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Cost and Energy optimization for Big Data Processing in Geo-Spread Data Centers

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Abstract

The high volume of demands on big data processing produces a heavy load on calculation, storage, and communication in data storage, which hence determines the required operational measures to data storage. Data center resizing (DCR) has been proposed to reduce the computation cost by adjusting the number of activated servers via task placement. MINLP (Mixed Integer Non Linear Programming) is the problem of non-joint optimization. MILP (Mixed Integer Linear Programming) is the problem of joint optimization of Task Assignment, Data Placement, and Data Movement. Markov chain is used to derive the execution time of data centers.

Keywords – Demand, Big data, Measures, Linear Programming

1 Introduction

Data explosion leads to demand for big data processing in data centers that are distributed at different geographic regions. Data computation, storage, and communication in data centers, which hence incurs considerable operational expenditure to data center providers. Computation tasks conducted only when the corresponding data is available due to tight coupling between data .Task assignment, data placement and data movement, deeply influence the operational expenditure of data centers. Many efforts have been made to lower the computation or communication cost of data centers. Data center resizing (DCR) has been proposed to reduce the computation cost by adjusting the number of activated servers via task placement. Based on DCR, some studies have explored the geographical distribution nature of data centers and electricity price heterogeneity to lower the electricity cost. Big data service frameworks, e.g., comprise a distributed file system underneath, which distributes data chunks and their replicas across the data centers for fine-grained load-balancing and high parallel data access performance. To reduce the communication cost, a few recent studies make efforts to improve data locality by placing jobs on the servers where the input data reside to avoid remote data

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loading. Although the above solutions have obtained some positive results, they are far from achieving the cost efficient big data processing because of the following weaknesses. First, data locality may result in a waste of resources. For example, most computation resource of a server with less popular data may stay idle. The low resource utility further causes more servers to be activated and hence higher operating cost. Second, the links in networks vary on the transmission rates and costs according to their unique features, e.g. the distances and physical optical fiber facilities between data centers. However, the existing routing strategy among data centers fails to exploit the link diversity of data center networks. Due to the storage and computation capacity constraints, not all tasks can be placed onto the same server, on which their corresponding data reside. It is unavoidable that certain data must be downloaded from a remote server. In this case, routing strategy matters on the transmission cost, the transmission cost, e.g., energy, nearly proportional to the number of network link used. The more link used, the higher cost will be incurred. Therefore, it is essential to lower the number of links used while satisfying all the transmission requirements. Third, the Quality-of-Service (QoS) of big data tasks has not been considered in existing work. Similar to conventional cloud services, big data applications also exhibit Service-Level-Agreement (SLA) between a service provider and the requesters. To observe SLA, a certain level of QoS, usually in terms of task completion time, shall be guaranteed. The QoS of any cloud computing tasks is first determined by where they are placed and how many computation resources are allocated.

Besides, the transmission rate is another influential factor since big data tasks are data-centric and the computation task cannot proceed until the corresponding data are available. Existing studies, e.g., on general cloud computing tasks mainly focus on the computation capacity constraints, while ignoring the constraints of transmission rate.

2 Related Works

In 2015, 71% of worldwide data center hardware spending will come from the big data processing, it's predicted by Gartner. In Data center resizing (DCR) data locality may result in a waste of resources. Less popular data may stay idle and the low resource utility causes more servers to be activated and hence higher operating cost. Links in networks vary on the transmission rates and costs according to their unique features. If the routing strategy among data centers fails then it is unavoidable to download from a remote server. In this case, routing strategy matters on the transmission cost. The Quality-of-Service (QoS) of big data tasks has not been considered in existing work. Big data processing translated into big price due to its high demand on computation, communication resources. Decrease the system reliability by continuous processing. Consumes high energy for high computation process its cause negative impacts to

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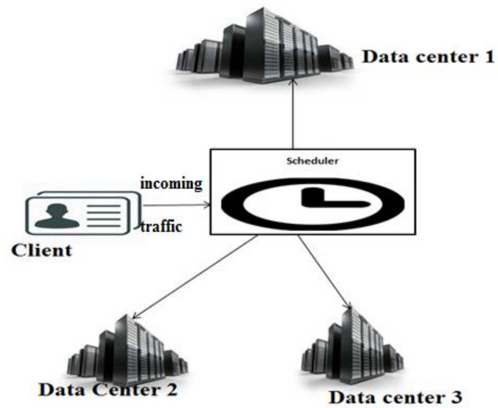
environment. In our proposed mechanism, formulate the cost minimization problem based on the closed-form expression in a form of mixed integer nonlinear programming (MINLP). Linearize it as a mixed-integer linear programming (MILP) problem for solving the complexity of MINLP. Cost for high computational data is minimized. Reduce the system operation increases system reliability. Energy Consumption is minimized.

3 System Design

In this section, we introduce the system model. From this architecture, determines with the following components, Data center1, Data Center 2 and Data center 3. Also determines with Client and the scheduler process



4 Methodologies

4.1 Uploading of data in big data

Select the big data and stored into the hadoop environment for performing map reduce on hadoop. The data should be loaded into the VM server location. After uploading the file the data segmentation is performed for further process.

4.2 Packet Separation

Packet segmentation improves network performance by splitting the packets in received Ethernet frames into separate buffers. Packet segmentation may be responsible for splitting one into multiple so that reliable transmission of each one can be performed individually. The packet processing system is specifically designed for dealing with the network traffic. Segmentation may be required when the

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data packet is larger than the maximum transmission unit supported by the network.

4.3 Job Responsibility

The Data Center should be selected according to computation and storage capacity of servers resides in the data center. Identification of Data Center is important matter for minimizing operational expenditure of servers reside in the each data centers. Data chunks can be placed in the same data center when more servers are provided in each data center. Further increasing the number of servers will not affect the distributions of tasks. Task is assigned to data center according to Memory requirement for effectively processing of data.

4.4 Loading of data

A Data Placement on the servers and the amount of load capacity assigned to each file copy so as to minimize the communication cost while ensuring the user experience. Optimization scheme that simultaneously optimize the virtual machine (VM) placement and network flow routing to maximize energy savings.

4.5 Assessment Process

We present the performance results of our joint-optimization algorithm using the MILP formulation. Evaluate server cost, communication cost and overall cost under different total server numbers.

5 Algorithm Description

Mixed Integer Non Linear Programming is the Non Joint Optimization problem. Mixed-integer optimization provides a powerful framework for mathematically modeling many optimization problems that involve discrete and continuous variables. The important factor for minimizing cost is Task Assignment, Data Loading and Data Movement. Optimization of these three factors will reduce the overall cost of network. The Non Joint Optimization technique individually optimizes these factors. So time increasing will lead to increase of operational cost of overall network. To reduce the System complexity (Continuous processing) of overall network is causing the unreliability of system. To reduce the system complexity of overall network, we linearize the MINLP by changing some operational parameters of MILP. MILP is a Joint Optimization of Task Assignment, Data Loading and Data Movement. Branch and Bound, Outer-Approximation, Generalized Benders and Extended Cutting Plane methods, as applied to nonlinear discrete optimization problems that are expressed in algebraic form. The solution of MINLP problems with convex functions is presented first, followed by a brief discussion on extensions for the non-convex case. Properties of the algorithms are first considered for the case when the nonlinear functions are convex in the discrete and continuous variables. Extensions are then presented for handling nonlinear equations and non-convexities.

6 Literature Review

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[21] Describe about, Computing equipment can be safely and efficiently hosted within a given power budget. Load variation and statistical effects are the main dynamic sources of inefficiency in power deployment. Large-scale Internet services require a computing infrastructure that can be appropriately described as a warehouse-sized computing system. The cost of building datacenter facilities capable of delivering a given power capacity to such a computer can rival the recurring energy consumption costs themselves. Therefore, there are strong economic incentives to operate facilities as close as possible to maximum capacity, so that the non-recurring facility costs can be best amortized. That is difficult to achieve in practice because of uncertainties in equipment power ratings and because power consumption tends to vary significantly with the actual computing activity. Effective power provisioning strategies are needed to determine how much computing equipment can be safely and efficiently hosted within a given power budget. In this paper we present the aggregate power usage characteristics of large collections of servers (up to 15 thousand) for different classes of applications over a period of approximately six months. Those observations allow us to evaluate opportunities for maximizing the use of the deployed power capacity of datacenters, and assess the risks of over-subscribing it. We find that even in well-tuned applications there is a noticeable gap (7 - 16%) between achieved and theoretical aggregate peak power usage at the cluster level (thousands of servers). The gap grows to almost 40% in whole datacenters. This headroom can be used to deploy additional compute equipment within the same power budget with minimal risk of exceeding it. We use our modeling framework to estimate the potential of power management schemes to reduce peak power and energy usage. We find that the opportunities for power and energy savings are significant, but greater at the cluster-level (thousands of servers) than at the rack-level (tens). Finally we argue that systems need to be power efficient across the activity range, and not only at peak performance levels. [9] Describe about, Video-on-Demand (VoD) services require frequent updates in file configuration on the storage subsystem, so as to keep up with the frequent changes in movie popularity. This defines a natural reconfiguration problem in which the goal is to minimize the cost of moving from one file configuration to another. The cost is incurred by file replications performed throughout the transition. The problem shows up also in production planning, preemptive scheduling with set-up costs, and dynamic placement of Web applications. We show that the reconfiguration problem is NP-hard already on very restricted instances. We then develop algorithms which achieve the optimal cost by using servers whose load capacities are increased by $O(1)$, in particular, by factor $1 + \delta$ for any small $0 < \delta < 1$ when the number of servers is fixed, and by factor of $2 + \varepsilon$ for arbitrary number of servers, for some $\varepsilon \in [0, 1)$. To the best of our knowledge, this particular variant of the

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data migration problem is studied here for the first time. [3] Describe about, In light of the challenges of effectively managing Big Data, we are witnessing a gradual shift towards the increasingly popular Linked Open Data (LOD) paradigm. LOD aims to impose a machine-readable semantic layer over structured as well as unstructured data and hence automate some data analysis tasks that are not designed for computers. The convergence of Big Data and LOD is, however, not straightforward: the semantic layer of LOD and the Big Data large scale storage do not get along easily. Meanwhile, the sheer data size envisioned by Big Data denies certain computationally expensive semantic technologies, rendering the latter much less efficient than their performance on relatively small data sets. In this paper, we propose a mechanism allowing LOD to take advantage of existing large-scale data stores while sustaining its "semantic" nature. We demonstrate how RDF-based semantic models can be distributed across multiple storage servers and we examine how a fundamental semantic operation can be tuned to meet the requirements on distributed and parallel data processing. Our future work will focus on stress test of the platform in the magnitude of tens of billions of triples, as well as comparative studies in usability and performance against similar offerings.

7 Conclusion

From this Cost and Energy optimization for Big Data Processing in Geo-Spread Data Centers has been implemented. To study the data placement, task assignment, data center resizing and routing for minimize the overall operational cost. Characterize the data processing process using a two-dimensional Markov chain Derive the expected completion time in closed-form. To tackle the high computational complexity of solving our MINLP, we linearize it into an MILP problem. Additionally in future, Fault tolerance mechanisms either consume significant extra energy to detect and recover from the failures. Fault-tolerant describes a computer system or component designed so that, in the event that a component fails, a backup component or procedure can immediately take its place with no loss of service.

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