Cluster Analysis for Usage Behavior with Job Accounting Data

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ABSTRACT

High-Performance Computing (HPC) fosters scientific research by providing large-scale resources to run simulations and computing tasks. Understanding the workload of a High-Performance Computing center is a challenging task and requires adequate analytical data collection and algorithms. This study presents a usage behavior analysis on clustering job accounting data from a Quanah cluster, using three different clustering algorithms and three validation methods. The result reinforces the usefulness of hierarchical clustering in the domain of job accounting data. Four behavior categories were identified, including data-intensive and memory-intensive jobs, providing insights into the usage patterns.

1 INTRODUCTION

High-Performance Computing (HPC) serves researchers and domain experts on numerous computing tasks regarding science, engineering, security, and commerce. To improve productivity and maximize the computing power of supercomputers, researchers are expected to have system-specific knowledge to develop codes, and job submission scripts, starting with system information such as software libraries supported by the HPC system or the number of computing cores should be for a specific job on the system [11]. It is crucial to understand the current HPC workloads and their evolution to assist informed future scheduling research and enable efficient scheduling in future HPC systems [8]. To investigate the HPC platform performance and whether HPC users used the resources productively, we conduct this usage behavior analysis, using three clustering algorithms with three validation methods. Four behavior categories were identified, separating data-intensive jobs and computational intensive jobs.

The rest of this paper is organized as follows: Section 2 presents an overview of existing research that is related to this paper. Section 3 introduce the approach and methodology. Section 4 presents the experimental result on clustering algorithms and internal clustering validation. Section 5 concludes the paper with outlook for future work direction.

2 RELATED WORK

Usage behaviors of the world's fastest academic Kraken supercomputer were analyzed in [11] with clustering algorithms, where the job statistics of each behavior category were utilized to construct a knowledge-based recommendation, providing users with guidance and instructions in setting up job parameter values, job queuing time and runtime estimation. K-means clustering is also applied in job heterogeneity analysis [8] to detect the minimum number of dominant job geometries in an HPC workload. System usage patterns and anomalous behavior due to failure/misuse can be revealed with a lightweight job-centric measurement tool [2], providing analyses at different levels of granularity: comprehensive job, application, and system-level resource use measurement. Having insights into the usage behavior can help enhance resource allocation and management strategies, such as in a contention-aware resource scheduling [6, 7].

3 APPROACH

This study encompasses the following research and development activities: First, the data of two months of job accounting data provided is examined to understand the metric in the job accounting information and extract features from it. An accounting record is written to the accounting file for each job having finished. The feature vectors were calculated based on these attributes:

- $N_n = slots/C_n$, number of allocated nodes: total cpu cores used by a job, divided by the number of cores on each node, which is 36 for the Quanah cluster.
- $M_u = mem\_used$, memory used
- $T_q = start\_time - submit\_time$, job queue time
- $T_r = end\_time - start\_time$, job runtime

Secondly, the appropriate clustering algorithms are selected and applied to the job accounting data. Two kinds of clustering algorithms, partitioning clustering, and hierarchical clustering, will be analyzed, then we determine the appropriate number of behavior categories, such as data-intensive jobs and computational-intensive jobs. In this work, three clustering methods are applied to analyzed usage behavior:

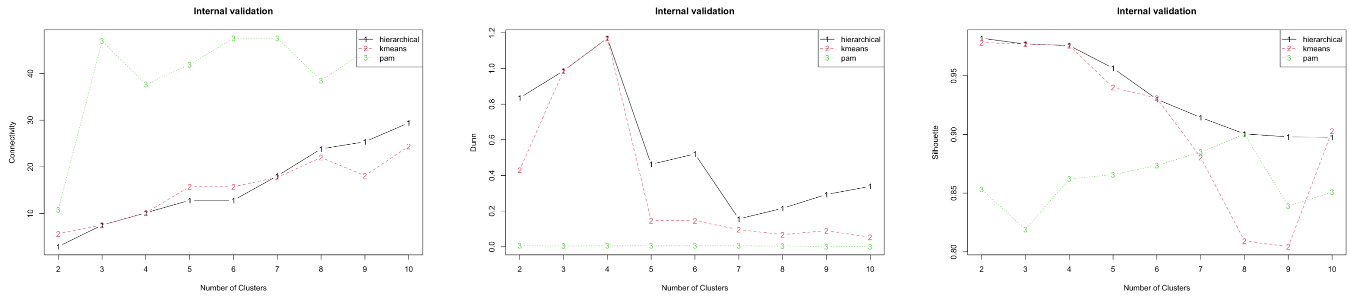
- Partitioning clustering, including k-means [1] and Partitioning Around Medoids (PAM) [10];
- Hierarchical clustering [5]

To evaluate the clustering performance, three validation methods were used [11]:

- Connectivity measures cluster connectedness [3].
- Dunn index is the ratio of the smallest distance between objects in different clusters to the largest intra- cluster distance [4].
- Silhouette width measures the degree of confidence in the clustering assignment of an object [9].

Connectivity and Silhouette are both measurements of connectedness, while the Dunn Index is the ratio of the smallest distance between observations not in the same cluster to the highest intra-cluster distance. A Dendrogram can be used in accordance with the algorithm to identify the categories.

The last step is to discuss and analyze the findings from the cluster analysis. By exploring the usage behavior, we can gain insights into the system and then work out the strategy to use the resource productively.



(a) Connectivity measure

(b) Dunn index measure

(c) Silhouette width measure

Figure 1: Internal cluster validation using Connectivity, Dunn index and Silhouette width measures, on three clustering methods with different number of clusters.

4 EXPERIMENTAL RESULTS

4.1 Dataset

The data for this study were collected from July 30, 2020, to September 9, 2020, from a Quanah cluster. During data collection, 457,486 jobs in 28 different disciplines were submitted to HPC from 208 accounts. Among these records, 8,368 incorrect records were removed. For the demonstration purpose, this work studies a subset of 5,000 records from the collected data. After that, feature vectors were computed based on the number of allocated nodes, memory used, job queue time, and job runtime.

4.2 Cluster Analysis and Validation

Three clustering approaches were applied to the job accounting data for the task of analyzing usage behavior. The performance evaluation results are depicted in Figure 1a, 1b, and 1c. In terms of connectivity, the lower the value, the better the algorithm; this contrasts with Dunn index and Silhouette width measures, where higher values indicate higher clustering performance. From Figure 1, we can observe that if the number of clusters is greater than 4, the performance decreases, especially in Figure 1b. This also helps balance the resolution of the job clustering result. Hence, four clusters were selected. We can also observe that the hierarchical algorithm (demonstrated by the solid black lines) performs better than other clustering methods, shown in all three validation methods. Thus, the hierarchical clustering algorithm was chosen.

	c1	c2	c3	c4
N_n	-0.06245942	1.1613313	0.032082330	9.7548869
M_u	-0.26620137	0.1396214	2.935955618	-0.1550245
T_q	-0.06311562	1.5081793	-0.051266155	9.3432636
T_r	-0.10061960	2.0422596	0.001263427	15.6839426

Table 1: The means of each job feature in the Quanah dataset

The calculated means of job features in each category are listed in Table 1. The dataset was scaled before feed into the clustering algorithms; thus, the negative values are apprehensible. The four categories are demonstrated explicitly in the Dendrogram in Figure 2. Several intriguing findings can be observed.

First, the behavior category c3 can be considered as the group of data-intensive jobs. Jobs in this category use a significant amount of memory (M_u) but a relatively less number of computing nodes (N_n).

Secondly, the jobs in category c4 are computational intensive jobs, which requires a significantly large amount of resource for computing, compared to all other categories. They have both the longest queue time and runtime. Besides the fact that these jobs use fewer memory resources, a possible explanation is that these massive jobs are not well-tuned, not optimized, or not appropriately prioritized. They do not have the resources to speed up execution.

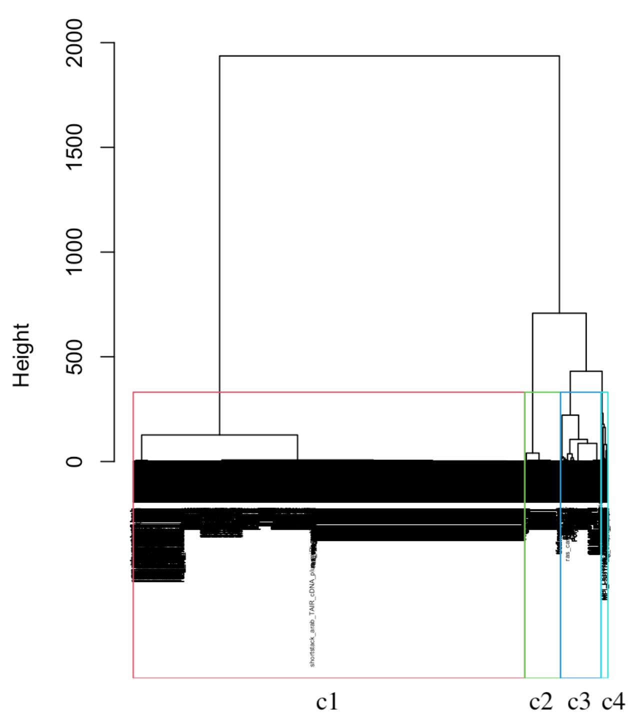


Figure 2: Cluster dendrogram from the hierarchical algorithm. Four categories are formed on the Quanah dataset.

	Score	Method	Clusters
Connectivity	2.9290	hierarchical	2
Dunn	1.1701	hierarchical	4
Silhouette	0.9820	hierarchical	2

Table 2: Optimal score among three clustering algorithms, with three validation measures.

Thirdly, the jobs in category c1 have the lowest values across all dimensions, but Figure 2 shows that they comprise nearly 90% of the data points. These are lightweight, simple jobs that demand fewer resources and are very common from the observation. A possible explanation for this phenomenon is that these are simple testing jobs or "Hello World" jobs, in which the user can be a learner.

Although the two HPC systems are different, with different job accounting data characteristics, our findings show several similarities to the conclusion in [11] in terms of the usefulness of hierarchical clustering algorithm for usage behavior analysis in job accounting data.

5 CONCLUSIONS

In this work, we present a case study of analyzing usage behavior applied in the domain of job accounting data. Hierarchical algorithms demonstrate their effectiveness and help achieve the balance upon the constraints in unsupervised clustering. Future work will focus on the scalability of such techniques and the effect of parameters from HPC datasets on the clustering result.

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