LITERATURE REVIEW: Parallel DBSCAN Clustering Algorithm using Apache Spark

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1 Introduction

Analyzing big data is a very challenging problem today. Parallel computing is a type of computing architecture in which several processors execute or process an application or computation simultaneously. Parallel computing helps in performing large computations by dividing the workload between more than one processor, all of which work through the computation at the same time. By distributing the computations across hundreds or thousands of machines, the execution time reduces to a reasonable amount of time.

MapReduce framework has been devised to deal with big data in parallel. Google's MapReduce or its open-source equivalent Hadoop is a powerful tool for building such applications. With MapReduce, rather than sending data to where the application or logic resides, the logic is executed on the server where the data already resides, to expedite processing. This algorithm uses two user-defined functions which are called map and reduce functions [6]. Both map and reduce functions take a key-value pair as input and may output key-value pairs. This algorithm starts with applying a map operation to each logical record in the input to compute a set of intermediate <key, value> pairs, and then applying a reduce operation to all the values that shared the same key, to combine the derived data appropriately [2].

Apache Spark is an open-sourced programming model that supports a much wider class of applications than MapReduce. Apache Spark has a great performance for multi-pass applications that require low-latency data sharing across multiple parallel operations.

This study is about applying the DBSCAN algorithm using the framework Spark. DBSCAN (Density-based spatial clustering of applications with noise) is an unsupervised learning data clustering approach that is commonly used in data mining and machine learning. Based on a set of points, DBSCAN groups together points that are close to each other based on a distance measurement and a minimum number of points. Also, this algorithm simply finds outliers point which are in low-density regions. This algorithm is popular since it can divide data into clusters with arbitrary shapes. Moreover, DBSCAN does not require the number of the clusters a priori as well as it is insensitive to the order of the points in the dataset [3]. However, applying DBSCAN with real-world data is challenging due to the size of datasets has been growing exponentially. This algorithm goes through each point of the database multiple times. The time complexity of the DBSCAN is O(n) which can be

reduced to O(n log n) in some cases (n is the number of objects to be clustered). So the execution time for this algorithm highly increases when it comes to the massive dataset.

2 Literature Review

Presenting a parallel DBSCAN algorithm using the new big data framework Spark is receiving attention in recent years. As opposed to MapReduce based approaches for DBSCAN parallelization [5], [6], [1], there are few studies on DBSCAN clustering using Spark.

A pioneer algorithm [4] for presenting a scalable DBSCAN algorithm with Spark, first reads data from the Hadoop Distributed File System (HDFS) and forms Resilient Distributed Datasets (RDDs), transforming them into data points. Certainly, this process is done in the Spark driver. It then pushes all the data into multiple executors. Within each executor, partial clusters are built and sent to the driver. There are no points that are shared between different partial clusters. The algorithm applies kd-tree to find the neighbours of a node. This is resulted to avoid communication between executors to reduce complexity from O(n2) to O(nlogn). Each executor only computes the points that belong to it. Otherwise, there would be a lot of overlap of computation between different executors. Consequently, shuffle operations are prevented which costs a lot.

This algorithm introduces the term: SEEDs, which are points that do not belong to the current partition. These are additional points that are placed in each partial cluster. After all the partial clusters are collected through the shared variable accumulator, the algorithm identifies the clusters that are supposed to be merged by SEEDs. Merging is done in driver code too. These SEEDs serve as something like markers so that we can easily identify outer master partial clusters by using them and merge them into a bigger cluster. The SEEDs are not related to the locations. If the current point's index is beyond the range of current partition it is taken as a SEED. So the main goal on the executor side is to place SEEDs, and on the driver side, we dig out SEEDs and identify master partial clusters and merge them.

Taking advantage of Java Programming language, two data structures Hashtable and Queue are used in this algorithm. The complexity order of Put function in Hashtable is O(1 + n/K) where K is the hash table size. If K is large enough, the result is effectively O(1). Moreover, Method containsKey(key) is O(1).

References

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