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A Survey on Data Placement Strategies for Cloud based Scientific Workflows

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ABSTRACT
Scientific workflows perform computations exceeding single workstation's capabilities. When running such data intensive workflows in the cloud distributed across several physical locations, the execution time and the resource utilization efficiency highly depends on the initial placement and distribution of the input datasets across these multiple virtual machines in the Cloud. The ideal data placement scheme optimizes the execution of the data intensive scientific workflows in cloud by assigning the tasks to the execution site in such a way that the file transfers and the cost associated are reduced. Several data placement strategies in cloud based scientific workflows are reviewed. A data placement scheme which uses big data to improve the performance and also the data movement cost is studied. BDAP (Big Data Placement strategy), improves workflow performance by minimizing data movement across multiple virtual machines.

Keywords
Cloud computing, Big data, Scientific workflow, Data placement, Virtual machine.

1. INTRODUCTION
Workflow is a sequence of operations declared as a work of a person or group. Scientific workflow is an amalgamation scientific problem solving and traditional workflow techniques. Workflows are represented as Directed Acyclic graphs in which the tasks are represented as vertices and the dataflow among the tasks is represented as the edges. Workflows have been used in a number of scientific applications such as astronomy, bioinformatics, earthquake detection and physics [1]. Workflows can be either compute intensive or data intensive [2]. Compute intensive workflows are when the amount of the data used by the tasks are small. Data intensive workflows are when the time used for execution of tasks are greater than computation time.

Scientific workflows were executed on different platforms such as Clusters and Grids [3] [4]. As the Scientific workflows are data intensive in nature they require good storage and processing power. Cloud computing has become a promising tool for the researchers to execute their scientific workflows. To improve the throughput and performance of the application cloud computing is required. Cloud computing provides different computing resources which are scalable and efficient. Cloud provides security, reduces the overhead and increases the resource utilization.

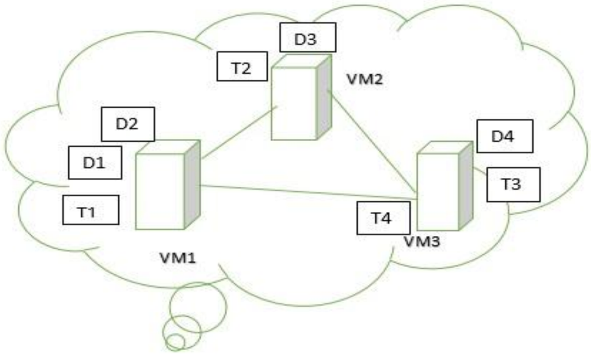

Fig1: Virtual Machine Configuration

Scientific workflows are divides as a number of data sets and are placed on the virtual machines, as these data sets are huge in size usually ranging from some terabytes to petabytes. There is a need for the data management between these virtual machines so as to maximize locality and minimize the transfer of data sets between the virtual machines. Consider the fig 1. It shows that there are three virtual machine and each virtual machine is assigned a number of data sets and tasks. For a scientific workflow to be executed its data needs to be placed on the execution sites of the virtual machines. When a task is assigned to the execution site it may require files which are not present on the virtual machine. This may lead to increase in the file transfers which could increase the access latency. Therefore it is necessary to place the files on the same execution site if they are accessed by the same tasks [2]. A data placement strategy is required to manage the data in such a way.

2. DATA MANAGEMENT CHALLENGES
Workflow lifecycle consists of workflow creation, Planning, Execution and Storage phase [5]. Workflow Creation: Analysis, input data and Components need to be discovered. Planning: Resources needed for execution are selected. Execution: Actual computation takes place, Data needs to be staged in and out of computational resources and results. Data needs to be managed in three stages data discovery, setting up the data, generation of the derived data and archiving of the data.

Workflow Creation: Scientists should be able to discover the data sets and workflow templates. This can be done by querying various catalogs. Standards must be implemented in the representation of the data provenance. In workflow creation the steps of how a workflow has been designed can be retraced. The challenge here lies in finding out why those design decisions were made by the users.

Workflow Planning and execution: In workflow creation phase scientists specify the applications, workflows and data sets required and in the planning phase the location of the desired data sets needs to be discovered and possibly map those data sets to the resources where computations will take place. A scheduler or workflow mapper does this job, they need to optimize the workflow based on user criteria. The workflow execution does not start until it has all its computational data products. The challenge in workflow planning is to find the resources whose capabilities match the requirements of the workflow. The challenge in workflow execution is estimating the storage for the output data products and the ability to receive accurate information from the resources.

Data generation and Archiving: There must be some additional components to extract and save the data in the catalog. Therefore, standards and formats for metadata catalog need to be defined. Provenance captures information about which data were used during the workflow execution, which software was run, and what were the computing, storage, and other resources used to obtain the results. The main challenge is to find the important information components which need to be stored in provenance catalog.

These are the different data management challenges relating to data discovery and storage in scientific workflows. Maintaining the Integrity of the Specifications

3. DIFFERENT DATA PLACEMENT STRATEGIES

Many of the previous studies have focused on the task assignment and the data placement of scientific workflows. Different data placement strategies are discussed in this section.

Yuan [6] proposed a data placement strategy which takes two types of data sets into consideration one which is the initial data set before the workflow initiation and second is the intermediate or the generated datasets in between the workflow execution. For a Scientific workflow it is necessary to place the datasets on the same execution site required by the same tasks. But in some cases it may happen that a dataset must be placed in a particular fixed location, then it becomes a challenge to move such large datasets. Yuan proposed a matrix based K-means clustering strategy to place the data on cloud based scientific workflows [6]. K-means binary clustering is applied to pre cluster datasets and the tasks are assigned greedily to execution site such that it contains most of the input datasets. Most interdependent datasets are placed together which reduces data movement. Yuan's clustering technique is sensitive to the selection point in any iteration.

Catalyurek [2] proposed a hyper graph partitioning based method for data placement in the cloud. This method tries to solve both the task assignment and the data placement problems using multi constraint hyper graph partitioning. The total file size to be reduced is equal to the cut size and minimizing the cut size is the objective of the problem. It is a two phase scheduling approach, in the first phase the data placement and the task assignment are done and in the second phase the execution takes place with respect to the dependencies. This method tries to reduce the communication cost and tries to place the input, output and intermediate data on execution sites.

Wei Guo [7] proposed a data placement strategy based on genetic algorithm on a cloud computing platform. This work tries to lower the distributed transaction costs by reducing the communication costs between two data centers. The data placement strategy is based on the genetic algorithm and also takes care of the load balance problem. It reduces the distributed transaction cost and also balances the load among different data centers.

Qiang Li [8] proposed a data placement strategy based on consistent hashing and clustering algorithm. The hashing algorithm places the data on a specific storage server to achieve better data placement. This provides with the better scalability and better fault tolerance. The clustering in this method is improved by using two methods: Case based reasoning and coordination filtering. This clustering technique has improved clustering accuracy when compared to K-means clustering technique.

The above discussed were some of the strategies for data placement in the cloud environment. But as the data is growing more and more, the datasets of a scientific workflow are becoming huge in volume and variety. Therefore Big Data is becoming the new trend for storing these huge scientific workflows on the cloud.

4. BIG DATA FOR SCIENTIFIC WORKFLOWS ON CLOUD

Scientific data workflows have a set of technology challenges which can be addressed by big data tools and middleware [9]. Scientific workflows model huge amount of data sets which are physically distributed over the internet it becomes difficult to manage it with data management tools and techniques.

Therefore, Big Data technology is focused in scientific computing research. The most important characteristics of big data are volume, velocity, variety. Fig 2 shows the characteristics of the big data which are taken into consideration for modelling the scientific workflows. Scientific workflow have huge volumes of data of different variety which need to be analyzed and processed. The main focus here is how big data partitions, distributes and places the data on the virtual machines of the cloud.

4.1 Big Data Placement Strategy

Big Data Placement Strategy (BDAP) [10] clusters the most interdependent datasets and stores them in the same virtual machine, it applies for both the initial and the intermediate data sets. BDAP compares the randomly generated set of data placement schemes and returns the best scheme which maximizes the interdependency within the VM and minimizes the interdependency among the VM. After the data placement it assigns and schedules the workflow tasks to the VM. Clustering technique is used in which datasets – objects, Virtual Machines – clusters, data interdependency – separation measure. BDAP uses a heuristic function to return the best data placement scheme. Heuristic function is based on the data interdependency among the virtual machine and within the virtual machine.

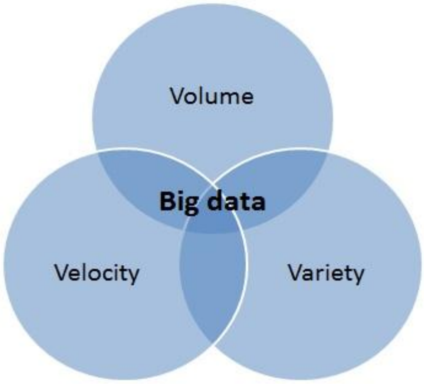

Fig 2: Big Data Characteristics

Heuristic function in BDAP selects the data placement scheme with higher data interdependency greedy value, DG (Ψ).

DG (Ψ) = VMDw+1/VMDb+1

Within-Virtual Machine Data Interdependency (VMDw):

$$VMDw(\psi) = \sum_{i=1}^{I} \sum_{\substack{\psi(dj1)=vmi \\ \psi(dj2)=vmi}} dp(dj1, dj2)$$

Between-Virtual Machine Data Interdependency (VMDb):

$$VMDb(\psi) = \sum_{i1 \neq i2}^{I} \sum_{\substack{\psi(dj1)=vmi1 \\ \psi(dj2)=vmi2}} dp(dj1, dj2)$$

Where dp (dj1, dj2) is the data interdependency between task dj1 & dj2.

A Good Data placement scheme is with a higher DG value.

BDAP Algorithm:

Step 1: Calculate the data interdependency matrix (DM)

Step 2: Generate a set of random legal data placement schemes.

Step 3: Compute the heuristic value of each scheme.

Step 4: If the termination conditions are not satisfied then, apply the selection, crossover and mutation to generate a new population of legal data placement schemes.

Step 5: If the termination conditions are satisfied then return the best data placement Scheme.

Selection is the process of choosing two schemes for recombination and generation two new schemes. Crossover combines two selected schemes to reproduce two new schemes. The idea is that the new generated schemes may be better and have higher heuristic value if they take the best characteristics from their parent schemes. Mutation operator generates new version of it such that a virtual machine position in the scheme have been randomly changed. Mutation prevents BDAP to be trapped in a local maximum heuristic value.
BDAP uses synthetic scientific workflows based on scientific workflows such as montage, cybershake etc as shown in fig 3. Workflow communication cost is calculated by varying the number of data sets. It reduces the workflow communication cost effectively when compared to the other data placement strategies.

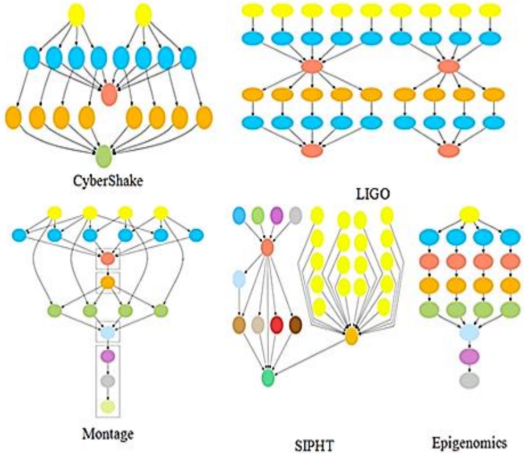

Fig 3: Structure of five scientific workflows

BDAP minimizes the total data movement between the virtual machines in the cloud thereby reducing the workflow communication cost.

5. CONCLUSION

Different Data Placement Strategies are reviewed in this paper. This study shows different placement strategies for cloud based scientific workflows. K-means clustering, Consistent Hashing, and genetic algorithms have been used to reduce the movement of the data between the data centers or the virtual machines in the cloud. But using big data for scientific workflows has proven to outperform the previous methods. BDAP reduces the total movement of the datasets and also the workflow communication cost. Data replication has not be considered in this strategy therefore, BDAP can be extended to workflows taking replication into consideration and also for the execution of the multiple workflows

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7. REFERENCES

[1] G. Juve and E. Deelman, "Scientific workflows and clouds," Journal of Crossroads, vol. 16, no. 3, pp. 14-18, 2010.

[2] U. V. Catalyurek, K. Kaya and B. Ucar, "Integrated Data Placement and Task Assignment for Scientific Workflows in clouds," In Proceedings of the fourth international workshop on Data-intensive distributed computing, pp. 45-54, 2011.K.

[3] T. Fahringer, R. Prodan, R. Duan, J. Hofer, F. Nadeem, F. Nerieri, S. Podlipnig, J. Qin, M. Siddiqui, H.-L. Truong, A. Villazon, and M.

[4] Tera-Grid. http://www.teragrid.org/.

[5] E. Deelman and A. Chervenak, "Data Management Challenges of Data- Intensive Scientific workflows," In Cluster Computing and the Grid, 2008. CCGRID'08. 8th IEEE International Symposium on, pp. 687-692, 2008.

[6] D. Yuan, Y. Yang, X. Liu and J. Chen "A data placement strategy in scientific cloud workflows," Future Generation Computing Systems 26, no. 8, pp. 1200-1214, 2010.

[7] Wei Guo, Xinjun Wang "A Data Placement Strategy Based on Genetic Algorithm in Cloud Computing Platform," In 10th Web Information System and Application Conference, pp 369-372, 2013.

[8] Qiang Li, Kun Wang, Member, Suwei Wei, Xuefeng Han, Lili Xu, "A data placement strategy based on clustering and consistent hashing algorithm in Cloud Computing," In 9th International Conference on Communications and Networking in China (CHINACOM), pp 278-283, 2014.

[9] J. Wang, D. Crawl, I. Altintas, W. Li, "Big Data Applications Using Workflows for Data parallel Computing," Journal of Computing in Science and Engineering, vol. 16, no. 4, pp. 11-21, 2014.

[10] Mahdi Ebrahimi, Aravind Mohan, Andrey Kashlev, and Shiyong Lu, "BDAP: A Big Data Placement Strategy for Cloud-Based Scientific Workflows," In Big Data Computing Service and Applications, 2015. First IEEE International Conference, pp 105-114.