Cost Minimization for Big Data Processing in Geo-Distributed Data Centres

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Abstract

Demand on big data is being increasing day by day and also increasing heavy burden on computation, storage and communication in data centres, which lead to considerable expenditure to data centre providers. So, cost minimization became an issue for the upcoming big data. One of the main feature of big data is coupling of data and computation as computation task. This can be done only when that corresponding is available for computation. Three tasks like data placement, task assignment and data movement influence the expense of data centres. In this paper we study how to minimize cost through joint optimization of these above three factors for big data service in geo distributes data centres. Here we propose 2-D Markov chain to describe time to complete a particular task with consideration of data transmission and computation to derive average task completion time in closed time. In addition, we here model the problem as mixed integer nonlinear programming and propose a solution to linearize it.

Keywords : big data, markov chains, data centres, nonlinear programming, geo-distributed..

1. Introduction

In recent years data explosion is leading for rising demand in big data processing which are distributed among different geographical centres[1-4]. For example Google have 13 data centers over 8 countries in 4 continents. Big data analysis have already shown its potential to improve decision-making, risk minimization and to develop new products and services as big data has more computation and communication resources, it reached high cost[5-6]. Gartner predicted that by 2015, 71% of worldwide data center hardware spending will come from the big data processing, which will surpass \$126.2 billion. therefore there is a great need in concentrating about cost minimization for big data processing in geo-distributed data centers[7-9].

Many efforts have been made to reduce cost for data processing. One of the thing that is proposed for reducing computation cost is Data Center Resizing (DCR) .It is done by adjusting the number of activated servers via task placement[10]. In light of DCR, some studies have investigated the geological appropriation nature of server farms and power value heterogeneity to lower the power cost. In spite of the fact that the above arrangements have acquired some positive results, they are a long way from accomplishing the expense efficient enormous

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information preparing due to the accompanying shortcomings. Initially, information territory might bring about a misuse of assets. For instance, most calculation asset of a server with less prominent information might stay sit out of gear. The low asset utility further causes more servers to be actuated and thus higher working taken a toll.

Second, the connections in systems shift on the transmission rates and expenses as indicated by their one of a kind elements, e.g.the separations and physical optical ber offices between server farms. Be that as it may, the current steering procedure among server farms neglects to misuse the connection differing qualities of information center systems. Because of the capacity and calculation limit limitations, not all errands can be set onto the same server, on which their comparing information dwell. It is unavoidable that specific information must be downloaded from a remote server. For this situation, steering technique matters on the transmission cost.

Third, the Quality-of-Service (QoS) of enormous information errands has not been considered in existing work. Like customary cloud administrations, enormous information applications likewise show Service-Level-Agreement (SLA) between an administration supplier and the requesters. To watch SLA, a specific level of QoS, ordinarily as far as undertaking culmination time, should be ensured. The QoS of any distributed computing undertakings is dictated by

where they are put and what number of calculation assets are apportioned. In addition, the transmission rate is another in entail component since enormous information assignments are information driven and the calculation undertaking can't continue until the comparing information are accessible.

To manage the high computational unpredictability of solving MINLP, we linearize it as a blended whole number straight programming (MILP) issue, which can be explained utilizing business solver. Through broad numerical concentrates on, we demonstrate the high efficiency of our proposed joint-improvement based calculation.

2. Proposed system

2.1 Related work

Substantial scale server farms have been conveyed everywhere throughout the world giving administrations to a huge number of clients. As indicated by, a server farm might comprise of vast numbers of servers and devour megawatts of force. A huge number of dollars on power cost have represented an overwhelming weight on the working expense to server farm

suppliers. Thusly, lessening the power cost has gotten significant consideration from both the scholarly world and industry. Among the mechanisms that have been proposed so far for server farm vitality administration, the methods that pull in loads of consideration are assignment arrangement and DCR.

To handle the difficulties of viably overseeing enormous information, numerous recommendations have been proposed to enhance the capacity also, calculation process. The key issue in enormous information administration is dependable and effective information position. To accomplish this objective, Sathiamoorthy et al present a novel group of deletion codes that are efficiently repairable and offer higher unwavering quality contrasted with Reed-Solomon codes. They likewise systematically demonstrate that their codes are ideal on an identified trade off in the middle of territory and least separation. Yazd et al make utilization of flexibility in the information square position approach to build vitality efficiency in server farms and propose a booking calculation, which considers vitality efficiency notwithstanding decency and information territory properties. Hu et al propose an instrument permitting connected open information to exploit existing expansive scale information stores to meet the prerequisites on dispersed and parallel information preparing.

Besides, how to assign the calculation assets to assignments has additionally drawn much consideration. Cohen et al present new outline reasoning, strategies and experience giving another attractive, light-footed and profound information examination for one of the world's biggest publicizing systems at Fox Audience

System, utilizing the Greenplum parallel database framework. Kaushik et. al propose a novel, information driven calculation to diminish vitality costs and with the certification of warm unwavering quality of the servers. Chen et al consider the issue of together planning every one of the three stages, i.e., map, shuffle and lessen, of the MapReduce handle and propose a pragmatic heuristic to battle the high planning many-sided quality.

Existing work on server farm cost enhancement, huge information administration or information position basically concentrates on maybe a couple components. To manage huge information handling in geo-conveyed server farms, we contend that it is vital to together consider information position, undertaking task and information flow directing in a systematical way.

2.2 System model

In this segment, we present the framework model. For the convenience of the perusers, the

real documentations utilized as a part of this paper are recorded in Table 1.

2.3 Network model

We consider a geo-distributed data center topology as show in Fig. 1, in which all servers of the same data center (DC) are connected to their local switch, while data centers are connected through switches. There are a set I of server farms, what's more, every server farm i belongs to I comprises of a set J_i of servers that are associated with a switch m_i belongs M with a nearby transmission expense of C_L . All in all, the transmission cost C_R for between server farm traffic is more prominent than C_L , i.e., $C_R > C_L$. Without loss of consensus, all servers in the system have the same calculation asset and capacity limit, both of which are standardized to one unit. We use J to indicate the arrangement of all separates.

$$w^{(u,v)} = \begin{cases} C_R, & \text{if } u, v \in M, \\ C_L, & \text{otherwise.} \end{cases}$$

2.4 Task model

We consider huge information undertakings focusing on information put away in a circulated le framework that is based on geo-appropriated information focuses. The information are isolated into a set K of lumps. Each lump k has a place K , which is normalized to the server stockpiling limit. P-way imitation is utilized as a part of our model. That is, for every lump, there are precisely P duplicates put away in the dispersed framework for strength and adaptation to internal failure.

It has been generally concurred that the undertakings landing in information focuses amid a period can be seen as a Poisson process. Specifically, let a_k be the normal undertaking entry rate asking for lump k . Since these undertakings will be appropriated to servers with a fixed likelihood, the undertaking landing in every server can be additionally viewed as a Poisson process.

2.5 Problem formulation

In this area, we first present the imperatives of information and undertaking arrangement, remote information stacking, and QoS. At that point, we give the complete detailing of the cost minimization issue in a blended whole number nonlinear programming structure.

2.6 Constraints of data and task placement

We define a double variable y_{jk} to signify whether piece k is put on server j as takes after,

In the appropriated framework, we keep up P duplicates for each piece $k \in K$, which prompts the accompanying imperative

$$\sum_{j \in J} y_{jk} = P, \forall k \in K.$$

Furthermore, the data stored in each server j belongs to J cannot exceed its storage capacity, i.e.,

$$\sum_{k \in K} y_{jk} \cdot \phi_k \leq 1, \forall j \in J.$$

As for task distribution, the sum rates of task assigned to each server should be equal to the overall rate,

$$\lambda_k = \sum_{j \in J} \lambda_{jk}, \forall k \in K.$$

Finally, we define a binary variable x_j to denote whether server j is activated, i.e.,

$$x_j = \begin{cases} 1, & \text{if this server is activated,} \\ 0, & \text{otherwise.} \end{cases}$$

2.7 Linearization

We watch that the imperatives are nonlinear due to the results of two variables. To linearize these requirements, we define another variable δ_{jk} as takes after:

$$\delta_{jk} = y_{jk} \lambda_{jk}, \forall j \in J, \forall k \in K,$$

which can be equivalently replaced by the following linear constraints:

$$\begin{aligned} 0 &\leq \delta_{jk} \leq \lambda_{jk}, \forall j \in J, \forall k \in K, \\ \lambda_{jk} + y_{jk} - 1 &\leq \delta_{jk} \leq y_{jk}, \forall j \in J, \forall k \in K. \end{aligned}$$

The constraints can be written in linear form as:

$$\begin{aligned} f_{jk}^{(u,v)} &\leq \delta_{jk} \phi_k, \forall (u,v) \in E, u, j \in J, k \in K, \\ \sum_{(u,j) \in E} f_{jk}^{(u,j)} &= (\lambda_{jk} - \delta_{jk}) \cdot \phi_k, \forall j \in J, k \in K. \end{aligned}$$

The constraints can be written in non linear form as:

$$\begin{aligned} \gamma^{(u,v)} \mu_{jk} z_{jk}^{(u,v)} + 1 - \mu_{jk} z_{jk}^{(u,v)} - \lambda_{jk} &\geq \frac{u_{jk}}{D}, \\ &\forall (u,v) \in E, \forall j \in J, \forall k \in K. \end{aligned}$$

We define it as: $\epsilon_{jk}^{(u,v)} = \mu_{jk} z_{jk}^{(u,v)}$

The constraints can be written by:

$$\gamma^{(u,v)} \epsilon_{jk}^{(u,v)} + \mu_{jk} - \epsilon_{jk}^{(u,v)} - \lambda_{jk} \geq \frac{u_{jk}}{D},$$

$$\forall (u,v) \in E, \forall j \in J, \forall k \in K.$$

The constraints can be linearized by:

$$0 \leq \epsilon_{jk}^{(u,v)} \leq \mu_{jk}, \forall (u,v) \in E, \forall j \in J, \forall k \in K,$$

$$\mu_{jk} + z_{jk}^{(u,v)} - 1 \leq \epsilon_{jk}^{(u,v)} \leq z_{jk}^{(u,v)}, \forall j \in J, \forall k \in K.$$

we can linearize the MINLP problem into a mixed- integer linear programming (MILP)

as *MILP*:

$$\begin{aligned} \min : & (26), \\ \text{s.t.} : & (3) - (5), (7), (9), (11) - (13), \\ & (25), (28) - (31), (34) - (36), \\ & x_j, y_{jk}, z_{jk}, u_{jk} \in 0, 1, \forall j \in J, k \in K. \end{aligned}$$

2.8 Performance Evaluation

In this segment, we introduce the execution aftereffects of our joint-improvement calculation ("Joint") utilizing the MILP plan. We additionally look at it against a different optimization plan calculation ("Non-joint"), which first finds a least number of servers to be actuated and the movement steering plan utilizing the system stream model as depicted in Segment IV-B.

In our analyses, we consider $|J| = 3$ server farms, each of which is with the same number of servers. The intra-and between server farm join correspondence expense are set as $C_L = 1$ also, $C_R = 4$, separately. The cost P_j on each initiated server j is set to 1. The information size, stockpiling necessity, and assignment entry rate are all haphazardly created. To take care of the MILP issue, business solver Gurobi [26] is utilized.

Increments from 36 to 48, the correspondence expenses of both calculations diminish essentially. This is on account of more errands what's more, information lumps can be set in the same server farm when more servers are given in every server farm. Subsequently, the correspondence expense is significantly lessened. Be that as it may, after the number of server achieving 48, the correspondence expenses of both calculations merge. The reason is that most undertakings and their comparing information lumps can be put in the same server farm, or even in the same server. Further expanding the number of servers won't influence the disseminations of errands on the other hand information lumps any more. Comparable results are seen in Fig. 3(c). At that point, we research how the undertaking landing rate influences

the taken a toll by means of changing its worth from 29.2 to 43.8.

[Fig. 1] Performance Evaluation 1

The assessment results are appeared in Fig. 4. We first notice that the aggregate expense appears as an expanding capacity of the undertaking entry rates in both calculations. A looser QoS requirement also helps and cost-efficient routing strategies as illustrated in Fig. Moreover, the advantage of our "Joint" over "Non-joint" can be always observed in Fig. Finally, Fig investigates the effect of the number of replicas for each data chunk, which is set from 1 to 6. An interesting observation from Fig. is that the total cost decreases and then increases with

the increasing number of replicas. Initially, when the replica number increases from 1 to 4, a limited number of activated servers are always enough for task processing, as shown in Fig. Meanwhile, it improves the possibility that task and its required data.

[Fig. 2] Performance Evaluation 2

3. Conclusion

In this paper, we jointly study the data placement, task assignment, data center resizing and routing to minimize the overall operational cost in large-scale geo-distributed data centers for big data applications. We will characterize the data processing process using a two-dimensional Markov chain and derive the expected completion time in closed-form, based on which the joint optimization is formulated as an MINLP problem. To tackle the high computational complexity of solving our MINLP, we linearize it into an MILP problem. Through extensive experiments, we show that our joint-optimization solution has substantial advantage over the approach by two-step separate optimization. Several interesting phenomena are also observed from the experimental results.

References

- [1] I. Marshall and C. Roadknight, 'Linking cache performance to user behaviour, Comput. Netw. ISDN Syst., (1998), Vol.30, No.223, pp.2123-2130.
- [2] L. Rao, X. Liu, L. Xie, and W. Liu, Minimizing electricity cost: Optimization of distributed internet data centers in a multi-electricity-market environment, Proc. 29th Int. Conf. Comput. Commun., (2010), pp.19.
- [3] R. Uргаonkar, B. Uргаonkar, M. J. Neely, and A. Sivasubramaniam, Optimal power cost management using stored energy in data centers, Proc. Int. Conf. Meas. Model. Comput. Syst., (2011), pp.221-232.

- [4] H. Xu, C. Feng, and B. Li, Temperature aware workload management in geo-distributed datacenters, Proc. Int. Conf. Meas. Model. Comput. Syst., **(2013)**, pp.3336.
- [5] R. Raghavendra, P. Ranganathan, V. Talwar, Z. Wang, and X. Zhu, No'power' struggles: Coordinated multi-level power management for the data center, Proc. 13th Int. Conf. Archit. Support Program. Lang. Oper. Syst., **(2008)**, pp.48-59.
- [6] L. Gu, D. Zeng, S. Guo, Y. Xiang, and J. Hu, A General Communication Cost Optimization Framework for Big Data Stream Processing in Geo-Distributed Data Centers, IEEE Transactions on Computers, **(2016)**, Vol.65, No.1, pp.19-29.
- [7] W. Chen, I. Paik, and P. C. K. Huang, Transformation-based Streaming Workflow Allocation on Geo-Distributed Datacenters for Streaming Big Data Processing, IEEE Transactions on Services Computing, **(2016)**, Vol.PP, No.99, pp.1-14.
- [8] X. Xu, W. Dou, X. Zhang, and J. Chen, EnReal: An energyaware resource allocation method for scientific workflow executions in cloud environment, IEEE Trans. on Cloud Computing, **(2016)**, Vol.4, No.2, pp.166-179.
- [9] I. Toyoshima, S. Yamaguchi, and Y. Murakami, Two sufficient conditions on refactorizability of acyclic extended free choice workflow nets to acyclic well-structured workflow nets and their application, IEICE Trans. Fundamentals, **(2015)**, Vol.E98, No.2, pp.635-644.
- [10] W. Chen, I. Paik, and Z. Li, Topology-aware optimal data placement algorithm for network traffic optimization" IEEE Trans. on Computers, **(2016)**, Vol.65, No.8, pp.2603-2617.

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