmica. Em nossos experimentos, apresentamos que as consultas otimizadas com nossa abordagem de ajuste apresentaram acelerações de até 25%, contrastando com a abordagem atual que degradou o desempenho em várias ocasiões. Especificamente, a abordagem atual de ajuste pode causar variações no tempo de execução entre -171% e 27% em relação à configuração padrão. Mais importante ainda, nosso método de ajuste leva a uma melhor utilização de recursos, diminuindo o uso da CPU e a paginação de memória em até 40%. Nossa abordagem também reduziu a quantidade total de dados gravados

em discos em $5\times$. Nossa abordagem de ajuste tem um cache usado para evitar a recriação de perfis de tarefas MapReduce semelhantes. Nosso cache reduziu a geração de perfils em 50% para a carga de trabalho TPC-H, permitindo até o ajuste parcial de consultas ad-hoc antes de sua execução. Palavras-chave: Sintonia da camada física. Processamento de consulta em MapReduce. SQL-On-Hadoop.

# ABSTRACT

The increasing need to process large amounts of semi- and non-structured data has led to the development of specialized processing engines like MapReduce. MapReduce is a programming model designed to process large-scale semi-structured data in a distributed and parallel fashion. SQL-on-Hadoop systems are SQL-like interfaces build on top of MapReduce processing engines to query semi-structured data in large-scale. However, the number of computing nodes, the number of systems in the software stack, and the controlling mechanisms provided by MapReduce engines increase the complexity and the operational costs of maintaining a large SQL-on-Hadoop cluster. Increasing performance of such engines is a key factor that can be achieved by delegating the right amount of physical resources. Yet, regular users and even expert administrators struggle to understand and tune MapReduce jobs to achieve good performance. This skill gap has given rise to a successful line of research on automatically tuning MapReduce parameters, originating several tuning advisors. Yet, the problem of automatically tuning SQL-on-Hadoop queries remains largely unexplored today as the current approach of applying MapReduce tuning advisors direct to SQL-on-Hadoop queries entail a number of problems. For instance, the Hive SQL-on-Hadoop engine compiles HiveQL queries into a workflow of MapReduce jobs, and it would be straightforward to assume that by tuning the underlying Hadoop processing engine, HiveQL queries would benefit as well. However, this assumption does not hold when existing tuning advisors are naively applied to HiveQL queries due to the design choices of Hive, Hadoop, and the tuning advisors. This thesis addresses the question of how to properly tune SQL-on-Hadoop queries? By "properly" we mean, when tuning SQL-on-Hadoop queries, the generation of the tuning setups has to consider several characteristics that are only present in jobs generated by SQL-on-Hadoop systems. These characteristics include: (i) at the level of individual queries, all MapReduce jobs that constitute a query plan are executed with identical configuration settings. (ii) despite profiling and search heuristics being performed in a job-basis to generate tuning setups, only one tuning setup is applied to the query and the remaining tuning

setups are simply discarded. (iii) Hadoop tuning advisors treat the MapReduce functions as black boxes and make simplifying modeling assumptions that may hold for classical MapReduce jobs (Sort, Grep), but they are not true for SQL-like queries like HiveQL where jobs contain multiple relational algebra operators like joins and aggregators. We extended the Hive query processor for tune SQL-on-Hadoop queries. This extension comprises an approach called non-uniform tuning that enables SQL-on-Hadoop systems to have a fine-grained control for tuning queries, where jobs receive specialized tuning setups. We present a conceptual model, called code-signature, that uses static information available upfront execution to match jobs with similar resource consumption patterns. We also present a tuning cache that stores tuning setups, generated by third part tuning advisors, and recycle them between jobs that have the similar resource consumption. The extension works together as a single solution for automatic tuning of SQL-on-Hadoop queries. In order to validate our solution, we conduct an experimental study focused on Hive over Hadoop because (i) Hive is a good representative of native SQL-on-Hadoop systems (like System-R did for relational database systems); (ii) both Hive and Hadoop are highly popular for analytical processing; and (iii) Hadoop parameter tuning has been studied extensively in recent years. For populate the Tuning Cache, we employ Starfish, the first cost-based optimizer for finding (near-) optimal configuration parameter settings and the only publicly available tuning advisor for academic research purposes. In our experiments, we present that queries optimized with our tuning approach always presented positive speed ups up to 25%, contrasting the current approach that degraded performance in several occasions. Specifically, the current tuning approach can cause variations in the execution run time between -171% and 27% over default configuration. Most importantly, our tuning method leads to considerable better resource utilization, decreasing CPU usage and Memory paging over 40%. Also reducing the total amount of data written to disks in $5\times$. Our tuning approach has a Tuning Cache used to avoid reprofiling similar jobs. Our Tuning Cache reduced the profilings in 50% for TPC-H queries, enabling upfront tuning of ad-hoc queries. Keywords: Physical-layer tuning. MapReduce query processing. SQL-On-Hadoop.

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# Chapter 1

# Introduction

The progress of computer technology simplified many daily activities in wide aspects, such as, connecting people despite their distances, bringing customers to stores without taken them out of home, and providing a large variety of tailor made services that ranges from movie recommendations to directed product advertisements. The facilities provided by such applications come at the cost of generating, storing and processing large amounts of data. Traditionally, raw data is extracted from one or many sources and, then, transformations such as data cleaning, and filtering are performed. After the data is harvested and standardized with such transformations, it is loaded in a database system for later querying. Data Warehouse systems have been extensively employed in such scenario, also known as the extract-transform-load (ETL) data workflow.

In ETL, data is prepared upfront querying, therefore, the set of transformations must be performed for every new batch of data. More specifically, data have to be stored in a staging area, and then, costly transformations like cleaning, filtering and aggregations are performed. ETL is the most common method for loading large data into database systems. It guarantees that all data is stored following a trustworthy, concise and structured way. Yet, data might be produced at such a high pace that the extraction and transformations become overloaded and hard to manage. Examples include web logs, radio-frequency identification tags, sensor networks, and social networks (Vaisman and Zimnyi, 2016). One of the solutions for this problem is to provide the data warehouse capabilities directly on raw non-structured and semi-structured data sets, or to provide processing engines that are capable of scaling out such transformations according to the pace of data production.

The increasing need to process large amounts of semi- and non-structured data has led to the development of specialized processing engines like MapReduce (Dean and Ghemawat, 2004).

MapReduce was primarily designed for batch processing of long-running jobs on clusters of commodity machines, as a solution for cheap processing of non-structured data. In MapReduce, jobs are handcrafted to compute, for instance, distributed sort and grep, to count URL access frequency, to build term-vectors per host, reverse web-link graphs, web-page rankings, and inverted indexes (Dean and Ghemawat, 2004). MapReduce restricts such handcrafted transformations in pre-defined functions to ease the parallelization of large computations, hiding from the developers the common problems of distributed processing (e.g., data synchronization, data replication, concurrency control, task scheduling, fault tolerance), and transparently coordinating the execution of custom jobs across thousands of nodes. MapReduce is the precursor of such data processing engines and its architecture and programming model is largely adopted as a canonical representation, originating several others including Hadoop (Dean and Ghemawat, 2004), Dryad (Isard et al., 2007), Spark (Armbrust et al., 2015a), Flink (Apache Software Foundation, 2015), and Mammoth (Shi et al., 2015).

Later, the programming support to other use cases, including interactive (Agarwal et al., 2013), graph (Sakr et al., 2017), streaming (Katsifodimos and Schelter, 2016) and analytical (Thusoo et al., 2009) workloads, was introduced by systems built on top of MapReduce-based processing engines. Regarding analytical workloads, support is provided by SQL-like interfaces such as Pig (Gates et al., 2009), Hive (Thusoo et al., 2009) and SparkSQL (Armbrust et al., 2015a). In such interfaces, also known as SQL-On-Hadoop systems (Chen et al., 2014; Floratou et al., 2014; Pokorny, 2011; Stonebraker, 2010; Stonebraker et al., 2010), declarative queries are evaluated over data typically stored in distributed file systems such as the Hadoop Distributed File System (HDFS) (Shvachko et al., 2010), then, they are converted to MapReduce jobs by the SQL-on-Hadoop's query processor. Hive (Thusoo et al., 2010) was the first SQL-on-Hadoop system to provide an SQL-like query language, namely HiveQL (Thusoo et al., 2010), and can use MapReduce or Tez as its underlying processing engine for executing queries. Shark (Xin et al., 2013) and SparkSQL (Armbrust et al., 2015b) also support HiveQL but use the Spark processing engine as their runtime instead of MapReduce. On the other hand, Impala (Kornacker et al., 2015) uses its own processing engine to execute queries, bypassing the MapReduce computing model in order to provide better support for interactive queries. Similar to Impala, Apache Tajo (tajo), Presto (presto), and Drill (drill), also utilize a custom runtime for processing SQL queries following a shared-nothing parallel database architecture.

Facebook reports that their Hive data warehouse stores more than 15PB of data and loads more than 60TB of new data every day (Menon, 2012; Thusoo et al., 2009; Thusoo et al., 2010). All this data is stored in the Hadoop processing engine, more specifically, in its underlying distributed file system (HDFS), and both run together over thousands of machines (Borthakur et al., 2011). Compression is applied to reduce the amount of stored data (with reported compression ratio of 1:7). However, the amount of stored data is usually increased by a factor of $3\times$ or more because HDFS uses data replication as a fail-over mechanism. The replication of the data, together with other internal controlling mechanisms (that hide from developers the problems of processing such distributed queries, *e.g.*, concurrency control, task scheduling, data synchronization) inflict such an impact in the operational costs of maintaining a large SQL-on-Hadoop cluster as well as in the performance of the MapReduce processing engines (Ciritoglu et al., 2018; Zaharia et al., 2008). In this scenario, performance can be understood in terms of execution run time as well as in terms of resource consumption. Thus, deploying SQL-on-Hadoop systems to execute distributed queries over large amounts of data is advantageous because it widely facilitates and simplifies the daily activities of database administrators and data scientists. Yet, it comes at high operational costs due to the number of computing resources (e.g, disk, network) required to provide a reliable framework to run such distributed queries.

Increasing performance is a key driving factor that can be achieved by delegating the right amount of physical resources to jobs (e.g., memory size, number of cores). The performance of the underlying processing engines (such as MapReduce and Spark) and custom runtimes (e.g., of Impala, Tajo) is governed via a large number of configuration parameters that control memory distribution, I/O optimization, task parallelism, and data compression (Herodotou et al., 2011; Ding et al., 2015; Bei et al., 2017). For example, both MapReduce and Spark have over 200 parameters each, out of which 20-40 can have significant impact on the performance and stability of the cluster. Several studies have shown that MapReduce jobs can experience up to an order of magnitude difference in execution time between good and bad parameter settings (Babu, 2010; Jiang et al., 2010).

However, regular users and even expert administrators struggle to understand and tune them to achieve good performance. A recent report highlights that the proliferation of MapReduce goes hand-in-hand with continuous lamentations regarding the lack of professionals who can tune a Hadoop cluster (Heudecker and Adrian, 2015). This skills gap has given rise to a successful line of research on automatically tuning MapReduce and Spark parameters, originating several

tuning advisors that employ a variety of techniques such as cost models, simulation, and machine learning (Liu et al., 2015; Liao et al., 2013; Shi et al., 2014; Liu et al., 2012; Bei et al., 2016; Li et al., 2014b; Bei et al., 2017; Van Aken et al., 2017; Herodotou et al., 2011, 2020). These tuning advisors are designed specially for tuning common MapReduce workloads (Sort, Grep, WordCount). However, employing them straightforwardly to SQL-on-Hadoop queries entails a number of problems.

Shared-nothing parallel database systems support a vast set of multi-tenant workloads, yet, no configuration tuning approach works well universally (Abadi et al., 2020). This thesis presents a set of techniques and mechanisms to overcome the problems that arise when applying MapReduce tuning advisors to tune SQL-on-Hadoop queries. We focus on physical-layer tuning of SQL-on-Hadoop queries, i.e., the allocation of the right amount of physical resources (*i.e.,* memory, cores, bandwidth) to queries in order to reduce the execution costs (*i.e.*, running time, resource usage). For example, in MapReduce, regulating the size of memory buffers leads queries to spill less data into disk, consequently, making less disk operations; also, increasing the number of threads may speed up queries by increasing the degree of parallelism.

We conduct an experimental study focused on Hive over Hadoop because (i) Hive is a good representative of native SQL-on-Hadoop systems (like System-R did for relational database systems); (ii) both Hive and Hadoop are highly popular for analytical processing; and (iii) Hadoop parameter tuning has been studied extensively in recent years (Khaleel, 2018; Cai et al., 2017; Deshpande et al., 2018; Khan et al., 2017; Kumar et al., 2017; Jain, 2017; Bei et al., 2017; Lee and Fortes, 2016; Zhang et al., 2016). We explore the impact of Hadoop parameter tuning on Hive, identify the potential use of existing Hadoop tuning advisors for optimizing Hive performance, and propose a set of mechanisms for parameter tuning of SQL-on-Hadoop systems. For tuning Hadoop, we employ Starfish (Herodotou et al., 2011; Herodotou and Babu, 2011), the first cost-based optimizer for finding (near-) optimal configuration parameter settings and the only publicly available tuning advisor for academic research purposes.

## 1.1 Problem Statement

MapReduce-based processing engines expose a vast number of configuration parameters that regulate the amount of physical resources given to jobs. Such configuration parameters highly influences the performance of the jobs (good parameter settings are proven to speed up execution

up to an order of magnitude (Babu, 2010; Jiang et al., 2010)). When submitting a MapReduce job, administrators can configure it by hard-coding its configuration in the source code, or instrumenting it via command line. In both cases, the configuration parameters are set in a job basis, where jobs have different configuration settings according to their requirements. Note, the optimal amount of resources required by each job differs because they process different operations over different data sets.

These settings can be configured not only by administrators, which are the deep connoisseurs of the infrastructure and the most recommended experts to determine the tuning values, but also by developers, who might be greedy in delegating resources expecting that their jobs finish as soon as possible. However, since finding the optimal tuning setup for a single job is time consuming and error prone, MapReduce processing engines delegate the tuning activity to tuning advisors. Several MapReduce tuning advisors calculate the (near-) optimal configuration settings at the cost of a high overhead due to the requirements for calculating such tuning setups.

A MapReduce tuning advisor monitors a test-run of the job to measure its resource consumption, generating a representation called *execution profile*. Given an execution profile, the tuning advisor employs a modeling technique (e.g., cost or analytical modeling, machine learning, simulation) to estimate the execution time of the given job under a given tuning setup (Glushkova et al., 2019; Zhang et al., 2013a; Song et al., 2013; Cherkasova, 2011). These models commonly represent the environment where jobs are executed, more specifically, the underlying processing engine and hardware, which makes tuning advisors very attached to specific software versions. Then, the tuning advisor enumerates and search over the high-dimensional space of parameter values in order to identify the tuning setup that will produce the smallest execution time. Different advisors will employ different search strategies, ranging from grid search and exhaustive enumeration to hill climbing and genetic algorithms.

Similar to tuning a MapReduce job, a Hive administrator can tune a HiveQL statement by assigning the tuning setup in the query code, or when submitting the query via Hive command line. However, *the generation of the tuning setup and its impact in the performance of the HiveQL query is influenced by several aspects that are only present in jobs generated by SQL-on-Hadoop systems* . For instance, Hive translates a given HiveQL statement to a workflow of MapReduce jobs to be executed on Hadoop or Tez. Precisely, a HiveQL statement is parsed and validated against the data dictionary, compiled into a tree of logical operators, and finally optimized to produce a physical query execution plan (Floratou et al., 2014; Thusoo et al., 2010). This

allows for various logical optimizations such as selection and projection pushdowns, as well as join reordering and join physical method selection. The final execution plan has the form of a Directed Acyclic Graph (DAG) of MapReduce *jobs*, where each job is executed on the cluster as a set of parallel Map and Reduce *tasks*. During the generation of the final execution plan, *Hive replicates the given tuning setup to all jobs in the query plan, i.e., at the level of individual HiveQL queries, all MapReduce jobs that constitute a query plan are executed with identical configuration settings*.

The replication of the same configuration settings to all jobs in the query plan restricts the tuning to a query-level and forbid developers and administrators to tune jobs of the same query plan separately. Hence, when administrators are tasked with tuning a query, they must find a single setting of parameter values to use on a per-query basis, or even for the complete query workload. Even with the help of a MapReduce tuning advisor, the same tuning setup will still be replicated to the entire query plan, driving SQL-on-Hadoop queries to under-perform. For instance, a job may need a tuning setup for disk intensive sequential scan operations, but it receives a tuning generated for a job with memory bound sort operations (see Chapter 5).

When MapReduce tuning advisors are applied for tuning SQL-on-Hadoop queries, they generate tuning setups in a job basis, *i.e.*, *MapReduce tuning advisors will profile and run search heuristics to find the (near-) optimal tuning setup for every job in the query plan. Yet, only one tuning setup is selected for tuning the query, and the remaining tuning setups are simply discarded*. In this case, an important amount of time is wasted for generating tuning setups that will never be used, adding an unnecessary overhead for the entire tuning activity. Also, there is no guarantee that the selected tuning setup is the best choice for tuning the query.

Administrators may test-run all generated tuning setups in order to find the best tuning setup among generated ones. In a few specific scenarios, such as running analytic queries repeatedly in a static environment, it may be acceptable to spend so much time in test-runs. However, dynamic aspects that are common in the life cycle of SQL-on-Hadoop systems like the continuous growth of the data, updates in the data sets, as well as updates in the hardware and software stacks would force administrators to re-evaluate the test-runs frequently. Thus, constantly re-evaluate all test-runs for such a dynamic ecosystem is impractical.

The propagation of the same tuning setup and the dynamic aspects of the SQL-on-Hadoop ecosystems are not the only factors that complicate the tuning of SQL-on-Hadoop queries. For instance, jobs compiled by Hive have different characteristics from classical

MapReduce jobs due to the application of common MapReduce optimizations including chain folding and job merging (Miner and Shook, 2012a). These optimizations make jobs compiled from SQL-on-Hadoop queries to contain multiple relational algebra operators, which makes them to have different and more complex resource consumption patterns than common MapReduce jobs (e.g., Sort, Grep).

However, *almost all Hadoop tuning advisors treat the Map and Reduce functions as black boxes and make simplifying modeling assumptions*. For example, some make the proportionality assumption (Herodotou and Babu, 2011), based on which the execution time of a function will double if its input size is doubled. *This assumption may hold for classical MapReduce jobs like Grep, but it is not true for jobs that contain multiple relational algebra operators like joins and aggregators*. Hence, the modeling, and consequently the tuning recommendations, might not be optimal. Also, performance dependencies between jobs complicate the performance modeling made by MapReduce tuning advisors. For example, setting the number of Reduce tasks or enabling output compression for one MapReduce job will affect the performance of the subsequent job as it will affect the number of Map tasks and the need for decompression for the second job, respectively.

## 1.2 Research Question

The problem of automatically tuning SQL-on-Hadoop queries remains largely unexplored today. Thus, given that Hive compiles HiveQL queries into a workflow of MapReduce jobs, it would be straightforward to assume that *by tuning the underlying Hadoop processing engine, HiveQL queries would benefit as well*. However, this assumption does not hold when using the existing tuning advisors naively, due to the design choices of Hive, Hadoop, and the tuning advisors.

This thesis addresses the question: *How to properly tune SQL-on-Hadoop queries?* By properly we mean, when tuning SQL-on-Hadoop queries, the generation of the tuning setups has to consider several characteristics that are only present in jobs generated by SQL-on-Hadoop systems. These characteristics include:

I. *Hive replicates the given tuning setup to all jobs in the query plan, i.e., at the level of individual HiveQL queries, all MapReduce jobs that constitute a query plan are executed with identical configuration settings*. This replication of tuning setup through the query plan is not a problem specific to Hive, but is present in other SQL-on-Hadoop

systems. This happens due to architectural design choices, and requires extending current SQL-on-Hadoop query processors to enable support job-specific tuning.

II. *Tuning Advisors profile and run search heuristics to find the (near-) optimal tuning setup in a job-basis. However, only one tuning setup is selected to be applied in the query, and the remaining tuning setups are simply discarded*. This inflicts a heavy burden in the tuning activity, that has to discard several profiling executions.

III. *Almost all Hadoop tuning advisors treat the Map and Reduce functions as black boxes and make simplifying modeling assumptions. These simplified assumptions may hold for classical MapReduce jobs like Grep, but it is not true for jobs that contain multiple relational algebra operators like joins and aggregators*. Modeling techniques should consider that: (i) SQL-on-Hadoop query processors merge several relational operators in one single job, making them to have more complex resource consumption patterns, (ii) The performance of jobs may depend on the performance of their preceding jobs, which has to be modeled in the tuning advisor's cost-model, and (iii) the search space of possible configurations severely increases due to the dependency between jobs.

## 1.3 Motivation

SQL-on-Hadoop systems have become popular for processing semi-structured data. This is most because writing queries for SQL-on-Hadoop systems is more productive than custom-coding MapReduce jobs for MapReduce frameworks. This greatly improves the productivity of data scientists. However, the productivity is also impacted by the performance of queries, and automatic tuning such systems is still a challenge.

MapReduce tuning advisors report speed ups from 24% up to 13× for common MapReduce workloads (Herodotou et al., 2011). As we previously discussed in Section 1.1, SQL-on-Hadoop systems delegate to its users the tuning of queries, and even with the help of MapReduce tuning advisors, the generated tuning setups cannot be straightforwardly applied to SQL-on-Hadoop queries. The problems stated in Section 1.2 shows that there is room to explore the full potential of tuning in SQL-On-Hadoop by providing an approach for properly tuning SQL-on-Hadoop systems.

## 1.4 Contributions

To the best of our knowledge, this is the first study on parameter tuning for SQL-on-Hadoop systems. Two previous studies (Floratou et al., 2014; Chen et al., 2014) compared the execution time of TPC-H and TPC-DS like queries across different SQL-on-Hadoop offerings, namely Hive, Impala, Stringer, Presto, and Shark. However, none of them considered parameter tuning nor investigated cluster resource utilization patterns. The results presented in this study show that parameter tuning can have a drastic impact on the performance of HiveQL queries and the efficient usage of cluster resources.

We advocate that query processors of SQL-On-Hadoop systems should ingest MapReduce tuning advisers in order to automatically tune SQL-on-Hadoop queries. Moving the decisions about the distribution of physical resources into the query optimizer have been proposed (Herodotou and Babu, 2010; Viswanathan et al., 2018). This in turn has lead us to extend the Hive query processing engine to improve Hadoop parameter tuning on Hive. The core contributions in this thesis are as follows:

- We study the impact of MapReduce parameter tuning on SQL-on-Hadoop systems (namely Hive) and shows that the approach taken by current Hadoop tuning advisors is not directly applicable for tuning Hive.
- We present the problems that rise when tuning SQL-on-Hadoop engines with current MapReduce tuning advisors.
- We explore an alternative approach, and experimentally show how a current Hadoop tuning advisor can provide good and robust performance for Hive queries.
- We present the two main mechanisms that are required to enable automatic tuning of SQL-on-Hadoop queries, namely, the Non-Uniform tuning approach and the Tuning Cache.
- We introduce a conceptual model to identify and match similar jobs in order to recycle tuning setups for equivalent jobs.
- We present the tuning cache mechanism, which can leverage any existing tuning advisor designed for MapReduce frameworks in a black box approach, and employ them to optimize jobs compiled from SQL-on-Hadoop queries.

## 1.5 List of Publications

This thesis is based on the following original publications:

- **Investigating Automatic Parameter Tuning for SQL-on-Hadoop Systems.** Lucas Filho, Edson Ramiro; Scherzinger, Stefanie; Almeida, Eduardo Cunha de; Herodotou, Herodotos; Big Data Research Journal [under review]; 2020
- **Don't Tune Twice: Reusing Tuning Setups for SQL-on-Hadoop Queries** Lucas Filho, Edson Ramiro; de Almeida, Eduardo Cunha; Scherzinger, Stefanie; **ER'19**. *International Conference on Conceptual Modeling.* 2019 (**Best Paper Award with Student as First Author**)
- **DejaVu: Recycling Tuning Setups in Hive Query Compilation** Filho, Edson Ramiro Lucas; de Almeida, Eduardo Cunha; Scherzinger, Stefanie; **ER'19, Demonstration**. *International Conference on Conceptual Modeling.* 2019
- **A Non-Uniform Tuning Method for SQL-on-Hadoop Systems.** Lucas Filho, Edson Ramiro; de Melo, Renato Silva; de Almeida, Eduardo Cunha; **AMW'13**. *13th Alberto Mendelzon International Workshop on Foundations of Data Management.* 2019
- **The Uniform Tuning Problem on SQL-On-Hadoop Query Processing.** Lucas Filho, Edson Ramiro; **SIGMOD'17 Ph.D. Competition**. *Proceedings of the 2017 ACM International Conference on Management of Data.* 2017

## 1.6 Document Structure

The content of this document is organized as follows: Chapter 2 presents the theoretical foundation, the MapReduce programming model and its architecture, the MapReduce tuning advisors, the details of Hive query processing and tuning. Chapter 2 presents problems that emerge when employing MapReduce tuning advisers to SQL-on-Hadoop queries. Chapter 3 and 5.1 present the mechanism to overcome these problems. Chapter 4.6 shows the impact of the presented solutions. Chapter 6 presents lessons learned, future directions and concludes.

# Chapter 2

# Theoretical Foundation & Related Work

In this Chapter we present the MapReduce programming model and its distributed implementation. We, then, contextualize the specific type of tuning approach addressed by this thesis. We present architectural details of MapReduce tuning advisors, including the techniques employed to profile jobs, the list of tuning parameters addressed by the Spark and MapReduce tuning advisors, as well as the heuristics, modeling techniques and benchmarks used to validate the MapReduce and Spark tuning advisors. We present how the Hive query processor translates HiveQL queries to graph of MapReduce jobs, and the current approach for tuning HiveQL queries today.

## 2.1 The MapReduce Programming Model

The MapReduce programming model consists of a small set of pre-defined functions organized as a pipeline, that perform several transformations on data. The functions are *split*, *map*, *combine*, *shuffle*, and *reduce*, respectively. Such pre-defined functions are distributed across a cluster (possibly with thousands of machines) to be executed, in turn, by various parallel instances called *tasks*. Each task is executed over a share of the input data previously stored in the same machine. These functions are designed to process text files line-by-line and are exposed to developers to be customized. For example, to read and write files in different formats (e.g., xml, binary, compressed) or to perform specific transformations. The MapReduce programming model follows a divide-and-conquer strategy that process data with a highly distributed and parallel pipeline. This enables the processing of large amounts of data with horizontal scalability (more machines are added to the cluster as more processing is required). Figure 2.1 illustrates

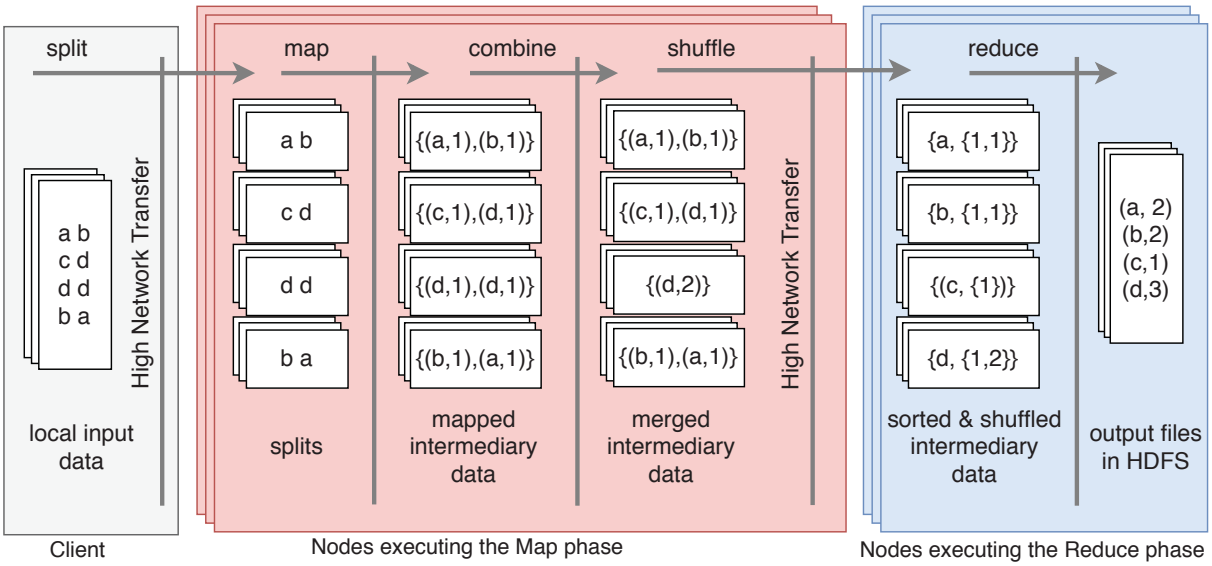



Figure 2.1: The data workflow through the MapReduce pipeline for the execution of the WordCount. Vertical bars represent functions. Boxes represent chunks of data files. Boxes at the left side of each vertical bar represent the input data for the following function. Boxes at the right side of each vertical bar represent the output of the previous function.

the data workflow through the MapReduce pipeline for the WordCount program, which counts the occurrence of each word in a given text file.

The MapReduce data workflow begins with the distribution and load of the input data across the cluster. For loading data in the cluster, first, the *split* function reads (a large mount of) input data from a local repository (usually stored in a staging storage in the client side) and divides it into several small chunks called *splits*. By default, splits have 64MB each, but can be configured to any size. As soon as a split is created, it is copied to a distributed file system, for instance, the Hadoop Distributed File System (HDFS). HDFS, then, receives the splits and spread them across the cluster. It also replicates the splits among the nodes as a fault tolerance mechanism, with a default replication factor of 3×. In Figure 2.1, starting from left to the right, the first vertical bars illustrate the transformation of the split function. Note that the distribution of the data and the data replication itself make the split function to be network intensive. At the end of the split, each node of the cluster has an equal share of the input data. Once the data is loaded in the distributed file system, it can be used many times by the following functions. Then, the pipeline is executed in two distinct "waves" of functions, where functions *map*, *combine*, *shuffle* are executed in Map phase and the *reduce* function is executed in the Reduce phase.

The *map* is the next function to be invoked in the pipeline. However, the map function does not read the output of the split function directly, but from an intermediary function called *RecordReader* that is not exposed to developers and is transparently executed. The objective

of the RecordReader is to translate each split to *records*. For example, in the case of text files, partial texts (splits) are translated to lines (records). Note that processing text files is the majority of the use cases where MapReduce is employed. RecordReader, then, invokes the map function to process each generated record, passing as argument a pair of `key` and `value`, where the `key` is the position of the line in the partial text (split) and the `value` is the content of the line itself (record). Each instance of the RecordReader has an instance of the map function associated to it, that receives a list of records in the form of $\langle key, value \rangle$ pairs to be processed.

In MapReduce it is mandatory for developers to write the code of the map function, because it is where the transformations (such as filtering and mapping) take place. Code 2.1 presents the java code for the map function of the WordCount program. The map iterates over all received records. For each word in each line (record) the map emits a pair of $\langle key', value' \rangle$, where the $key'$ is the current word being processed and $value'$ is the number one representing the count for this word. At the end, each instance of the map function will also return a list of $\langle key', value' \rangle$ pairs. The second vertical bar in Figure 2.1 illustrates the transformation of the splits in pairs of $\langle word, 1 \rangle$. Note that the received and emitted key and value pairs can be of any type, since their types are parameterized when writing the Map function, more specifically, when extending the Mapper class: `extends Mapper<Input Key, Input Value, Output Key, Output Value>`.

The set of $\langle key', value' \rangle$ pairs produced by an instance of the map function is called intermediary data, and is stored in the same machine that executes this current map instance. The next function in the pipeline, called *combine*, performs aggregations on the intermediary pairs, merging all intermediary values that have the same key. For instance, in Figure 2.1 there are intermediary pairs sharing the same key `d`, *i.e.*, the pairs $\langle d, 1 \rangle$ and $\langle d, 1 \rangle$. Combine, then, replaces them with one single pair $\langle d, 2 \rangle$, having the same key $d$ and the aggregation of its intermediary values $1, 1$. The combine function can drastically decrease the number of intermediary pairs that are generated and, consequently, decrease the amount data transmitted through the network by the next function called *shuffle* (executed between the Map and Reduce phases).

The shuffle function organizes the intermediary data by key, where all pairs sharing the same key, including pairs stored in different machines, are transmitted to one single machine. The objective of the shuffle function is to gather values with the same key to enable the reduce function to perform complete aggregations. The shuffle also produces a pair $\langle key', \{values\} \rangle$, where the `key'` is the key produced by the map function, and $\{values\}$ is a list of all values that shares `key'` (with possible partial-aggregations performed by combine). During the shuffle, all

pairs with the same key are transmitted from many machines to the one single machine. If there are more keys than available machines, one single machine will store more than one key. Shuffle is a network intensive operation, since it transmits all pairs between nodes to sort them.

The last function of the pipeline is called *reduce*. It iterates over the $\langle key', \{values\}\rangle$ pairs produced by shuffle. Similar to the combine function, the reduce performs aggregations. However, while the combiner performs partial aggregations on intermediary data, the reduce aggregates all values organized by shuffle in $\{values\}$. For instance, Code 2.2 presents the reduce function of the WordCount example, which sums up all values to count the occurrence of each word. The final output is saved by the reduce to the distributed file system, where the output file has a list of ordered unique $keys$ (words), and their aggregated $values$ (occurrences).

```
1  public static class TokenizerMapper extends
   ↪  Mapper<Object,Text,Text,IntWritable>{
2    private final static IntWritable one = new IntWritable(1);
3    private Text word = new Text();
4    public void map(Object key, Text value, Context context)
5                throws IOException, InterruptedException {
6      StringTokenizer itr = new StringTokenizer(value.toString());
7      while (itr.hasMoreTokens()) {
8        word.set(itr.nextToken());
9        context.write(word, one);
10     }
11   }
12 }
```

Code 2.1: The Map function of the WordCount example.

```
1  public static class IntSumReducer
2                extends Reducer<Text,IntWritable,Text,IntWritable> {
3    private IntWritable result = new IntWritable();
4    public void reduce(Text key, Iterable<IntWritable> values, Context
     ↪  context)
5                throws IOException, InterruptedException {
6      int sum = 0;
7      for (IntWritable val : values) {
8        sum += val.get();
9      }
10     result.set(sum);
11     context.write(key, result);
12   }
13 }
```

Code 2.2: The Reduce function of the WordCount example.

## 2.2 The MapReduce Framework

MapReduce frameworks, such as Hadoop, implements the necessary mechanisms to transparently coordinate the distributed execution of the MapReduce pipeline across large clusters. Hadoop is organized in two layers: $(i)$ the Hadoop MapReduce processing engine, that is responsible for orchestrating the execution of jobs through the MapReduce pipeline, and $(ii)$ the distributed file system, namely HDFS, that is responsible for organizing and maintaining the partitions of the data in the cluster. Both layers follow a master-slave architecture.

Figure 2.2 illustrates the processes of both layers implemented by Hadoop. A MapReduce program in execution is called *job*, and its execution is coordinated by the *JobTracker*. A job is composed by several *tasks*, which are instances of the functions of the MapReduce pipeline executing in the slave machines. More specifically, the JobTracker is responsible for keeping track of the available resources in the cluster for scheduling the tasks to be executed. The *TaskTracker* is the service running in each node of the cluster that receives the tasks and execute them. Each *task* process the *splits* stored in the same machine where it is running. The TaskTracker has several configurations that can be used to manage execution, including the degree of parallelism intra-node (number of cores, number of map and reduce tasks), the buffering of local and intermediary data, and data compression. These configurations severely impact performance and are addressed in details in Section 2.4.

The HDFS coordinator is called *NameNome*, which stores the file system hierarchy, i.e., it stores the identification of the blocks stored by each slave machines. In the slave machines a process called *DataNode* manages the local blocks (storing the splits). When a map function asks for a split to be parsed, the TaskTracker inquires the DataNode that is running in the same machine for the local splits. In case there is a required split that is stored in a remote DataNode, the TaskTracker will contact this remote DataNode directly (via RPC). Also, DataNodes communicate directly for replicating data blocks. The various Hadoop processes communicate via several protocols including RPC, SSH, and internal protocols like Heartbeat (used by the slave machines to request tasks from the JobTracker).

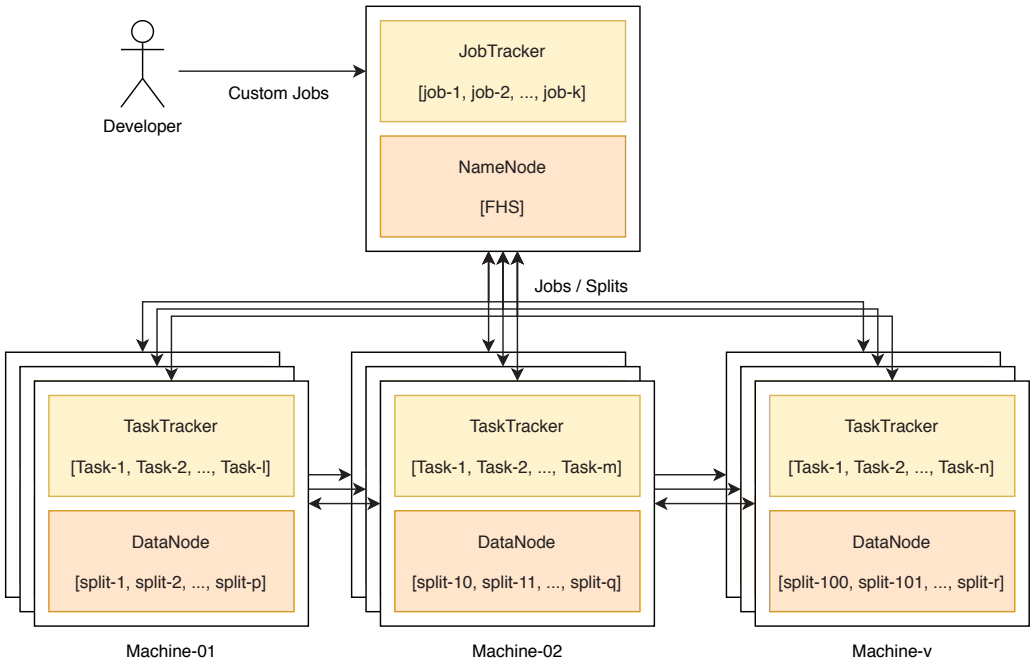



Figure 2.2: The Apache Hadoop master and slave services required to run the MapReduce pipeline.

## 2.3 Concepts of Database Tuning

Database tuning is the activity of making database applications to "run faster", where "running faster" usually means to achieve higher throughput or to lower response time (Shasha and Bonnet, 2002). Administrators can make database applications to "run faster" by adjusting the different levels of abstraction of a database system, from the conceptual and logical models to the physical models, algorithms and delegation of resources. The efficiency of each of these levels can be explored by customizing the design, implementations and even the configuration settings. Such customizations focus on specificities related to the use case or to the workload, where fine grained adjustments can have an impact in throughput, resource usage or response time. Thus, database tuning can be conducted in several ways and, for clarification, next, we distinguish between the different strategies that are understood as database tuning. The strategies of database tuning are categorized as follows:

I. *Application-level tuning* is the strategy that changes the way a task is performed (Bonnet and Shasha, 2009c), *i.e.*, the way an application interacts with the database. For example, developers may unconsciously and inadvertently use aggregation functions in transactions with critical response time, consequently, moving data from the database to the application side to perform aggregations. This movement of data degrades performance

because aggregation functions read considerable amounts of data. Rewriting such queries to avoid these unnecessary data movements by pushing aggregations to the database side is a type of application-level tuning.

II. *Physical-design tuning* adjusts the physical and conceptual schemes of a database system to keep it consistent with the updates in the application requirements or changes in the characteristics of the performance (Bonnet and Shasha, 2009b). For instance, the physical-design tuning creates (or drops) structures such as indexes and table partitions according to the variances of the workload (one large index might be replaced by a sort of smaller indexes that favors performance). Note that, creating indexes is a costly operation that entails a trade-off: accelerating some queries that perform selection operations at the expense of adding extra costs to queries that perform insert and update operations.

III. *Physical-layer tuning*: consists of picking, sizing and configuring the components of the hardware and software stack on which the database server runs (Bonnet and Shasha, 2009a). In a broader way, tuning the physical layer entails planning and sizing not only for disk, memory, and network capacity and throughput, but for any software (and hardware) present in the stack that supports the database system. In the case of SQL-on-Hadoop, the software stack includes the SQL-on-Hadoop query interface, the underlying MapReduce framework, the Java Virtual Machines, File Systems, network protocols and the operating system. As aforementioned, the underlying MapReduce processing engines have several configuration parameters that can be used to control memory distribution, I/O optimization, task parallelism, and data compression. Different from *physical-design tuning*, where some queries are optimize at the expense of others, in *physical-layer tuning* all queries benefit when one system of the software stack is optimize.

This thesis focuses on physical-layer tuning of SQL-on-Hadoop queries. However, we only address the configuration of the MapReduce processing engine, specifically Hadoop, not considering the parameters of other software components. For example, in MapReduce, regulating the size of memory buffers lead queries to spill less data into disk, consequently, making less disk operations; also, increasing the number of threads may speed up queries by increasing the degree parallelism.

## 2.4 Tuning Advisors for Hadoop (Related Work)

The goal of a Hadoop tuning advisor is to propose a set of parameter values that will maximize performance, where performance can be understood as minimizing job execution time and/or improving cluster resource utilization. Section 2.4.1 presents the current tuning parameters addressed by the related work. Section 2.4.2 presents how MapReduce tuning advisers profile jobs. Section 2.4.3 presents modeling techniques and heuristics employed by the related work.

### 2.4.1 Configuration parameters

Administrators and developers can configure MapReduce jobs by hard-coding their configuration in the source code, or instrumenting it via command line. Code 2.3 presents the main function of the WordCount example, with hard-coded configuration. First, developers create an instance of the MapReduce job, where this instance represents all the information required to guide the MapReduce pipeline during the execution of this job. The required information includes the types and custom classes used by each function of the MapReduce pipeline. Then, the configuration parameters are set. In Code 2.3, 10 parameters are set. Note that the input and output paths are also configured. In the end, the job is submitted to batch execution.

The execution behavior of MapReduce jobs is governed by several configuration parameters that changes from version to version. Figure 2.3 presents the number of parameters exposed by popular MapReduce and SQL-on-Hadoop engines through their releases. Note that the number of parameters commonly increases along the evolution of the systems. This is expected behavior due to the addition of new features. The number of configuration parameters is important because they determine the number of possible configurations, *i.e.*, the size of the search space. For instance, while Pig and SparkSQL have about 100 parameters, Hive has almost a thousand, which is an order of magnitude higher.

```java
public static void main(String[] args) throws Exception {
  Configuration conf = new Configuration();
  Job job = Job.getInstance(conf, "word count");
  // Set custom classes to job
  job.setJarByClass(WordCount.class);
  job.setMapperClass(TokenizerMapper.class);
  job.setCombinerClass(IntSumReducer.class);
  job.setReducerClass(IntSumReducer.class);
  job.setOutputKeyClass(Text.class);
  job.setOutputValueClass(IntWritable.class);
  // Set specific resources to job
  job.set("io.sort.factor", 87);
  job.set("io.sort.mb", 847);
  job.set("io.sort.record.percent", 0.4459251820234309);
  job.set("io.sort.spill.percent", 0.5920997906668477);
  job.set("mapred.compress.map.output", false);
  job.set("mapred.inmem.merge.threshold", 407);
  job.set("mapred.job.reduce.input.buffer.percent", 0.6996886038644994);
  job.set("mapred.job.shuffle.input.buffer.percent", 0.5655164261825228);
  job.set("mapred.job.shuffle.merge.percent", 0.6084975996871561);
  job.set("mapred.reduce.tasks", 8);
  // Set input and output file
  FileInputFormat.addInputPath(job, new Path(args[0]));
  FileOutputFormat.setOutputPath(job, new Path(args[1]));
  // Submit job to be executed by the cluster
  System.exit(job.waitForCompletion(true) ? 0 : 1);
}
```

Code 2.3: The Main function of the WordCount example.

The set of specific values found by a tuning advisor for Hadoop parameters is called *tuning setup*. Searching the (near-) optimal tuning setup is very time consuming and expensive, because the number of combinations of the possible configurations grows exponentially. However, it is evident that not all configuration parameters impact performance, and tuning advisors usually prune out parameters with no impact on performance, decreasing the search space considerably. Efforts to decrease the search space includes setting upper and lower boundaries of the domain of each tuning parameter, both in Hadoop (Liu et al., 2012; Wu and Gokhale, 2013; Liao et al., 2013; Kumar et al., 2017; Bei et al., 2017) and Spark (Gu et al., 2018; Perez et al., 2018). These boundaries restrict the search space within such ranges, but not all tuning advisors report the used boundaries.

A notable amount of work has been done over the last decade on automating the selection process of configuration parameters. In the literature, we found that 48 parameters can have a significant impact on performance for Hadoop and 35 parameters for Spark. Table 2.1 and Table 2.2 lists the tuning parameters addressed by Hadoop and Spark tuning advisors. The

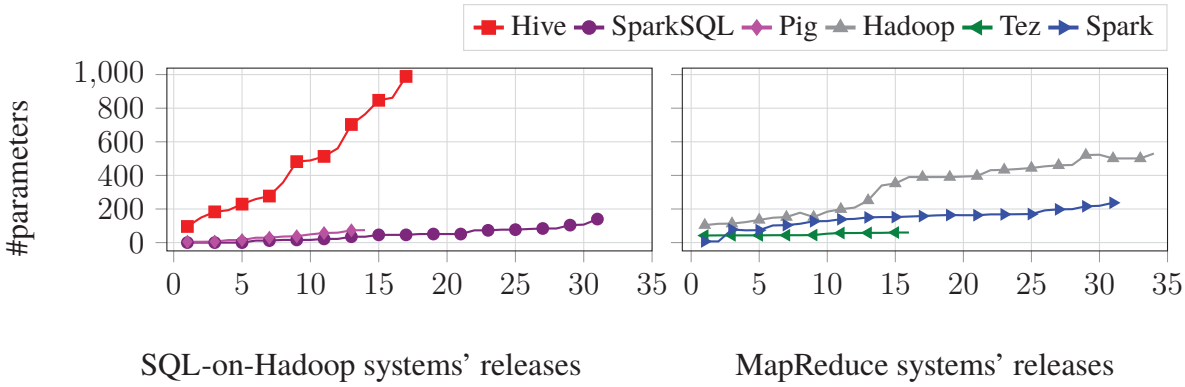



Figure 2.3: Number of tuning parameters growing over system releases [1]. These values were obtained from the configuration files or the source code.

analysed tuning advisors carried out the selection of tuning parameters in three different ways: based on previous work (Wang et al., 2012; Wu and Gokhale, 2013; Liao et al., 2013; Li et al., 2014b; Ding et al., 2015; Prabhu et al., 2015; Xu et al., 2015; Wee and Zahid, 2015; Khan et al., 2017; Kumar et al., 2017; Cai et al., 2017; Bao et al., 2018a; Gu et al., 2018; Nguyen et al., 2018; Gounaris, 2018), based on industry experts (Herodotou et al., 2011; Yigitbasi et al., 2013; Li et al., 2014a; Liu et al., 2015; Chen et al., 2015; Khaleel, 2018; Deshpande et al., 2018; Wang et al., 2017; Zhang et al., 2018; Deshpande et al., 2018; Zhang et al., 2019), or based on their own analysis (Shi et al., 2014; Bei et al., 2017; Petridis et al., 2017; Perez et al., 2018). Among the analysis to characterize the tuning parameters with most impact on performance we observe the employment of manual selection (Zhang et al., 2015) and techniques like Principal Component Analysis (PCA) (Yang et al., 2012). We also observed efforts to model the influence of single tuning parameters (Zhang et al., 2013b, 2016; Lee and Fortes, 2016).

One problem with the current methods for selecting the most impactful tuning parameters is that they do not consider that tuning parameters change during the evolution of the MapReduce systems. One configuration that optimizes a job may lose its effectiveness, or even become obsolete, because of architectural updates. For instance, an inadvertent user may employ a tuning advisor in a non-supported MapReduce release and misconfigure the MapReduce job. In this case, the analysis to determine the most important tuning parameters should be performed at every system release. For instance, *io.sort.record.percent* has been removed in Hadoop release 0.21.0, yet, it is been optimized by several tuning advisors for further releases (>0.21) (Shi et al., 2014; Kumar et al., 2017; Xu et al., 2015; Chen et al., 2015; Li et al., 2014a).

[1]The start and end releases are Hadoop from 0.23.11 to 2.8.0, Spark from 0.5.0 to 2.2.0, Tez from 0.5.0 to 0.8.5, Hive from 0.3.0 to 2.1.1, Pig from 0.1.0 to 0.16.0, and SparkSQL from 1.1.0 to 2.2.0.

| Tuning Parameter | AACT (Li et al., 2014a) | AutoTune (Zhang et al., 2013b) | Chen (Chen et al., 2015) | Gunther (Liao et al., 2013) | Jain (Jain, 2017) ⋇ | JellyFish (Ding et al., 2015) ⋇ | Johnston (Johnston et al., 2015) | Kambatla (Zhang et al., 2015) | Khaleel (Khaleel, 2018) ⋇ | Khan (Khan et al., 2017) | Kumar (Kumar et al., 2017) ⋇ | Lee (Lee and Fortes, 2016) ⋇ | MEST (Bei et al., 2017) ⋇ | MR-COF (Liu et al., 2015) | mrEtalon (Cai et al., 2017) ⋇ | MROnline (Li et al., 2014b) ⋇ | MRTuner (Shi et al., 2014) | Panacea (Liu et al., 2012) | PPABS (Wu and Gokhale, 2013) | Prasad (Deshpande et al., 2018) ⋇ | Predator (Wang et al., 2012) | RFHOC (Xu et al., 2015) | Starfish (Herodotou et al., 2011) | SVR (Yigitbasi et al., 2013) | Swathi (Prabhu et al., 2015) | Wee (Wee and Zahid, 2015) ⋇ | Zhang (Zhang et al., 2016) ⋇ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| dfs.block.size | ✓ | | ✓ | | | | | | | | | | | ✓ | | | ✓ | | ✓ | | | | | | | | |
| dfs.replication | ✓ | | | | | | | | | | | | | | | | | | | | | | | | | | |
| io.file.buffer.size | ✓ | | | | | | | | | | | | | | | | | | | | | | | | | | |
| io.sort.factor | ✓ | | ✓ | | ✓ | ✓ | | | ✓ | ✓ | ✓ | | ✓ | ✓ | | ✓ | ✓ | ✓ | ✓ | | ✓ | ✓ | ✓ | | ✓ | ✓ | |
| io.sort.mb | ✓ | | ✓ | ✓ | | ✓ | | | ✓ | ✓ | ✓ | | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | |
| io.sort.record.percent | ✓ | | ✓ | | | | | | | | ✓ | | | ✓ | | | ✓ | ✓ | | | ✓ | ✓ | ✓ | | | | |
| io.sort.spill.percent | | | ✓ | | | ✓ | | | ✓ | ✓ | ✓ | | ✓ | ✓ | ✓ | ✓ | | | ✓ | | ✓ | ✓ | ✓ | | | | |
| mapred.child.java.opts | | | | | | | | | | ✓ | | | | | | | | | ✓ | | ✓ | | | | ✓ | | |
| mapred.compress.map.output | | | ✓ | ✓ | | | | | ✓ | | ✓ | | ✓ | | | | ✓ | | | | ✓ | ✓ | ✓ | | ✓ | | |
| mapred.heartbeats.in.second | | | | | | | | | | | | | ✓ | | | | | | | | | | | | | | |
| mapred.inmem.merge.threshold | ✓ | | ✓ | | | ✓ | | | | | ✓ | | ✓ | | ✓ | ✓ | | | | | ✓ | ✓ | ✓ | | | | |
| mapred.job.reduce.input.buffer.percent | ✓ | | ✓ | | | ✓ | | | | | ✓ | | ✓ | | ✓ | ✓ | ✓ | | | | ✓ | | ✓ | | ✓ | | |
| mapred.job.reuse.jvm.num.tasks | | | ✓ | | | | | | | | ✓ | | ✓ | | | | | | | | ✓ | | | | ✓ | | |
| mapred.job.shuffle.input.buffer.percent | ✓ | | ✓ | | ✓ | ✓ | | | ✓ | ✓ | ✓ | | ✓ | ✓ | ✓ | ✓ | | | | | ✓ | ✓ | ✓ | | | | |
| mapred.job.shuffle.merge.percent | | | ✓ | | | ✓ | | | | | ✓ | | ✓ | ✓ | ✓ | ✓ | | | | | ✓ | ✓ | ✓ | | | | |
| mapred.job.tracker.handler.count | | | | | | | | | | | | | ✓ | | | | | | | | | | | | | | |
| mapred.map.child.java.opts | | | ✓ | | | ✓ | | | | | | | ✓ | | ✓ | | | | | | | | | | | ✓ | |
| mapred.map.memory.mb | | | | | | | | | | | | | ✓ | | ✓ | ✓ | | | | ✓ | | | | | | ✓ | |
| mapred.map.output.compress.codec | | | | | | | | | | | | | ✓ | | | | | | | | ✓ | | | | ✓ | | |
| mapred.map.tasks | | | | | | | | | | | ✓ | | | | | | ✓ | ✓ | | | | | | | | | |
| mapred.map.tasks.speculative.execution | | | | | | | | | | | | | ✓ | | | | | | | | ✓ | | | | | | |
| mapred.max.split.size | | | | | | | | | | | | | | | | | ✓ | | | ✓ | | | | | | | |
| mapred.merge.recordsBeforeProgress | | | | | | | | | | | | | ✓ | | | | | | | | | | | | | | |
| mapred.min.split.size | | | | | | | | | | | | | | | ✓ | | ✓ | | | ✓ | ✓ | | | | | | |
| mapred.output.compress | | | ✓ | ✓ | | | | | | | ✓ | | ✓ | | | | | | | | ✓ | ✓ | ✓ | | | | |
| mapred.output.compress.codec | | | | | | | | | | | | | ✓ | | | | | | | | ✓ | | | | | | |
| mapred.output.compress.type | | | | | | | | | | | | | ✓ | | | | | | | | ✓ | | | | | | |
| mapred.reduce.child.java.opts | | | ✓ | | | ✓ | | | | | | | ✓ | | ✓ | | | | | | | | | | | ✓ | |
| mapred.reduce.memory.mb | | | | | | | | | | | | | ✓ | | ✓ | ✓ | | | | ✓ | | | | | | ✓ | |
| mapred.reduce.parallel.copies | | | ✓ | | | ✓ | | | | ✓ | | | ✓ | | ✓ | ✓ | ✓ | ✓ | ✓ | | | | | | | ✓ | |
| mapred.reduce.slowstart.completed.maps | | | ✓ | | | | | | | | ✓ | | ✓ | | | | | | | | ✓ | | | | | | |
| mapred.reduce.tasks | ✓ | ✓ | | ✓ | | | | | ✓ | ✓ | ✓ | | ✓ | ✓ | ✓ | | ✓ | ✓ | | | ✓ | ✓ | ✓ | ✓ | | | |
| mapred.reduce.tasks.speculative.execution | | | | | | | | | | | | | ✓ | | | | | | | | | | | | | | |
| mapred.tasktracker.indexcache.mb | | | | | | | | | | | | | ✓ | | | | | | | | | | | | | | |
| mapred.tasktracker.map.tasks.maximum | | | ✓ | ✓ | | | ✓ | ✓ | ✓ | ✓ | | | ✓ | ✓ | | | ✓ | ✓ | ✓ | | ✓ | | | ✓ | ✓ | | |
| mapred.tasktracker.reduce.tasks.maximum | | | ✓ | ✓ | ✓ | | ✓ | ✓ | ✓ | ✓ | | | ✓ | ✓ | | | ✓ | ✓ | ✓ | | ✓ | | | ✓ | ✓ | | |
| mapreduce.job.max.split.locations | | | | | | | | | | | | | ✓ | | | | | | | | | | | | | | |
| mapreduce.map.cpu.vcores | | | | | | | | | | | | | ✓ | | | ✓ | | | | | | | | | | | |
| mapreduce.reduce.cpu.vcores | | | | | | | | | | | | | ✓ | | | ✓ | | | | | | | | | | | |
| mapreduce.reduce.shuffle.memory.limit.percent | | | | | | ✓ | | | | | | | ✓ | | ✓ | ✓ | | | | | | | | | | | |
| mapreduce.shuffle.connectionkeepalive.enable | | | | | | | | | | | | | ✓ | | | | | | | | | | | | | | |
| min.num.spills.for.combine | | | | | | | | | | | | | | | | | | | | | ✓ | | | | | | |
| tasktracker.http.threads | | | ✓ | | | | | | | | | | ✓ | | | | | | | | | | | | | | |
| yarn.app.mapreduce.am.command-opts | | | | | | | | | | | | | ✓ | | | | | | | | | | | | | | |
| yarn.app.mapreduce.am.job.task.-listener.thread-count | | | | | | | | | | | | | ✓ | | | | | | | | | | | | | | |
| yarn.app.mapreduce.am.resource.mb | | | | | | | | | | | | | ✓ | | | | | | | | | | | | | | |
| yarn.resourcemanager.scheduler.class | | | | | | | | | | | | | | | | | | | | | | | | | | ✓ | |
| yarn.scheduler.capacity.maximum-applications | | | | | | | | | | | | ✓ | | | | | | | | | | | | | | | ✓ |

Table 2.1: Hadoop tuning advisers and the supported tuning parameters. Note that the old and new names of the tuning parameters are listed together. Tuning advisers with ⋇symbol use the new names of the tuning parameter. Tuning advisers without symbol use the old names of the tuning parameters.

| Tuning Parameters | AutoTune (Bao et al., 2018b) | Gounaris (Gounaris, 2018) | Gu (Gu et al., 2018) | Hedgehog (Zhang et al., 2018) | Nguyen (Nguyen et al., 2018) | Otterman (Zhang et al., 2019) | Petridis (Petridis et al., 2017) | PETS (Perez et al., 2018) | Prasad (Deshpande et al., 2018) | Wang (Wang et al., 2017) |
|---|---|---|---|---|---|---|---|---|---|---|
| hive.exec.reducers.bytes.per.reducer | - | | | | | | | | ✓ | |
| spark.broadcast.blockSize | - | | ✓ | | ✓ | | | ✓ | | ✓ |
| spark.broadcast.compress | - | | ✓ | | | | | | | ✓ |
| spark.default.parallelism | - | | ✓ | | ✓ | ✓ | | ✓ | | ✓ |
| spark.driver.cores | - | | ✓ | | ✓ | ✓ | | | | ✓ |
| spark.driver.maxResultSize | - | | ✓ | | | | | | | |
| spark.driver.memory | - | | ✓ | | ✓ | ✓ | | | | ✓ |
| spark.executor.cores | - | | ✓ | ✓ | ✓ | ✓ | | | ✓ | ✓ |
| spark.executor.instances | - | | | ✓ | | | | | | |
| spark.executor.memory | - | | ✓ | ✓ | ✓ | ✓ | | ✓ | ✓ | ✓ |
| spark.io.compression.codec | - | ✓ | | | | | ✓ | ✓ | | ✓ |
| spark.io.compression.lz4.blockSize | - | | | | | | | ✓ | | |
| spark.io.compression.snappy.blockSize | - | | | | | | | ✓ | | |
| spark.kryo.referenceTracking | - | | | | | | | ✓ | | |
| spark.locality.wait | - | | | | ✓ | | | ✓ | | |
| spark.memory.fraction | - | | | | ✓ | | | ✓ | | |
| spark.memory.storageFraction | - | | | | ✓ | | | ✓ | | |
| spark.rdd.compress | - | ✓ | ✓ | | | | ✓ | ✓ | | |
| spark.reducer.maxSizeInFlight | - | ✓ | ✓ | | ✓ | | ✓ | ✓ | | ✓ |
| spark.serializer | - | ✓ | | | | | ✓ | ✓ | | |
| spark.shuffle.compress | - | ✓ | ✓ | | ✓ | ✓ | ✓ | ✓ | | ✓ |
| spark.shuffle.consolidateFiles | - | ✓ | | | | | ✓ | | | |
| spark.shuffle.file.buffer | - | ✓ | | | ✓ | | ✓ | | | |
| spark.shuffle.io.maxRetries | - | | ✓ | | | | | | | |
| spark.shuffle.io.preferDirectBufs | - | ✓ | | | | | ✓ | ✓ | | |
| spark.shuffle.io.retryWait | - | | ✓ | | | | | | | |
| spark.shuffle.manager | - | ✓ | | | | ✓ | ✓ | | | ✓ |
| spark.shuffle.memoryFraction | - | ✓ | | | | ✓ | ✓ | | | |
| spark.shuffle.service.index.cache.entries | - | | ✓ | | | | | | | |
| spark.shuffle.sort.bypassMergeThreshold | - | | | | | | | ✓ | | |
| spark.shuffle.spill.compress | - | ✓ | | | ✓ | ✓ | ✓ | ✓ | | ✓ |
| spark.speculation | - | | ✓ | | | | | | | ✓ |
| spark.sql.shuffle.partitions | - | | | | | | | | ✓ | |
| spark.storage.memoryFraction | - | ✓ | | | | ✓ | ✓ | | | |
| spark.storage.memoryMapThreshold | - | | | | | | | ✓ | | |

Table 2.2: Spark tuning advisers and the supported tuning parameters.

### 2.4.2 Profiling the job resource usage

Tuning advisors have to monitor job execution to synthesize its resource consumption in one single representation, called *execution profile*. This single representation makes possible for tuning advisors to determine, for instance, whether the job is CPU- or disk-bound and, then, recommend specific settings. This monitoring activity is called *profiling*, and each tuning advisor compiles different information from many sources including data flows, processing times and access costs to resources, e.g., tracking job counters (Liao et al., 2013; Li et al., 2014b), real-time statistics (Ding et al., 2015), job execution times (Bei et al., 2017) or the execution times of the MapReduce phases (Bei et al., 2016), instrumentation of the JVM (Liu et al., 2015; Herodotou et al., 2011), and execution logs (Shi et al., 2014; The Apache Software Foundation, 2018) for proposing tuning setups.

Inevitably, the more information the tuning advisor traces during profiling, the more overhead it adds to the job execution, consequently, to the entire tuning activity. For instance, Starfish (Herodotou et al., 2011) uses dynamic instrumentation of the JVM to collect a job execution profile, for which the authors report a profiling overhead of up to 46%. To speed up profiling, Starfish can profile only a sample of the JVM tasks: when profiling only 20% of the JVM tasks, the overhead drops to 10%. However, sampling the tasks that are profiled might not be fully representative of the entire job and, consequently, can produce less effective tuning setups.

### 2.4.3 Searching for the (near-) optimal tuning setup

Given an execution profile, the tuning advisor estimates the execution time of the given job under a given tuning setup (Glushkova et al., 2019; Zhang et al., 2013a; Song et al., 2013; Cherkasova, 2011). Such performance models employ a set of techniques to prototype the influence of the tuning knobs in the job's performance, including: (*i*) rule-based models, where rules are analytically stated to generate the values to be set in the tuning knobs (*e.g.*, rules of thumbs), (*ii*) cost-based models (Herodotou et al., 2011; Wang et al., 2012; Zhang et al., 2013b; Shi et al., 2014; Li et al., 2014b; Prabhu et al., 2015; Liu et al., 2015; Ding et al., 2015; Zhang et al., 2016; Cai et al., 2017), where the relations between the internal components of the engine and the tuning parameters are expressed in mathematical equations, and (*iii*) model-based (Yigitbasi

[2]https://issues.apache.org/jira/browse/MAPREDUCE-64

et al., 2013; Li et al., 2014a; Xu et al., 2015; Chen et al., 2015; Khan et al., 2017; Bei et al., 2017; Khaleel, 2018), where the relationship between the tuning setup and the performance of the job is projected by machine learning, logic models, or regression models.

The first MapReduce tuning advisors are rule-based, and they commonly performed exhaustive search to identify the most suitable tuning setup. These approaches may have to run jobs several times until find the proper tuning setup. For instance, Gunther (Liao et al., 2013) takes 10 to 24 trials to find the most suitable tuning for Sort, TeraSort, Nutch and K-means applications. One possible optimization for rule-based tuning advisors is to recycle tuning setups for jobs with similar resource requirements. For instance, in the case of PPABS (Wu and Gokhale, 2013) uses a modified version of K-means++ to match similar jobs, and PStorM (Ead, 2012) employs *Control Flow Graphs* of map and reduce functions to match similar jobs.

In contrast to rule-based tuning advisors, cost-based advisors do not require exhaustive trial sessions to find the most suitable tuning setup. For instance, their cost-model can be used as objective function for heuristics. This severely decreases the search time, but it forces cost-models to be sufficient accurate in order to model all necessary aspects regarding the tuning knobs being tuned. The tuning advisor will enumerate and search over the high-dimensional space of parameter values in order to identify the tuning setup that will produce the smallest execution time. In the case of cost-based tuning advisors, the objective function may not only represent run time, but any objective such as reducing resource usage or meet time and pricing constraints. For instance, completing a job within a deadline or with a certain amount of physical resources.

Different advisors will employ different search strategies, ranging from grid search and exhaustive enumeration to recursive random search, hill climbing, and genetic algorithms. In order to give an idea of both the complexity of the problem, as well as the plethora of solutions proposed, we refer to Tables 2.3 and 2.4. These tables list prominent Hadoop and Spark tuning advisors with their year of publication, the speedups gained, the supported Hadoop and Spark versions, as well as the heuristics employed. There are efforts to decrease the size of the search space. For instance, in order to accelerate the search for optimal tuning setups MEST (Bei et al., 2017) employs the model trees algorithm to filter out non-optimal parameters using genetic programming. Thus, MEST speed up the time for identifying tuning values up to 2.18×.

The workloads chosen for evaluating Hadoop tuning advisors are listed in tables 2.5 and 2.6. It is interesting to note that the simple jobs [*Tera*] *Sort*, *Word Count*, and *Grep* are among the most commonly used workloads, whereas very few systems report the use of handcrafted

HiveQL queries or employ a small subset of TPC-H and TPC-DS. Hence, most experiments evaluate advisors for MapReduce jobs that implement or mimic a single SQL operator. Micro-benchmarking means that only a single scenario is examined, whereas the workloads generated by the Hive query optimizer implement several query operators per MapReduce job. Consequently, it is not clear how well tuning advisors perform against complex SQL-like analytical workloads. This thesis explores a *macro-benchmark* examination (see Chapter 4) of query execution that includes the evaluation of query plans with many HiveQL operators.

| Tuning Advisor | Year | Hadoop | Speedup | Heuristic |
|---|---|---|---|---|
| Kambatla (Zhang et al., 2015) | 2009 | - | 4x | Exhaustive Search |
| Starfish (Herodotou et al., 2011) | 2011 | 0.20.2 | 13.9x | Random Recursive Search |
| Predator (Wang et al., 2012) | 2011 | - | 5x | Grid Hill Climbing |
| Panacea (Liu et al., 2012) | 2012 | - | 3x | Exhaustive Search |
| SVR (Yigitbasi et al., 2013) | 2013 | 0.20.2 | 3x | Exhaustive Search |
| PPABS (Wu and Gokhale, 2013) | 2013 | 1.0.4 | 38.40% | Simulated Annealing |
| Gunther (Liao et al., 2013) | 2013 | 0.20.3 | 33.00% | Genetic Algorithm |
| AutoTune (Zhang et al., 2013b) | 2013 | 1.0.0 | - | - |
| MRTuner (Shi et al., 2014) | 2014 | 1.0.3 | 4.41x | Producer, Transporter, Consumer |
| MROnline (Li et al., 2014b) | 2014 | 2.1.0 | 30.00% | Smart Hill Climbing |
| AACT (Li et al., 2014a) | 2014 | 2.2.0 | 10x | Exhaustive Search |
| JellyFish (Ding et al., 2015) | 2015 | YARN | 74.00% | Hill Climbing |
| Swathi (Prabhu et al., 2015) | 2015 | 1.2.1 | 32.97% | Exhaustive Search |
| Chen (Chen et al., 2015) | 2015 | 1.2.1 | 8x | Stochastic Hill Climbing |
| MR-COF (Liu et al., 2015) | 2015 | 0.20.2 | 35.00% | Genetic Algorithm |
| RFHOC (Xu et al., 2015) | 2015 | 1.0.4 | 7.4x | Genetic Algorithm |
| Wee (Wee and Zahid, 2015) | 2015 | 2.6.0 | 10.00% | Genetic Algorithm |
| Zhang (Zhang et al., 2016) | 2016 | 2.6.0 | 40.00% | Double-Threshold Heuristic |
| Lee (Lee and Fortes, 2016) | 2016 | 2.7.2 | 29.00% | Fuzzy Inference |
| Khan (Khan et al., 2017) | 2016 | 1.2.1 | 71.00% | Particle Swarm Optimization |
| Kumar (Kumar et al., 2017) | 2017 | 1.0.3, 2.7.3 | 66.00% | SPSA$*$ |
| Jain (Jain, 2017) | 2017 | 2.7.2 | 38.51% | Exhaustive Search |
| MEST (Bei et al., 2017) | 2017 | 2.6.0 | - | Genetic Algorithm |
| Prasad (Deshpande et al., 2018) | 2018 | YARN | - | Exhaustive Search |
| mrEtalon (Cai et al., 2017) | 2018 | 2.4.0 | 30.00% | Simulated Annealing |
| Khaleel (Khaleel, 2018) | 2018 | 2.6.0 | 73.39% | Genetic Algorithm |

Table 2.3: Hadoop tuning advisers, ordered by year of publication. Listing reported speed up, Hadoop version supported, and heuristics employed. $*$SPSA: Simultaneous Perturbation Stochastic Approximation.

| Tuning Adviser | Year | Spark | Speedup | Heuristic |
|---|---|---|---|---|
| Petridis (Petridis et al., 2017) | 2017 | 1.5.2 | 10x | Trial-and-Error |
| Wang (Wang et al., 2017) | 2017 | 1.6.1 | 36% | Recursive Random Search |
| AutoTune (Bao et al., 2018a) | 2018 | - | 63.7% | Two-Step Multiple Bound |
| Gounaris (Gounaris, 2018) | 2018 | 1.5.2 | 4x | Greedy Algorithm |
| Gu (Gu et al., 2018) | 2018 | - | 42.8% | Neural Network |
| Hedgehog (Zhang et al., 2018) | 2018 | 2.1 | 19.6% | Marginal Utility Law |
| Nguyen (Nguyen et al., 2018) | 2018 | 2.0.2 | 40.0% | Recursive Random Search |
| PETS (Perez et al., 2018) | 2018 | 4.78x | 82% | Fuzzy Inference |
| Prasad (Deshpande et al., 2018) | 2018 | - | - | Exhaustive Search |
| Otterman (Zhang et al., 2019) | 2019 | 2.2.0 | 30% | Simulated Annealing |

Table 2.4: Spark tuning advisers, ordered by year of publication. Listing reported speed up, supported version, and the heuristic employed.

| Tuning Advisers | Adjacent list | Biagram | Electrocardiograph Analysis | Grep | Histogram | Inverted Index | K-Core | K-Means | LinkGraph | Nutch | PageRank | Pi Estimation | Sort | TeraSort | Text Classification | Travel Logistics Workload | Weakly Connected Components | Word Co-Occurrence | WordCount | Custom Queries | Hive Aggregation | Join | Order By | TPC-DS (Subset) | TPC-H (Subset) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| AACT (Li et al., 2014a) | | | | | | | | | | | | ✓ | | ✓ | | | | | ✓ | | | | | | |
| AutoTune (Zhang et al., 2013b) | | | | | | | | | | | | | | | | | | | | ✓ | | | | | ✓ |
| Chen (Chen et al., 2015) | | | | | | | | | | | | | | ✓ | | | | ✓ | ✓ | | ✓ | | | | |
| Gunther (Liao et al., 2013) | | | | | | | | ✓ | | ✓ | | | ✓ | ✓ | | | | | | | | | | | |
| Jain (Jain, 2017) | | | | | | | | | | | | | | | | | | | ✓ | | | | | | |
| JellyFish (Ding et al., 2015) | | | | ✓ | ✓ | ✓ | | | | | | | | ✓ | ✓ | | | | ✓ | | | | | | |
| Kambatla (Zhang et al., 2015) | | | | ✓ | | | | | | | | | ✓ | | | | | | ✓ | | | | | | |
| Khaleel (Khaleel, 2018) | | | | | | | | | | | | | | ✓ | | | | | ✓ | | | | | | |
| Khan (Khan et al., 2017) | | | | | | | | | | | | | ✓ | | | | | | ✓ | | | | | | |
| Kumar (Kumar et al., 2017) | | ✓ | | ✓ | | ✓ | | | | | | | | ✓ | | | | ✓ | | | | | | ✓ | |
| Lee (Lee and Fortes, 2016) | | | | ✓ | | | | | | | | | | ✓ | | | | | ✓ | | | | | | |
| MEST (Bei et al., 2017) | | | | | | | | ✓ | | | ✓ | | ✓ | ✓ | | | | | ✓ | | | | | | |
| MR-COF (Liu et al., 2015) | | | | ✓ | | | | | | | | | ✓ | | | | | | ✓ | | | | | | |
| mrEtalon (Cai et al., 2017) | | ✓ | | | | ✓ | | | ✓ | | | ✓ | ✓ | ✓ | | | | ✓ | ✓ | | | ✓ | ✓ | | |
| MROnline (Li et al., 2014b) | | ✓ | | ✓ | | ✓ | | | | | | ✓ | | ✓ | | | | | ✓ | | | | | | |
| MRTuner (Shi et al., 2014) | | | | | | | | | | | ✓ | | | ✓ | ✓ | | | | | | | | | | |
| Panacea (Liu et al., 2012) | | | | | | | ✓ | ✓ | | | ✓ | | | | | | ✓ | | ✓ | | | | | | |
| PPABS (Wu and Gokhale, 2013) | | | | ✓ | | | | | | | | | | ✓ | | | | | ✓ | | | | | | |
| Prasad (Deshpande et al., 2018) | | | | | | | | | | | | | | | | ✓ | | | | | | | | ✓ | |
| Predator (Wang et al., 2012) | | | | | | | | | | | | | | ✓ | | | | | ✓ | | | | | | |
| RFHOC (Xu et al., 2015) | ✓ | | | | | ✓ | | | | | | | ✓ | ✓ | | | | | ✓ | | | | | | |
| Starfish (Herodotou et al., 2011) | | | | | | | | | | | | | | ✓ | | | | ✓ | ✓ | | | | | | |
| SVR (Yigitbasi et al., 2013) | | | | | | | | | | | | | ✓ | | | | | | ✓ | | | | | | |
| Swathi (Prabhu et al., 2015) | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| Wee (Wee and Zahid, 2015) | | | ✓ | | | | | | | | | | | | | | | | | | | | | | |
| Zhang (Zhang et al., 2016) | | | | | | | | | | | | | ✓ | ✓ | | | | | ✓ | | | | | | |

Table 2.5: Benchmarks employed by Hadoop tuning advisers.

| Tuning Advisers | Bayesian Classification | Connected Component | Decision Trees | Gradient Boosting Trees | Grep | K-Means | Logistic Regression | LogQuery | Matrix Factorization | PageRank | PageRanking | PaaS Workload | Shuffling | Sort | Sort-By-Key | Support Vector Machine | TeraSort | TPC-DS Subset | Triangle Count | WordCount |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| AutoTune (Bao et al., 2018a) | ✓ | | | ✓ | | ✓ | ✓ | | | | ✓ | | | | | ✓ | | | | ✓ |
| Gounaris (Gounaris, 2018) | | | | | | ✓ | | | | | | | ✓ | | ✓ | | | | | |
| Gu (Gu et al., 2018) | | | | | | ✓ | | ✓ | | | ✓ | | | | | | | | | ✓ |
| Hedgehog (Zhang et al., 2018) | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| Nguyen (Nguyen et al., 2018) | | ✓ | ✓ | | | ✓ | | | ✓ | | ✓ | | | | | ✓ | ✓ | | ✓ | ✓ |
| Otterman (Zhang et al., 2019) | ✓ | | | | ✓ | | | | | | | | | ✓ | | | | | | ✓ |
| Petridis (Petridis et al., 2017) | | | | | | ✓ | | | | | | | ✓ | | ✓ | | | | | |
| PETS (Perez et al., 2018) | ✓ | | | | | ✓ | | | | ✓ | | | | ✓ | | | ✓ | | | ✓ |
| Prasad (Deshpande et al., 2018) | | | | | | | | | | | | ✓ | | | | | | ✓ | | |
| Wang (Wang et al., 2017) | ✓ | | | | ✓ | | | | | | | | | ✓ | | | | | | ✓ |

Table 2.6: Benchmarks employed by Spark tuning advisers.

## 2.5 Query Execution in Hive

Hive (Thusoo et al., 2010), an open source project originally built at Facebook, was the first SQL-on-Hadoop query engine built on top of Hadoop MapReduce to leverage its scalability, fault tolerance, and scheduling features. Hive also introduced HiveQL, a SQL-like query language that has become the standard SQL interface for large-scale data (Floratou et al., 2014). Hive can process structured and semi-structured data. Code 2.4 presents a Hive example of a query for loading semi-structured data from logs of the Apache Web Server. Hive also can read a number of semi-structured formats such as JSON and XML, and many other formats including Avro, ORC, Parquet and CSV. Hive also enables developers to write their own Serialization and De-serialization libraries.

Hive internally uses a query optimizer that resembles traditional relational optimizers to translate a given HiveQL statement to a workflow of MapReduce jobs to be executed on Hadoop. Specifically, a HiveQL statement is first parsed and validated against the data dictionary, compiled into a tree of logical operators, and finally optimized to produce a physical query execution plan (Floratou et al., 2014; Thusoo et al., 2010). This allows for various logical optimizations such as selection and projection pushdowns, as well as join reordering and join physical method selection. Physical-layer tuning such as partition pruning is also performed when an input table is split over several HDFS folders to avoid processing unnecessary data (Huai et al., 2014). The final execution plan has the form of a Directed Acyclic Graph (DAG) of MapReduce *jobs*. Each job is executed on the cluster as a set of parallel Map and Reduce *tasks*. By now, Hive supports other execution engines such as Spark and Tez.

As a further, MapReduce-specific optimization, the Hive query optimizer merges jobs by applying *chain folding* and *job merging*, which are both considered generic MapReduce design patterns (Miner and Shook, 2012b). As a simple example, chain folding collapses sequences of Map-only jobs into a single Map-only job (In Hive and Spark terminology, merged jobs are called *stages*. This thesis follows the convention of Hadoop processing and use the general term *job*). Job merging further merges jobs that process the same input data, such as joins applying a common join predicate. Hence, *each resulting MapReduce job will typically evaluate several query operators*. Similar optimizations have also been proposed in Stubby (Lim et al., 2012), YSmart (Lee et al., 2011), and MRShare (Nykiel et al., 2010) as they are very effective in speeding up query execution by reducing the number of intermediate files that are written out to

HDFS in between MapReduce jobs. In MapReduce processing, such communication costs can dominate execution run times (Rajaraman and Ullman, 2011).

Figure 2.4 presents the query execution plan for TPC-H query 7 consisting of a DAG of 6 MapReduce jobs. This particular DAG has the form of a tree, where jobs 1 and 2 are the leaves and the final job 6 is the root. As can be seen, each MapReduce job evaluates several query operators (e.g., Job 2 contains two TableScans, a Filter, and a Join among others). The output of each MapReduce job is written to a temporary HDFS file, to be processed by the next upstream job in the workflow.

```
1  -- impose a schema to Apache log files
2  CREATE TABLE serde_regex(
3  host STRING, identity STRING, user STRING, time STRING,
4  request STRING, status STRING, size STRING, referer STRING, agent STRING)
5  ROW FORMAT SERDE 'org.apache.hadoop.hive.contrib.serde2.RegexSerDe'
6  WITH SERDEPROPERTIES (
7    "input.regex" = "([^ ]*) ([^ ]*) ([^ ]*) (-|\\[[^\\]]*\\]) ([^
     ↪  \"]*|\"[^\"]*\") (-|[0-9]*) (-|[0-9]*)(?: ([^ \"]*|\"[^\"]*\") ([^
     ↪  \"]*|\"[^\"]*\"))?",
8    "output.format.string" = "%1$s %2$s %3$s %4$s %5$s %6$s %7$s %8$s %9$s"
9  ) STORED AS TEXTFILE;
10
11 -- load Apache log files to Hive
12 LOAD DATA LOCAL INPATH "../data/files/apache.access.log"
13 INTO TABLE serde_regex;
14 LOAD DATA LOCAL INPATH "../data/files/apache.access.2.log"
15 INTO TABLE serde_regex;
16
17 -- query logs
18 SELECT * FROM serde_regex ORDER BY time;
```

Code 2.4: Example: Loading Apache access log files directly to Hive using Hive serialization and de-serialization with regular expressions.

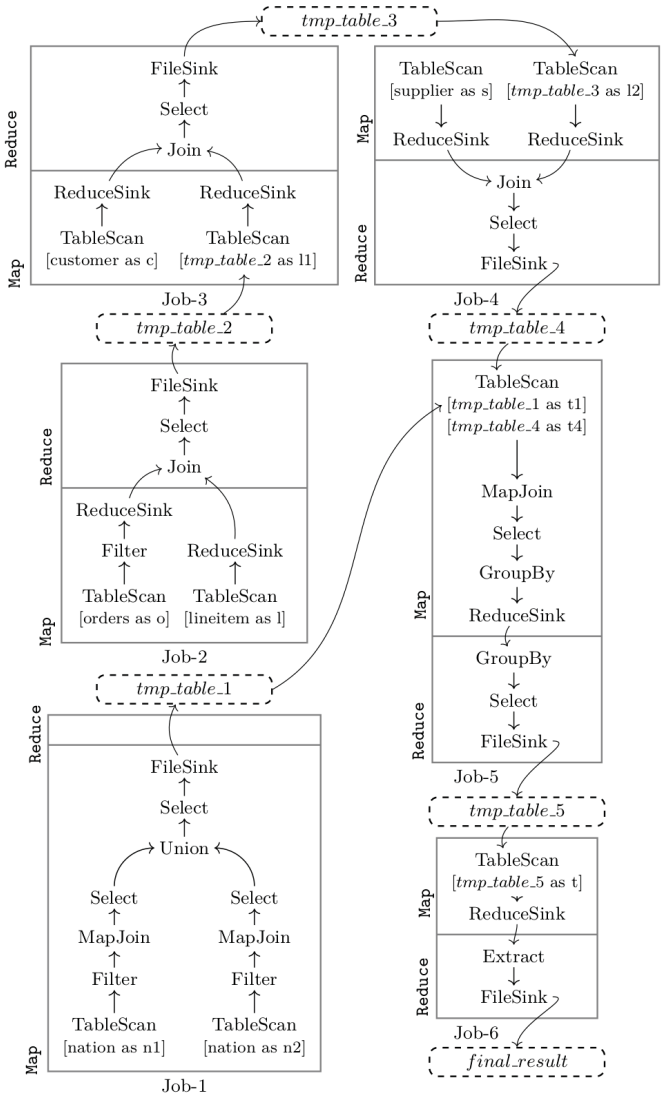



Figure 2.4: Hive query plan for TPC-H query 7.

## 2.6 Parameter Tuning in Hive

For tuning, a Hive administrator may configure more than 400 parameters for Hive, in addition to about 200 parameters for Hadoop. The authors in (Poggi et al., 2016; Sarma et al., 2013) show how sensitive these settings are to the software and hardware stack. Even different implementations of the JVM (*e.g.*, OpenJVM vs. IBM JVM) already impact performance (Chiba et al., 2018). Yet, the problem of automatically setting these parameters in Hive remains largely unexplored today.

A Hive administrator can assign a tuning setup to a query plan in the query code (as presented in Code 2.5), or when submitting the query via the command line. Note in Code 2.5 that the TPC-H query 7 is split in two statements, and each statement generates more than one job, composing a single query plan. The Hive query processing engine then propagates this

tuning setup to all MapReduce jobs in the query plan, *i.e.*, at the level of individual HiveQL queries, all MapReduce jobs that constitute a query plan are executed with identical Hadoop configuration settings. Hence, when administrators are tasked with tuning a query, they must find a single setting of Hadoop parameter values to use on a per-query basis.

Out-of-the-box, Hive does not support a more fine-grained tuning (e.g., on a per-job basis). We refer to this approach as *uniform tuning* (a term introduced by us in (Lucas Filho, 2017)) and will discuss it in more detail in Chapter 3. Figure 2.5 (a) presents the tuning workflow in Hive query processor. First, the developer submit test-run his query offline with a tuning advisor in order to generate the tuning setup. Then, the developer submit his query with the tuning setup. Hive query compiler propagates the same tuning uniformly to all jobs in the query plan and queue all job in the underlying execution engine for execution. This thesis presents an alternative for the Uniform tuning, called Non-Uniform tuning. An overview of the Non-Uniform tuning workflow is illustrated in Figure 2.5 (b), where a third part tuning advisor and our tuning cache are binded to query processor to enable automatic tuning of queries with per-job optimization.

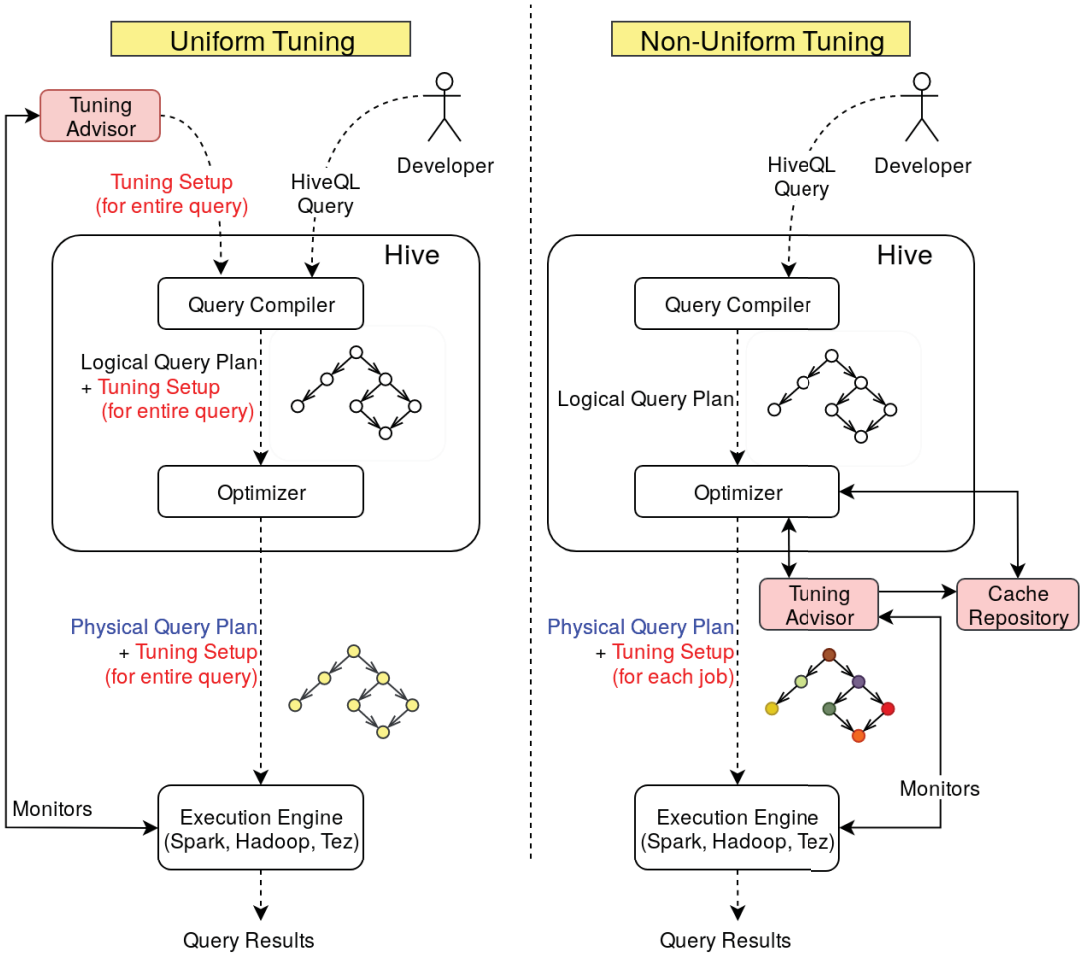



Figure 2.5: (a) Uniform and (b) Non-Uniform tuning workflow.

```
-- tuning setup
set io.sort.mb=1050;
set io.sort.factor=71;
set io.sort.spill.percent=0.6384423483547961;
set io.sort.record.percent=0.4047263226436847;
set mapred.reduce.tasks=8;
set mapred.job.shuffle.input.buffer.percent=0.39740110059427025;
set mapred.inmem.merge.threshold=698;
set mapred.job.shuffle.merge.percent=0.478719537866803;
set mapred.compress.map.output=false;
set mapred.output.compress=false;
set mapred.job.reduce.input.buffer.percent=0.44076501931810713;
-- TPC-H query 7, 1st statement
insert overwrite table q7_volume_shipping_tmp
select * from (
  select n1.n_name as supp_nation, n2.n_name as cust_nation,
         n1.n_nationkey as s_nationkey, n2.n_nationkey as c_nationkey
  from nation n1 join nation n2
  on n1.n_name = 'FRANCE' and n2.n_name = 'GERMANY'
  UNION ALL
  select n1.n_name as supp_nation, n2.n_name as cust_nation,
         n1.n_nationkey as s_nationkey, n2.n_nationkey as c_nationkey
  from nation n1 join nation n2
  on n2.n_name = 'FRANCE' and n1.n_name = 'GERMANY') a;
-- TPC-H query 7, 2nd statement
insert overwrite table q7_volume_shipping
select supp_nation, cust_nation, l_year, sum(volume) as revenue
from (select supp_nation, cust_nation, year(l_shipdate) as l_year,
   l_extendedprice * (1 - l_discount) as volume
   from q7_volume_shipping_tmp t join
   (select l_shipdate, l_extendedprice, l_discount, c_nationkey,
    ↪  s_nationkey
    from supplier s join
      (select l_shipdate, l_extendedprice, l_discount, l_suppkey,
       ↪  c_nationkey
       from customer c join
         (select l_shipdate, l_extendedprice, l_discount, l_suppkey,
          ↪  o_custkey
          from orders o join lineitem l
          on o.o_orderkey = l.l_orderkey and l.l_shipdate >= '1995-01-01'
            and l.l_shipdate <= '1996-12-31'
          ) l1 on c.c_custkey = l1.o_custkey
       ) l2 on s.s_suppkey = l2.l_suppkey
 ) l3 on l3.c_nationkey = t.c_nationkey and l3.s_nationkey = t.s_nationkey )
  ↪  shipping
group by supp_nation, cust_nation, l_year
order by supp_nation, cust_nation, l_year;
```

Code 2.5: TPC-H Query 7 from the official TPC-H Benchmark for Hive.

# Chapter 3

# Tuning SQL-on-Hadoop Systems

In this Chapter we formulate the problem of finding the most efficient tuning setup for SQL-on-Hadoop query plans. We present an experimental analysis of the impact of the *uniform parameter tuning* on the execution of HiveQL queries to motivate our contributions in the upcoming chapters. We also explore the costs of the Uniform Tuning approach, used by current SQL-on-Hadoop systems.

## 3.1 The SQL-on-Hadoop Tuning Problem

First, let us formulate the search for the optimal tuning setup for a single MapReduce job. Let us define a MapReduce job $j$ as a tuple of the form $j = (O, D, C)$, in which $O$ is the set of *code* it executes (e.g., MapReduce functions implementing several relational algebra operators), $D$ is the set of *data* that are read and processed by $j$, and $C$ is the set of *configuration parameters* exposed by the processing engine (e.g., Hadoop, Spark, Tez) that is used to allocate resources to job $j$, where every configuration parameter $c_i \in C$ has a different domain $dom(c_i)$ of size $s_i$.

Now, suppose that we have a computable function $\sigma : J \times \mathcal{C} \mapsto \mathbb{R}$, where $J$ is a set of possible MapReduce jobs, and $\mathcal{C} = \{C_1, \ldots, C_k\}$ is the collection of all possible configurations, and the function $\sigma(j, C_i)$ determines the computational cost of executing job $j$ under the tuning setup $C_i$. We define the task of searching for the most efficient tuning setup for a single MapReduce job (where the *most efficient tuning setup* is the configuration that minimizes the response time or the resource usage of a MapReduce job) as the *Advisor Function*, as follows:

**Definition 1 (Advisor Function):** *Given a set $\mathcal{C}$ representing all possible configuration parameters, and a cost function $\sigma : J \times \mathcal{C} \mapsto \mathbb{R}$. We denote as $f(j)$ the advisor function $f : J \mapsto \mathcal{C}$ which is responsible for finding the most efficient tuning setup $C_j$ for a given $j \in J$ such that:*

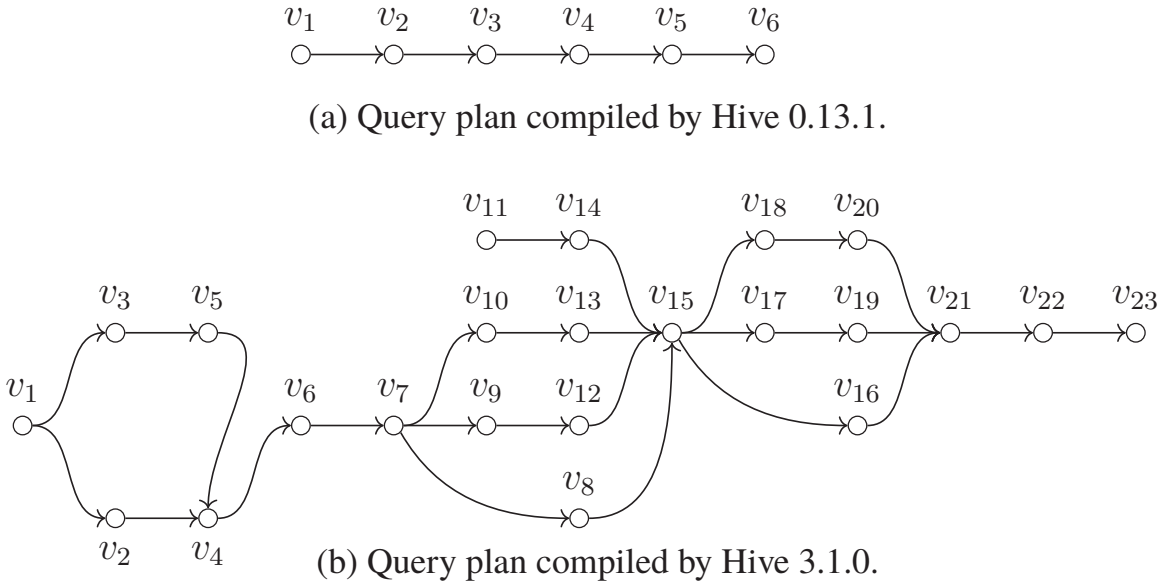
$$f(j) = C_j = \min_{C_x \in \mathcal{C}} \sigma(j, C_x) \tag{3.1}$$

The Advisor Function is implemented by third part Tuning Advisors that employ a diverse set of modeling and searching techniques for finding optimal tuning setups, as detailed in Chapter 2. Equation 3.1 models the search for the tuning setup for a given job, which always finds the optimal tuning setup for a given job. However, in practice, Tuning Advisors employ approximation techniques such as search heuristics due to the high dimensionality of the problem. Consequently, Tuning Advisors always generate sub optimal results.

Thus, Tuning Advisors generate sub-optimal results because of: (i) modeling techniques that may fail to model important aspects of the system that have dynamic characteristics, such as updates in the hardware stack or natural evolution of the data sets, and (ii) the employment of search heuristics that have no guarantee of optimality for high dimensional spaces, such as Genetic Algorithm (Liao et al., 2013; Liu et al., 2015; Bei et al., 2017), and Particle Swarm Optimization (Khan et al., 2017).

Now, let us formulate the search for the optimal tuning setup for a SQL-on-Hadoop query. We use the TPC-H query 7 as a running example. Figure 2.4 illustrates in details the query plan for query 7 executing in Hive version 0.13.1, presenting the operators executed in the Map and Reduce phases as well as the tables that read. The complexity of the query plans grows across releases as the SQL-on-Hadoop query processing engines add support to new optimization techniques, operators, data format, etc. For instance, Figure 3.1 illustrates the compiled for two different versions of Hive, specifically, version 0.13.1 and 3.1.0. Observe that the query plan of query in Hive 3.1.0 has 3$\times$ more jobs than the query plan generated by Hive 0.13.1.

Let us define a SQL-on-Hadoop's *query plan* as a directed acyclic graph $G = (V, E)$, where the set of vertices $V$ represents MapReduce jobs, and the set of edges $E$ denotes the precedence between two jobs. Each directed edge is an ordered pair of vertices $e = (v_i, v_j) \in E$ that connects the jobs $v_i$ to $v_j$, when the execution of $v_i$ directly precedes $v_j$, depicted in Figure 3.1.




(a) Query plan compiled by Hive 0.13.1.

(b) Query plan compiled by Hive 3.1.0.

Figure 3.1: Query plans for TPC-H query 7.

A naive approach for searching for the most efficient tuning setup requires employing the advisor function for every job in the query execution plan, such that, the minimum cost of executing query $G$ would be given by:

$$\sum_{v \in V} \sigma(v, f(v)) \tag{3.2}$$

in which $f(v)$ provides the most efficient tuning for each job in the query plan.

However, directly applying $f(v)$, as in Equation 3.2, will not lead the query to achieve the optimal performance, because the performance of a job $v_j$ might be affected by the performance of its preceding job $v_i$. In other words, the Equation 3.2 gives the optimal tuning setup for each job only considering its local context, however, there is a global context that affects each job. For example, setting the number of Reduce tasks or enabling output compression for one MapReduce job $v_i$ will affect the performance of the subsequent job $v_j$ as it will affect the number of Map tasks and the need for decompression for the second job, respectively. Thus, there may exist a tuning setup $C_x \neq f(v_i)$ that drives the query to better overall performance due to its impact in $v_j$.

We formulate the problem of searching for the most efficient tuning setup for a SQL-on-Hadoop's query plan as a combinatorial optimization problem, and use this perspective to reason about how to improve the current approach. We define this problem as follows:

**Definition 2 (SQL-on-Hadoop's Tuning Problem):** *Given a directed acyclic graph* $G = (V, E)$ *representing a SQL-on-Hadoop's query plan, a set* $\mathcal{C}$ *of all possible configurations, and a cost function* $\sigma : V \times \mathcal{C} \rightarrow \mathbb{R}$. *Find the subset of configuration parameters* $\mathcal{C}' \subset \mathcal{C}$ *, that contains every element* $C_v \in \mathcal{C}'$ *associated to an element* $v \in V$*, such that, the total cost to process the* $G$ *is minimum, that is, considering the global context of each job, minimize*

$$\sum_{C_v \in \mathcal{C}'} \sigma(v, C_v) \tag{3.3}$$

Equation 3.3 finds the optimal tuning setup for a given query plan $G$, while Equation 3.2 finds sub-optimal setups. However, Equation 3.3 has to evaluate the tuning setup of each job considering the tuning setup of its preceding jobs, in a "back-tracking" fashion. On the opposite, Equation 3.2 has to evaluate the configuration of each job, without considering its preceding jobs. Thus, because of the large size of the search space the number of evaluations performed by Equation 3.3 might be higher than Equation 3.2, which directly impacts on the time for searching for the optimal tuning setup.

## 3.2 The Uniform Tuning Approach

The current tuning strategy used by SQL-on-Hadoop processing engines allocates the same physical resources to all jobs of a query plan by propagating the same tuning setup through the query plan. We name this approach as *Uniform Tuning*, and define it as follows:

**Definition 3 (Uniform Tuning):** *The Uniform Tuning strategy is the assignment of configurations to jobs such that* $C_u = C_v$ *for* $u, v \in V$ *and* $C_u, C_v \in \mathcal{C}$.

Despite the adviser function $f(v)$ finds the most efficient tuning setup $C_v$ for every job $v \in V$, in the case of the Uniform Tuning only one tuning setup $C_v$ is chosen to be propagated to all jobs in $V$. Thus, in Uniform Tuning $C_v$ improve the performance of some jobs at the expense of negatively affecting the performance of other jobs, impacting the overall performance. We execute the 22 TPC-H benchmark queries with all possible tuning setups in order to analyze the impact of the Uniform Tuning. The results of the impact of the Uniform Tuning presented in the following sections motivate our contributions.

### 3.2.1 Experiment Setup

Before analyzing the impact of the uniform Tuning, we present the environment used in all the experiments of this chapter. Our execution environment is a cluster of 10 machines (m5.2xlarge[1] with 8 CPU cores, 32 GiB of RAM, 500 GiB of disk), hosted at Amazon Web Services (AWS) cloud environment. The cluster runs Ubuntu 16.04 with Hive 0.13.1, Hadoop 0.22.2, and Starfish 0.3[2]. These specific Hadoop and Hive versions are those supported by the latest version of Starfish. The HDFS replication factor is set to 3 and the default block size is 128MB. The maximum number of Map and Reduce tasks that can be started on each node is set to fit the maximum capacity of the CPU (8 threads per node).

For our evaluation, we use TPC-H (TPC), a standard decision support benchmark consisting of 22 queries over 8 tables. Even though TPC-H was developed for evaluating traditional relational database systems, it is now widely used for evaluating SQL-on-Hadoop engines (Floratou et al., 2014). The TPC-H queries contain operations ranging from simple selection to complex joins and aggregations; thus, the generated MapReduce jobs exhibit a wide variety of characteristics. We generated the data with scale factor of 200, which yields 200GB.

We used the TPC-H benchmark queries in the version issued for Hive[3]. Some TCP-H queries consist of several HiveQL statements (e.g., Q15). In this case, we report the aggregated values. Table 3.1 summarizes the information for the 22 TPC-H queries executed with the default Hadoop configuration, listing the number of relevant HiveQL operators executed, the number of MapReduce jobs generated[4], the number of Map and Reduce tasks, the input data size, and the overall run time (i.e., the aggregated run times taken by Hadoop to execute the jobs of the query plan). As required by Starfish, all queries were profiled once using the default Hadoop configuration. All reported run times and statistics are averaged over 3 runs. In the remainder of the paper, all speedups are reported as the percentage of the run times w.r.t. the default configuration (our baseline), shown in the last column of Table 3.2.

[1] https://aws.amazon.com/ec2/instance-types/m5/

[2] https://www.cs.duke.edu/starfish/release.html

[3] https://issues.apache.org/jira/browse/HIVE-600

[4] Hive can evaluate parts of a query using local jobs rather than MapReduce jobs. We ignore such local jobs in our discussion.

| | HiveQL Operators | | | | | | | | | | Runtime information | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Query | Extract | File Sink | Filter | Group By | Join | Limit | Map Join | Reduce Sink | Select | Table Scan | Jobs | Map Tasks | Reduce Tasks | Input (GB) | Time (sec) |
| 1 | 1 | 2 | 1 | 2 | 0 | 0 | 0 | 2 | 3 | 2 | 2 | 608 | 162 | 149.44 | 231.0 |
| 2 | 1 | 6 | 1 | 2 | 1 | 1 | 4 | 4 | 4 | 7 | 6 | 153 | 38 | 27.71 | 123.7 |
| 3 | 1 | 4 | 3 | 2 | 2 | 1 | 0 | 6 | 2 | 6 | 4 | 772 | 205 | 187.35 | 349.3 |
| 4 | 1 | 4 | 2 | 4 | 1 | 0 | 0 | 5 | 5 | 5 | 4 | 758 | 202 | 182.76 | 323.7 |
| 5 | 1 | 7 | 1 | 2 | 2 | 0 | 3 | 6 | 6 | 9 | 7 | 822 | 56 | 187.62 | 348.0 |
| 6 | 0 | 1 | 1 | 2 | 0 | 0 | 0 | 1 | 2 | 1 | 1 | 601 | 1 | 149.44 | 125.3 |
| 7 | 1 | 6 | 3 | 2 | 3 | 0 | 3 | 8 | 8 | 10 | 6 | 972 | 259 | 187.62 | 620.0 |
| 8 | 1 | 8 | 2 | 2 | 2 | 0 | 5 | 6 | 8 | 10 | 8 | 817 | 209 | 192.20 | 503.5 |
| 9 | 1 | 7 | 1 | 2 | 3 | 0 | 2 | 8 | 6 | 10 | 7 | 1473 | 390 | 210.47 | 1321.0 |
| 10 | 1 | 5 | 2 | 2 | 2 | 1 | 1 | 6 | 2 | 7 | 5 | 794 | 207 | 187.35 | 347.5 |
| 11 | 1 | 5 | 1 | 4 | 0 | 0 | 3 | 3 | 5 | 5 | 5 | 108 | 3 | 23.13 | 90.7 |
| 12 | 1 | 3 | 1 | 2 | 1 | 0 | 0 | 4 | 3 | 4 | 3 | 745 | 199 | 182.76 | 240.7 |
| 13 | 1 | 4 | 1 | 4 | 1 | 0 | 0 | 5 | 4 | 5 | 4 | 164 | 44 | 37.91 | 185.0 |
| 14 | 0 | 2 | 1 | 2 | 1 | 0 | 0 | 3 | 2 | 3 | 2 | 629 | 167 | 154.02 | 196.3 |
| 15 | 1 | 3 | 1 | 4 | 0 | 0 | 2 | 3 | 5 | 3 | 4 | 618 | 164 | 149.70 | 206.7 |
| 16 | 1 | 5 | 3 | 2 | 1 | 0 | 1 | 4 | 5 | 6 | 6 | 181 | 38 | 27.71 | 141.3 |
| 17 | 0 | 4 | 2 | 4 | 1 | 0 | 1 | 4 | 5 | 5 | 4 | 1240 | 330 | 154.02 | 678.8 |
| 18 | 1 | 5 | 1 | 4 | 2 | 1 | 0 | 8 | 4 | 8 | 5 | 1463 | 389 | 187.35 | 709.7 |
| 19 | 0 | 2 | 1 | 2 | 1 | 0 | 0 | 3 | 2 | 3 | 2 | 630 | 167 | 154.02 | 408.0 |
| 20 | 1 | 6 | 3 | 6 | 0 | 0 | 4 | 4 | 8 | 6 | 6 | 743 | 171 | 177.15 | 370.0 |
| 21 | 1 | 9 | 5 | 6 | 3 | 1 | 2 | 10 | 10 | 12 | 9 | 2015 | 376 | 183.02 | 964.5 |
| 22 | 1 | 7 | 4 | 6 | 0 | 0 | 2 | 4 | 9 | 7 | 7 | 169 | 40 | 37.91 | 204.3 |

Table 3.1: TPC-H queries with their HiveQL Operators (aggregated), number of MapReduce jobs, number of Map and Reduce tasks, input data size, and run time in our execution environment. For more details about the occurrence of each operator per job, see Appendix B.

### 3.2.2 Experimental Methodology

The goal of uniform tuning is to find a good tuning setup to be used by all MapReduce jobs that comprise a given Hive query. However, current Hadoop tuning advisors, such as Starfish, only propose tuning setups for individual jobs. Hence, an intuitive strategy is to use Starfish to generate one good tuning setup for each job in the query plan, and then select one of those tuning setups for executing the entire query. The key rationale here is that the selected tuning setup will improve the performance of at least one MapReduce job and, hopefully, of the query as a whole.

For instance, let us consider query 7, with the query plan shown in Figure 2.4. Starfish produces six candidate tuning setups (shown in Table 3.2) based on the six MapReduce jobs of the query plan. Note that the parameter values for job-1 listed in Table 3.2 match the default values because these parameters apply only to jobs with both Map and Reduce phases, whereas job-1 is a map-only job. Hence, Starfish does not propose any other specific values for these

parameters. We analyze the performance induced by all candidate tuning setups in Section 3.2.3, and discuss alternative strategies for selecting a tuning setup for a query in Section 3.2.4.

| Tuning Knob | Description | Job-1 | Job-2 | Job-3 | Job-4 | Job-5 | Job-6 | Def. |
|---|---|---|---|---|---|---|---|---|
| io.sort.mb | Buffer size for sorting map output | 100 | 879 | 593 | 593 | 1050 | 547 | 100 |
| io.sort.factor | Number of streams to merge during map-side sorting | 10 | 32 | 64 | 64 | 71 | 22 | 10 |
| io.sort.record.percent | Fraction of io.sort.mb for storing metadata | 0.05 | 0.02 | 0.01 | 0.01 | 0.40 | 0.23 | 0.05 |
| io.sort.spill.percent | Threshold usage of io.sort.mb for beginning sort | 0.80 | 0.60 | 0.78 | 0.78 | 0.64 | 0.51 | 0.80 |
| mapred.inmem.merge.threshold | Map-side threshold for merging data during shuffle | 1000 | 470 | 651 | 651 | 698 | 568 | 1000 |
| mapred.job.reduce.input.buffer.percent | % of memory used to buffer map output during reduce | 0.00 | 0.17 | 0.30 | 0.30 | 0.44 | 0.24 | 0.00 |
| mapred.job.shuffle.input.buffer.percent | % of memory used to buffer map output during shuffle | 0.70 | 0.30 | 0.38 | 0.38 | 0.40 | 0.51 | 0.70 |
| mapred.job.shuffle.merge.percent | Reduce-side threshold for merging data during shuffle | 0.66 | 0.68 | 0.82 | 0.82 | 0.48 | 0.51 | 0.66 |
| mapred.reduce.tasks | Number of reduce tasks | –* | 36 | 36 | 36 | 8 | 8 | 1† |

Table 3.2: Selected parameter values generated by Starfish for each job of TPC-H query 7 and the default (out-of-the-box) tuning values shown on the right. (*Job-1 is a map-only job; hence, `mapred.reduce.tasks` is not set. †By default, Hive overrides `mapred.reduce.task` based on the input size of each job.)

### 3.2.3 Performance of Candidate Tuning Setups

Now, we focus our discussion on the impact of the six candidate tuning setups on query-7's performance, which ranges from a 35.2% slowdown to an 11% speedup in query execution time (as shown in Figure 3.2). To better understand the effect of the parameter values in the different tuning setups, let us examine the number of reduce tasks for query 7, one of the most impactful Hadoop parameters (Afrati et al., 2016). In the baseline configuration, Hadoop by default sets the number of reduce tasks to 1 (see Table 3.2). However, Hive overrides the Hadoop default configuration and sets the number of reduce tasks per job to the size of its input data, divided by 256MB[5]. The number of reduce tasks is the only parameter that Hive controls at the granularity of single jobs. In the execution of query 7, Hive does not set the number of reduce tasks for job-1, because it is a map-only job. Hive further sets 197, 25, 19, 17, and 1 reduce tasks for jobs 2–6, respectively. With this configuration, Hive executes query 7 in 620 seconds.

Next, let us consider the tuning setups generated by Starfish. Starfish recommends 36 reduce tasks for jobs 2–4, and 8 reduce tasks for jobs 5 and 6 (see Table 3.2). The number of reduce tasks recommended by Starfish diverge considerably from the estimation made by Hive, as Starfish uses more fine-grained information to calculate the tuning setups.

Following our experimental methodology, we apply each tuning setup generated by Starfish in turn. We will address the tuning setup generated for job-1 as tuning-1, for job-2 as

[5] `https://github.com/apache/hive/blob/master/ql/src/java/org/apache/hadoop/hive/ql/exec/Utilities.java#L3090`

tuning-2, and so on. When applying tuning-1 for executing the entire query, the number of reduce tasks is not set by Starfish because job-1 is a map-only job. Consequently, Hive estimates the same number of reduce tasks as in the default configuration (presented above). Tuning-1 achieves 1.37% of speedup, which is negligible and predictably close to the baseline. Tuning-2 achieves 11% of speedup and is the best case for query 7. Job-2 runs in 300 seconds and represents 48.39% of the overall run time of the query. Interestingly, we have observed that using the tuning setup for the job with the longest running time is the best option for query 7. However, as common with heuristics, this strategy does not work for all queries, as we demonstrate in Section 3.2.4. Tuning-3 and tuning-4 achieve about 6% of speedup. Both jobs take about 125 seconds each and together make up around 40% of the overall run time. Tuning-2, 3 and 4 set the number of reducers to 36, but the resulting run times are different due to the fine-grained configuration of the other parameters. The performance of the queries does not rely on the number of reduce tasks alone, but on the tuning setup as a whole. Finally, both tuning-5 and tuning-6 set the number of reducers to 8, degrading performance by 32.5% and 35.24%, respectively.

We replicated this process for all 22 TPC-H queries, and present in Figure 3.2 the speedup of each tuning setup relative to the default configuration. Tables 3.3 and 3.4 lists the tuning setups generated for all jobs from the 22 TPC-H queries. Query 6 is the only query comprising a single job. All other queries have more than one job and, consequently, more than one tuning setup. In Figure 3.2, we represent the speedup of each tuning setup by a black bar. The asterisk ($*$) marks the speedup of the tuning setup generated for the job with the longest run time within a query, i.e., the *dominant job* (elaborated further in Section 3.2.4). As observed in Figure 3.2, the run times vary considerably with uniform tuning. Speedups range from 1.3% in query 2 to 27% in query query 14. Slowdowns range from -171.1% in query 9 to -0.4% in query 10. It is interesting to note that there are a total of 39 tuning setups (out of 107) that degrade performance, for 15 out of the 22 queries.

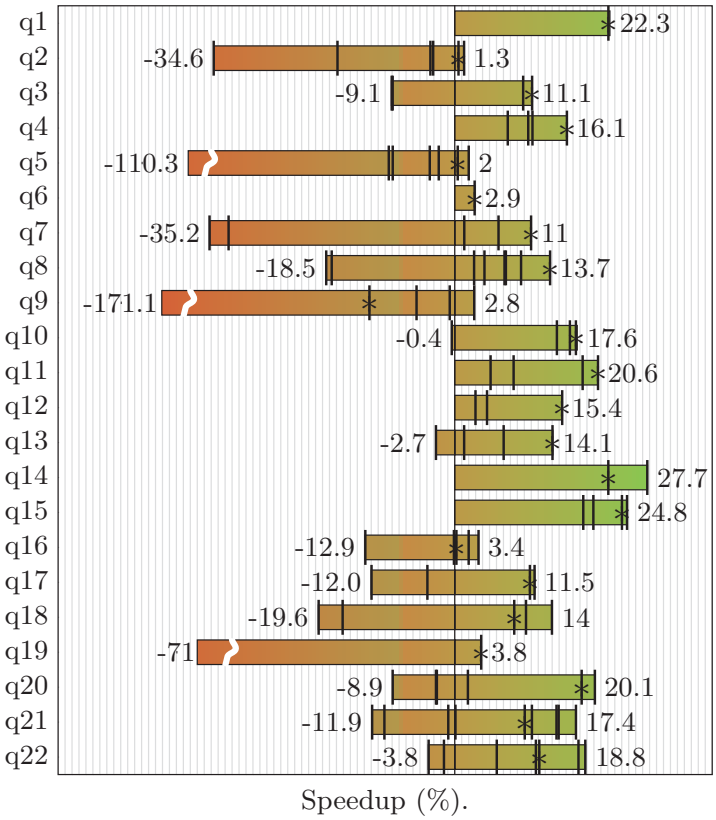



Figure 3.2: Speedups of TPC-H queries achieved by uniform tuning (in %) for each candidate tuning setup. The tuning setups generated for the dominant job (in terms of run time) are marked by $*$.

| Query | Job Id | io.sort.mb | io.sort.factor | io.sort.record.percent | io.sort.spill.percent | mapred.inmem.merge.threshold | mapred.job.reduce.input.buffer.percent | mapred.job.shuffle.input.buffer.percent | mapred.job.shuffle.merge.percent | mapred.reduce.tasks |
|---|---|---|---|---|---|---|---|---|---|---|
| Query-1 | 1 | 568 | 100 | 0.090 | 0.776 | 675 | 0.035 | 0.638 | 0.853 | 8 |
| | 2 | 100 | 10 | 0.050 | 0.800 | 1000 | 0.000 | 0.700 | 0.660 | 1 |
| Query-2 | 1 | 100 | 10 | 0.050 | 0.800 | 1000 | 0.000 | 0.700 | 0.660 | 0 |
| | 2 | 100 | 10 | 0.050 | 0.800 | 1000 | 0.000 | 0.700 | 0.660 | 0 |
| | 3 | 655 | 82 | 0.010 | 0.683 | 110 | 0.261 | 0.490 | 0.468 | 25 |
| | 4 | 668 | 57 | 0.016 | 0.574 | 969 | 0.441 | 0.461 | 0.475 | 25 |
| | 5 | 1126 | 53 | 0.351 | 0.716 | 928 | 0.772 | 0.278 | 0.420 | 8 |
| | 6 | 758 | 76 | 0.500 | 0.726 | 916 | 0.181 | 0.560 | 0.203 | 8 |
| Query-3 | 1 | 809 | 42 | 0.011 | 0.526 | 818 | 0.124 | 0.515 | 0.416 | 24 |
| | 2 | 618 | 97 | 0.011 | 0.665 | 710 | 0.726 | 0.721 | 0.778 | 36 |
| | 3 | 1212 | 24 | 0.012 | 0.528 | 558 | 0.065 | 0.657 | 0.424 | 8 |
| | 4 | 818 | 16 | 0.012 | 0.589 | 673 | 0.759 | 0.375 | 0.749 | 8 |
| Query-4 | 1 | 579 | 25 | 0.015 | 0.548 | 641 | 0.697 | 0.590 | 0.730 | 23 |
| | 2 | 1254 | 34 | 0.010 | 0.514 | 163 | 0.716 | 0.726 | 0.613 | 25 |
| | 3 | 572 | 93 | 0.024 | 0.742 | 222 | 0.101 | 0.482 | 0.611 | 8 |
| | 4 | 914 | 15 | 0.188 | 0.841 | 952 | 0.318 | 0.550 | 0.367 | 8 |
| Query-5 | 1 | 100 | 10 | 0.050 | 0.800 | 1000 | 0.000 | 0.700 | 0.660 | 0 |
| | 2 | 100 | 10 | 0.050 | 0.800 | 1000 | 0.000 | 0.700 | 0.660 | 0 |
| | 3 | 100 | 10 | 0.050 | 0.800 | 1000 | 0.000 | 0.700 | 0.660 | 0 |
| | 4 | 959 | 39 | 0.011 | 0.747 | 936 | 0.712 | 0.309 | 0.855 | 30 |
| | 5 | 715 | 76 | 0.010 | 0.534 | 432 | 0.232 | 0.553 | 0.545 | 21 |
| | 6 | 1131 | 42 | 0.431 | 0.673 | 727 | 0.583 | 0.212 | 0.563 | 8 |
| | 7 | 1239 | 99 | 0.176 | 0.811 | 615 | 0.740 | 0.621 | 0.833 | 8 |
| Query-6 | 1 | 874 | 75 | 0.402 | 0.719 | 758 | 0.335 | 0.550 | 0.738 | 8 |
| Query-7 | 1 | 100 | 10 | 0.050 | 0.800 | 1000 | 0.000 | 0.700 | 0.660 | 0 |
| | 2 | 879 | 32 | 0.015 | 0.605 | 470 | 0.174 | 0.299 | 0.675 | 36 |
| | 3 | 593 | 64 | 0.010 | 0.785 | 651 | 0.304 | 0.381 | 0.818 | 36 |
| | 4 | 593 | 64 | 0.010 | 0.785 | 651 | 0.304 | 0.381 | 0.818 | 36 |
| | 5 | 1050 | 71 | 0.405 | 0.638 | 698 | 0.441 | 0.397 | 0.479 | 8 |
| | 6 | 547 | 22 | 0.230 | 0.510 | 568 | 0.240 | 0.510 | 0.510 | 8 |
| Query-8 | 1 | 100 | 10 | 0.050 | 0.800 | 1000 | 0.000 | 0.700 | 0.660 | 0 |
| | 2 | 100 | 10 | 0.050 | 0.800 | 1000 | 0.000 | 0.700 | 0.660 | 0 |
| | 3 | 665 | 56 | 0.013 | 0.553 | 734 | 0.147 | 0.544 | 0.418 | 23 |
| | 4 | 931 | 47 | 0.011 | 0.576 | 974 | 0.680 | 0.543 | 0.806 | 36 |
| | 5 | 741 | 33 | 0.011 | 0.527 | 258 | 0.154 | 0.697 | 0.627 | 22 |
| | 6 | 100 | 10 | 0.050 | 0.800 | 1000 | 0.000 | 0.700 | 0.660 | 0 |
| | 7 | 910 | 54 | 0.172 | 0.742 | 594 | 0.444 | 0.615 | 0.563 | 8 |
| | 8 | 1230 | 41 | 0.262 | 0.582 | 241 | 0.659 | 0.604 | 0.270 | 8 |
| Query-9 | 1 | 100 | 10 | 0.050 | 0.800 | 1000 | 0.000 | 0.700 | 0.660 | 0 |
| | 2 | 555 | 67 | 0.011 | 0.682 | 750 | 0.318 | 0.770 | 0.809 | 180 |
| | 3 | 555 | 67 | 0.011 | 0.682 | 750 | 0.318 | 0.770 | 0.809 | 180 |
| | 4 | 616 | 67 | 0.010 | 0.571 | 912 | 0.433 | 0.775 | 0.632 | 144 |
| | 5 | 569 | 25 | 0.012 | 0.714 | 713 | 0.563 | 0.817 | 0.599 | 36 |
| | 6 | 1107 | 18 | 0.166 | 0.780 | 744 | 0.129 | 0.896 | 0.243 | 8 |
| | 7 | 1038 | 30 | 0.034 | 0.672 | 648 | 0.664 | 0.282 | 0.702 | 8 |
| Query-10 | 1 | 1220 | 36 | 0.358 | 0.697 | 568 | 0.580 | 0.737 | 0.633 | 25 |
| | 2 | 100 | 10 | 0.050 | 0.800 | 1000 | 0.000 | 0.700 | 0.660 | 0 |
| | 3 | 587 | 83 | 0.011 | 0.677 | 621 | 0.576 | 0.605 | 0.382 | 36 |
| | 4 | 632 | 99 | 0.012 | 0.500 | 848 | 0.295 | 0.400 | 0.349 | 20 |
| | 5 | 765 | 40 | 0.010 | 0.706 | 325 | 0.000 | 0.637 | 0.727 | 21 |
| Query-11 | 1 | 100 | 10 | 0.050 | 0.800 | 1000 | 0.000 | 0.700 | 0.660 | 0 |
| | 2 | 100 | 10 | 0.050 | 0.800 | 1000 | 0.000 | 0.700 | 0.660 | 0 |
| | 3 | 618 | 42 | 0.013 | 0.506 | 675 | 0.091 | 0.300 | 0.622 | 8 |
| | 4 | 618 | 42 | 0.013 | 0.506 | 675 | 0.091 | 0.300 | 0.622 | 8 |
| | 5 | 1292 | 68 | 0.325 | 0.873 | 962 | 0.170 | 0.777 | 0.591 | 3 |

Table 3.3: Selected parameter values for each MapReduce job of TPC-H queries 1-11.

| Query | Job Id | io.sort.mb | io.sort.factor | io.sort.record.percent | io.sort.spill.percent | mapred.inmem.merge.threshold | mapred.job.reduce.input.buffer.percent | mapred.job.shuffle.input.buffer.percent | mapred.job.shuffle.merge.percent | mapred.reduce.tasks |
|---|---|---|---|---|---|---|---|---|---|---|
| Query-12 | 1 | 592 | 42 | 0.016 | 0.646 | 925 | 0.403 | 0.713 | 0.357 | 28 |
| | 2 | 100 | 10 | 0.050 | 0.800 | 1000 | 0.000 | 0.700 | 0.660 | 1 |
| | 3 | 1028 | 40 | 0.332 | 0.832 | 211 | 0.047 | 0.394 | 0.325 | 7 |
| Query-13 | 1 | 551 | 21 | 0.011 | 0.729 | 332 | 0.389 | 0.665 | 0.709 | 27 |
| | 2 | 604 | 39 | 0.016 | 0.502 | 215 | 0.363 | 0.723 | 0.874 | 8 |
| | 3 | 1279 | 62 | 0.489 | 0.692 | 314 | 0.461 | 0.838 | 0.717 | 8 |
| | 4 | 946 | 11 | 0.107 | 0.706 | 908 | 0.593 | 0.618 | 0.277 | 8 |
| Query-14 | 1 | 645 | 48 | 0.455 | 0.662 | 673 | 0.293 | 0.348 | 0.585 | 21 |
| | 2 | 100 | 10 | 0.050 | 0.800 | 1000 | 0.000 | 0.700 | 0.660 | 1 |
| Query-15 | 1 | 745 | 63 | 0.257 | 0.885 | 745 | 0.610 | 0.362 | 0.230 | 8 |
| | 2 | 669 | 16 | 0.223 | 0.696 | 30 | 0.156 | 0.252 | 0.827 | 8 |
| | 3 | 516 | 48 | 0.011 | 0.713 | 964 | 0.639 | 0.513 | 0.617 | 8 |
| | 4 | 532 | 84 | 0.334 | 0.845 | 36 | 0.614 | 0.343 | 0.427 | 2 |
| Query-16 | 1 | 100 | 10 | 0.050 | 0.800 | 1000 | 0.000 | 0.700 | 0.660 | 0 |
| | 2 | 100 | 10 | 0.050 | 0.800 | 1000 | 0.000 | 0.700 | 0.660 | 0 |
| | 3 | 538 | 81 | 0.011 | 0.695 | 703 | 0.644 | 0.535 | 0.867 | 25 |
| | 4 | 100 | 10 | 0.050 | 0.800 | 1000 | 0.000 | 0.700 | 0.660 | 0 |
| | 5 | 520 | 31 | 0.016 | 0.515 | 289 | 0.144 | 0.896 | 0.688 | 20 |
| | 6 | 1261 | 98 | 0.014 | 0.515 | 952 | 0.316 | 0.571 | 0.318 | 8 |
| Query-17 | 1 | 547 | 78 | 0.010 | 0.678 | 913 | 0.606 | 0.724 | 0.594 | 72 |
| | 2 | 543 | 57 | 0.011 | 0.560 | 840 | 0.172 | 0.740 | 0.689 | 72 |
| | 3 | 745 | 57 | 0.010 | 0.550 | 786 | 0.251 | 0.471 | 0.482 | 8 |
| | 4 | 830 | 56 | 0.134 | 0.776 | 88 | 0.288 | 0.634 | 0.519 | 7 |
| Query-18 | 1 | 549 | 26 | 0.024 | 0.751 | 964 | 0.250 | 0.869 | 0.520 | 27 |
| | 2 | 624 | 97 | 0.012 | 0.731 | 752 | 0.486 | 0.663 | 0.414 | 36 |
| | 3 | 644 | 79 | 0.013 | 0.544 | 707 | 0.510 | 0.607 | 0.775 | 72 |
| | 4 | 539 | 59 | 0.129 | 0.848 | 525 | 0.011 | 0.419 | 0.406 | 8 |
| | 5 | 622 | 87 | 0.125 | 0.521 | 473 | 0.309 | 0.706 | 0.824 | 8 |
| Query-19 | 1 | 612 | 88 | 0.012 | 0.574 | 405 | 0.263 | 0.452 | 0.898 | 144 |
| | 2 | 1192 | 27 | 0.026 | 0.539 | 24 | 0.130 | 0.495 | 0.601 | 8 |
| Query-20 | 1 | 980 | 50 | 0.463 | 0.890 | 346 | 0.244 | 0.265 | 0.648 | 8 |
| | 2 | 856 | 47 | 0.011 | 0.550 | 888 | 0.341 | 0.568 | 0.484 | 25 |
| | 3 | 100 | 10 | 0.050 | 0.800 | 1000 | 0.000 | 0.700 | 0.660 | 0 |
| | 4 | 555 | 67 | 0.013 | 0.594 | 704 | 0.288 | 0.561 | 0.501 | 21 |
| | 5 | 638 | 49 | 0.012 | 0.665 | 863 | 0.490 | 0.439 | 0.442 | 8 |
| | 6 | 1256 | 94 | 0.224 | 0.579 | 536 | 0.273 | 0.306 | 0.407 | 8 |
| Query-21 | 1 | 513 | 29 | 0.013 | 0.632 | 776 | 0.794 | 0.571 | 0.508 | 72 |
| | 2 | 647 | 61 | 0.015 | 0.527 | 798 | 0.702 | 0.529 | 0.854 | 36 |
| | 3 | 100 | 10 | 0.050 | 0.800 | 1000 | 0.000 | 0.700 | 0.660 | 0 |
| | 4 | 100 | 10 | 0.050 | 0.800 | 1000 | 0.000 | 0.700 | 0.660 | 0 |
| | 5 | 714 | 25 | 0.011 | 0.626 | 483 | 0.391 | 0.422 | 0.341 | 23 |
| | 6 | 539 | 81 | 0.012 | 0.596 | 777 | 0.169 | 0.414 | 0.568 | 28 |
| | 7 | 633 | 86 | 0.015 | 0.549 | 460 | 0.359 | 0.865 | 0.856 | 25 |
| | 8 | 1209 | 47 | 0.423 | 0.614 | 550 | 0.590 | 0.599 | 0.599 | 8 |
| | 9 | 1260 | 51 | 0.138 | 0.736 | 70 | 0.000 | 0.370 | 0.277 | 8 |
| Query-22 | 1 | 100 | 10 | 0.050 | 0.800 | 1000 | 0.000 | 0.700 | 0.660 | 0 |
| | 2 | 100 | 10 | 0.050 | 0.800 | 1000 | 0.000 | 0.700 | 0.660 | 0 |
| | 3 | 1297 | 82 | 0.273 | 0.654 | 877 | 0.053 | 0.338 | 0.859 | 8 |
| | 4 | 665 | 24 | 0.012 | 0.748 | 234 | 0.000 | 0.347 | 0.896 | 24 |
| | 5 | 605 | 40 | 0.011 | 0.561 | 384 | 0.200 | 0.334 | 0.294 | 8 |
| | 6 | 861 | 68 | 0.321 | 0.656 | 854 | 0.750 | 0.237 | 0.719 | 8 |
| | 7 | 726 | 29 | 0.443 | 0.509 | 458 | 0.591 | 0.709 | 0.295 | 8 |

Table 3.4: Selected parameter values for each MapReduce job of TPC-H queries 12-22.

### 3.2.4 Strategies for Selecting a Tuning Setup

System administrators have several options for assigning tuning setups to Hive queries: (1) to rely on intuition (or chance) for selecting a good tuning setup, (2) to rely on heuristics, such as selecting the tuning setup of the longest running job in the query, or (3) to exhaustively test-run all candidate tuning setups.

**(1) Feeling lucky:** Selecting the wrong tuning setup can severely degrade performance. For instance, tuning-6 of query 7 degrades performance by 35.24%, while the worse-case scenario for query 9 is -171.1% (i.e., 2.7× slower). On the one hand, the probability of degrading performance is the number of bad tuning setups divided by the number of available tuning setups, which is 33% in the case of query 7. On the other hand, the probability of selecting the (near-) optimal tuning setup is 1 divided by the number of available tuning setups, which is only 16% in the case of query 7.

The 22 TPC-H queries produce 107 jobs in total with a 20% probability of selecting the (near-) optimal tuning setups for each query. Thus, relying on chance in selecting a tuning setup is likely to produce a tuning setup where query execution will under-perform, or even significantly degrade.

**(2) Tuning the dominant job:** One natural strategy would be to select the tuning setup generated for the job dominating the runtime. The intuition behind this strategy is that by improving the execution time of the longest running job in the query, the overall query runtime should be improved as well (even if the performance of some of the smaller jobs degrades). In Figure 3.2, the runtimes achieved with this strategy are marked with an asterisk (*). As this figure illustrates, the speedup achieved with this strategy can vary significantly as in some cases tuning the dominant job leads to the best case of uniform tuning, while in others it actually degrades performance. As a mid-case example, let us consider query 21, the query with the highest number of jobs (nine jobs in total[6]). The dominant job in query 21 is job-1, which consumes 32% of the total run time. The tuning setup generated for job-1 achieves only 10% of speedup. However, the tuning setup generated for job-2 performs better, achieving 18.8% of speedup, even though job-2 amounts to 24% of the total run time (and thus less than job-1).

[6]Run times of each job of query 21 (seconds): job-1: 309, job-2: 240, job-3: 6, job-4: 111, job-5: 84, job-6: 99, job-7: 91, job-8: 12, job-9: 12, total of 964 seconds.

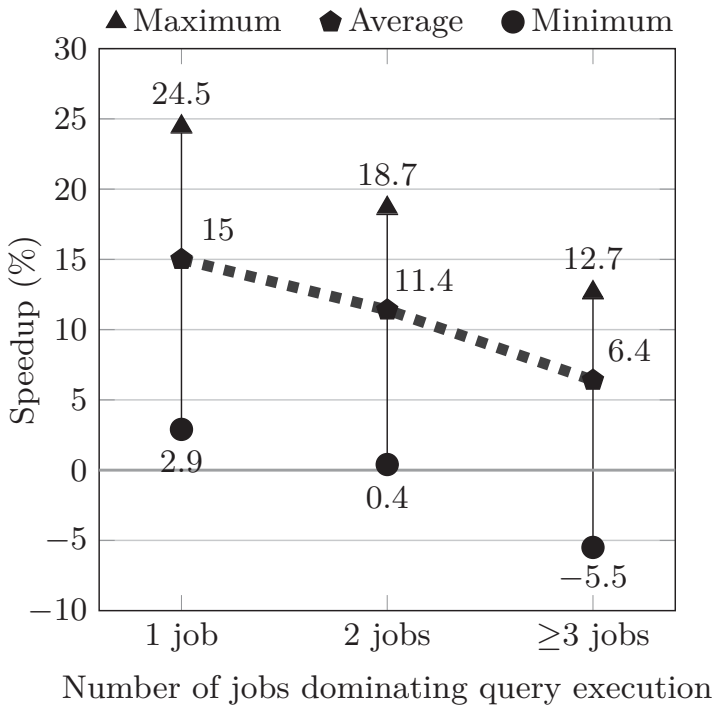



Figure 3.3: Maximum, average, and minimum speedup of uniform tuning (using Option 2) for queries with 1, 2, or more dominant (i.e., long running) jobs within the same query plan.

To further study this strategy, we organize the TPC-H queries into 3 different cases: $(A)$ when the query has one job that dominates query execution time. $(B)$ when the query has 2 jobs, where the sum of their run times dominates the query execution time, and $(C)$ when the query has 3 or more jobs, where the sum of their run times dominates query execution time. For this experiment, we say that a job or jobs *dominate* query execution time when their total run time constitutes at least 70% of the total query execution time. Figure 3.4 visualizes the share of individual jobs in the query execution time and presents the percentage of the dominant job (or jobs) in the total query execution time. The cases $A$, $B$, and $C$ contain 6, 9, and 7 queries, respectively. Thus, the cases are of roughly similar size.

Figure 3.3 summarizes the maximum, average, and minimum speedup achieved via uniform tuning (using the tuning setup of the longest-running job) for the three cases. Observe that uniform tuning tends to be very effective in case $(A)$, because most of the queries in this case have one single job dominating even over 90% of query execution time. Queries in case $(A)$ resemble single MapReduce jobs for which Starfish can generate good tuning setups. However, only 6 out of the 22 TPC-H queries fall into case $(A)$. The dashed trend line indicates that as the number of long-running jobs increases in a query, the strategy of uniform tuning based on the longest running job becomes less effective. Note that the average speedup decreases by about

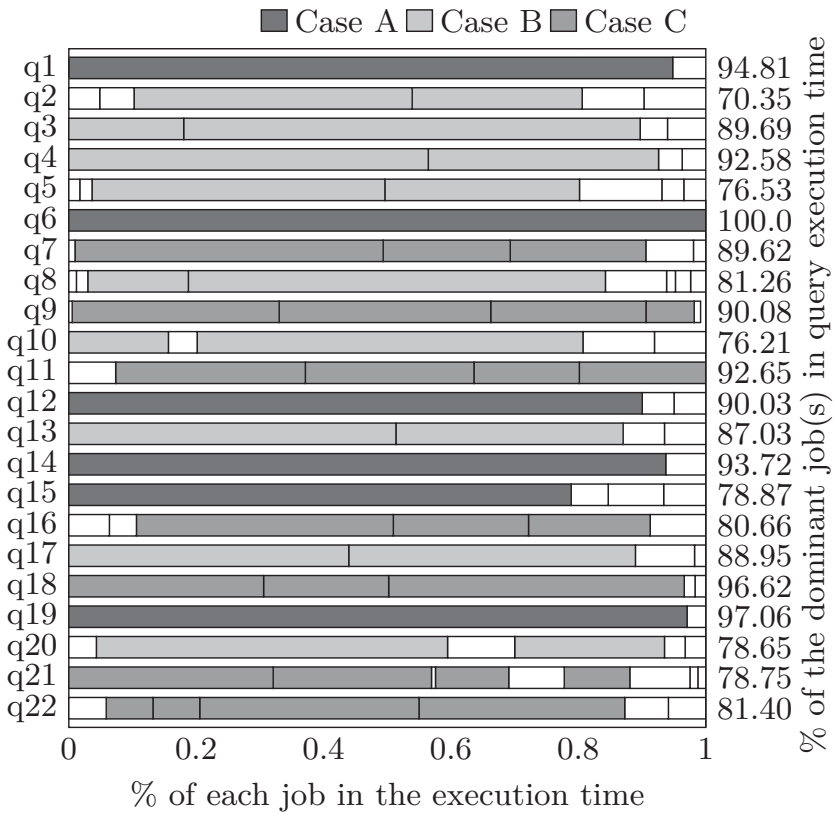



Figure 3.4: The execution breakdown of jobs in the query run time (run with default configuration). Right: Percentage of the dominant job(s) in the query execution time. Jobs are classified into cases A–C, depending on their share of query runtime.

half from case $(B)$ to $(C)$. In case $(C)$, tuning setups generated for the dominant jobs may even degrade performance (observed for queries 9 and 16). Hence, one tuning setup generated for a specific job is not necessarily effective for other jobs. It is a clear case of "one size does not fit all".

**(3) Exhaustive search:** The last option for selecting a tuning setup is to exhaustively test-run all candidate tuning setups, as we did in our experiments. We profile the queries (a first complete execution) for generating the tuning setups and then we test-run all setups.

For instance, query 21 with 9 jobs requires 10 executions: one for profiling and generating the tuning setups, and 9 runs for testing. In total, the 22 TPC-H queries produce 107 jobs and require 129 test runs. The entire test-runs take 7.47$\times$ more time than running with the default configuration, which is rather impractical, as also confirmed in discussions with Hive practitioners.

## 3.3 Discussion

The current approach for tuning SQL-on-Hadoop queries relies on replicating the same tuning setup to all jobs in the query plan. This leads to the problem of finding the best tuning setup that benefits the query plan as a whole when replicated. Finding the best tuning might be impossible due to the different characteristics of each job, once they implement a different mix of relational algebra operators.

Current strategies for selecting this tuning setup can be very expensive (like exhaustive search where we test-run all tuning candidates), or based on heuristics (like tuning the dominant resource consumption job). When tuning for dominant jobs, we observe that tuning queries with tuning setups of dominant jobs can speed up run time for queries with 1 or 2 dominant jobs. However, tuning setups of dominant jobs begin to lose their effectiveness when the execution time is equally distributed by 3 or more jobs, as presented in Figure 3.3. For instance, from the 22 TPC-H queries, tuning the dominant jobs can speed up 70% of the queries. Yet, further analysis is required to determine whether different workloads present the same distribution of dominant jobs.

Tuning SQL-on-Hadoop queries require a large amount of manual work to test-run available tuning alternatives. Test-run all alternatives is time consuming, for instance, it takes $7.47\times$ to test-run all tuning alternatives for TPC-H. Even after testing all available alternatives, there is no guarantee that the chosen tuning setup is optimal. And after a tuning setup is chosen, Hive forbids users to apply tuning setups in a job-basis, which also drives to sub-optimal performance. In the next Chapter, we present our alternative approach to automatically tune SQL-on-Hadoop queries in a job-basis as an extension of Hive.

We validated our approach with the TPC-H benchmark, which is a decision support benchmark that examines large volumes of data and consists of 22 ad-hoc queries. These queries have broad industry relevance and are extensively used by the database community.

# Chapter 4

# Intra-Query Physical-Layer Tuning

In this Chapter, we present the *non-uniform* tuning approach as an alternative to *uniform* tuning: Each MapReduce job in a HiveQL query is executed with its own tuning setup. We also present the impact of *non-uniform* tuning on query execution run time, and compare both approaches.

## 4.1 The Non-Uniform Tuning Approach

For a query plan $G = (V, E)$, there are jobs that implement different sets of SQL operators, i.e., there are jobs $u, v \in V$ where we have $O_u \neq O_v$. Consequently, we assume that these jobs have different resource consumption needs (Boncz et al., 2013). The resource consumption of the 22 TPC-H queries, running with default configuration, is listed in Appendix A. For instance, while a job $u$ requires disk bandwidth due to a *TableScan* operator, another job $v$ requires memory throughput due to a *Sort* operator. One job of a query plan may implement multiple algebra operators due to MapReduce optimization techniques like chain folding and job merging. In this case, the resource consumption requirements are more complex than of single TableScan or Sort operators.

Thus, the optimum of the SQL-on-Hadoop Tuning Problem, presented in Equation 3.3, can only be found when tuning each job of the query plan with appropriate tuning setups. We name this approach as *Non-Uniform Tuning*, and define it as follows:

**Definition 4 (Non-Uniform Tuning):** *The Non-Uniform Tuning approach is the assignment of different configurations to jobs such that $C_u \neq C_v$ for any $u, v \in V$ that has $O_u \neq O_v$.*

We observed in our experiments that there are cases where, in the same query plan, different jobs implement the same set of query operators. In these cases, the same tuning setup

can be applied, although the behavior of such jobs might differ due to the distribution of the data, selectivity and similar aspects. We discuss these cases in Section 5.1.

Next, we compare the performance of the Uniform and Non-Uniform tuning approaches.

## 4.2 Performance of Non-Uniform Tuning

**Claim 1:** *Considering $\mathcal{C}'$, from Definition 2, the Non-Uniform tuning approach, performs better than the Uniform tuning, or equal, in the worst-case.*

Consider that $C_u$ is the tuning setup generated for job $u$, for $u \in V$. Let $C_u$ be assigned using the uniform tuning, *i.e.*, be the tuning setup assigned to all jobs $v \in V$. Now, consider the case with non-uniform tuning, in which for the same query plan $G$, the most efficient tuning for every job $v$ can be naively obtained by calling interactively the function $f(v)$. Directly from Definition 3.1 we have the following inequality

$$\sigma(v, f(v)) \leq \sigma(v, C_u) \tag{4.1}$$

for every job $v \in V$.

The inequality says that, in the best case for the uniform tuning, the arbitrary tuning setup $C_u$ can be the most efficient for $v$, but there are no guarantees that it will happen. While attributing a tuning setup $C_v$ chosen by the function $f(v)$, we know that it is always the optimal tuning setup for $v$. Consequently, the total cost required to execute all jobs $v \in V$ of the query plan $G$ using the adviser function, can be written as Equation 3.2. So, from the inequality (4.1) we can compare the total costs of the two approaches, as follows:

$$\sum_{v \in V} \sigma(v, f(v)) \leq \sum_{v \in V} \sigma(v, C_u),$$

i.e., the computational cost for executing the query plan $G$ using the non-uniform assignment method is at most equals to the cost for the uniform method. However, we know Equation 3.2

is the naive approach that generates sub-optimal solution for tuning a query plan, and that the optimal solution is found by Definition 3, such that,

$$\sum_{C_v \in \mathcal{C}'} \sigma(v, C_v) \leq \sum_{v \in V} \sigma(v, f(v)) \leq \sum_{v \in V} \sigma(v, C_u) \tag{4.2}$$

The advantage of using the uniform tuning method is that it is simple and straightforward, i.e., the SQL-on-Hadoop engine just replicates the chosen tuning setup. On the other hand, there are no guarantees that the chosen tuning setup will perform well during the query's execution.

Our proposal of non-uniform tuning personalizes the tuning setup for each job and the optimal assignment of tuning setups is guaranteed. In other words, the SQL-on-Hadoop's Tuning Problem can be solved optimally with the Non-Uniform tuning method. Furthermore, a direct consequence of the Non-Uniform tuning approach is the improvement in the performance of the query plan, as stated in Claim 1.

## 4.3 Cost of the Non-Uniform Tuning

Denoting $C_v$ as the configuration for a vertex $v \in V$ and considering that every tuning parameter $c_i$ of the configuration $C_v$ has a different domain $dom(c_i)$ of size $d_i$. The computational cost for the worst case of finding an optimal solution for the non-uniform tuning can be stated as follows.

**Theorem 1:** *The cost of finding the optimal Non-Uniform tuning for a query plan $G = (V, E)$, is of $\mathcal{O}(|V|n^m)$, where $n = \max_{1 \leq i \leq m}\{d_i\}, m = |C_v|$.*

**Proof 1:** *We can enumerate all possible configurations for a single $v$ by the following product:*

$$\prod_{i=1}^{m} d_i.$$

*Since different domains have different sizes (including infinite domains), let the max size for a parameter domain be $n = max_{1 \leq i \leq m}\{d_i\}$. An upper bound for such product is*

$$\prod_{i=1}^{m} d_i \leq \prod_{i=1}^{m} n = n^m$$

*Thus, it is required time $\mathcal{O}(n^m)$ to find the optimal configuration for a job $v$. Consider that we want to find the optimal configuration for every vertex $v \in V$, that is,*

$$\prod_{v \in V} \mathcal{O}(n^m), \tag{4.3}$$

*therefore, we need time $\mathcal{O}(n^m|V|)$ for the whole graph $G$.*

□

Similarly, the cost of finding the optimal configuration for the uniform tuning is $\mathcal{O}(n^m)$, since we need to find only one optimal configuration $C_0$ which is propagated to the entire graph.

## 4.4 Non-Uniform Tuning Methodology

As of today, there is no mechanism in Hive for applying tuning setups at the level of individual jobs within the same query plan, even though MapReduce jobs can be configured individually when submitted separately. We therefore extended the Hive query processing engine to switch between tuning setups, executing each job with its own tuning setup. Our extension does not change the current query processing workflow, described in Section 2.5. Instead, our extension just rewrites the configuration of every job right before it is queued in Hadoop for processing. Our fork of Hive is fully functional, to the point where a Hive administrator can enable our extension by merely setting a single, new parameter (`hive.optimize.selftuning`) to true.

We run the TPC-H queries with our extension to analyze the performance impact of non-uniform tuning. For instance, let us consider TPC-H query 7 again. When the query is submitted, it is processed and optimized by the Hive query processing engine: All its jobs have been created and all Hive optimizations have been performed with the query plan looking as depicted in Figure 2.4. At this point, our extension calls Starfish to profile and optimize every job of query 7 (recall Section 2.4), and stores the recommended tuning setups in a cache repository.

The cache repository is presented in Section 5.1. Briefly, the cache associates the *code signature* of each job with its recommended tuning setup. A code signature is a set of annotations generated during query compilation that capture the query operators executed as part of a job, along with some basic data properties (similar to the information contained in Figure 2.4). The code signature can be used to uniquely identify a job within the same query plan. When query 7

is submitted again, the code signature of each job is used as a key to look up the corresponding tuning setup from the cache and apply it to the job. Hence, each job in query 7 is submitted with the parameters shown in Table 3.2.

During the experiments, we monitored the resource utilization of each query from its submission until its completion. We employed the *Collectl* tool[1] to collect performance data related to the consumption of CPU, memory, network, and disk I/O. *Collectl* runs a light-weight monitoring service on each machine of the cluster that reads runtime system information from the Linux's `/proc` virtual file system with negligible overhead[2]. When required in our analysis, we also use information from the Hadoop job counters, which are automatically collected by the Hadoop framework during the execution of MapReduce jobs.

In order to compute the overall resource consumption of the TPC-H workload (which will facilitate our analysis), we: $(1)$ calculate the average consumption per second for each resource from the aggregated values collected on all machines in the cluster; and $(2)$ sum up the averages for each resource, for all queries, to produce the *accumulated resource consumption*. We compare the resource utilization of uniform and non-uniform tuning in Section 4.6.1 and provide an in-depth analysis of query 7 in Section 4.6.2.

The experiments presented in the following sections use the experimental setup presented in Section 3.2.1.

## 4.5 Performance of Uniform vs. Non-Uniform Tuning

The uniform and non-uniform tuning approaches can both optimize queries, however, with different impact on performance. Figure 4.1 presents the speedups for both approaches, including the best and worst cases of uniform tuning. On the one hand, the best case of uniform tuning optimizes queries up to 27.7% (query 14) and does not degrade the performance of any query. The best case of uniform tuning optimizes the runtime of the entire TPC-H workload by 12.1%. Non-uniform tuning achieves a similar overall speedup of 12.2% for the entire TPC-H workload, and is as good as the best case of uniform tuning. On the other hand, the worst case of uniform tuning degrades the performance of 14 out of the 22 queries, with severe slowdowns for queries 5, 9, and 19. The worst case of uniform tuning degrades the performance of the overall TPC-H

[1] `http://collectl.sourceforge.net/`
[2] `http://collectl.sourceforge.net/Performance.html`

workload by 40.8%. Hence, non-uniform tuning presents a great and *robust* advantage over uniform tuning.

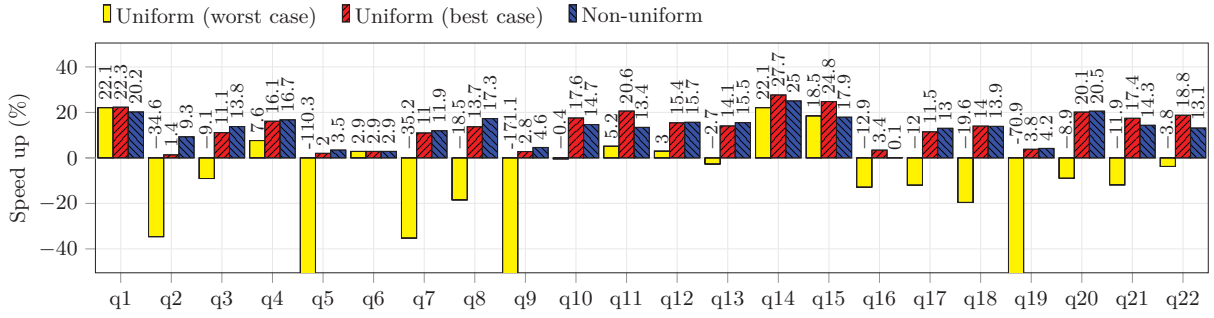



Figure 4.1: Speedup of uniform and non-uniform tuning approaches relative to the default configuration.

To further understand the impact of non-uniform tuning to query performance and compare it to uniform tuning, let us consider query 7 again. The best case of uniform tuning applies the recommended parameters of job-2 (see Table 3.2) to all jobs in query 7 and achieves an 11% speedup. The non-uniform tuning approach assigns each job its very own tuning setup and thereby achieves a 12% speedup. Even though the difference in speedup is small, there are significant advantages to non-uniform tuning with regards to improved resource utilization, as we will see shortly. The increased performance is attributed mainly to the additional speedup achieved for jobs 4 and 5. In particular, the higher values for parameters `mapred.job.reduce.input.buffer.percent` and `mapred.job.shuffle.input.buffer.percent` enable the reduce tasks to buffer more intermediate data in memory, spilling less data to disk, and thereby reducing the amount of both write and read disk I/O performed. In fact, the tuning setup for job-4 completely avoids data spills on the reduce side and eliminates a total of 15.1 GB of local disk I/O. As for the remaining jobs, 1 and 6 are short-running and unaffected by the particular choices of parameters. Job 2 is executed with the same settings in both cases, while the performance of job 3 is similar in both cases.

Overall, non-uniform tuning avoids degrading performance by allocating job-specific physical resources, while uniform tuning allocates the same amount of resources to all jobs in the query plan. Regarding the strategy of tuning based on the dominant job, uniform tuning loses its effectiveness when queries have more than one job dominating query execution. As we have seen in Section 3.2.4, uniform tuning is effective for optimizing queries in case $(A)$, and ineffective on queries in cases $(B)$ and $(C)$. Non-uniform tuning, however, is effective in all three cases.

Another advantage of non-uniform tuning is the self-tuning nature of the approach. Human intervention becomes impractical when any ordinary OLAP workload generates tens to hundreds of jobs and many more possible tuning setups.

In our experiments, optimizing each job individually in non-uniform tuning always leads to better performance results but not always the best. As we can observe from Figure 4.1, the best-case of uniform approach is a little better (0.1–7.2% higher speedup) than the non-uniform one for 9 out of the 22 TPC-H queries. There are two main reasons for this behavior. First, almost all Hadoop tuning advisors (including Starfish) treat the Map and Reduce functions as black boxes and make simplifying modeling assumptions. For example, some make the proportionality assumption (Herodotou and Babu, 2011), based on which the execution time of a function will double if its input size is doubled. This assumption may hold for simple jobs like WordCount or Sort, but it is not true for jobs that contain multiple relational algebra operators like joins and aggregators. Hence, the modeling, and consequently the tuning recommendations, might not be optimal. Second, performance dependencies between jobs complicate the task of a tuning advisor. For example, setting the number of Reduce tasks or enabling output compression for one MapReduce job will affect the performance of the subsequent job as it will affect the number of Map tasks and the need for decompression for the second job, respectively. Hence, it is harder to generate optimal tuning setups for later jobs in a query execution plan. Overall, there is a dire need for (1) better modeling techniques when the MapReduce jobs are generated by the query compilers of SQL-on-Hadoop systems, especially since there is inside knowledge of which operations the jobs will perform, and (2) better optimizers that can take into consideration the interdependencies of jobs and holistically optimize the entire workflow.

## 4.6 Impact on Resource Utilization

Apart from execution time speedup, Hadoop parameter tuning can have a significant impact on the physical resources that are consumed during the execution of HiveQL queries. In this section, we study and compare the impact of uniform and non-uniform tuning on resource utilization.

### 4.6.1 Resource Utilization of Uniform vs. Non-uniform Tuning

Figure 4.2 depicts the relative percentage of the accumulated resource consumption of the TPC-H workload running with uniform and non-uniform tuning, compared against the default

configuration (our baseline). Overall, non-uniform tuning consumes significantly less computing resources across all relevant metrics. For instance, non-uniform tuning leads to 35% less CPU utilization and 40% less memory usage than the baseline, whereas the best case of uniform tuning leads to 13% and 12% reductions, respectively. To better understand these results, we discuss next the effect of the number of MapReduce tasks as well as other relevant parameters to the execution behavior of the TPC-H queries.

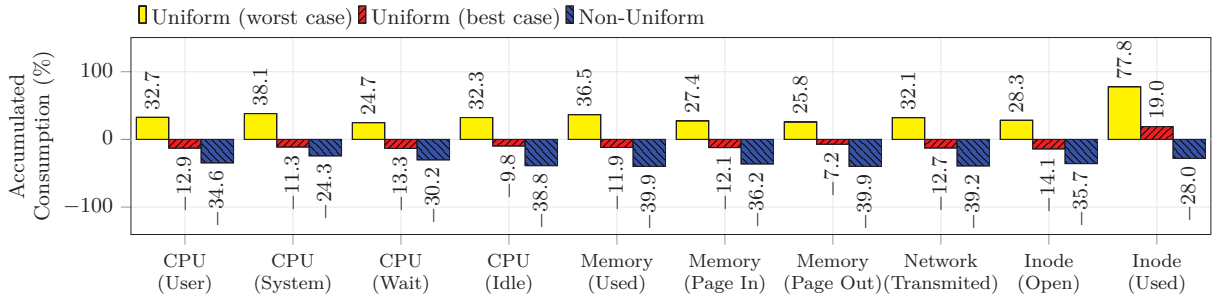
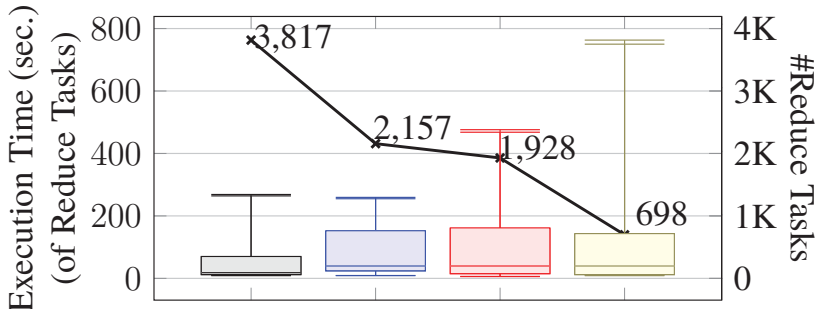



Figure 4.2: The accumulated resource consumption percentage of uniform and non-uniform tuning relative to the default configuration (baseline). Less is better.

Under default configuration, the 22 TPC-H queries are executed with 107 MapReduce jobs comprising 16,475 map and 3,817 reduce tasks (yielding 20,292 tasks in total). The number of map tasks is determined by the input data size, as was previously discussed in Section 3.2.3. Consequently, both the uniform and the non-uniform tuning create almost the same number of map tasks as the default configuration, differing by less than 1%. The number of reduce tasks, however, varies considerably among the different approaches (as can be seen on Figure 4.3), revealing an interesting trade-off: On the one hand, if the number is set too high, the many short-running reduce tasks increase the scheduling and launching overheads. On the other hand, if the number is set too low, the tasks fail to exploit the potential for cluster parallelization. Rather, each reduce task will need to process a large amount of intermediate data that will probably not fit in the memory buffers. This leads to an increased number of disk spills. Therefore, setting the appropriate number of reduce tasks for each job (along with a few other important parameters) is crucial for a balanced resource utilization and overall performance.

Figure 4.3 presents the distribution of the execution time of the reduce tasks for each tuning approach. First, we observe the (expected) inverse relationship between the average execution time and the number of reduce tasks. Interestingly, the non-uniform tuning and the best case of uniform tuning decrease the number of reduce tasks by 1.8× and 2.0×, respectively, but each task on average takes only 1.5× and 1.6× more time to complete, compared to the default

configuration. Nonetheless, the most important difference is the variability in task execution time. Both uniform tuning approaches exhibit stretched distributions, with worst-case outliers that are almost 20× larger than the corresponding average execution time. Non-uniform tuning, on the other hand, leads to the smallest range of execution time values, showcasing once again the robustness of this method. Finally, the default configuration uses a large number of reduce tasks with shorter execution times (and naturally low variability). Even though the execution times of the individual reduce tasks are shorter, there are more tasks and their management overheads increase the execution time of the overall job. Thus, the actual query execution times are generally inferior to non-uniform tuning, as shown in Figure 4.1 and also discussed in Section 4.5.




| | Default | Non Uniform | Uniform (best) | Uniform (worst) |
|---|---|---|---|---|
| Average | 53.79 | 81.37 | 88.55 | 109.21 |
| Std.Dev. | 64.97 | 76.39 | 95.12 | 167.33 |
| Range | 255.11 | 246.10 | 462.17 | 2,136.51 |
| Max | 264.11 | 255.10 | 468.17 | 2,145.51 |

Figure 4.3: Distribution of execution times of the reduce tasks for each tuning approach.

Another positive artifact of reduced execution time variability is the reduction or elimination of *straggler tasks*, i.e., tasks that make slower progress compared to other tasks. When Hadoop detects a straggler task, it will run a *speculative copy* of that task on another node to finish computation faster. As soon as one of the two tasks completes, the other one is killed. In one execution run of the TPC-H queries with the default configuration, we observed that 191 reduce tasks were killed. This implies that there are 5% more reduce tasks than needed that are being launched and scheduled[3]. Non-uniform tuning and the best case of uniform tuning decrease the number of failed reduce tasks to less than 1%, thereby reducing the number of straggler tasks by 5×.

[3]This effect is consistently reproducible across repeated runs. Across our three runs, we observed an average number of failed reduce tasks of 185.33, and a standard deviation of 6.03.

In addition to setting the number of reduce tasks correctly, several other parameters (e.g., `mapred.job.reduce.input.buffer.percent` and `mapred.job.shuffle.input.buffer.percent`) can regulate the percentage of memory used to buffer map outputs during shuffle and reduce phases. When these buffers fill up, Hadoop starts to write the map outputs to the local file system. The amount of memory given to map and reduce tasks directly impacts the amount of data spills (on the map or reduce side, respectively). Note that the data written between jobs in a query plan and the final results of the queries are written to the distributed file system and not affected by parameter settings. Figure 4.4 presents the accumulated data written to the local and distributed file systems during the shuffle and reduce phases. Considering the total amount of data materialized to the local file system, non-uniform tuning writes 5.3× (584.4GB) less than the default configuration. In fact, the non-uniform tuning completely eliminates data spills on the reduce side from 92 out of the 107 jobs generated from the TPC-H, which yields 4.2× more jobs without data spills on the reduce side than the default configuration. The best-case of uniform tuning writes 1.9× (340.7GB) less data, while the worst-case of uniform tuning writes only 8.8% (63.4GB) less.

As a consequence of writing less data to the local file system, non-uniform tuning is more parsimonious with other resources as well (see Figure 4.2). For instance, setting the job-specific buffer sizes appropriately (e.g., `io.sort.mb`, `mapred.job.reduce.input.buffer.percent`), we observe 39.9% fewer page outs with non-uniform tuning, and, consequently, the CPU waits 30.2% less. The decrease in memory page outs, in addition to the reduced data spills, are instrumental in reducing the number of open files by 35.7%. Other parameters such as `io.sort.spill.percent` and `mapred.job.shuffle.merge.percent`, when set appropriately, enable better overlapping between CPU processing and I/O, contributing to lower CPU waits.

### 4.6.2 In-Depth Analysis for Query 7

Figure 4.5 presents the utilization of CPU, memory, and network for query 7. Table 4.1 further presents the average run time for each job of query 7, during its execution with the default configuration, non-uniform tuning, and best and worst cases of uniform tuning. In Figure 4.5, solid black lines indicate the beginning of each job in the sequential query plan schedule, and dashed lines indicate the end of the query execution. The submission of the jobs follows a sequential order derived from the query plan in Figure 2.4. The data presented is an average of

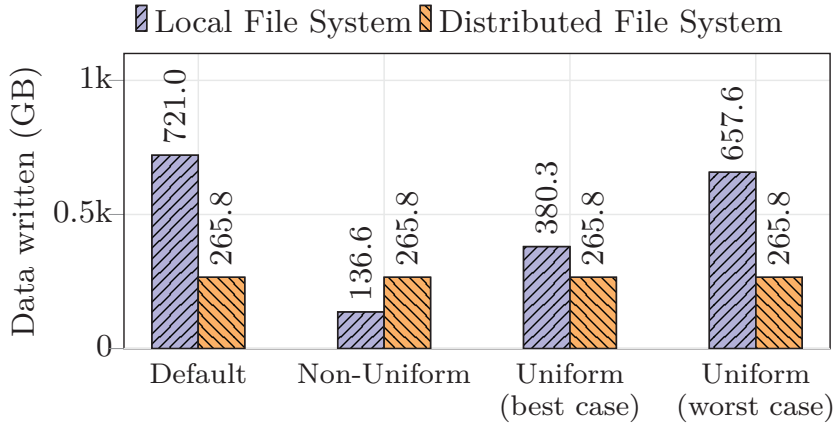



Figure 4.4: The total amount of data written to the local and distributed file system during the shuffle and reduce phase of the 22 TPC-H queries.

the data from 10 machines in the cluster, measured during a single execution. Note that job-1 is a small job that executes in only about 6 seconds across all configurations (and hence almost not visible in Figure 4.5), because it is a map-only job executing on the small table *nations*. Similarly, job-6 is also a small job that materializes the query results to the final table, running in 12 seconds on average across all configurations. In our discussion below, we will focus on jobs 2, 3, and 4, which perform one join operation each and together constitute more than 90% of the total execution time of query 7.

We first analyze the effect of the tuning approaches to CPU utilization. Consider job-2, which filters table *orders* (34GB) and scans table *lineitem* (150GB) during the map phase, and performs a join during the reduce phase. Our first observation from Figure 4.5 is that the default configuration and the worst case of uniform tuning exhibit low CPU utilization during the first half of the job (i.e., the map phase), whereas the opposite is true for the non-uniform tuning and the best case of uniform tuning. The explanation is traced to the settings of `io.sort.mb`, which determines the map output buffer size, and `io.sort.spill.percent`, which sets a threshold for when to sort and spill the buffered data (see Table 3.2). The small buffer size (100MB and 547MB in default configuration and worse case of uniform tuning, respectively) in combination with the small threshold (0.51) in the worse case of uniform tuning, leads job-2 to sort and spill small chunks of data more frequently during the map phase, which, consequently, induce low CPU utilization.

Another interesting observation is the lower variation in CPU utilization for non-uniform tuning compared to the other cases, especially for job-4. In the best case of uniform tuning, the low values for `io.sort.spill.percent`, `mapred.inmem.merge.threshold`, and

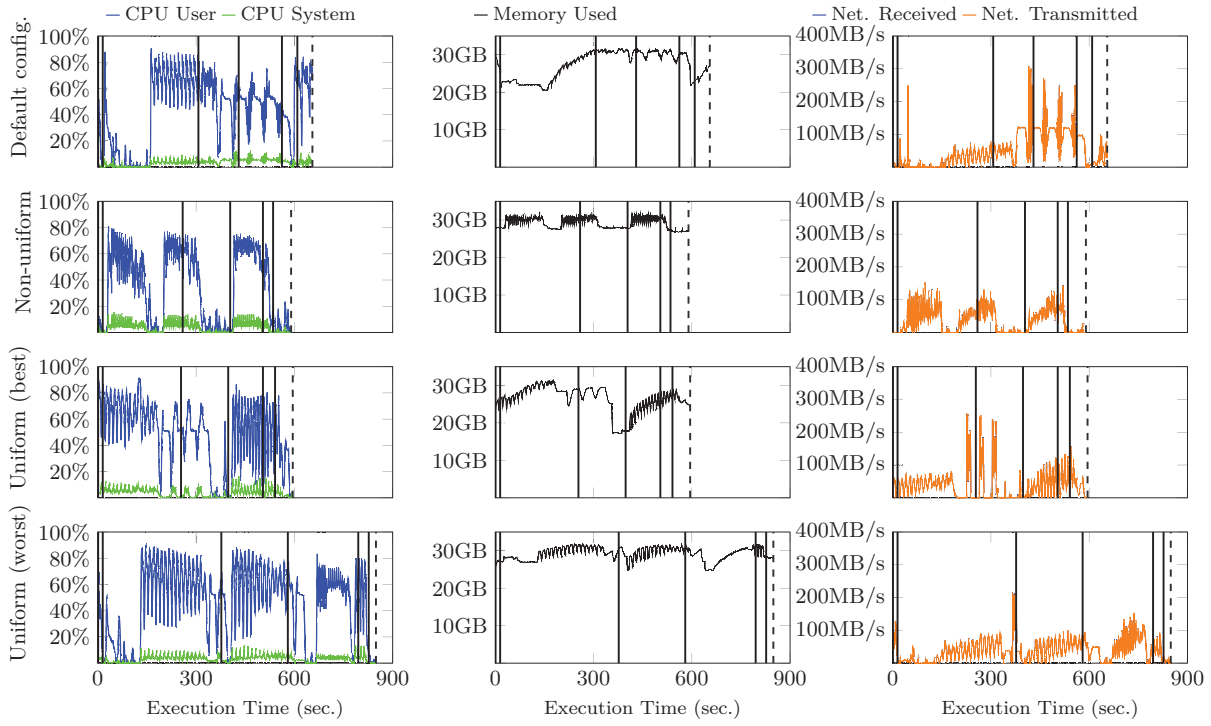



Figure 4.5: Average resource consumption of the 10 machines of the cluster during a single execution of TPC-H query 7. Solid black lines indicate the beginning of each of the 6 jobs in the query plan, and dashed black lines indicate the end of query execution.

`mapred.job.shuffle.merge.percent` are causing frequent rounds of sort-spill-merge operations, leading to variability in CPU usage. The settings used in the non-uniform tuning case, on the other hand, achieve a better overlap between the CPU processing and I/O spills, leading to higher CPU utilization, and ultimately, to a lower job execution time.

Let us consider memory utilization next, also shown in Figure 4.5. Our first observation is the low memory usage of job-2 during default configuration, which is attributed to the low `io.sort.mb` setting (100MB). The map functions of job-2 perform only scan and filter operations, which do not require much execution memory. Even though there is a lot of available memory, only 100MB can be used by each map task for buffering map output data, leading to a significant under-utilization of memory. On the contrary, the high `io.sort.mb` settings used by the other approaches (ranging from 547MB to 1050MB) enable map tasks to buffer more output data and better utilize memory.

The memory consumption of job-3 in the best case of uniform tuning experiences a noticeable drop during the reduce phase. The low setting of `mapred.reduce.input.buffer.percent` at 0.17 means that only a small percentage of memory is used to buffer map output data during the reduce execution. In addition, job-3, which joins the table *customer*

| | Default config. | Non-uniform | Uniform best-case | Uniform worst-case |
|---|---|---|---|---|
| job-1 | 6.0 | 6.0 | 5.5 | 5.0 |
| job-2 | 300.0 | 252.0 | 248.0 | 371.5 |
| job-3 | 123.7 | 145.0 | 144.0 | 203.0 |
| job-4 | 132.0 | 100.0 | 105.5 | 214.5 |
| job-5 | 46.3 | 31.0 | 37.0 | 32.5 |
| job-6 | 12.0 | 12.0 | 12.0 | 12.0 |
| Total | 620.0 | 546.0 | 552.0 | 838.5 |

Table 4.1: Average run time (in seconds) per job of query 7 running with the default configuration, non-uniform, and uniform tuning.

(4.6GB) with the output of job-2 (20GB), uses 36 reduce tasks. Hence, each reduce task processes approximately 0.6GB of data. The combined effect of the two aforementioned factors contribute to the reduced memory usage of job-3.

Finally, let us now observe network consumption. Recall that Figure 4.5 shows an average of data from 10 machines, so when one machine is transmitting data, another machine is receiving it. Thus, the amount of data transmitted and received through the network at a given point in time are congruent. Network consumption may be affected by many factors, including how the data is distributed across the nodes of the cluster, how balanced the tasks are scheduled to each node, and the replication degree of data. Hence, individual configuration parameters have a lower impact on network utilization compared to other resources. Nonetheless, the overall settings used by non-uniform tuning lead to a smoother network consumption compared to other approaches, which occasionally suffer from big network spikes.

## 4.7 Discussion

The Non-Uniform tuning method can lead queries to achieve better performance than the current uniform tuning method. On one hand, the uniform tuning approach is simple and can be applied to any query processor, since it only requires the replication of the same tuning setup through the query plan. Replicating tuning setups may facilitate the design of query processors and avoid database designers to bind to the query processor a whole new family of systems (tuning advisors). Binding tuning advisors to query processors might not be a good trade-off when considering the design challenges and the speed up presented by current tuning advisors. Mainly for SQL-on-Hadoop queries that are designed for batch processing of long-running jobs and

queries are expected to take long running times. However, the benefits that physical-layer tuning brings to SQL-on-Hadoop queries includes not only speed ups but also a high impact on the resource consumption, as demonstrated in Section 4.6.

Thus, on the other hand, the non-uniform tuning implies increasing the complexity of SQL-on-Hadoop query processors when binding a tuning advisor. Despite the increase in the design complexity, the better control over resources are evident. Such fine-grained control of resources might increase as the demand for cloud-based processing engines in shared environments increases as well.

# Chapter 5

# Recycling Tuning Setups

In this Chapter we present the recycling of tuning setups with the Tuning Cache. We have implemented the Tuning Cache as an extension of the Hive query processor in the form of a Hash table, where the keys are code-signatures and the values are the tuning setups. The Tuning Cache leverages tuning setups generated by the Starfish tuning adviser (Herodotou et al., 2011).

At the best of our knowledge, Starfish is the only cost-based tuning adviser publicly available for MapReduce frameworks. It generates tuning setups base on *execution profiles* that are collected in an off-line profiling phase. Profiling is a costly operation that employs dynamic instrumentation (BTrace) to monitor the invocation of several methods executing in the map and reduce tasks. For instance, Starfish can capture the arguments of a specific method to determine the amount of data being processed, or the time taken to process such data. Profiling overhead is up to 46% when Starfish is profiling 100% of map and reduce tasks. Starfish is able to profile a sample of tasks at the cost of degrading the quality of tuning being generated (Herodotou and Babu, 2010; Herodotou et al., 2011; Herodotou and Babu, 2013). Thus, in these experiments, we run Starfish with sampling turned off to obtain high-quality tuning profiles.

We use Starfish 0.3.0[1], which ties us to Hadoop 0.20.2 and Hive 0.6.0, unless stated otherwise. We point out that the Tuning Cache is a generic data structure not restricted to any particular version of Hive or Hadoop. We evaluate the TPC-H queries provided for Hive[2]. The data has been generated with a scale factor of 10. This amounts to 10.46GB of data when stored on disk.

Our setup is a cluster with three physical machines, where the distributed file system and job coordinators were isolate on one machine, so that they do not influence the monitoring and

[1]Starfish is available at `https://www.cs.duke.edu/starfish/release.html`.
[2]See `https://issues.apache.org/jira/browse/HIVE-600` for the TPC-H queries.

profiling of jobs. In particular, each machine has a Intel(R) Core(TM) i3-3240 CPU @ 3.40GHz, 4GB of RAM, 1TB of disk. We used the *collectl* tool[3] tool to measure CPU, memory, network, and disk consumption. The reported execution times are averaged over 10 runs. All our profiling runs are configured with the out-of-the-box configuration. We first consider the reuse of tuning setups at the level of single MapReduce jobs, and later at the level of SQL queries.

## 5.1 The Tuning Cache

In order to automatically tune SQL-on-Hadoop queries, we present the Tuning Cache, a complementary approach to the non-uniform tuning that recycles tuning setups to avoid recalculating tuning setups for similar jobs. It assigns tuning setups to MapReduce jobs upfront execution, where the tuning setups are produced by a third-party tuning adviser. We use the *code signature* of a MapReduce job as lookup key in the Tuning Cache. We introduce the notion of a code signature shortly. We then discuss how the Tuning Cache manages tuning setups.

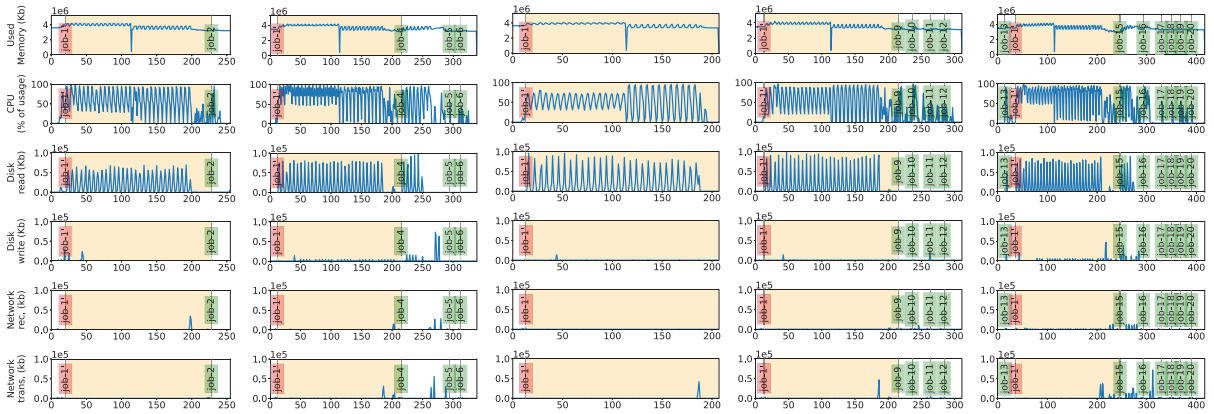
### 5.1.1 Code Signatures

During query compilation, SQL-on-Hadoop query processors annotate the resulting MapReduce jobs with several descriptive properties. The Hive Java API makes these annotations accessible: Each job is annotated with a list of the physical query operators that are implemented by this job. For each operator, a *cardinality* is given. For instance, a job may execute two *Filter*-operations (i.e., selection in relational algebra), as well as one aggregation. Each job is further annotated with the estimated size of its input.

**Example 1:** TCP-H query 1 is compiled by Hive into two jobs. The first job is annotated with the operators *Filter*, *Select*, and *GroupBy*. Each operator has cardinality 2. The job is further annotated with the operators *TableScan*, *ReduceSink*, and *FileSink*, each with a cardinality of 1. In the setup of our experiments (see Section 4) the estimated input size is stated as 7.24GB. □

Our assumption is that these declarative annotations are related to the resource profile of these jobs. Further, we hypothesize that jobs with the same annotations may be executed with the same tuning setups, even though they differ in their Java code. In our experiments, we are able to confirm this. For now, we argue on an intuitive level.

[3] `http://collectl.sourceforge.net`




(5.1.1) Query 1 (5.1.2) Query 4 (5.1.3) Query 6 (5.1.4) Query 15 (5.1.5) Query 20

Figure 5.1: Execution of selected TPC-H queries. The jobs labeled 1' share the same code signature and apparently have similar resource profiles. This suggests that they would benefit from the same tuning setup.

**Example 2:** Let us consider Figure 5.1, where we have run selected TPC-H queries with a default tuning setup. For each query, we execute the MapReduce jobs according to the query plan. Evidently, the queries have different query plans, and therefore a different number of jobs. However, visual inspection suggests that certain jobs have similar resource profiles. Thus, we have highlighted these jobs with a shaded background. Incidentally, these jobs also share the same code signature. In Figure 5.1, we have labeled jobs with a unique code signature with a unique job identifier (e.g., jobs 2, 3, and 4), and we have labeled the jobs with the same code signature as job 1'.

Thus, this suggests that tuning setups may be shared between jobs with the same code signature: Once one instance of job 1' has been profiled, we reuse its tuning setup for the other jobs with the same signature. Thus, we simply skip profiling these jobs. □

In fact, similarity of resource consumption between common MapReduce jobs (e.g., sort, grep, WordCount) has already been identified (Zhang et al., 2015). However, we believe to be the first work to model Hive jobs specifically to identify this similarity. The main difference of our model is that it calculates the code-signature of a given job at compiling time, instead of running or sampling it.

Since the MapReduce jobs are compiled from queries, the query plans of syntactically different queries nevertheless often contain jobs with the same query annotations. Formally, we capture these annotations by the *code signature* of a job, as defined next.

### 5.1.2 Code Signature Definition

Consider the query plan definition in Section 3.1, where a job $v \in V$ is a tuple of the form $v = (O, D, C)$ in which $O_v$ is the set of code it executes. Consider that O implements a finite set of relational algebra operators, thus, $O = \{o_1, \ldots, o_n\}$, where $o$ is a physical algebra operator. For instance, Hive version 0.6.0 knows 16 different physical operators.

During query compilation, the query processor assigns the implemented physical query operators to each job, as well as it annotates several statistics such as their cardinalities. Consider that we have a function $\phi : V \times O \to \mathbb{N}$, where $V$ is the set of jobs and $O$ is the set of operators, and the function $\phi(v, o)$ returns the occurrence of each operator $o$ in a job $v$, that is,

$$\phi(v, o) = \begin{cases} n & \text{job } j \text{ implements operator } o \text{ exactly } n \text{ times} \\ 0 & \text{otherwise.} \end{cases}$$

Now, consider that we have a function $\omega : V \mapsto \mathbb{N}$, which $\omega(v) = \Delta$, where $\Delta$ is the order of magnitude of the expected input data for the given MapReduce job $v$.

The code signature is the composition of the functions $\omega$ and $\phi$. Let us define the code signature function $\theta$ as follows:

**Definition 5:** The *code signature* of a MapReduce job $v$ in $V$ is an ordered $(|O| + 1)$-tuple,

$$\theta(v) = \langle \omega(v), \phi(v, o_1), \phi(v, o_2), \ldots, \phi(v, o_n) \rangle \tag{5.1}$$

where the first element is always the order of the magnitude of the input data of $v$, and the following elements are the occurrence of each operator.

In the following example, we omit operators from the code signature with a cardinality of zero, for the sake of brevity.

**Example 3:** We continue with TPC-H query 1. The code signature of the first job is

$$\langle 9,\ \textit{Tablescan} : 1,\ \textit{Filter} : 2,\ \textit{Select} : 2,\ \textit{Groupby} : 2,\ \textit{Reducesink} : 1,\ \textit{Filesink} : 1 \rangle$$

The order of magnitude of the input size is 9.

### 5.1.3 Architecture of the Tuning Cache

We implemented the Tuning Cache in the Hive query processing engine. Figure 5.2 visualizes the architecture of the Tuning Cache. Initially, a query is submitted and classic query compilation follows. At the end of query optimization, the physical query plan is produced. The Tuning Cache, then, modifies each job at a time just before execution. Consider that at this point the Tuning Cache is empty.

First, at step-1, the Tuning Cache calculates the code-signature of every job in the query plan, denoted by $\{v_1, v_2, \ldots, v_3\}$, and annotates each code signature in its respective job. The annotation of code-signatures for jobs is performed at once since it is only reading and annotating the query plan.

In step-2, with all jobs annotated with their respective code-signatures, the Tuning Cache look up in the *Code Signature Cache* for tuning setups. The Code Signature Cache is a hash table that maps code-signatures to tuning setups. At this point, if the Code Signature Cache returns a tuning setup for a code-signature, the job is them reconfigured with the tuning setup (step-5) and sent for execution (step-6). However, considering that the cache is empty, for every miss, the job is flagged to be profiled.

For each cache miss, a third party Tuning Advisor is called to optimize the job and to generate a tuning setup (Step 3). In our experiments we employed Starfish, which will then start monitoring Hadoop services that track job execution to generate execution profiles. Since the job is queue to be executed, job profiling will only be enabled at the beginning of the job's execution. The monitoring module generates the *execution profiles* and, then, sends them back to the tuning advisor for generation of the corresponding tuning setups (step-4). Profiling is a heavy operation that is amortized by the Tuning Cache because it is only performed in the jobs that have a *miss* in the Code Signature Cache. The profiling execution generates the same query results, but paying the profiling overhead. Thus, when a job is set to be profiled, there is no need to be executed twice. The following jobs having the same code-signature will benefit from this execution by using the pre-calculated tuning setup.

In step-4, the tuning setup is generated by the third party Tuning Advisor following the techniques previously described in Section 2.3. After the generation of the tuning setups, denoted $C_1, C_2, \ldots, C_n$, Step-5, then, stores the tuning setups with the corresponding code-signatures. Note that in the case of a cache miss, the tuning setup is only stored in the Code Signature cache

after the complete execution of the job and generation of the tuning setup. There may be the case of a cache miss in between the calculation of the tuning setup.

Step-5 only happens in the case of a cache hit, and it reconfigures the job using the retrieved tuning setups. As the cache becomes populated, we observe more cache hits. In the best case, we have cache hits for all jobs in the query plan. Then we can simply reuse the tuning setups of similar jobs, and need not turn to Starfish for profiling at all.

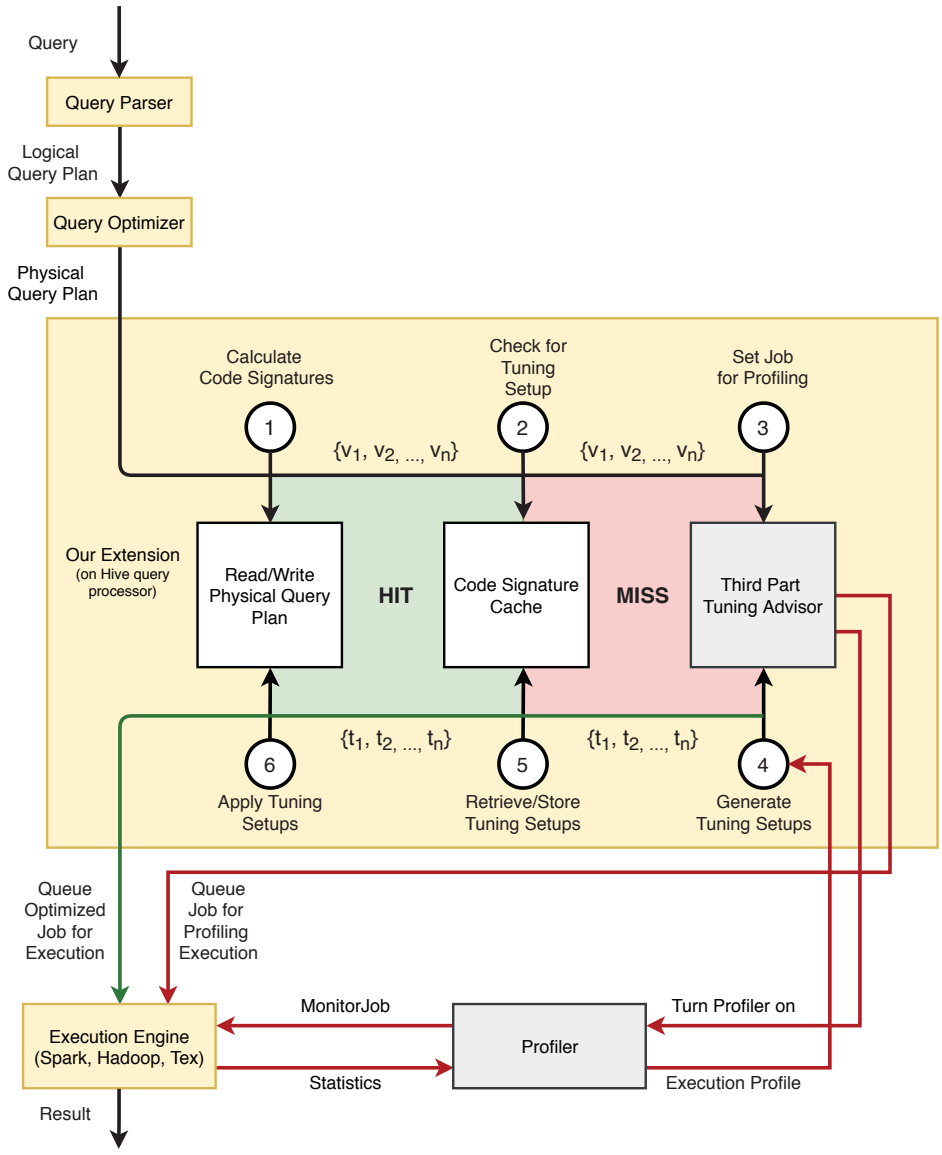



Figure 5.2: The architecture of the extension made in the Hive query processing engine. Illustration of the lookups in the code signature cache. For a cache miss, a third-party tuning adviser is run to generate a tuning setups.

## 5.2 Recycling Tuning Setups at the Job Level

First, we analyze the distribution of the code-signatures in TPC-H queries. Then, we confirm that the code-signature is indeed a viable basis for recycling tuning setups among jobs.

### 5.2.1 Repeating Code-Signatures

We have compiled the TPC-H queries into query plans. Figure 5.3 shows the number of jobs with the same code signature. There is one code signature that is actually shared by 16 jobs. In fact, this job occurs in over 70% of all TPC-H queries. Moreover, for 75% of all MapReduce jobs, there is at least one other job with the same code signature. Only a quarter of all jobs has a unique code-signature. Thus, there is a considerable share of recurring code-signatures. Note, the distribution of the code-signature through the queries can differ when using different software versions. This happens because different versions of Hive will generate different query plans, as previously discussed in Chapter 3.

We executed TPC-H and TPC-DS [4] in Hive (3.0) and Hadoop (2.0), in order to observe the distribution of the code-signature in other workloads and software version. This experiment solo was executed in a Debian 5.4, 4 Intel(R) Core(TM) i7-7500U CPU @ 2.70GHz with 12GB of RAM and 128GB of disk (SSD). The distribution of TPC-H remains the same, having 81% of its jobs sharing at least one code-signature, depicted in Figure 5.4. The code-signature that most repeat represents about 17% of the jobs. Figure 5.5 presents the distribution of TPC-DS. In TPC-DS, there are 94 unique code-signatures representing a total of 1049 jobs. There are 1022 jobs that share at least one code-signature, representing 97% of the workload. The code-signature that is the most frequent is shared by 238 jobs, representing 22% of the workload. Having such a high sharing means that 94 unique code-signature can represent all the workload, *i.e.*, when executing with the Tuning Cache we would pay only 9% of the total profiling overhead to optimize the entire workload.

[4] `https://github.com/hortonworks/hive-testbench`


Figure 5.3: MapReduce jobs compiled from TPC-H queries: Counting jobs that share the same code signature. Executing in Hive 0.6.0 and Hadoop 0.20.0

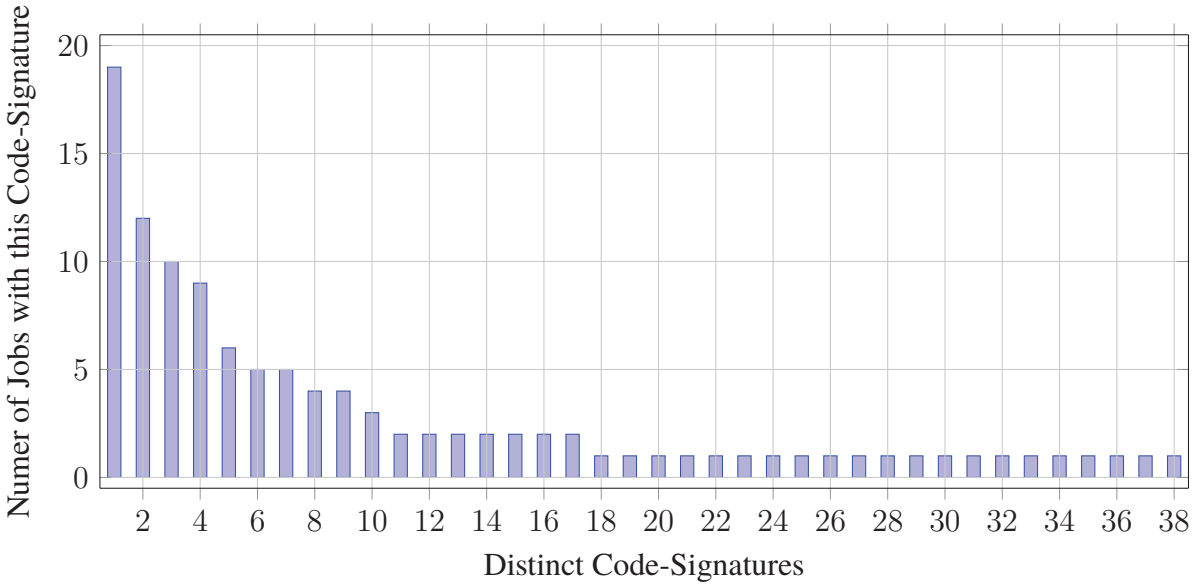



Figure 5.4: MapReduce jobs compiled from TPC-H queries: Counting jobs that share the same code signature. Executing in Hive 3.0 and Hadoop 2.0.

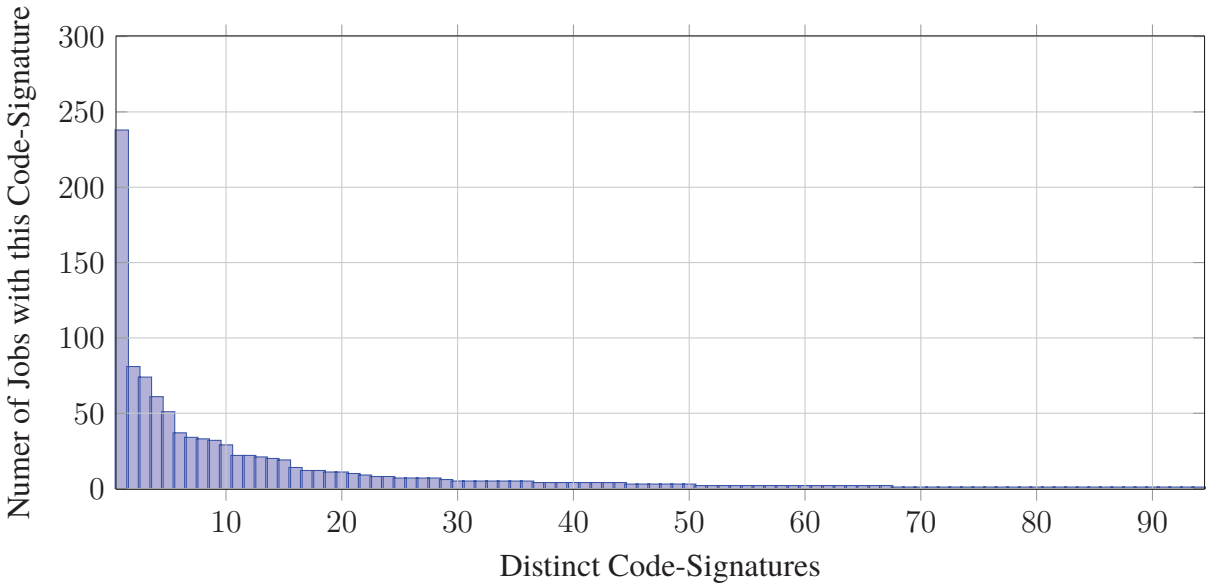



Figure 5.5: MapReduce jobs compiled from TPC-DS queries: Counting jobs that share the same code signature. Executing in Hive 3.0 and Hadoop 2.0.

### 5.2.2 Justifying the Recycling of Tuning Setups

We experimentally examine our hypothesis, stating that we may recycle tuning setups for jobs with the same code signature in Figure 5.6. We choose 5 representative MapReduce jobs that all share the same code signature. When compiled into query plans, we obtain 20 MapReduce jobs. For each job $j$ of those five jobs, we define two groups of jobs:

I. The five jobs that share the same code signature. For these jobs, we obtain the 5 tuning setups from Starfish.

II. The remaining jobs within the same query plan. These have different code signatures. Again, we obtain the tuning setups from Starfish.

We then execute job 1 of query 1 with all the tuning setups from groups (1) and (2), shown in the first and second bar respectively. We repeat this procedure for the other jobs listed. In general, the jobs executing with the tuning setups of group (1) show better performance than with the tuning setups of group (2). The reported execution times are averaged over 10 runs. The error bars mark the minimum and maximum execution times. There is noticeably less variance in the execution times of group (1). Overall, we see that for jobs with the same code signature, we may use the tuning setups interchangeably. When jobs have different code signatures, this is not necessarily the case.

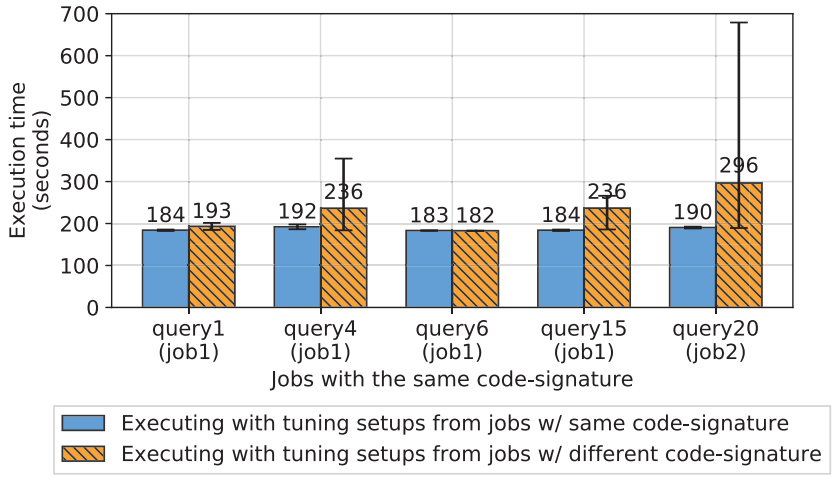



Figure 5.6: Jobs with the same code signature tend to benefit from the same tuning setups. This effect cannot be repeated for jobs with different code signatures.

Figure 5.7 presents the execution run time of jobs running with tuning setups generated for jobs with the same and different code signatures. Although in four cases the execution run times are bigger when sharing code-signatures (like in code-signature #8 and #17), the execution time of jobs sharing the same code-signature tend to have low standard deviation. In most cases, the execution run time is lower when sharing code-signatures. This shows that tuning setups can be shared between jobs with same code-signature. The same is not true for jobs with different code-signatures.


Figure 5.7: Execution run time of jobs running with tuning setups generated for jobs with same and different code-signatures. Low standard deviation means that reusing tuning setups from jobs that shares the same code-signature will produce similar execution run times. But, the standard deviation is high when using tuning setups from jobs with different code-signatures, because reusing tuning setups from jobs with different code-signatures produces different impact on performance.

## 5.3 Recycling Tuning Setups at the Query Level

We now employ the Tuning Cache for profiling the TPC-H queries. We first profile all 22 queries in the order specified by the benchmark and discuss the benefits of applying the Tuning Cache. We then contrast this with the total time spent on profiling if Starfish only samples the JVM tasks. We also consider different execution orders in profiling the TPC-H queries with the Tuning Cache, and show that the query order does not have as much impact on profiling time as one might expect. Finally, we compare the execution time of non-uniform tuning when we have the Tuning Cache available during profiling and when we profile all jobs with Starfish.

### 5.3.1 Profiling the TPC-H Queries in Order

We profile the 22 TPC-H queries in the order of the TPC-H benchmark specification. Figure 5.8(5.8.1) shows the profiling time per query. In total, over ten thousand seconds are spent on profiling. Even though the runs in Figure 5.8(5.8.1) do not make use the Tuning Cache, for the purpose of illustration, we visually distinguish two groups of jobs:

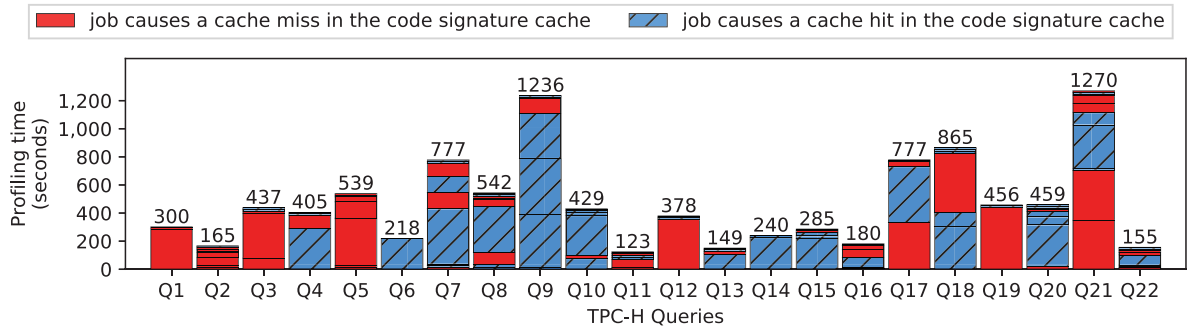
I. Jobs which cause a cache miss in the Tuning Cache,

II. and jobs which cause a cache hit in the Tuning cache.

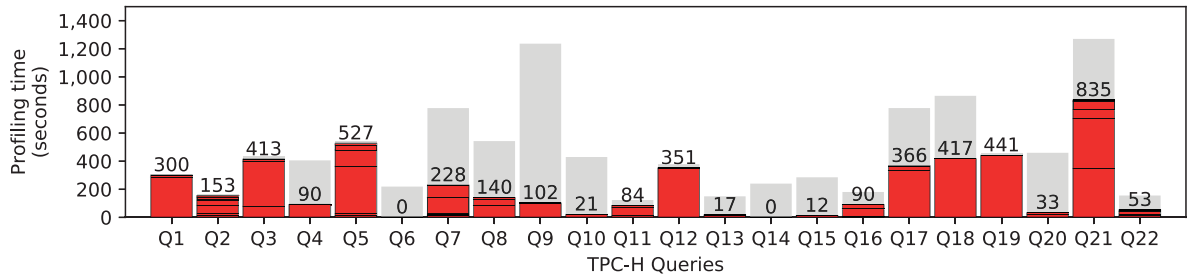
We can observe that for the first TPC-H query, all jobs would cause a cache miss. Yet already for the second and third queries, we'd have cache hits, even though the savings are minor. With the Tuning Cache becoming more populated, we get more cache hits, and in some cases, some substantial savings in the profiling time. For instance, for queries Q6 and Q14, we can recycle all tuning setups from the cache. Thus, they require no profiling at all.

Let us now turn to the quantitative assessment. In Figure 5.8(5.8.2), we use the Tuning Cache. Thus, we employ Starfish only for the jobs from group (1), and recycle the tuning setups for the jobs from group (2). The shaded grey area indicates the height of the original bars from Figure 5.8(5.8.1), for easier comparison.

Using the Tuning Cache reduces the total time spent on profiling from over ten to below five thousand seconds. Overall, we can cut down the time spent profiling by more than 50%.




(5.8.1) Total time Starfish spends profiling (no sampling): 10,396.97 seconds.




(5.8.2) Reduced profiling time leveraging the Tuning Cache. Total time spent profiling: 4,679.66 seconds.

Figure 5.8: The Tuning Cache reduces the profiling time by over 50% for TPC-H.

### 5.3.2 Recycling vs. Starfish Sampling

Starfish has its own strategy for reducing the profiling time, by sampling only a share of the JVM tasks. We compare this strategy with our approach of using Starfish (without sampling) in combination with the Tuning Cache. In Figure 5.9, we compare the total accumulated time spent on profiling for different modes of operation. The topmost line denotes profiling with Starfish, where sampling is turned off. This summarizes the experiment of Figure 5.8(5.8.1).

When we run Starfish with a sampling rate of 20% (nevertheless executing all tasks of the query), the total time spent on profiling is effectively reduced. However, sampling increases the error rate in the resulting tuning profiles (Herodotou et al., 2011).

In the given chart, the profiling time is lowest for the combination of Starfish and recycling from the Tuning Cache. Thus, we can profile in half of the time, without having to make the sacrifices due to sampling.

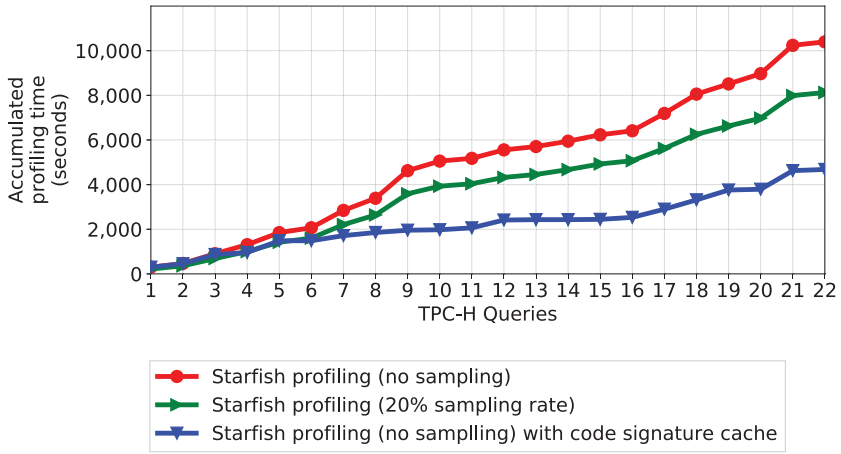



Figure 5.9: Accumulated time for profiling all queries.

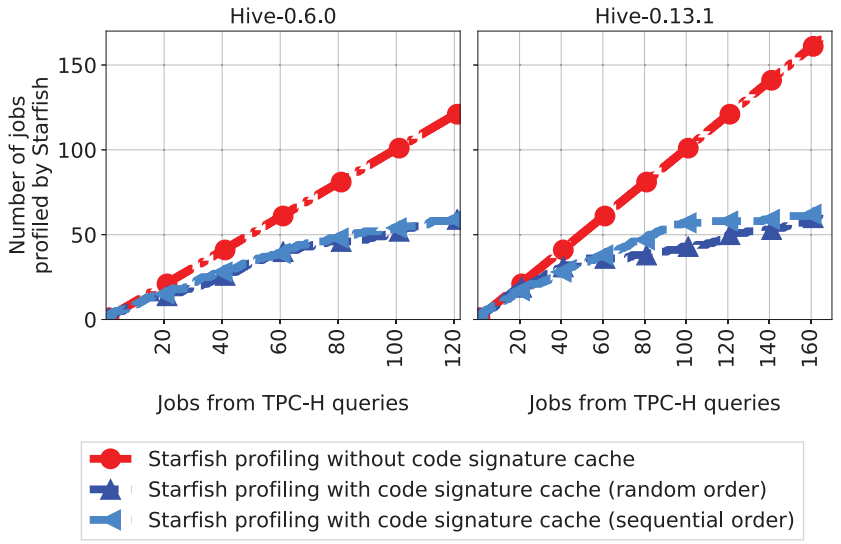



Figure 5.10: Accumulated time for profiling. Varying the order in query profiling.

### 5.3.3 Varying the Query Order

The recycling rate of tuning setups in the Tuning Cache, as reported in Figure 5.8(5.8.2), is influenced by the order in which the TPC-H queries are profiled.

In Figure 5.10, we vary the order of queries. Moreover, we contrast the MapReduce jobs produced by two different versions of Hive. On the horizontal axis, the charts show the total number of MapReduce jobs compiled from the TPC-H queries by the Hive query compiler. On the vertical axis, we denote the number of jobs which had to be profiled by Starfish.

The tuning adviser Starfish, when used stand-alone, profiles all jobs. We further compare Starfish in combination with the Tuning Cache. Regardless whether the queries are encountered

in order of their specification or in a randomly generated order, for this query workload, we can recycle tuning setups from the cache for about half of the jobs.

Thus, while the query compilers of Hive 0.6.0 and 0.13.1 produce a different number of jobs, the benefits of recycling is independent of the submission order.

## 5.4 Discussion

In summary, we can experimentally support our hypothesis that jobs with the same code signatures benefit from the same tuning setups. Therefore, we may recycle tuning setups. By reducing the number of jobs to be profiled, we can effectively cut down on the time required for physical-layer performance tuning.

Even when Starfish profiles only a sample of 20% of the tasks in the JVM, it does not reach this speedup (while the quality of tuning setups produced by Starfish degrades). Thus, coupling a third party tuning advisor with the Tuning Cache is a winning strategy for reducing profiling time.

For some queries, we were even able to directly assign tuning setups to MapReduce jobs, requiring no profiling at all. This is promising for processing ad-hoc queries, which normally do not benefit from up-front tuning. In our experiments with the TPC-H queries, we were able to cut down profiling time by half. Moreover, the mechanism is quite robust when the order of TPC-H queries varies.

# Chapter 6

# Conclusion

## 6.1 Lessons Learned

While there has been a significant amount of research on automatic parameter tuning for distributed computing platforms such as Hadoop and Spark (e.g., (Herodotou et al., 2011; Liu et al., 2015; Shi et al., 2014; Wang et al., 2016; Bao et al., 2018b)), there has been very little work on (i) how these parameters affect the execution and performance of SQL-on-Hadoop systems, and (ii) how to tune these parameters within the context of SQL-on-Hadoop workloads. This thesis attempt to bridge this gap by studying how current Hadoop tuning advisors can be employed for optimizing the performance of the popular SQL-on-Hadoop engine Hive. The major lessons learned from our experimental study are:

I. **Parameter tuning is important.** Tuning the underlying Hadoop parameters can have a significant impact on both the execution time and the resource utilization of queries executing on SQL-on-Hadoop systems. In particular, our results reveal that different parameter settings can cause run time variations between -171% (i.e., $2.8\times$ slower) and 25% speedup over default settings. At the same time, parameter tuning can have considerable influence on the resource utilization patterns, leading to better CPU utilization, improved memory usage, reduced disk usage, and more evenly distributed network utilization (i.e., fewer spikes).

   Reduced resource consumption can have major benefits for both the providers of Infrastructure-as-a-Service products, as well as their customers. From the customer's perspective, non-uniform tuning allows for more efficient resource consumption. Depending on the pricing model, lower resource consumption directly translates to lower

charges. For instance, storage costs in Amazon AWS Elastic Block Store (EBS) are $0.10 per GB per month for general purpose (gp2) volumes. The amount of data spilled to disk for intermediate data, as depicted by Figure 4.4, will be directly reflected in the billing costs. With reduced data spills, customers could also provision for lower (and cheaper) I/O per second (IOPS) rates. In addition, lower resource utilization allows for increased query throughput. Hence, more queries can be executed in the same amount of time, potentially reducing the cost of cloud deployments. From the provider's perspective, the non-uniform tuning has great potential to reduce infrastructure costs, such as air cooling with more efficient disk usage and data movement, and to increase machine throughput with less resource consumption and more concurrent clients.

II. **Uniform tuning is problematic.** The current practice of using one tuning setup per query (and by extension for all the jobs within each query) suffers from two main limitations. First, finding a tuning setup that equally benefits all jobs is difficult, if not impossible, since current Hadoop tuning advisors are designed for tuning one MapReduce job at-a-time. Hence, even though a particular tuning setup can speed up one job significantly, it may have a negative effect on other jobs in the same query, leading to a sub-optimal speedup or even an overall slowdown. Second, the process of selecting a good tuning setup is time-consuming, as it typically relies on trial-and-error. Even intuitive strategies such as tuning for the dominant job (i.e., the longest running job) in a query are not always effective and can actually slow down a query.

III. **Non-uniform tuning is promising.** Tuning each job in a query independently has been shown to provide runtime speedups that are similar to the best-observed speedups in our experiments. In addition, non-uniform tuning is very robust, since the speedup is always positive, it reduces the need for speculative execution, and, unlike the uniform tuning, does not suffer from any serious runtime variations. Most importantly, this method can also lead to considerably better resource utilization for the key resources, namely CPU, memory, disk, and network. Specifically, both CPU usage and memory paging were reduced by over 40%, while the total amount of data written to and read from the local file system was reduced by 5$\times$ compared to default settings. The aforementioned benefits are not bound to Starfish but rather are a consequence of the non-uniform tuning methodology that optimizes each job independently. We are confident that any Hadoop

tuning advisor that can recommend good tuning setups could be used in place of Starfish, with similar results.

IV. **Challenges apply to other SQL-on-Hadoop systems.** Even though we focus on tuning Hadoop parameters for Hive queries, we believe that our experimental results and conclusions generalize to other SQL-on-Hadoop systems as many of them fork the source code of Hive, like Shark and Hive on Tez, or present similar query processing approaches, like SparkSQL, Impala, and Drill. For instance, Impala spans query fragments to distributed processing deamons that resembles jobs. Impala updates system health information across all the deamons through a "statestore" component (in Impala terminology) and keeps all changes in the metadata of the SQL statements in "catalog" deamons. The non-uniform approach would leverage both deamons to swap tuning parameters according to the processing needs.

   The issues with uniform tuning apply to other types of systems as well. For instance, in Spark, a job consists of a directed acyclic graph of stages, where each stage comprises a collection of tasks. Yet, all parameters that affect resource configuration and scheduling (such as number of cores to use, memory sizes, etc.) are set at the level of jobs and apply uniformly to all stages and tasks. This problem has already been identified and efforts are made towards enabling administrators to specify task resource requirements and configuration at the stage level (SPIP). Currently, Spark tuning advisors such as (Wang et al., 2016; Singhal and Singh, 2017; Bao et al., 2018b) recommend parameters at the level of individual jobs. Our findings about the benefits of non-uniform tuning along with the push towards configuring jobs at the stage level are strong motivators for building new Spark tuning advisors that fully embrace non-uniform tuning.

V. **Recycling Tuning Setups** Automated tuning of SQL-on-Hadoop engines and MapReduce frameworks is a highly topical research area. Tuning adviser tools profile MapReduce jobs to produce suitable tuning setups. Naturally, profiling introduces an overhead. In pay-as-you-go environments, profiling can drive up the operational costs considerably. Therefore, ways for reducing the time spent on tuning are of great interest to the research community and practitioners alike.

   Existing tuning advisers cut down the profiling time by sampling, either monitoring only a share of the JVM tasks (as done by Starfish), by monitoring only a specific sample of

MapReduce jobs (as done by PStorM), or running the jobs with a sample of its data set. Thus, they trade time for the effectiveness of the resulting tuning setup.

Caching tuning setups reduced the profiling time by skipping profiling altogether for MapReduce jobs where we can recycle the tuning setups from similar jobs. To this end, we rely on our model of the code signature as a means for identifying similar jobs, and to populate the Tuning Cache. Our approach is appealingly simple, yet effective, and lets us cut back on profiling by nearly 50% in case of the TPC-H queries, without major sacrifices to the quality of tuning setups. Provided that we have successfully profiled enough similar queries (or rather, their MapReduce jobs), we may even supply ad-hoc queries with tuning setups, skipping up-front profiling altogether.

VI. **Automatic Tuning of SQL-on-Hadoop Systems**. In this thesis, we presented that the performance of SQL-on-Hadoop queries can achieve better performance with automatic tuning. However, automatic parameter tuning for SQL-on-Hadoop systems is only possible when combining two approaches: i) the non-uniform tuning method, presented in Chapter 4, together with ii) the Tuning Cache, a mechanism for recycling tuning setups that enable tuning queries up-front execution. But approaches were implemented as an extension of Hive query processor, and are enabled with a `hive.optimize.selftuning`, completely removing humans from the loop.

With this experimental study, we share our observations with the database research community. We hope to create an awareness for this problem as well as to initiate new research on automatic parameter tuning for SQL-on-Hadoop systems.

## 6.2 Future Work

Most Hadoop tuning advisors (e.g., (Liao et al., 2013; Liu et al., 2015; Ding et al., 2015)), including Starfish, treat the Map and Reduce functions as black-boxes. However, when the MapReduce jobs are generated from SQL-on-Hadoop engines, the information regarding the actual operators comprising the tasks is available. Such information can significantly improve the performance modeling employed by the tuning advisors, which in turn can improve the tuning setup recommendations. At the same time, current tuning advisors are designed for optimizing each job in isolation. However, SQL-on-Hadoop engines typically generate directed acyclic

graphs of MapReduce jobs, with various inter-dependencies, as discussed in Section 4.5. Hence, a new line of tuning advisors that will incorporate query-specific modeling and workflow-aware tuning is necessary for catering to the specific requirements of SQL-on-Hadoop engines.

As future work, we plan to refine the code signature by integrating the selectivity of query operators into the code signature. Moreover, we hope to be able to use the Tuning Cache for application-level tuning as well: By caching power hints for MapReduce jobs, we might be able to automatically suggest performance hints for similar jobs. This could be a great relief to the data analyst who has no prior background in database administration.

Another interesting research direction would be to push physical tuning decisions into the cost optimizer of an SQL-on-Hadoop engine. At optimization time, there is access to various statistics such as cardinality estimates and possible access paths, which can be used to (i) improve the effectiveness of the tuning choices, and to (ii) apply the selected tuning choices to the individual jobs (i.e., in a non-uniform way). The push towards non-uniform tuning also implies a push towards a fully automated tuning solution. Otherwise, it would be hard, if not impossible, for an administrator to manually specify parameters for individual jobs that are generated during a query execution. Overall, as the clusters are growing in size and the workloads are becoming more complex, it becomes ever more essential for SQL-on-Hadoop systems to offer self-managing features such as automatic performance tuning.

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# APPENDIX A – RESOURCE CONSUMPTION OF TPC-H QUERIES

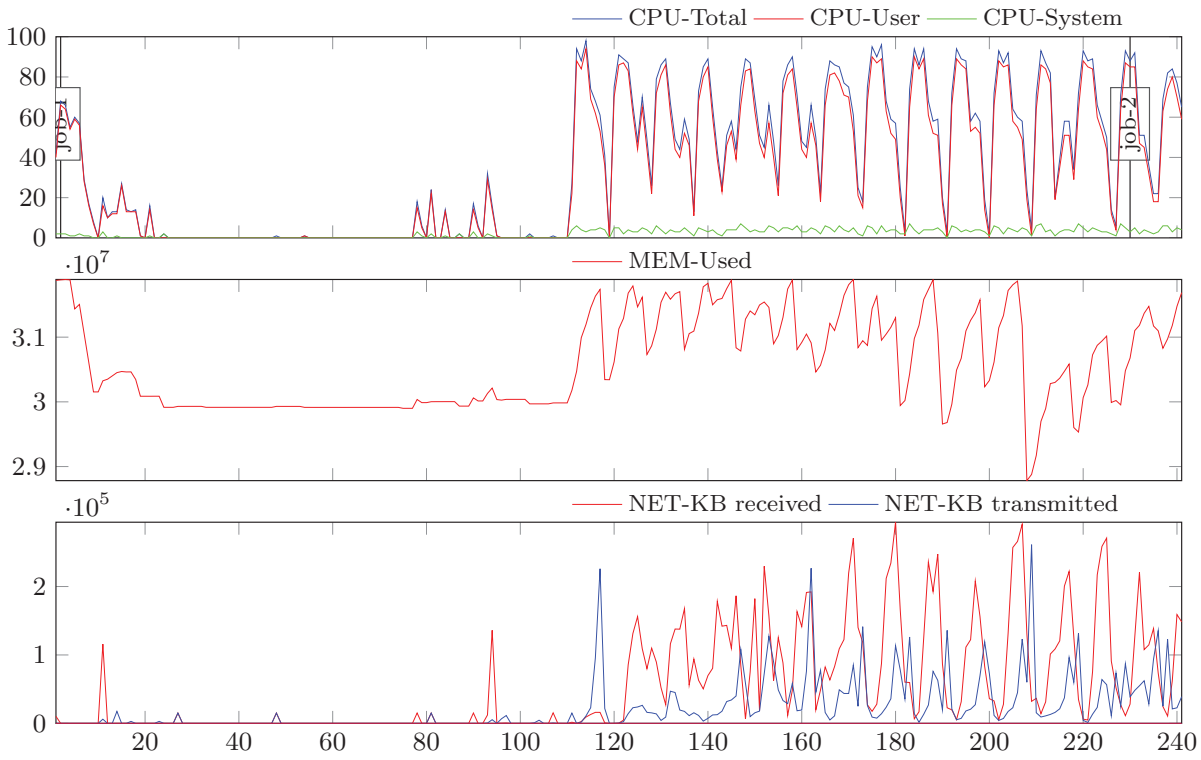


Figure A.1: Resource Consumption of TPC-H query 1 executing with default configuration.

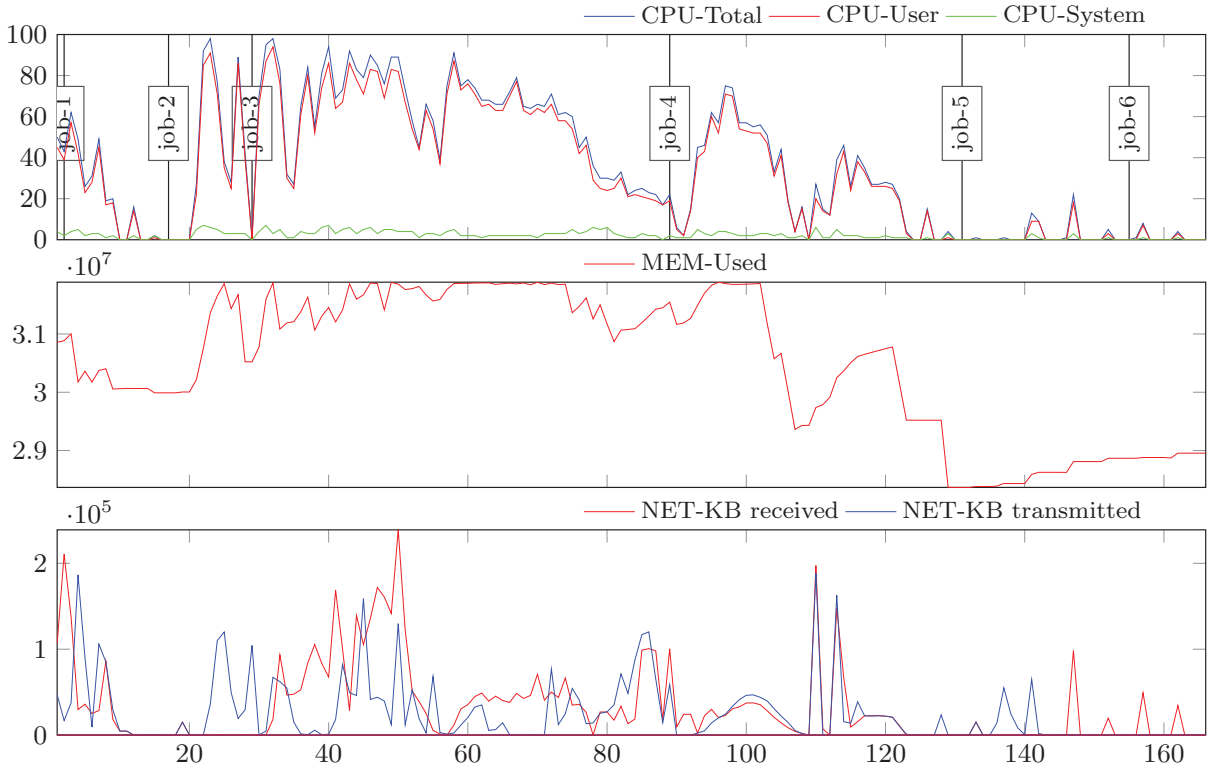


Figure A.2: Resource Consumption of TPC-H query 2 executing with default configuration.

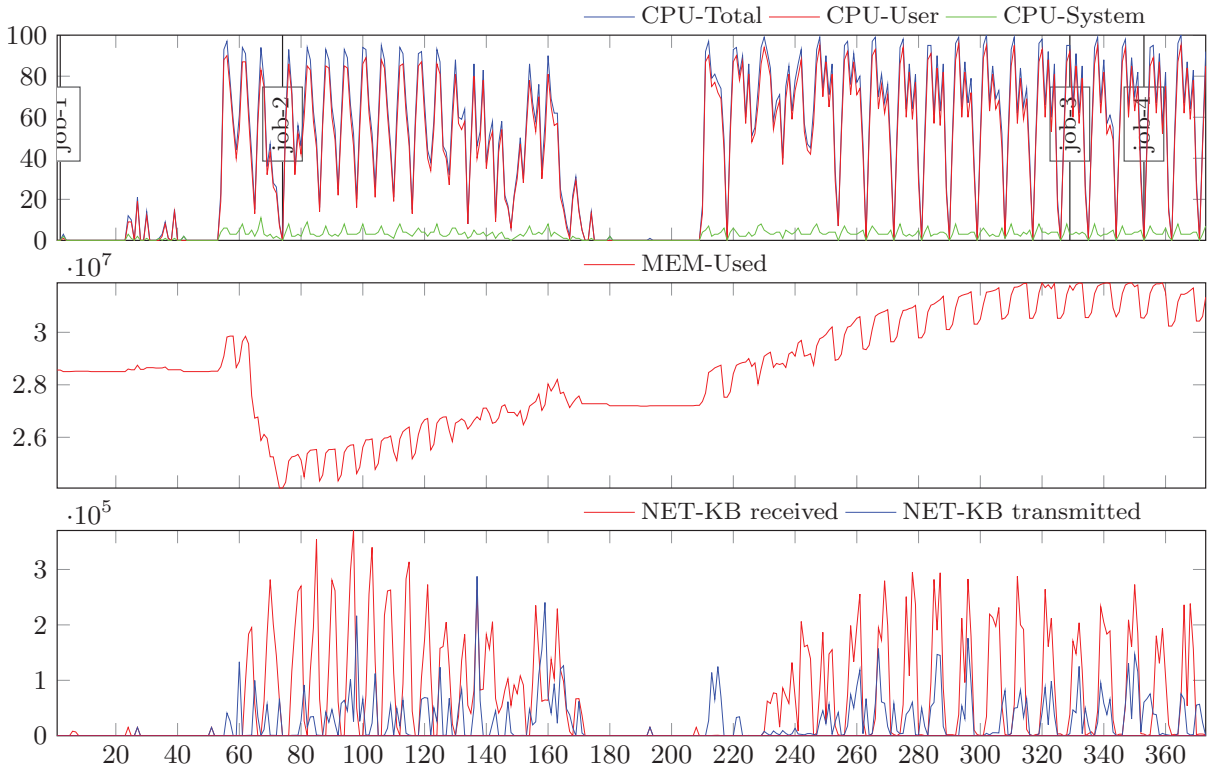


Figure A.3: Resource Consumption of TPC-H query 3 executing with default configuration.

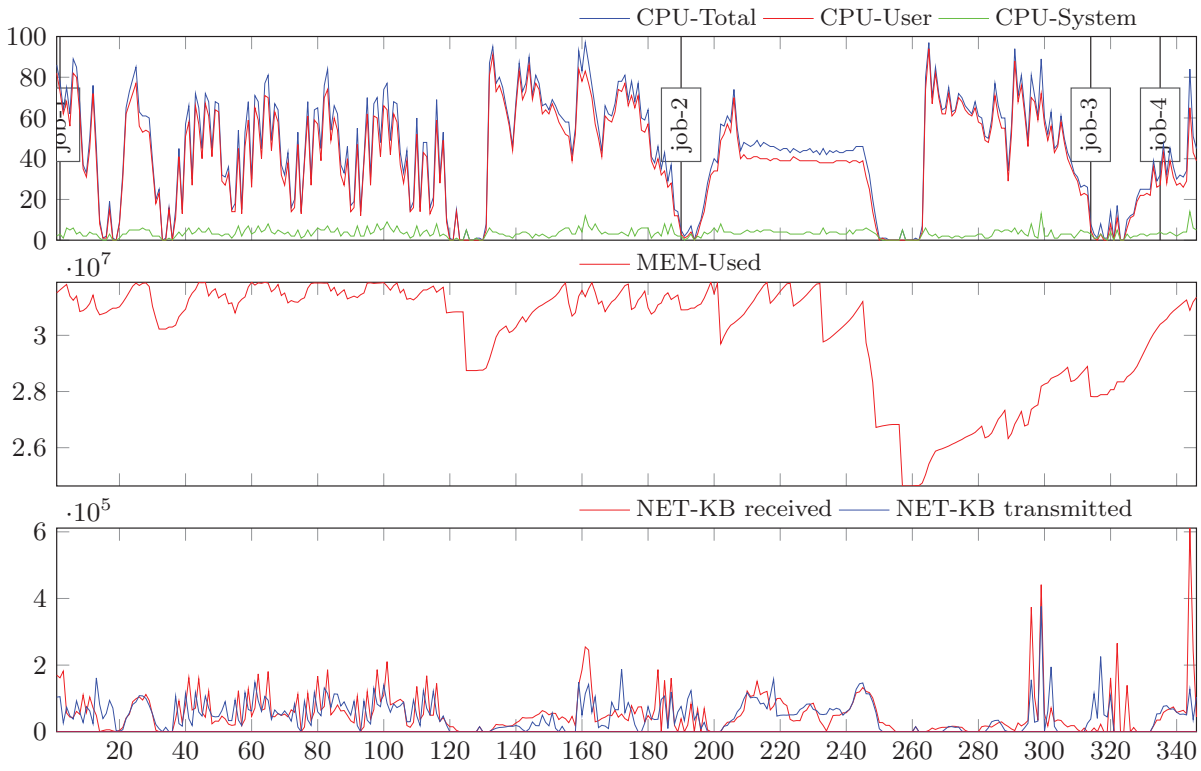


Figure A.4: Resource Consumption of TPC-H query 4 executing with default configuration.

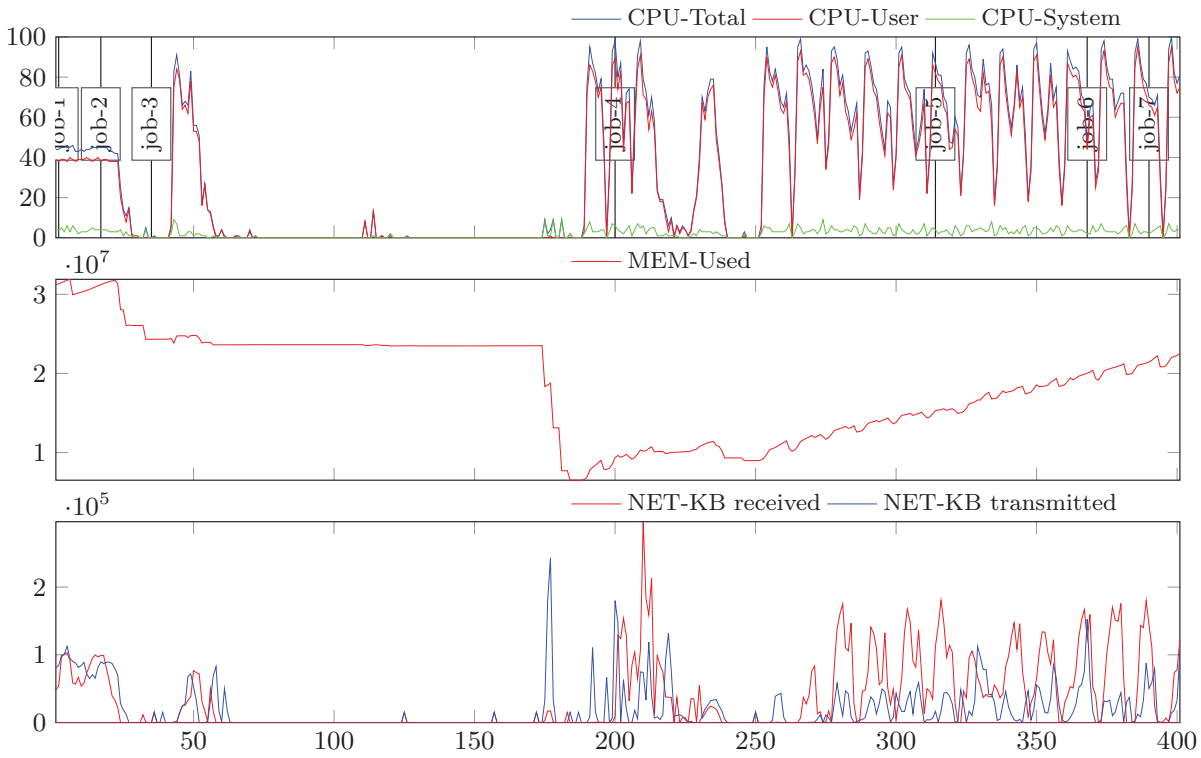


Figure A.5: Resource Consumption of TPC-H query 5 executing with default configuration.

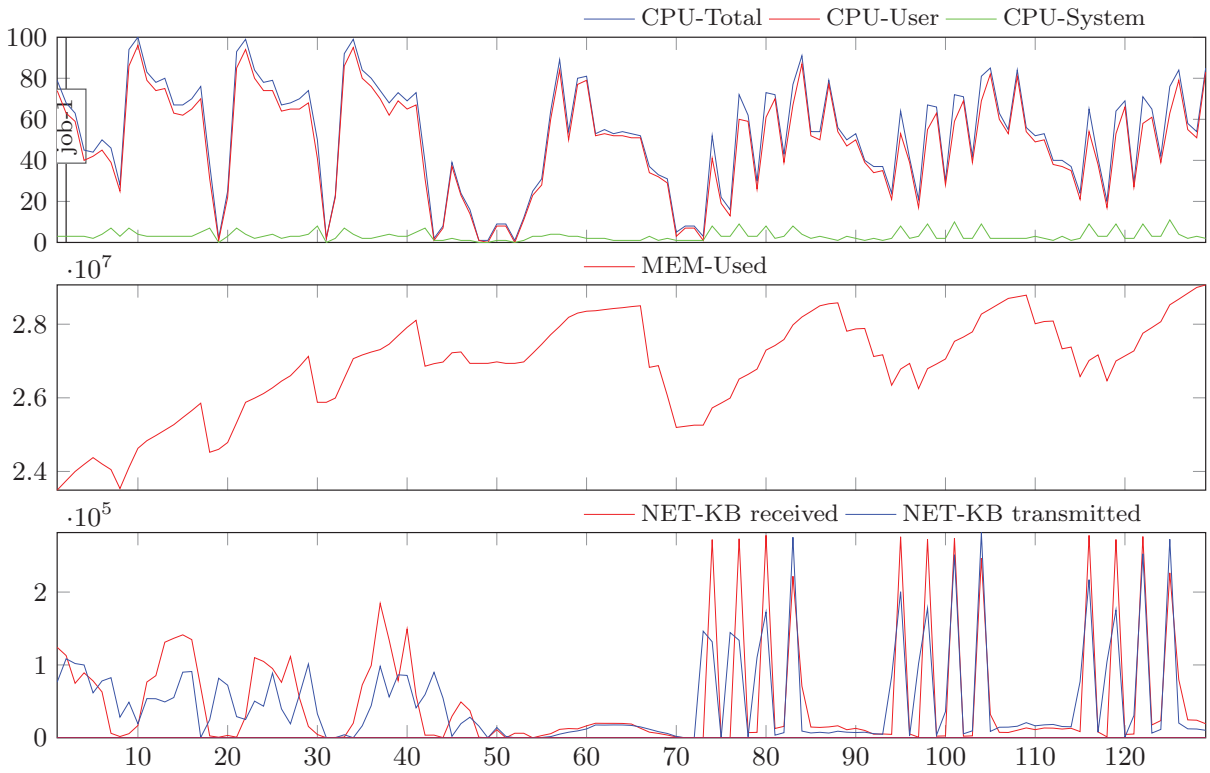


Figure A.6: Resource Consumption of TPC-H query 6 executing with default configuration.

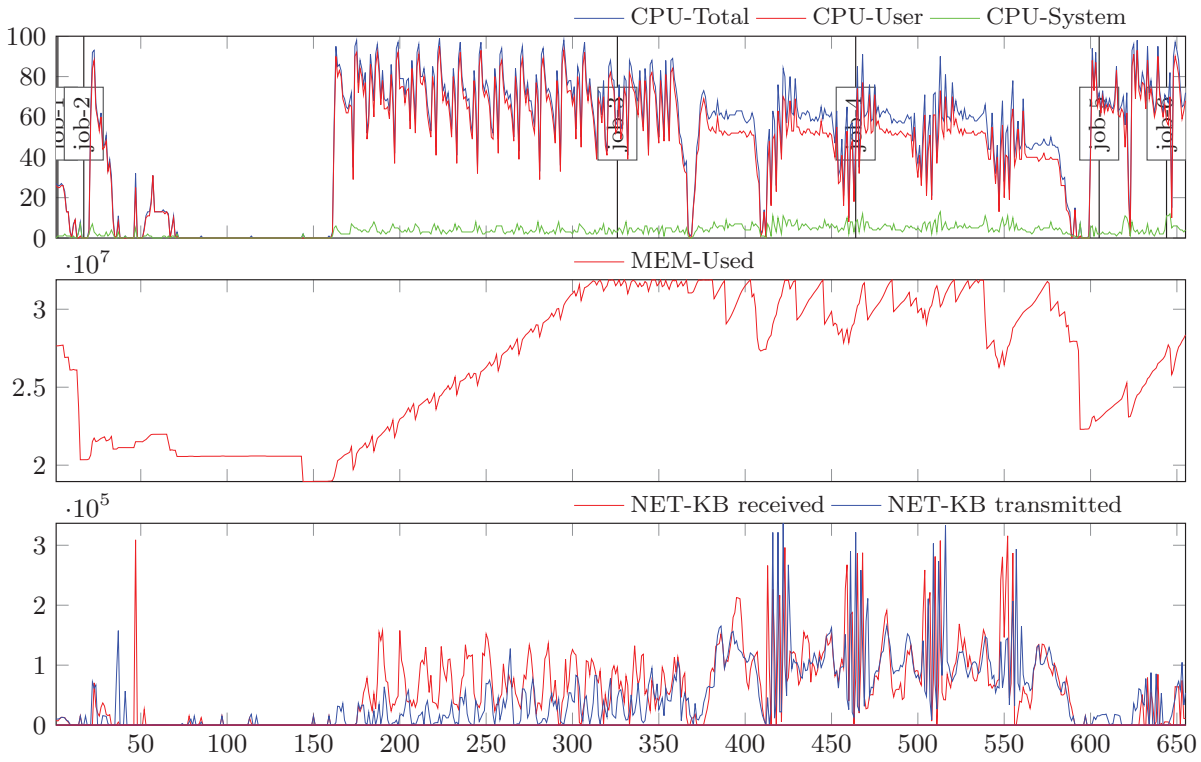


Figure A.7: Resource Consumption of TPC-H query 7 executing with default configuration.

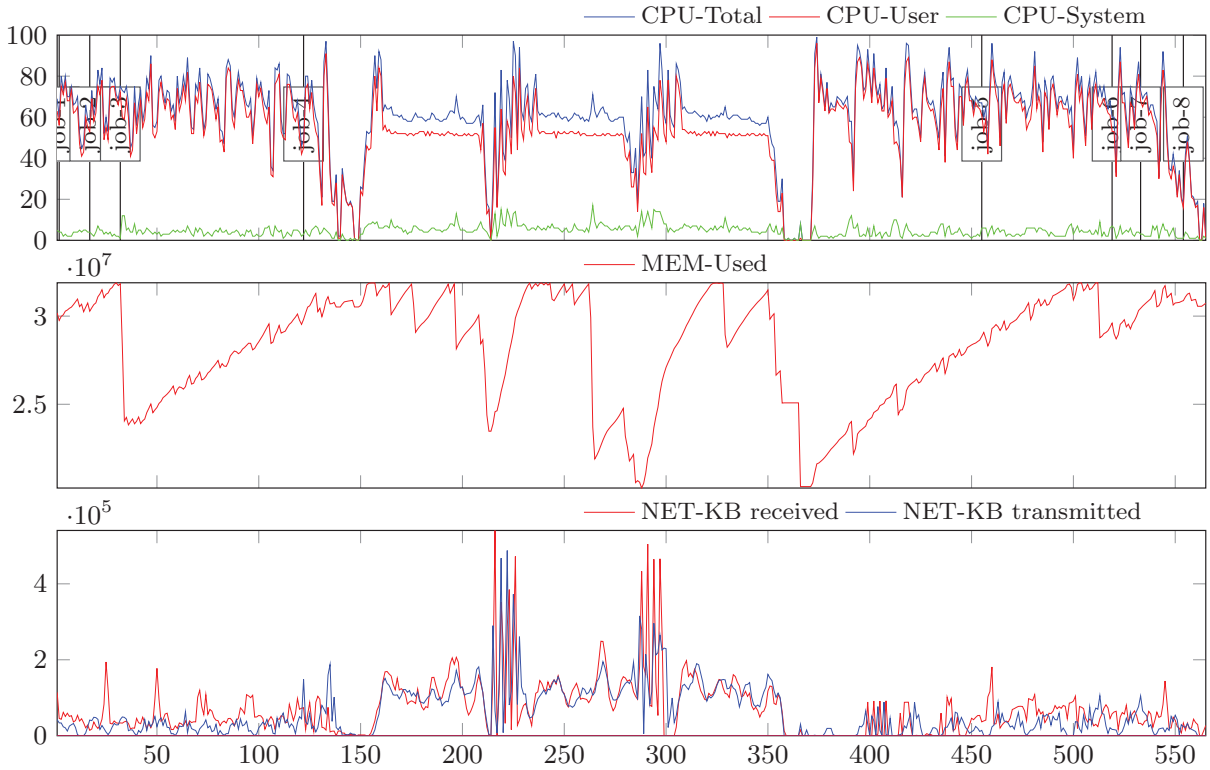


Figure A.8: Resource Consumption of TPC-H query 8 executing with default configuration.

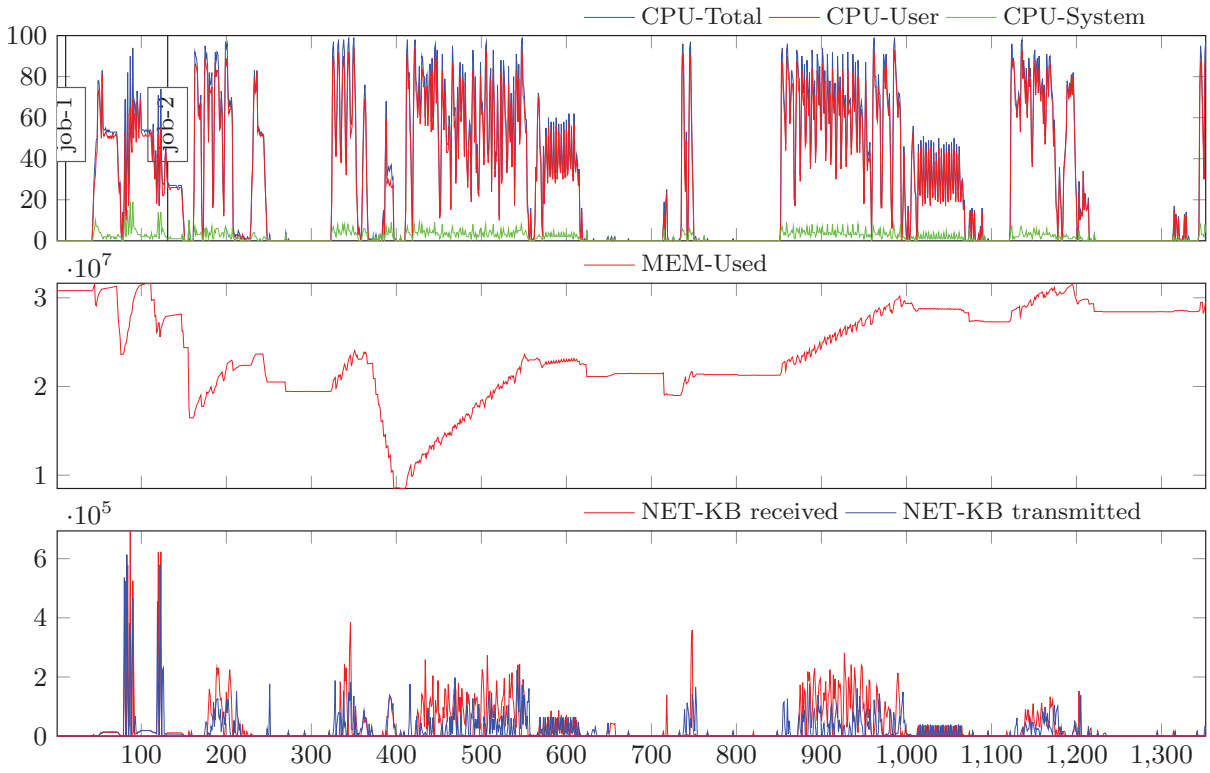


Figure A.9: Resource Consumption of TPC-H query 9 executing with default configuration.

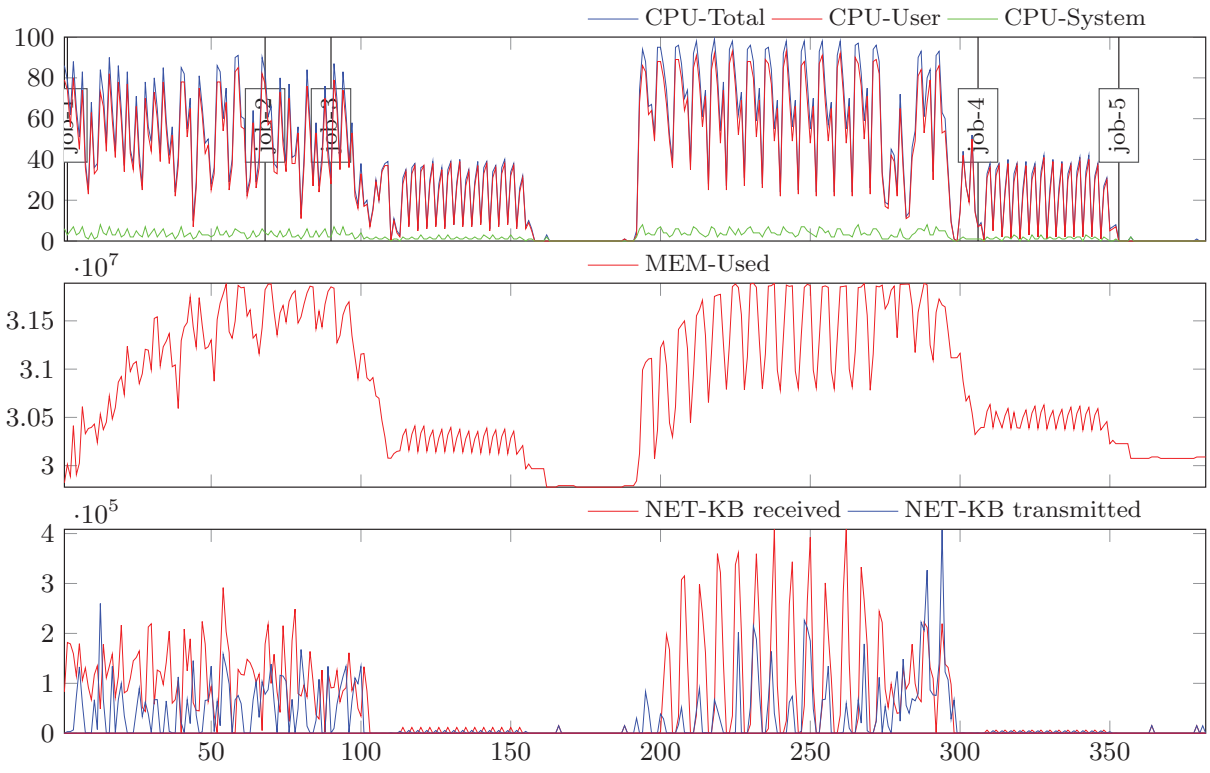


Figure A.10: Resource Consumption of TPC-H query 10 executing with default configuration.

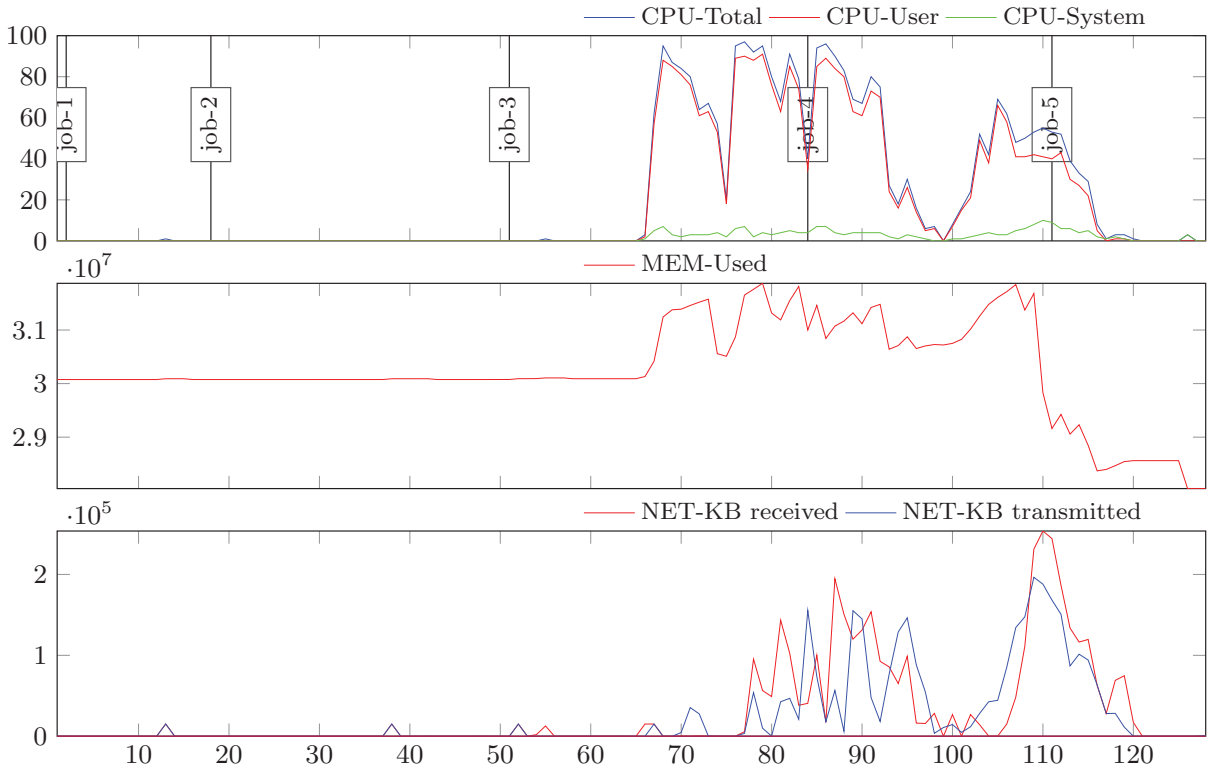


Figure A.11: Resource Consumption of TPC-H query 11 executing with default configuration.

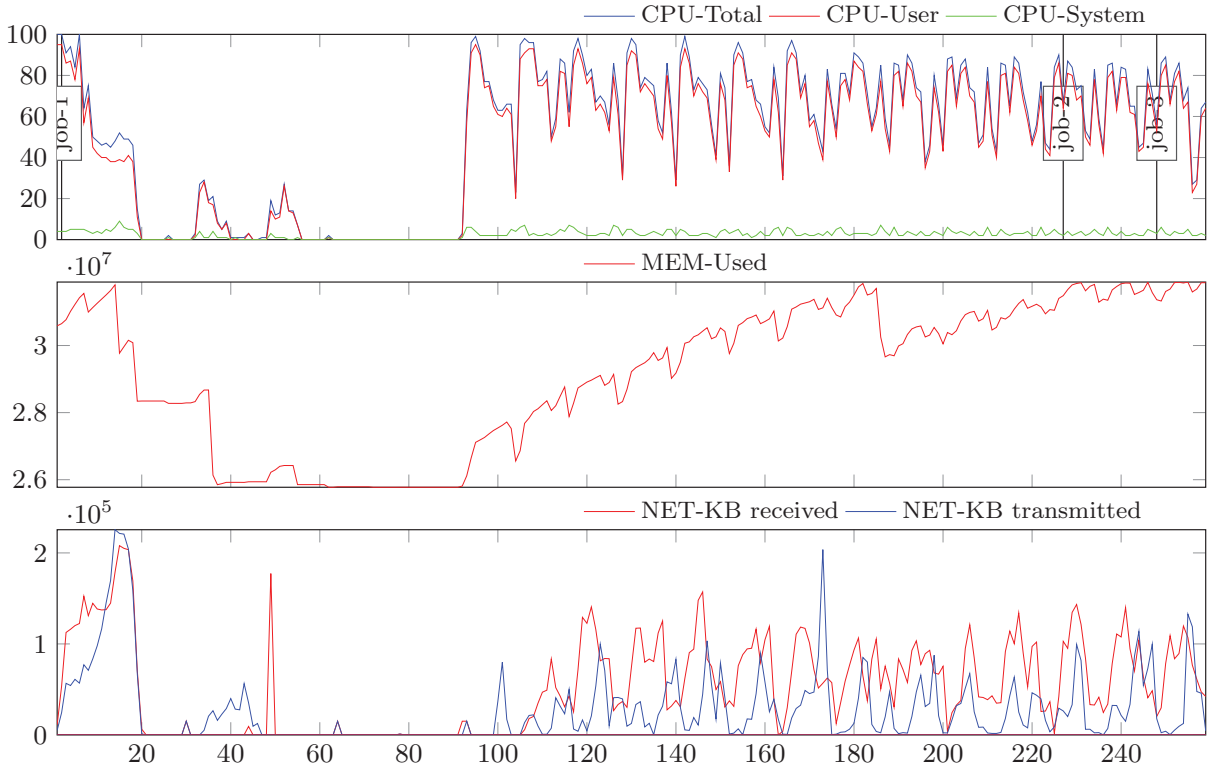


Figure A.12: Resource Consumption of TPC-H query 12 executing with default configuration.

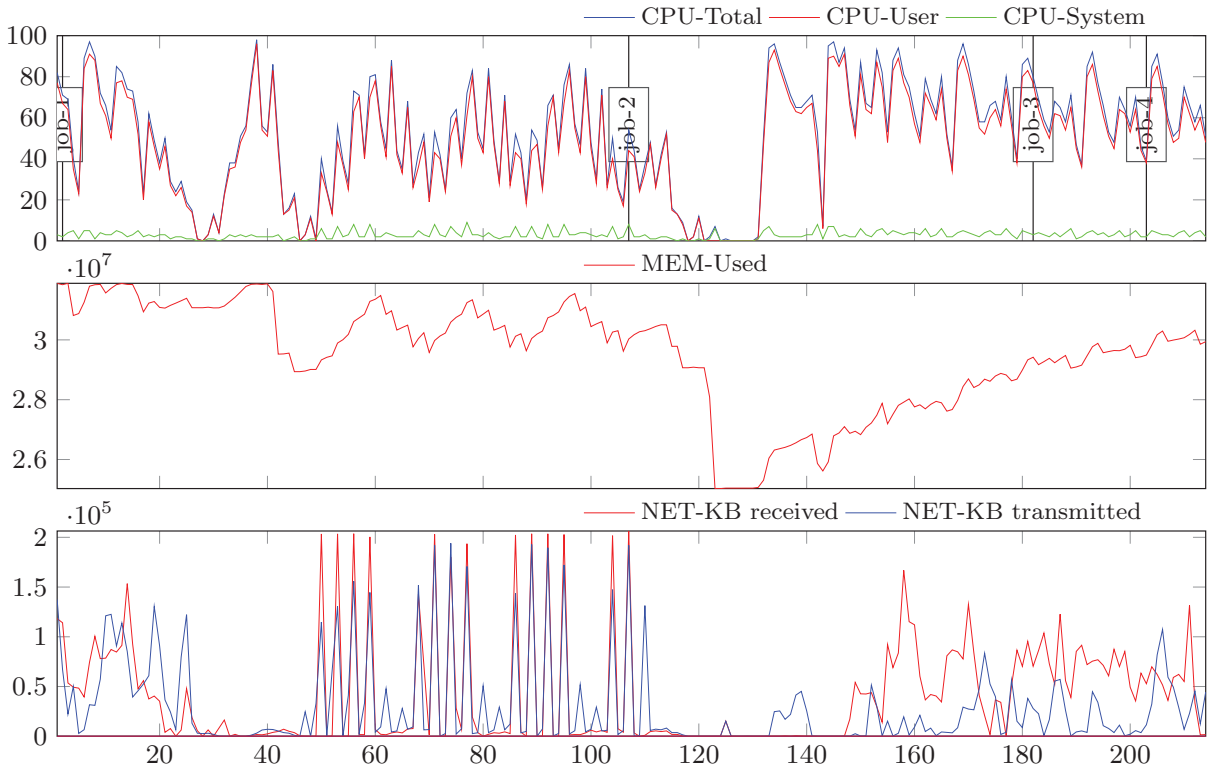


Figure A.13: Resource Consumption of TPC-H query 13 executing with default configuration.

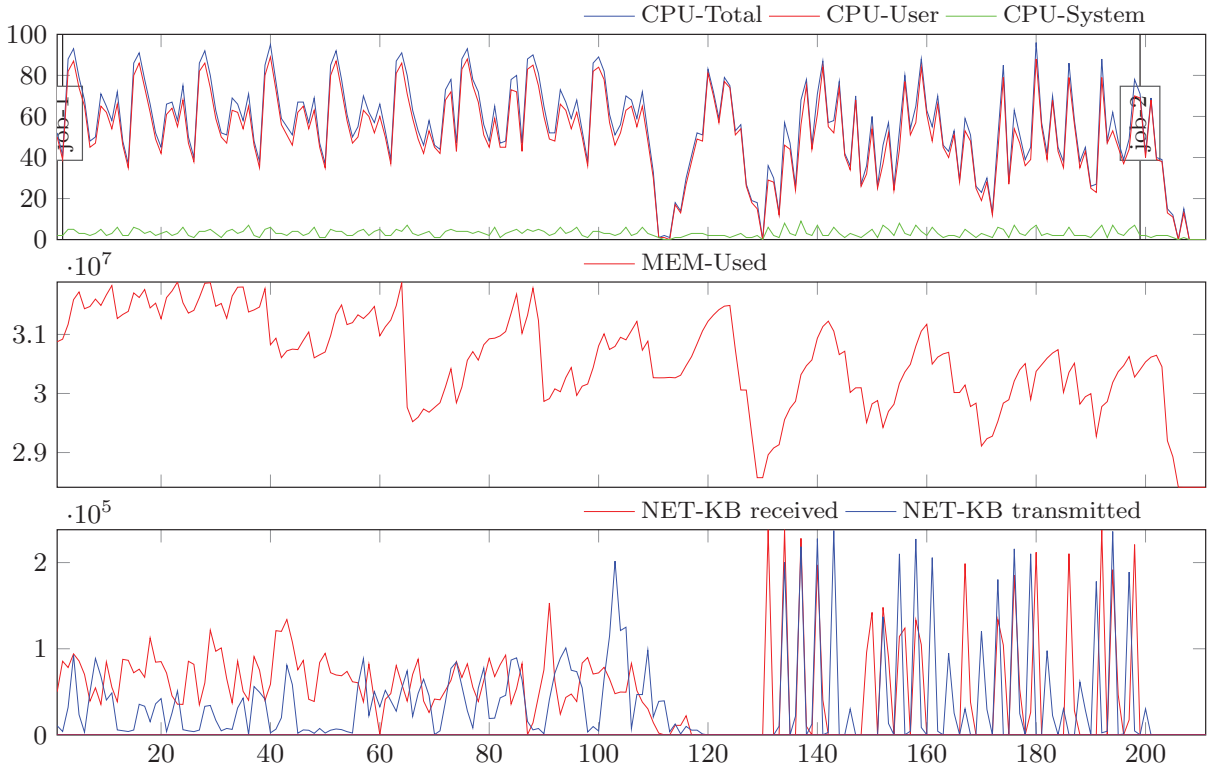


Figure A.14: Resource Consumption of TPC-H query 14 executing with default configuration.

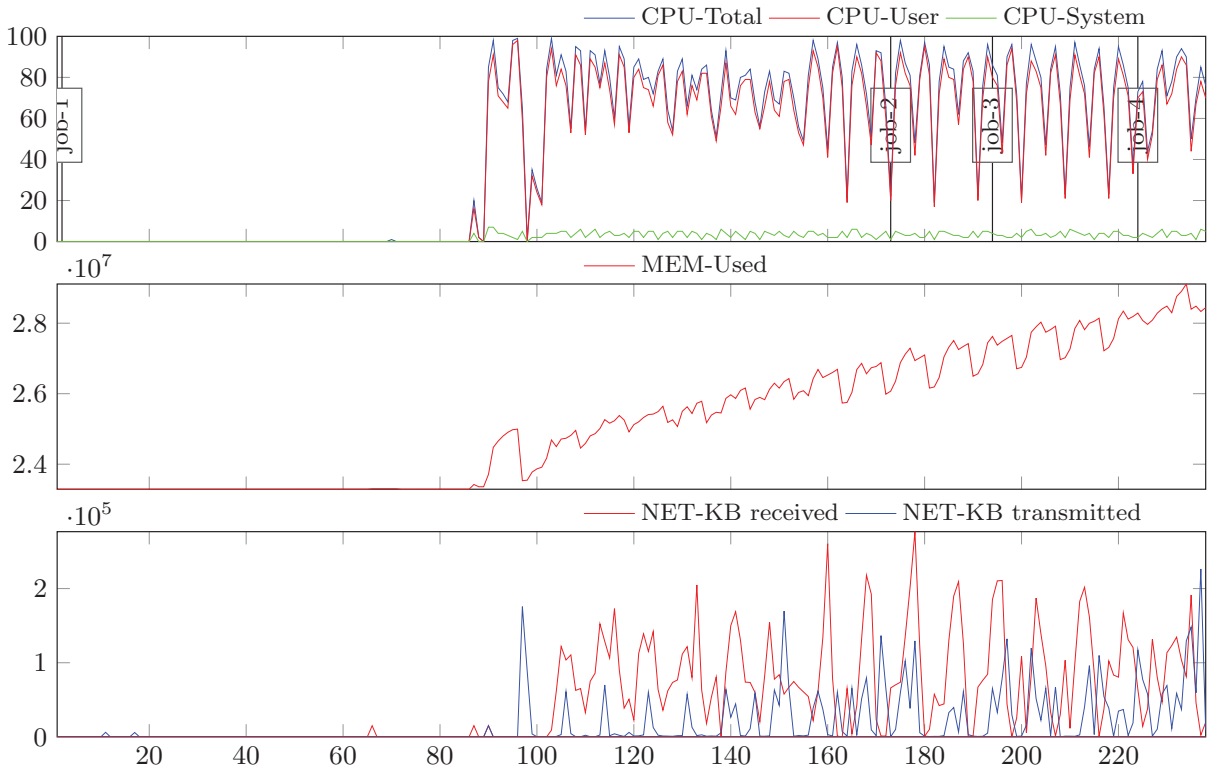


Figure A.15: Resource Consumption of TPC-H query 15 executing with default configuration.

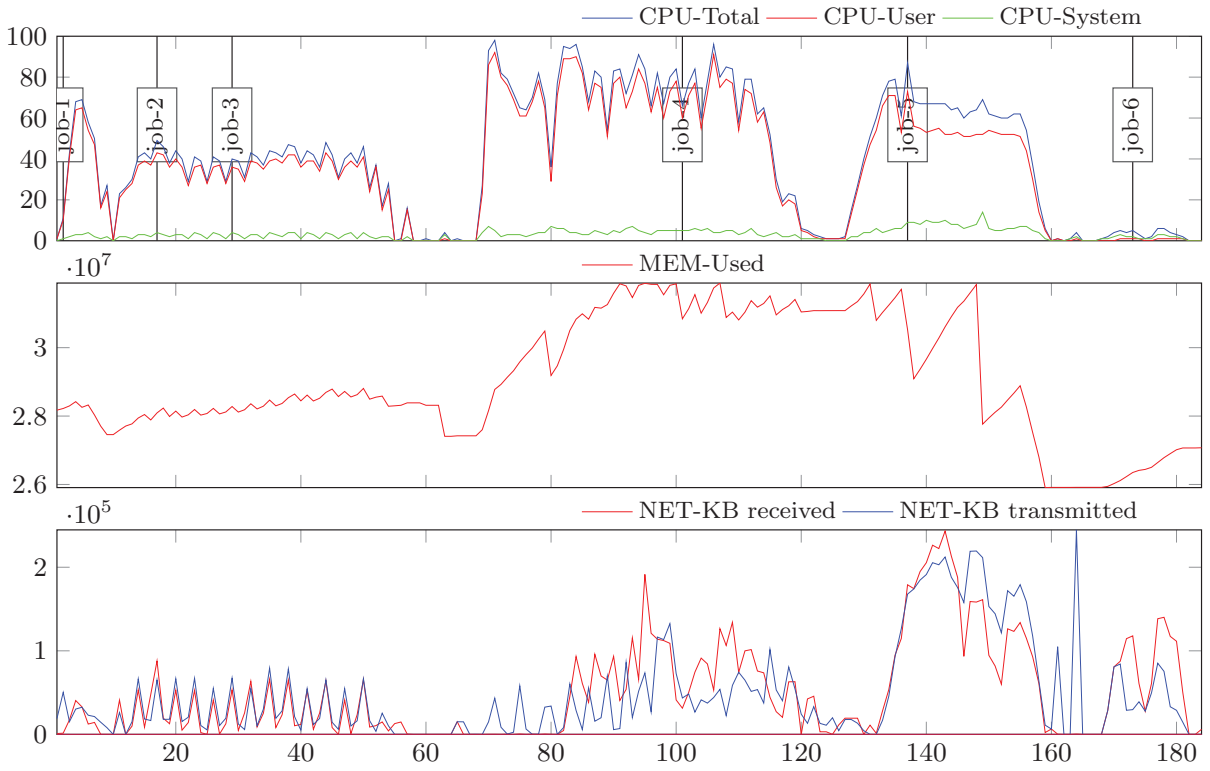


Figure A.16: Resource Consumption of TPC-H query 16 executing with default configuration.

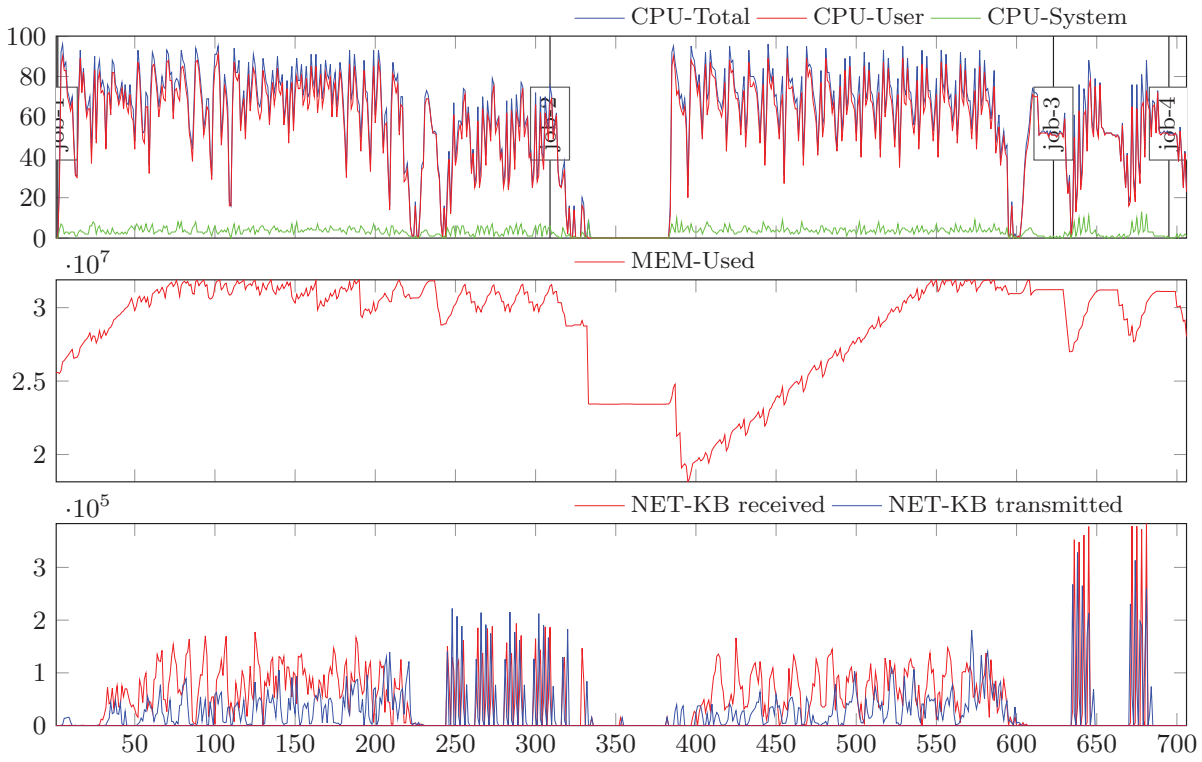


Figure A.17: Resource Consumption of TPC-H query 17 executing with default configuration.

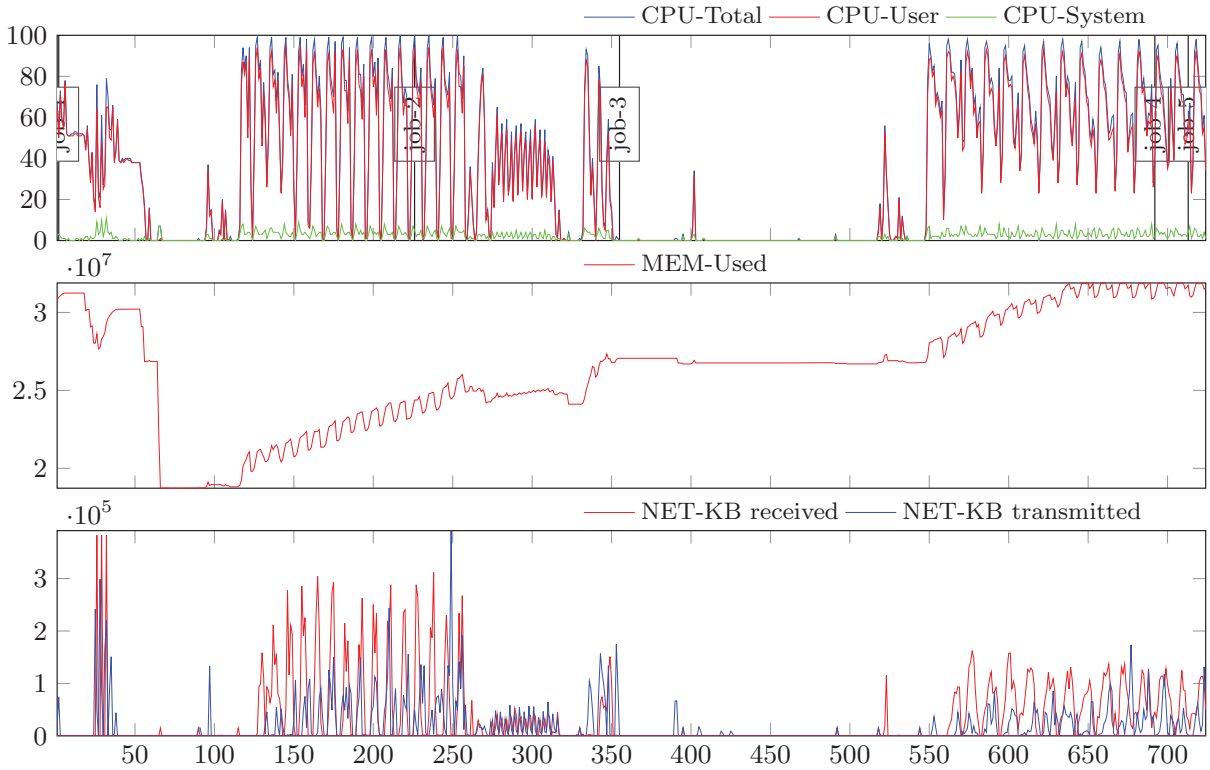


Figure A.18: Resource Consumption of TPC-H query 18 executing with default configuration.

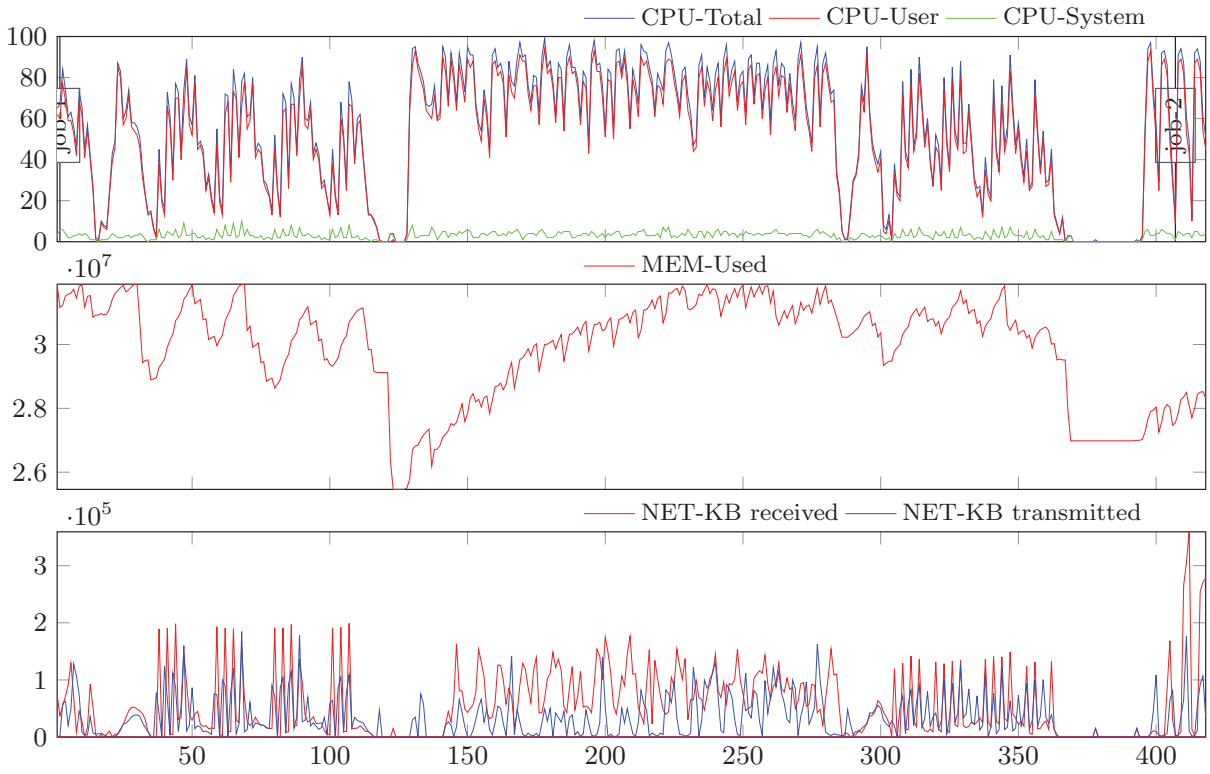


Figure A.19: Resource Consumption of TPC-H query 19 executing with default configuration.

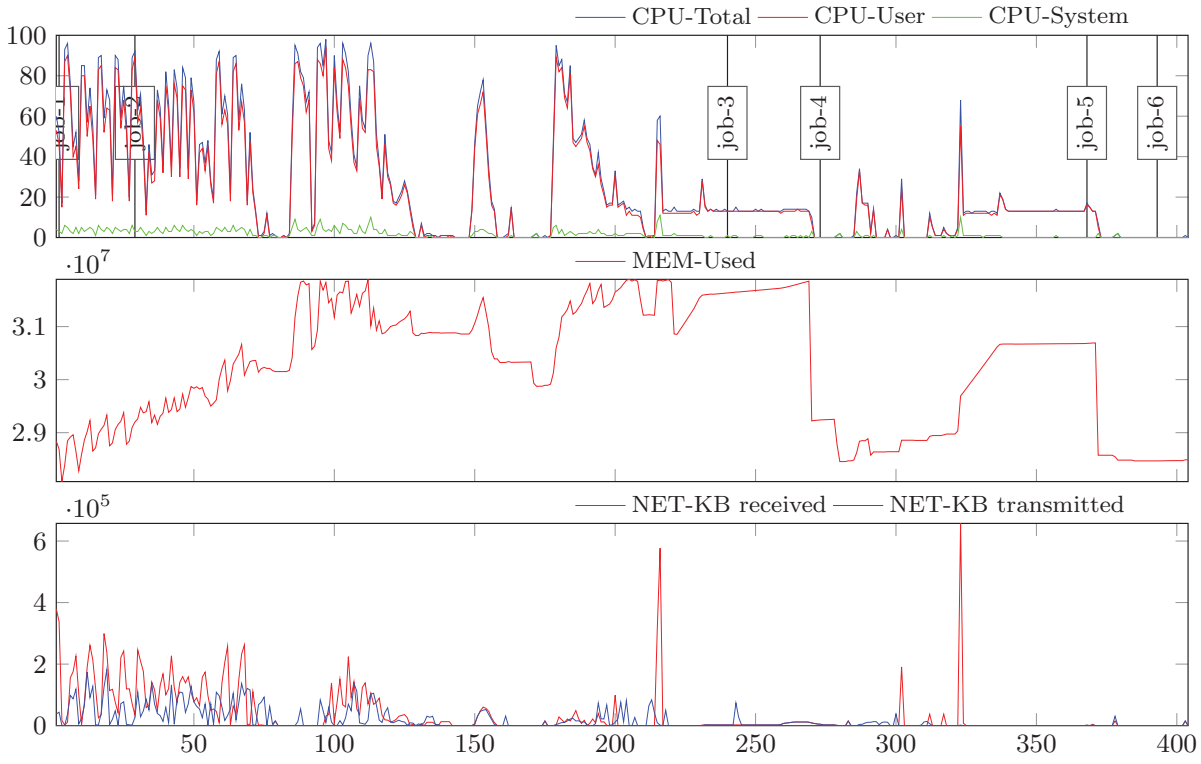


Figure A.20: Resource Consumption of TPC-H query 20 executing with default configuration.

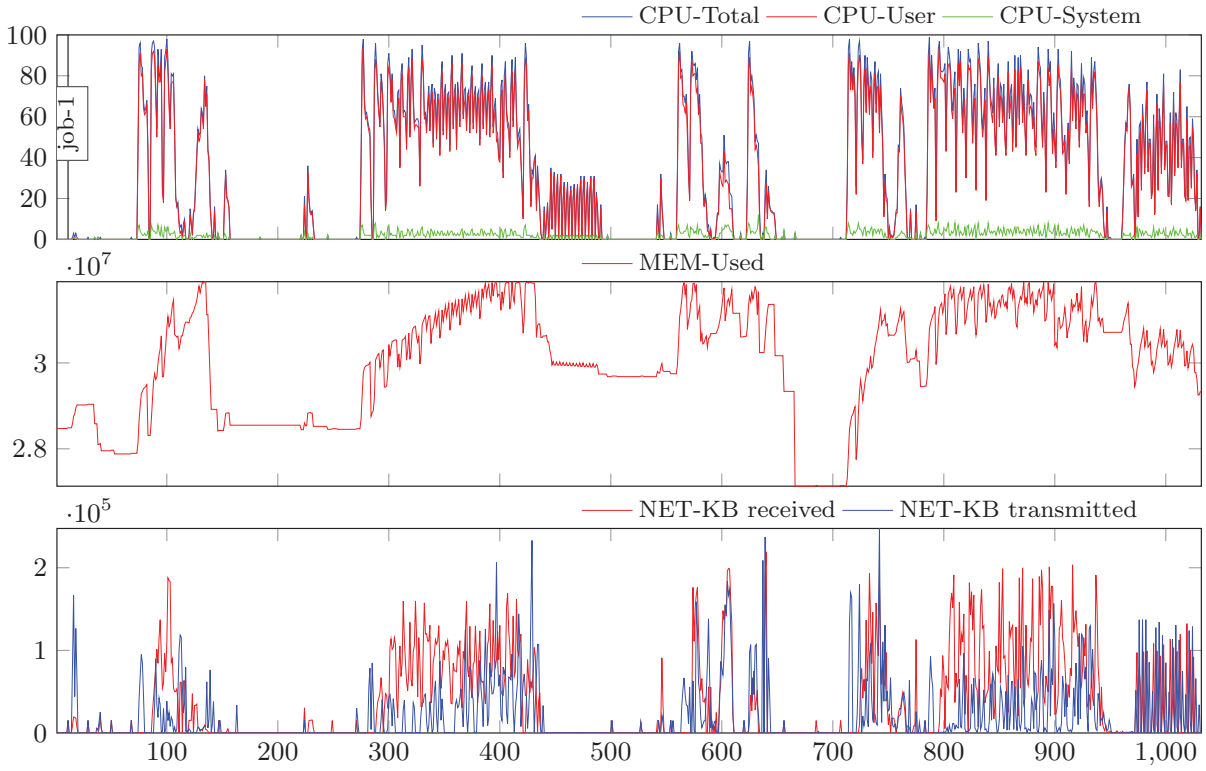


Figure A.21: Resource Consumption of TPC-H query 21 executing with default configuration.

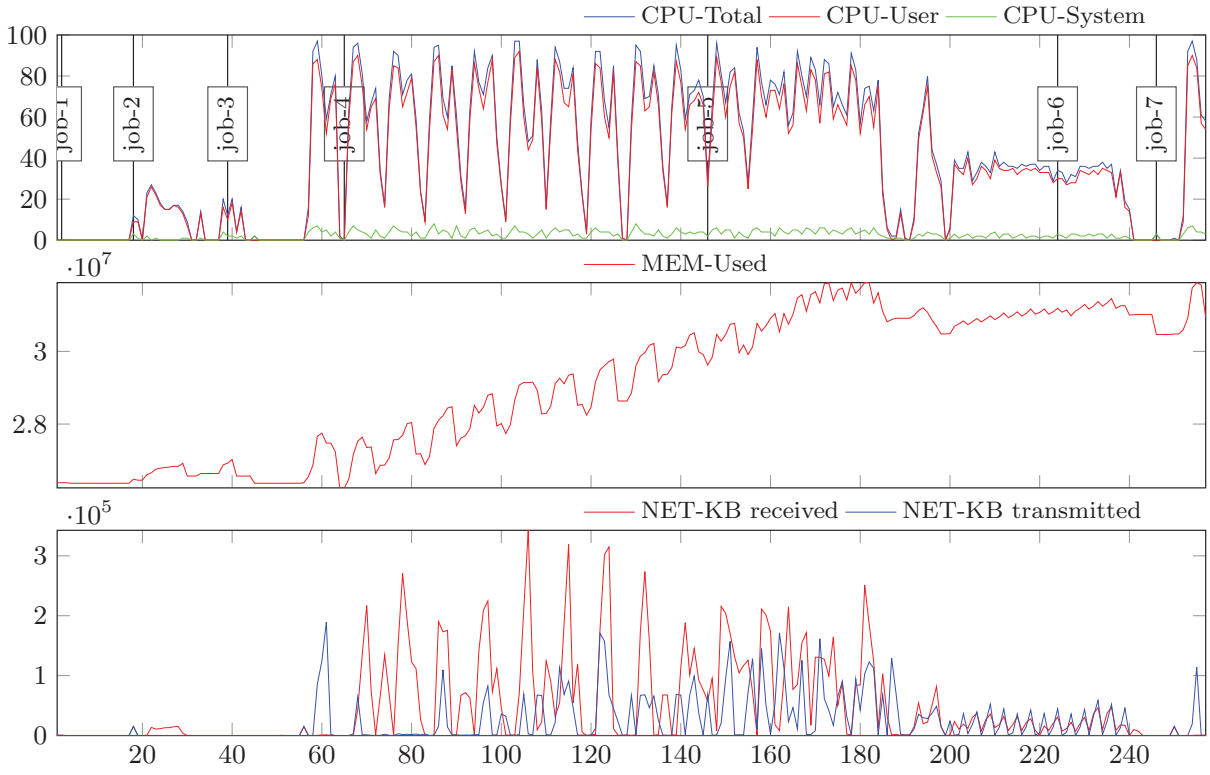


Figure A.22: Resource Consumption of TPC-H query 22 executing with default configuration.

# APPENDIX B – OCCURRENCE OF OPERATORS IN TPC-H QUERIES

| Job | FileSink | Filter | GroupBy | Join | Limit | MapJoin | ReduceSink | Select | TableScan |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 1 | 2 | 0 | 0 | 0 | 1 | 2 | 1 |
| 2 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 |

Table B.1: Occurrence of operators per job of TPC-H query 1.

| Job | FileSink | Filter | GroupBy | Join | Limit | MapJoin | ReduceSink | Select | TableScan |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 1 |
| 2 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 1 |
| 3 | 1 | 1 | 0 | 0 | 0 | 2 | 0 | 1 | 1 |
| 4 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 |
| 5 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 1 |
| 6 | 1 | 1 | 2 | 0 | 0 | 1 | 1 | 0 | 1 |
| 7 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 1 |
| 8 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 1 |
| 9 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 1 |

Table B.2: Occurrence of operators per job of TPC-H query 2.

| Job | FileSink | Filter | GroupBy | Join | Limit | MapJoin | ReduceSink | Select | TableScan |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 1 |
| 2 | 1 | 1 | 1 | 0 | 0 | 1 | 0 | 2 | 1 |
| 3 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 1 |
| 4 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 1 |

Table B.3: Occurrence of operators per job of TPC-H query 3.

| Job | FileSink | Filter | GroupBy | Join | Limit | MapJoin | ReduceSink | Select | TableScan |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 2 | 2 | 1 | 0 | 0 | 2 | 2 | 2 |
| 2 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 1 |
| 3 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 |

Table B.4: Occurrence of operators per job of TPC-H query 4.

| Job | FileSink | Filter | GroupBy | Join | Limit | MapJoin | ReduceSink | Select | TableScan |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 2 | 0 | 1 | 0 | 0 | 2 | 2 | 2 |
| 2 | 1 | 1 | 0 | 0 | 0 | 2 | 0 | 2 | 1 |
| 3 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 |
| 4 | 1 | 1 | 1 | 0 | 0 | 1 | 0 | 2 | 1 |
| 5 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 1 |
| 6 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 |

Table B.5: Occurrence of operators per job of TPC-H query 5.

| Job | FileSink | Filter | GroupBy | Join | Limit | MapJoin | ReduceSink | Select | TableScan |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 1 | 2 | 0 | 0 | 0 | 1 | 1 | 1 |

Table B.6: Occurrence of operators per job of TPC-H query 6.

| Job | FileSink | Filter | GroupBy | Join | Limit | MapJoin | ReduceSink | Select | TableScan |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 2 | 0 | 1 | 0 | 0 | 2 | 2 | 2 |
| 2 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 1 |
| 3 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 1 |
| 4 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 |
| 5 | 1 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 1 |
| 6 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 1 |
| 7 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 |

Table B.7: Occurrence of operators per job of TPC-H query 7.

| Job | FileSink | Filter | GroupBy | Join | Limit | MapJoin | ReduceSink | Select | TableScan |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 2 | 0 | 1 | 0 | 0 | 2 | 2 | 2 |
| 2 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 1 |
| 3 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 1 |
| 4 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 |
| 5 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 1 |
| 6 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 |
| 7 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | 1 | 1 |
| 8 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 1 |
| 9 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 |

Table B.8: Occurrence of operators per job of TPC-H query 8.

| Job | FileSink | Filter | GroupBy | Join | Limit | MapJoin | ReduceSink | Select | TableScan |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 1 |
| 2 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 1 |
| 3 | 1 | 1 | 0 | 1 | 0 | 0 | 2 | 2 | 2 |
| 4 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 |
| 5 | 1 | 1 | 1 | 1 | 0 | 0 | 2 | 2 | 2 |
| 6 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 1 |
| 7 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 |

Table B.9: Occurrence of operators per job of TPC-H query 9.

| Job | FileSink | Filter | GroupBy | Join | Limit | MapJoin | ReduceSink | Select | TableScan |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 2 | 0 | 1 | 0 | 0 | 2 | 2 | 2 |
| 2 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 1 |
| 3 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | 1 | 1 |
| 4 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 1 |
| 5 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 1 |

Table B.10: Occurrence of operators per job of TPC-H query 10.

| Job | FileSink | Filter | GroupBy | Join | Limit | MapJoin | ReduceSink | Select | TableScan |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 1 |
| 2 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 1 |
| 3 | 1 | 1 | 1 | 0 | 0 | 1 | 0 | 2 | 1 |
| 4 | 1 | 1 | 1 | 0 | 0 | 1 | 0 | 2 | 1 |
| 5 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 1 |
| 6 | 1 | 0 | 2 | 0 | 0 | 0 | 1 | 1 | 1 |
| 7 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 1 |
| 8 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 1 |
| 9 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 |

Table B.11: Occurrence of operators per job of TPC-H query 11.

| Job | FileSink | Filter | GroupBy | Join | Limit | MapJoin | ReduceSink | Select | TableScan |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 2 | 1 | 1 | 0 | 0 | 2 | 3 | 2 |
| 2 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 1 |
| 3 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 |

Table B.12: Occurrence of operators per job of TPC-H query 12.

| Job | FileSink | Filter | GroupBy | Join | Limit | MapJoin | ReduceSink | Select | TableScan |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 1 | 1 | 1 | 0 | 0 | 2 | 2 | 2 |
| 2 | 1 | 0 | 2 | 0 | 0 | 0 | 1 | 1 | 1 |
| 3 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 1 |
| 4 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 |

Table B.13: Occurrence of operators per job of TPC-H query 13.

| Job | FileSink | Filter | GroupBy | Join | Limit | MapJoin | ReduceSink | Select | TableScan |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 1 | 2 | 0 | 0 | 1 | 1 | 3 | 1 |

Table B.14: Occurrence of operators per job of TPC-H query 14.

| Job | FileSink | Filter | GroupBy | Join | Limit | MapJoin | ReduceSink | Select | TableScan |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 2 | 2 | 0 | 0 | 0 | 1 | 1 | 1 |
| 2 | 1 | 1 | 3 | 0 | 0 | 0 | 1 | 2 | 1 |
| 3 | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 1 |
| 4 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 |
| 5 | 1 | 0 | 0 | 0 | 0 | 1 | 1 | 2 | 1 |

Table B.15: Occurrence of operators per job of TPC-H query 15.

| Job | FileSink | Filter | GroupBy | Join | Limit | MapJoin | ReduceSink | Select | TableScan |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 1 | 2 | 0 | 0 | 0 | 1 | 1 | 1 |
| 2 | 1 | 1 | 2 | 0 | 0 | 0 | 1 | 2 | 1 |
| 3 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 1 |
| 4 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 |
| 5 | 1 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 1 |
| 6 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 1 |
| 7 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 |

Table B.16: Occurrence of operators per job of TPC-H query 16.

| Job | FileSink | Filter | GroupBy | Join | Limit | MapJoin | ReduceSink | Select | TableScan |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 1 | 2 | 0 | 0 | 1 | 1 | 2 | 1 |
| 2 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 2 | 1 |
| 3 | 1 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 1 |
| 4 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 1 |

Table B.17: Occurrence of operators per job of TPC-H query 17.

| Job | FileSink | Filter | GroupBy | Join | Limit | MapJoin | ReduceSink | Select | TableScan |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 2 | 2 | 0 | 0 | 0 | 1 | 1 | 1 |
| 2 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 1 |
| 3 | 1 | 1 | 1 | 1 | 0 | 0 | 3 | 1 | 3 |
| 4 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 1 |
| 5 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 1 |

Table B.18: Occurrence of operators per job of TPC-H query 18.

| Job | FileSink | Filter | GroupBy | Join | Limit | MapJoin | ReduceSink | Select | TableScan |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 2 | 2 | 0 | 0 | 1 | 1 | 2 | 1 |

Table B.19: Occurrence of operators per job of TPC-H query 19.

| Job | FileSink | Filter | GroupBy | Join | Limit | MapJoin | ReduceSink | Select | TableScan |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 1 |
| 2 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 1 |
| 3 | 1 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 1 |
| 4 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 1 |
| 5 | 1 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 1 |
| 6 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 2 | 1 |
| 7 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 |

Table B.20: Occurrence of operators per job of TPC-H query 20.

| Job | FileSink | Filter | GroupBy | Join | Limit | MapJoin | ReduceSink | Select | TableScan |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 2 | 2 | 0 | 0 | 0 | 1 | 2 | 1 |
| 2 | 1 | 2 | 2 | 0 | 0 | 0 | 1 | 1 | 1 |
| 3 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 1 |
| 4 | 1 | 2 | 0 | 1 | 0 | 0 | 3 | 3 | 3 |
| 5 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 |
| 6 | 1 | 0 | 2 | 0 | 0 | 1 | 1 | 0 | 1 |
| 7 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 1 |

Table B.21: Occurrence of operators per job of TPC-H query 21.

| Job | FileSink | Filter | GroupBy | Join | Limit | MapJoin | ReduceSink | Select | TableScan |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 0 | 2 | 0 | 0 | 0 | 1 | 1 | 1 |
| 2 | 1 | 1 | 2 | 0 | 0 | 0 | 1 | 2 | 1 |
| 3 | 1 | 2 | 0 | 0 | 0 | 1 | 0 | 2 | 1 |
| 4 | 1 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 1 |
| 5 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 1 |
| 6 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 |

Table B.22: Occurrence of operators per job of TPC-H query 22.