The Case for Dynamic Placement of Distributed Systems Components

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Abstract
Today distributed systems are made of many software components with complex interactions. One of the key challenges in such an environment is determining how to place the components so that the system performs efficiently. In this paper, we illustrate the importance of component placement with a case study, examining the performance of a common stream processing pipeline comprising Kafka, Spark, and Cassandra. We study three applications (word count, Twitter sentiment analysis, machine learning) and three placement strategies. Our results show that (i) placement has a significant impact on the application throughput (up to 52%) and (ii) the placement achieving best results differs depending on the application. We discuss why existing solutions for performance troubleshooting in distributed systems are not sufficient to help choosing an efficient placement or to detect if a chosen placement is significantly underperforming compared to others. Finally, we describe research directions to address this open problem.

Keywords : Distributed systems, performance optimization, application placement

1. Introduction

Applications deployed in distributed environments are composed of a variety of software components. These components provide different functionalities e.g., publish-subscribe messaging, real-time analysis and rendering of streaming data, and storage. Besides, in order to achieve scalability, each component can be divided into a number of partitions spread on separate machines for parallel processing. In addition, for fault tolerance and high availability, each component/partition typically has a number of replicas. Overall, all these components (and their internal replicas and partitions) have many interactions, involving both control messages and data. With such a complex and diverse architecture, it is generally difficult to understand the overall behavior of a distributed system and how its performance can be improved. First of all, it is difficult to determine whether or not a given system is performing efficiently with respect to the capacity of the underlying hardware resources. In particular, the existence of a saturated hardware resource does not guarantee that the resource is used efficiently (e.g., CPUs may be saturated due to contention on a spinlock). Conversely, the absence of resource saturation is not necessarily a sign of fluid operation (e.g., the system may be excessively idle due to a cascade of blocking interactions with a slow thread). Second, even if an inefficiency has been detected in the distributed system, it is often difficult to determine the root cause and/or how to fix it (e.g., if a deep modification is required or modest configuration changes are sufficient to alleviate the issue).

In this context, the present paper considers the following problem: *given an already deployed distributed system, is it possible to design a profiling tool able to (i) pinpoint that the system is significantly under-performing and (ii) suggest simple configuration changes to improve performance?* By "simple configuration changes", we mean actions such as adjusting the allocation of execution resources (e.g., thread pool tuning) or changing the placement of software components on the physical machines. In this paper, we only focus on the latter kind of configuration change (component placement). The crux of the problem here is that the proposed tool cannot rely on previous knowledge or trial-and-error (i.e., known performance results of alternative configurations), because a brute-force exploration of the configuration space is not viable. In this paper, make the case for the importance of this problem and report on preliminary experiments through a concrete case study. Using a distributed data processing pipeline implemented with a popular software stack (ZooKeeper, Kafka, Spark Streaming and Cassandra), we show that such a common distributed system can exhibit performance trends that are difficult to anticipate/explain and very sensitive to the impact of workload changes and simple placement decisions. In other words, there is no one-size-fits-all strategy for the placement of software components, and no easy way to assert if a given placement strategy is yielding "good enough" performance. Furthermore, we stress that the above problems are not specific to very complex systems with factors such as large-scale deployments, massive input load, churn, resource virtualization and multi-tenancy [23, 25]. Indeed, as we show, even a small-scale system deployed on a fixed set of dedicated machines can be impacted.

The remainder of the paper is organized as follows. First, we start by describing the data processing pipeline use case and the three different examined applications in Section 2. In Section 3, we present the evaluation methodology and the results. Finally, we discuss the related work in Section 4 and provide research directions to address the problem in Section 5.

2. Context

In this section, we first present the components of the processing pipeline that we study. Then, we briefly describe the three benchmark applications built on top of it.

2.1. Case Study: Data Processing Pipeline

We consider a data processing pipeline comprising ZooKeeper [7], a coordination service, Kafka [5], a distributed publish-subscribe messaging system, Spark Streaming [6], a Big Data processing and analysis framework, and Cassandra [4], a distributed NoSQL database management system. The above-described software stack is nowadays a de facto standard in production for data analytics. In our setup, we use a factor of replication of three for each component (additionally, the processing performed by Kafka and Spark is parallelized via sharding) and the whole pipeline is deployed on 6 dedicated physical machines. Additional details on the studied configurations are provided in §3.1.

2.2. Applications

For each of the three applications described below, the input data is ingested through Kafka, then processed by Spark Streaming, and the results are saved in Cassandra.

Word Count (WC) is a standard micro-benchmark for big data [11]. We use a randomly generated corpus of English words.

Twitter Sentiments Analysis (TSA) monitors people's opinion on different topics. We use the SentiWordNet [8] dictionary for opinion mining. As a dataset, we use recent tweets in English crawled through the Twitter API [21].
Flight Delays Prediction (FDP) uses machine learning (with a logistic regression classification algorithm) to predict the delays of airline flights. We use input data from the U.S. Department of Transportation's (DOT) Bureau of Transportation Statistics (BTS) [22].

3. Evaluation

3.1. Testbed and Methodology

We deploy the data processing pipeline on a fixed number of homogeneous machines (hereafter named "nodes") – in this setup, we use six nodes. Regarding the client side, we run each single client thread on a separate machine (we increase the number of client machines as needed to reach the system saturation point). The experiments are performed on the G5K [9] testbed using the Nova cluster. Each host has the same hardware configuration with two 8-core CPUs, 32GB RAM, a 600GB HDD, and a 10 Gbps Ethernet interface. For the software stack, we use Debian 8 with a 3.16.0 Linux kernel, OpenJDK version 1.8.0_131, ZooKeeper 3.4.10, Kafka 0.11, Spark Streaming 2.1.0, and Cassandra 3.0.9.
In order to build and operate a high-performance data processing pipeline, various placement strategies for the different software components can be chosen. Since a complete exploration of the configuration space is impractical, we study only a subset of the possible placement strategies, using the following methodology. We start by placing one component on dedicated nodes (one node per replica) and co-locating the other components on the remaining machines. This may help alleviate bottlenecks if the isolated component requires a large amount of resources (e.g., CPU time, memory bandwidth or I/O bandwidth). In addition, consolidating the remaining components on the other nodes may improve the performance of communications among them (local vs. remote). Given that there are three main components in the pipeline that we study (Kafka/ZooKeeper, Spark Master and Cassandra)[1], exploring the above-mentioned approach leads to studying three concrete deployment strategies. We then fine tune the number of Spark workers for each application, spreading them on three to six nodes[2], in order to optimize the application throughput. We end up with three placement strategies (*P1*, *P2*, *P3*). depicted in Figure 1. *P1* "isolates" the Cassandra components, while *P2* and *P3* respectively do the same for the Spark Master and the Kafka/ZooKeeper components.
The system and application settings are tuned independently for each application (WC, TSA, FDP). However, for a given application, we use the same settings between the different placements, i.e., the only change between the different configurations is the placement of the components. Table 1 shows the main settings for each application.

Application	Kafka no. Partitions	Kafka Replication Factor	Spark no. Workers	Spark Batch Interval (sec)	Cassandra no. Partitions	Cassandra Replication Factor
Word Count	12	3	6	4	3	3
Twitter Sentiment Analysis	32	3	3	2	3	3
Flights Delay Prediction	6	3	6	2	3	3

Table 1: Main settings for the three studied applications.

[1] ZooKeeper is only used by Kafka, which relies on it for storing metadata information and fault-tolerance. Given the tight coupling between Kafka and ZooKeeper, we systematically colocate Kafka and ZooKeeper. We have checked that ZooKeeper is never under-provisioned in our different configurations.
[2] We have checked that Spark workers never introduce saturation of hardware resources on their target nodes.

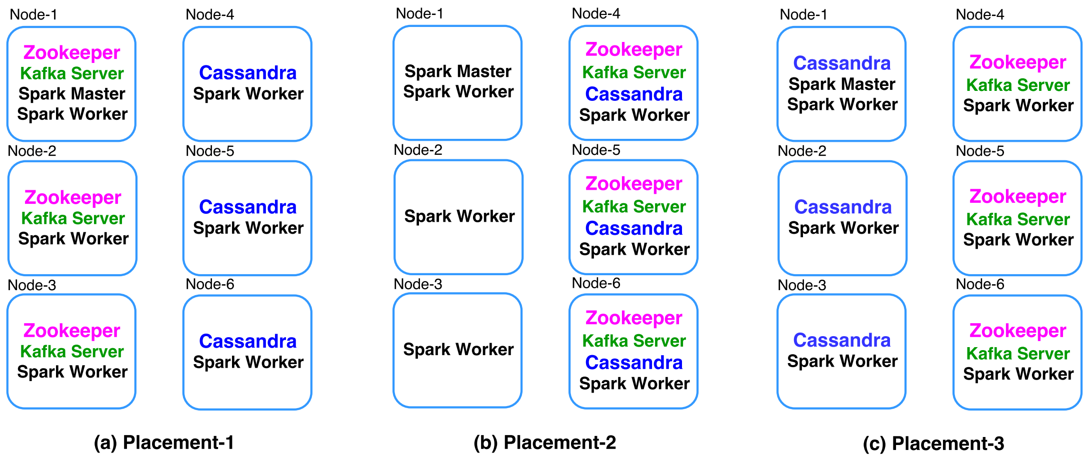


Figure 1: The three studied placement strategies for the data processing pipeline.

3.2. Results and Discussions

We examine the performance for the three placement strategies described earlier. For each application, our results show significant differences in throughput between the three strategies (up to **52%**, **27%**, and **48%**). We measure the system throughput as the number of input messages (injected by Kafka clients) that can be processed per time unit, varying the number of clients. For a given application, we compute the throughput differences using the worst performing placement as a baseline. Below, we mostly focus on the results for the highest input load.

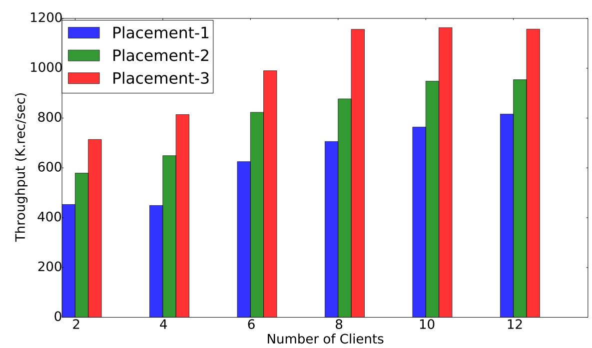
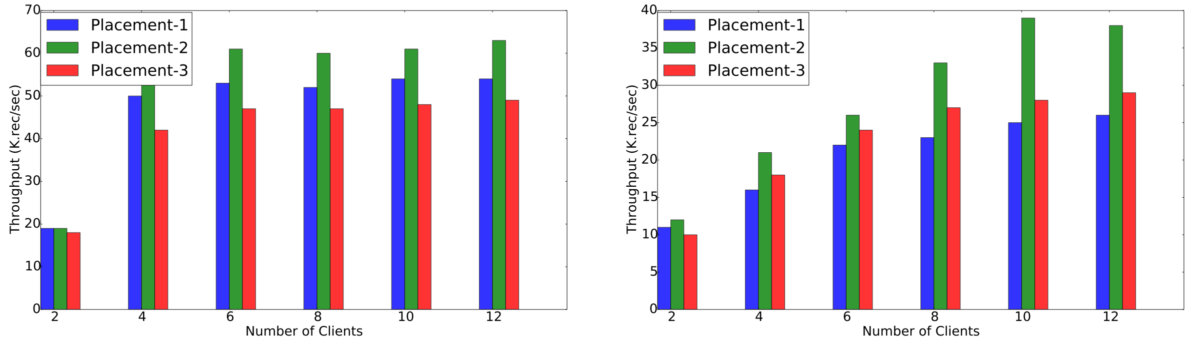


Figure 2: Throughput of the three placement strategies for the WC application

WC: As shown in Figure 2, *P3* achieves the best throughput, with respectively a 52% and a 23% improvement over *P1* and *P2*. Besides, *P2* achieves a 24% improvement over *P1*.
TSA: As shown in Figure 3a, *P3* achieves the worst throughput (unlike with WC). *P2* achieves the best throughput, with respectively a 15% and a 27% improvement over *P1* and *P3*. Besides, *P1* performs 11% better than *P3*.
FDP: This application yields yet another performance hierarchy. As shown in Figure 3b, *P2* achieves the best throughput, with resp. a 48% and a 33% improvement over *P1* and *P3*. Besides, *P3* performs 10% better than *P1*.

Table 2 shows the resources usage for the three studied applications for each placement (measured at the peak load). We can notice that these resources are far from being saturated, even in the worst case: e.g., CPU consumption and memory usage never exceed 55% and 25% respectively. Besides, these indicators do not necessarily exhibit large variations between the best and the worst strategies (e.g., *P3* vs. *P1* for WC). This discards trivial explanations for the observed performance differences between strategies.
To summarize, our results show that: (i) the placement achieving the best/worst results differs

depending on the application; (ii) the ratios of performance differences between placements vary significantly depending on the applications; (iii) none of the studied configuration exhibits any noticeable bottleneck/saturated hardware resource.



(a) TSA application throughput

(b) FDP application throughput

Figure 3: Throughput of the three placement strategies for the TSA and FDP applications.

Resource usage		**P1**			**P2**			**P3**		
		WC	**TSA**	**FDP**	**WC**	**TSA**	**FDP**	**WC**	**TSA**	**FDP**
CPU (%)	Max	25	55	32	35	53	48	25	53	23
	Avg	19	37	18	21	33	22	16	30	13
Memory (%)	Max	19	16	19	20	18	16	22	23	23
	Avg	10	10	9	10	8	15	12	13	10
Network I/O (MB/sec)	Max sent	57	39	316	78	38	338	85	33	314
	Avg. sent	15	12	96	20	13	76	29	11	71
	Max rece.	56	37	306	83	33	369	92	37	337
	Avg. rece.	14	11	93	19	12	73	28	11	69
Disk I/O (MB/sec)	Max	47	10	257	68	15	312	77	12	287
	Avg	11	5	69	14	6	55	21	5	52

Table 2: resources usage for the three studied applications.

4. Related work

There has been much research devoted to performance troubleshooting for distributed systems [20, 24]. Below, we discuss the most closely related works, organized into three categories.

Is the system performing efficiently?

CPI^2 [25] uses cycles-per-instruction (CPI) data obtained by hardware performance counters to identify slow tasks out of a set of independent but similar tasks running on a cluster of machines. To identify interfering tasks, CPI^2 looks for correlations between the CPI of the slow tasks and the CPU usage of the other tasks running on the same machine. CPI^2 then uses CPU hard capping to throttle the CPU consumption of interfering tasks and improve the performance of slow tasks. This technique is not sufficient for our problem, in which there are not only interferences between local tasks but also interdependencies (via synchronous and/or asynchronous interactions) between local and remote components. Altman et al. present the

WAIT tool [2], for pinpointing the causes of idle time in server applications. The tool provides a dashboard and a rule-based system for the business component of Java Enterprise applications, highlighting where threads wait (e.g., locks, database, network, disk). However, this tool only focuses on a single component, whereas, in our case, a complete view of all the components of an application is necessary to fully understand and debug performance [10, 12].

What are the performance issues and where do they lie?

In order to fix performance issues in a system, it is necessary to identify the symptoms ("*what?*") and also the root cause ("*where?*"). In the context of data analytics frameworks, Ousterhout et al. [17, 18] propose blocked time analysis, which allows quantifying how much faster a job would complete if its tasks never blocked on disk or network I/O. Applying their methodology to Spark, they identify several causes for performance issues including high CPU utilization, garbage collection, and disk I/O. This approach is useful but currently limited to the scale/context of a single component (Spark), with specific instrumentation and assumptions regarding the execution model. Pivot Tracing [16], is a recent monitoring framework for distributed systems that combines dynamic instrumentation with causal tracing. It correlates and groups system events across components and machines boundaries. As an example, this allows identifying the components that create resource contention downstream on other parts of the system. Pivot Tracing requires instrumentation provided by the developers or system users in order to propagate specific metadata. By design, Pivot Tracing is only aimed at pinpointing the root cause of known performance issues, not at detecting such issues, nor at suggesting optimizations.

How to place logical resources?

There has been much research devoted to improving the performance of distributed systems by optimizing the placement of its logical resources. By logical resources we refer to both (i) data and (ii) application components (i.e., code). In this Section, we first discuss related works regarding data placement [1, 14, 15]. Then, we discuss works concerning application placement [3, 13, 19, 26].

Agarwal et al. [1] present Volley, a system that optimizes data placement across geographically distributed data-centers by analysing request logs based on data access patterns and client locations to decide how to migrate data between data centers. The migration decision is taken according to administrator-defined trade-offs between performance and cost. Kumar et al. [15] develop SWORD, a workload-aware data placement and replication approach for minimizing resource consumption. SWORD focuses on deciding which data items should be replicated and where to place the data as well as the replicas. Moreover, SWORD monitors the workload changes in order to identify candidate sets of data items whose migration has the potential to reduce the query (request) span the most and then performs the migrations during periods of low load.

Karve, et al. [13] propose a controller that dynamically configures the placement of clustered Web applications consolidated on the same set of machines. The goal is to optimize the resource allocation and the load balancing between component instances according to the input load variations of the different applications/tiers. ClouDiA [26] is a deployment advisor mapping latency-sensitive application components (e.g., graph processing) to virtual machine instances in public clouds. Taking the application communication graph, ClouDiA outputs an optimized deployment plan minimizing the largest latency between application nodes. The above-mentioned works [13, 26] are focused on optimizing a specific objective function (resource consolidation under a service-level agreement or network latency) and do not consider the detection and analysis of bottlenecks in the system. Amiri et al. have introduced the ABACUS system [3,19], which handles dynamic function placement for a data-intensive application deployed on a cluster. ABACUS continuously collects statistics and dynamically migrates components across machines if it predicts that the net effect will improve the average application response time across all the applications that are accessing a given server. This work shares some goals and building blocks with our research but also has significant differences. ABACUS strongly relies on the assumption that all the application components are designed with a specific framework and a dedicated programming model. Moreover, the design of ABACUS is mostly aimed at applications with a specific topology (a set of client and server nodes) and a specific type of problem (figuring out which subset of components executing currently on clients can benefit the most from computing closer to the data, without overloading the servers). In contrast, our work (in progress) addresses a more general version of the problem: in particular, we do not make strong assumptions about the design or implementation of the software components (although our approach may require to instrument some of them), nor about the distributed topology of the application or the performance metrics to be optimized.

5. Conclusion and research directions

This paper highlights the fact that the placement of software components can have a significant impact on the performance of distributed systems and that selecting an efficient placement is not trivial. We aspire to build a tool that is able to automatically suggest a more efficient placement strategy.

In order to address this challenge, we are currently designing a tool that will combine several kinds of inputs and build on existing methodologies for providing better insight. In addition to metrics about utilization of hardware and OS-level resources, the tool will also gather (i) network-level statistics (latency, throughput, data volumes, timing of communication patterns) and (ii) application-specific indicators both for synchronous and asynchronous interactions between components (e.g., timing and contextual information about blocked time, growth rate of producer-consumer queues).

The tool will use the above-mentioned data to perform *distributed blocked time analysis*. This technique will extend notions from blocked time analysis [17] (identification of hardware and software bottleneck resources) and articulate them with insights from workflow-centric tools like Pivot Tracing [16] (distributed causality tracking of thread interactions and resource consumption). By bridging these different insights, we hope to both (i) detect inefficient interactions between components and (ii) identify better placement strategies through *"what-if"* simulations.

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