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Keywords: Clustering; Machine learning; Clustering Algorithms; Clustering Criteria; Clustering Platform; Clustering Criteria; Big Data; horizontal scaling platforms; MapReduce; Spark; P2P; vertical scaling platforms; Multi-cores; GPU; FPGA



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Article

A Survey on Dependency of Parallel Clustering Platforms on Clustering Algorithms with Their Clustering Criteria for Big Data

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Abstract: Clustering is a data mining task used for the data extraction from the data bases or files. Clustering is used to find unknown groups present in the data sources like files or data bases. This paper focuses on clustering algorithms performance dependency on the parallel clustering platforms and the clustering algorithms along with their clustering criteria. The problems with the present Traditional clustering algorithms were throughput and data source size changes (scalability). So they can't address the big data. So for handling the huge volumes of data, parallel clustering algorithms along with clustering criteria were used. For processing the big Data Parallel clustering algorithms are of two types based on computing platforms used. They were the horizontal scaling platforms and vertical scaling platforms.

Keywords: clustering; machine learning; clustering algorithms; clustering criteria; clustering platform; clustering criteria; big data; horizontal scaling platforms; MapReduce; Spark; P2P; vertical scaling platforms; multi-cores; GPU; FPGA

1. INTRODUCTION

In the present era data analysis technique clustering used to handle the emerging challenges related to big data. Data analysis technique is applied on the data set to partition it into two subsets. One set consists of similar instances and other consists of dissimilar instances [1]. For partitioning various clustering methods were used like Bi-clustering, Density Based, Graph Based, Grid Based, Hard Clustering, Hierarchical, Model Based, Partitioning, and Soft Clustering e.t.c.

Clustering technique is used to group data points into clusters from a file or data base. i.e Similar points are grouped into one cluster and other data points to another group. Clustering purpose is to identify the similar and dissimilar characteristics or patterns from the given data. Similar points are identified using similarity functions. After the clustering process, class labels were assigned to the clusters called as classification. Clustering process takes the input from the data sources and gives the clustered data as output. Clustering used in different applications like pattern recognition, Image Processing and analysis, document categorization, Stock market segmentation, exploratory data analysis, World Wide Web, metrology, Health Care department, social network analysis e.t.c [2]. The stages of clustering are shown in the Figure 1 below.

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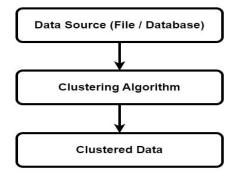


Figure 1. Clustering Stages.

Machine learning techniques are of three types. They were supervised, Semi-Supervised Learning and unsupervised. Clustering is unsupervised learning technique [3]. Machine learning techniques Classification are show in the Table 1 below.

 Table 1. Machine learning techniques Classification.

Algorithms of	Sub Methods	Details
Machine Learning List		
		It is used to predict continuous numeric values. Examples:
	Regression	Linear regression and support vector regression [4].
Supervised Learning		It is used to assign data points to predefined categories.
	Classification	Examples: decision trees, logistic regression, random forests,
		support vector machines [5].
		It is used to group similar data points into. Examples:
	Clustering	partition clustering, K-Means and DBSCAN [6].
		It is used to remove unnecessary features from a given data
Unsupervised	Dimensionality	set.
Learning	Reduction	Examples: Principal Component Analysis (PCA) and t-
		distributed Stochastic Neighbor Embedding (t-SNE)[7].
Semi-Supervised		It combines the aspects of supervised unsupervised learning
Learning		[8].

1.1. Challenges

The Challenges of Traditional Clustering Algorithms are addressed using Parallel Clustering Algorithms are show in the below Table 2.

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Clustering Algorithms		
Evaluation Criteria	Traditional	Parallel
Knowledge	Require prior knowledge	Not require prior
Data	Should be ordered	Ordered not required
Input Parameters	complex	Simple
Data Set	Not partitioned	Partitioned (chunks)
Problem	Specific Problem	All Problems
Operation Conditions	particular	All Conditions
Computational Costs	More	Less
Data it handle	can't handle heterogeneous	can handle heterogeneous
	data	data
Execution	Serial	Parallel
Speed	Less	More
Throughput	Less	More
Scalability	Less	More
Big Data Challenges	Can't Meet	Can Meet
Volume / Data Quantity	More	More
(Created / Stored)		

Velocity / Frequency	Less	Less
(Coming / Updated)		
Types Of Data	Less	More
(Data Forms And Sources From Where It Is Coming)		

1.2. Scope of the article

This paper focuses on parallel clustering algorithms on different Parallel computing platforms such as horizontal and the vertical scaling platforms to handle the huge volumes of Data. A horizontal scaling platform contains peer networks, MapReduce, and Spark platforms and which is used to add or remove machines to which the work load is distributed. vertical scaling platforms contains high Performance Computing Clusters (HPC), Multicore processors, Graphics Processing Unit (GPU), and Field Programmable Gate Arrays (FPGA) platforms which are used to add or remove power (processors, RAM, and hardware) to the present machine. It consists of.

1.3. Contributions

This Section deals with the contexts like different clustering algorithms with clustering criteria and parallel clustering platforms for handling huge volumes of Data.

2. LITERATURE SURVEY / Organization

This survey consists of two sections. They were

- a. Study of different clustering algorithms with clustering criteria.
- b. Study of different parallel clustering platforms.
- c. Use of clustering platforms and clustering algorithms with clustering criteria for clustering.

3. Study of different clustering algorithms with clustering criteria

In the market Different types clustering methods were there proposed by different researcher's persons. For each clustering method there will be one or more sub clustering Algorithms. Each sub clustering algorithm will have its own constraints. The major clustering methods available in the market were shown in Table 3 below, Clustering Algorithms Dependency on Clustering criteria is shown in Figure 2 and Big data platforms is shown in Figure 3.

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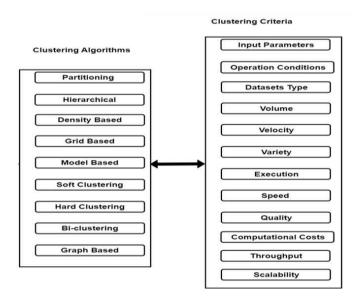


Figure 2. Clustering Algorithms Dependency on Clustering criteria.

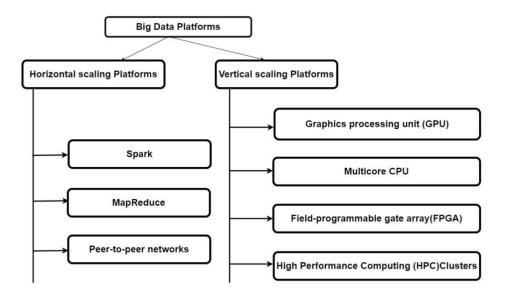


Figure 3. Big Data Platforms.

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Clustering	Details	Sub Clustering
Algorithm		Methods
Partitioning	It is a technique used to break a data source into two groups [9].	1. CLARA.
		2. CLARANS.
		3.EMCLUSTERING
		4. FCM.
		5. K MODES.
		6. KMEANS.
		7. KMEDOIDS.
		8. PAM.
		9. XMEANS
Hierarchical	It creates clusters based on objects similarity [10]	1. AGNES.
		2. BIRCH.
		3. CHAMELEON.
		4. CURE.
		5. DIANA.
		6. ECHIDNA
		7. ROCK.
Density Based	It creates clusters based on radius as a condition. i.e within	1. DBCLASD.
	radius one cluster and remaining other cluster(noise) [11].	2. DBSCAN.
		3. DENCLUE.
		4. OPTICS.
Grid Based	Clustering is done based on calculation values of density of	1. CLIQUE.
	cells using the grid [12].	2. OPT GRID.
		3. STING.
		4. WAVE CLUSTER.

	I	
Model Based	It uses statistical approach of assigning weights to every object.	1. EM.
	Based on object weights clustering is done [13].	2. COBWEB.
		3. SOMS.
Soft Clustering	It is based on assigned of individual data points to more than	1. FCM.
	one cluster [14].	2. GK.
		3. SOM.
		4. GA Clustering
Hard	It is based on assigned of individual data points to everyone	1. KMEANS
Clustering	cluster [15].	
Bi-clustering	It creates clusters based on cluster matrix rows and columns as	1. OPSM.
	a condition [16].	2. Samba
		3. JSa
Graph Based	It is based on graph theory that graph contains vertices or	1. Graph based k-means
	nodes. Here every node is assigned particular weights. Based	algorithm
	on graph node weights Clustering is done [17].	

Clustering Types:

Clustering technique is used to divide the given data set into two groups based on the objects similarity present in the data set. The Hard and Soft based Clustering groups of clustering are show in the Table 4 below and Hard and Soft based Clustering sets representation is also shown in Figure 4

Table 4. Hard Clustering verses Soft Clustering.

Clustering Type	Hard Clustering	Soft Clustering
All Data Point Assigned to	single cluster	multiple clusters
Similarity Clustering	maximum	minimum

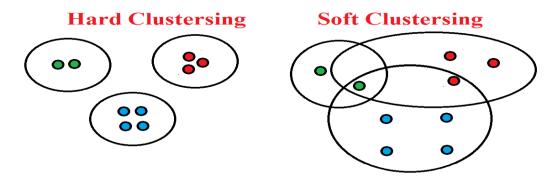


Figure 4. Soft and Hard Based Clustering.

Different Clustering Algorithms with Clustering Criteria

The clustering algorithm performance every time is based on the following constraints, parameters and user preferences. Different Clustering Algorithms with Clustering Criteria are show in the Table 5 below.

 Table 5. Different Clustering Algorithms with Clustering Criteria.

Clustering	Details
Criteria	
Data Mining	It is of two types. They were Descriptive or Predictive. Clustering is Descriptive
Tasks	Data Mining Tasks. Descriptive Data Mining task gives us the provide
	correlation, cross-tabulation, frequency, etc., from the data [18].
	Predictive Data Mining task is used to analyze and predict future occurrences
	of events or other data or trends [19].
Type of	Machine learning is of three types. They were Supervised / Unsupervised,
Learning /	Reinforced learning and unsupervised. Supervised / Reinforced machine
Knowledge	learning is based on output training data and the labeled input and [20] and
	unsupervised learning Machine learning processes unlabelled data [21].
	Reinforcement technique is used to train algorithms to learn from their
	environments [22].
Dimensionality	If the clustering algorithm deals with more types of data then it is said to be
	multi dimensional. (High / Low / Medium) [23].
Data Sources	Data Set / File / Data Base
Volume	Number of data points of a dataset. (Created / Stored)

Unstructured or Structured Data

If the data in the data set is in a standardized format (clearly defined) for the easy access by the systems or humans is called as Structured data [24]. If the data in the data set is not a standardized format (clearly defined) for the easy access by the systems or humans is called as Unstructured data [25]. Structured data is easily made into clusters but not Unstructured data. So algorithms are used to convert unstructured data to Structured data. So there is a requirement of unstructured data to be converted into unstructured data and it can discover new patterns. Clustering uses Structured in most cases.

Data Types used in Clustering

Two types of data are processed by the Clustering algorithms. They were Qualitative and Quantitative Data [26]. Clustering algorithm processes two types of data are shown in Figure 5 shown below.

Qualitative / Categorical type (Subjective) of data can be split into categories. Example: Persons Gender (male, female, or others) [27]. It is of three types. They were Nominal (sequenced), Ordinal (ordered) and binary (take true (1) / false (0)).

Quantitative / Numerical Data are measurable and are of two types. They were Discrete (countable, continuously, measurable) [28]. Example: Student height.

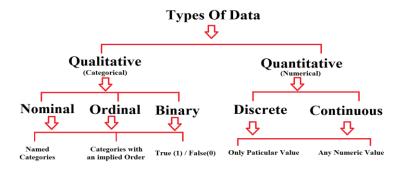


Figure 5: Clustering algorithm processes two types of data

ETL Operations used

Extraction, Transformation and loading operations are performed on the data source [29].

Data	It is used for data cleaning and data transforming to make it used for the
Preprocessed	analysis [30].
Data	Data Preprocessing Methods used in the market are cleaning, instance
Preprocessing	selection, normalization, scaling, feature selection, one-hot encoding, data
Methods	transformation, feature extraction and feature selection and dimensionality
	reduction [31].
Hierarchical	In Hierarchical clustering algorithms [32] is two types Divisive (Top-Down)
Clustering	[33] Or Agglomerative (Bottom-Up) [34].
Algorithms	
Туре	
No Of	It is the total count of two types of Clustering Algorithms (Main and sub).i.e.
Clustering	It is count of sum of total number of Main Clustering Algorithms and total
Algorithms	number of Sub Clustering Algorithms.
Algorithms	Hierarchical clustering algorithms Stops at a level defined by the user as his
Threshold /	Preferences.
Stops At What	
Level	
Algorithm	It uses different clustering applications to determine the number of clusters.
Stability	
Programming	It used For processing (Python, Java, .Net e.t.c) the clustering algorithm.
Language	
Number Of	Clustering Algorithm, Algorithm Constraints, Number of Levels and clusters
Inputs For The	per each level.
Clustering	
Process	

1	1	

Number Of	In Hierarchical clustering algorithms, divisive clustering (top-down) how
Levels	many split it goes down is the number levels. Or
	Agglomerative (bottom-up) how many merges it goes up to the number of
	levels.
Clusters Level	It is number of clusters at each level or stage
Wise	
Data Points per	It is always depends on the type of cluster algorithm used and its preferences
Cluster	defined by the user.
Similarity	It is used to quantify how similar or dissimilar two clusters are in a clustering
Functions /	analysis. Similarity measures are used to identify the good clusters in the given
Similarity	data set. There are so many Similarity measures used in the current market.
Measure.	They were Weighted, Average, Chord, Mahalanobis, Canberra Metric,
	Czekanowski Coefficient, Index of Association, Mean Character Difference,
	Pearson coefficient, Minkowski Metric, Manhattan or City blocks distance,
	KullbackLeibler Divergence, Clustering coefficient, Cosine, Kmean e.t.c[35].
Intra Cluster	It is the distance between the data points of one cluster to other. If its value is
Distance	low then the clusters are said to be tightly coupled other clusters are said to
	be loosely coupled [36].
Inter Cluster	It measures the dissimilarity / separation between different clusters. It
Distance	quantifies how distinct or well-separated the clusters are from each other [37].
Sum Of Square	It is a measure of difference the actual to the expected result of the model [38].
Error (SSE) Or	
Other Errors	
Clusters	It is clusters similarity in the data points [39].
Likelihood	
Clusters	It is clusters dissimilarity in the data points.
Unlikelihood	

Variable a Parameters At Each Level Outlier In a Clusters It	These are the input parameters which are changed during the running of the algorithm like threshold. In the clustering process any object doesn't belong to any cluster it is called as an outlier. It deals with the inertia for better clustering. It means lower inertia indicates better clustering. Inertia means Within-Cluster Sum of Squares.		
Parameters At Each Level Outlier In a Clusters	In the clustering process any object doesn't belong to any cluster it is called as an outlier. It deals with the inertia for better clustering. It means lower inertia indicates		
Each Level Outlier In a Clusters It	an outlier. It deals with the inertia for better clustering. It means lower inertia indicates		
Outlier In a Clusters It	an outlier. It deals with the inertia for better clustering. It means lower inertia indicates		
Clusters It	an outlier. It deals with the inertia for better clustering. It means lower inertia indicates		
Clusters It	It deals with the inertia for better clustering. It means lower inertia indicates		
	· ·		
Compactness b	better clustering. Inertia means Within-Cluster Sum of Squares.		
Purpose D	Develop and predict model		
Clustering It	It is the increasing and decreasing abilities of every cluster as a part o whole.		
Scalability			
Total Number of I	It is total number clusters generated by the clustering algorithm after its		
Clusters	execution.		
Interpretability U	Understandability , usability of clusters after is generation is called as		
Iı	Interpretability		
Convergence C	Convergence criterion is a condition by which controls the change in cluster		
C	centers. It should be always to be minimum.		
Clusters Shape E	Each clustering Algorithm handles the clustering in different shapes [40].		
C	Clustering Algorithm Cluster Shape		
K	K Means Hyper Spherical,		
C	Centroid Based Approach Concave Shaped Clusters,		
C	Cure Arbitrary,		
P	Partitional Clustering Ellipsoidal,		
C	Clarans Polygon Shaped,		
	Dbscan Concave E.t.c		
Execution R	Running the clustering Algorithm or Algorithms in serial or parallel.		
Output C	Clusters		
Velocity If	It is nothing but the frequency of Coming / Updated data to the clusters.		

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Throughput	It is the count of number of units processed by the system in the given		
	amount of time.		
Space	It of a clustering algorithm refers to the amount of memory or storage for		
Complexity	storing input data, data structures or variables required by the algorithm to		
	perform clustering on a given dataset.		
	Space Complexity=Auxiliary Space + Space For Input Values.		
Time	It is the time taken to run each and instructions of an algorithm. Time		
Complexity	Complexities of Clustering Algorithms		
	Clustering Algorithm Time Complexity		
	BIRCH O(n)		
	Chameleon O(n^2)		
	CLARA O(n)		
	CLARANS O(n^2)		
	Clique O(n)		
	CURE O(s^2*s)		
	K-Means O(n)		
	K-medoids O(n^2)		
	PAM O(n^2)		
	ROCK O(n^3)		
	Sting O(n)		
	e.t.c		
Clusters	It is a process used to representing clusters or groups of data points in a visual		
Visualization	format. It gives the insights into patterns, relationships, and structures within		
	the data. Techniques and tools for visualizing clusters: Scatter Plots,		
	Dendrogram, Heatmaps, t-Distributed Stochastic Neighbor Embedding,		
	Silhouette Plots, Principal Component Analysis Plot, K-Means Clustering		
	Plot, Hierarchical Clustering Dendrogram, Density-Based Clustering		
	Visualization, Interactive Visualization Tools: Matplotlib, Seaborn, Plotly,		
	D3.js, and Tableau [41].		

4. Overview of different Parallel clustering platforms

This section gives an outline about the two different Parallel data processing platforms of big data [42]. They were

- 1. Horizontal scaling platforms.
- 2. Vertical scaling platforms.

The different Parallel clustering platforms are shown in Figure 6 and Types of Big Data Platform along with Clustering Algorithm is depicted in Figure 7 below.

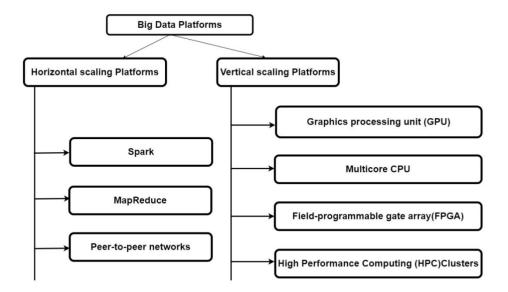


Figure 6. Types of Big Data Platforms.

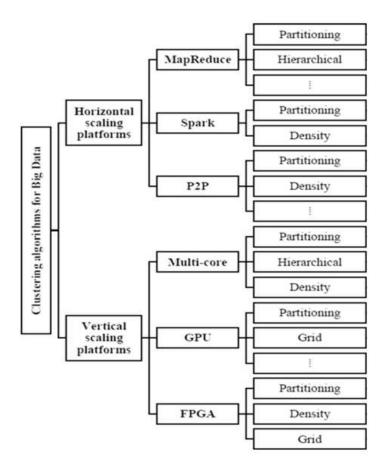


Figure 7. Types of Big Data Platform along with Clustering Algorithm.

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Parallel clustering platform: Horizontal scaling platforms

A horizontal scaling platform contains Map Reduce, Peer-to-peer networks and Spark and vertical scaling platforms which contains Field Programmable Gate Arrays, Graphics Processing Unit and Multi-core CPU. Parallel clustering platforms we use different clustering methods like Partitioning, Hierarchical, Density Based, Grid Based, Model Based, Soft Clustering, Hard Clustering, Bi-clustering, Graph Based e.t.c.

4.1. MapReduce

It is a software framework model for parallel programming introduced by Google used for parallel processing by splitting big datasets into parts chunks and executing them in parallel on multiple commodity servers and at the end it aggregates all the data from the multiple servers and returns the output back to the application. Hadoop platform written in languages like C++, Java, Python and Ruby, Which executes the Map Reduce Programs. In cloud computing platform, Map Reduce will run in parallel suing multiple systems in the cluster for data analysis. MapReduce program work in two phases. They were Map and Reduce [43]. MapReduce phases are show in the Table 6 below.

MapReduce phases NamePhase PurposeMap tasks (Splits & Mapping)splitting and mapping of dataReduce tasks (Shuffling, Reducing)Shuffle and reduce the data.

Table 6. MapReduce phases.

MapReduce program Phases

MapReduce for parallel programming model goes through the following Phases splitting, mapping, shuffling, and reducing. Normally user gets the input from the files or data base for these phases. All the Phases of MapReduce are shown in Table 7 below and All Phases of MapReduce are shown in the Figure 8 below.

Phases of	Details
MapReduce	
Splitting	The Input data set is broken down into small parts called as data chunks and
	is used by a single map.
Mapping	Splitting is input phase for mapping phase where each data chunk is given to
	the mapping function to measure the number of occurrences of each word

Mapping phase Output: (word, frequency)

Table 7. Phases of MapReduce.

Shuffling &	This phase is used to combine similar words with their frequency.
Sorting	
Reducing	It is used to give the consolidated summary of the given dataset.

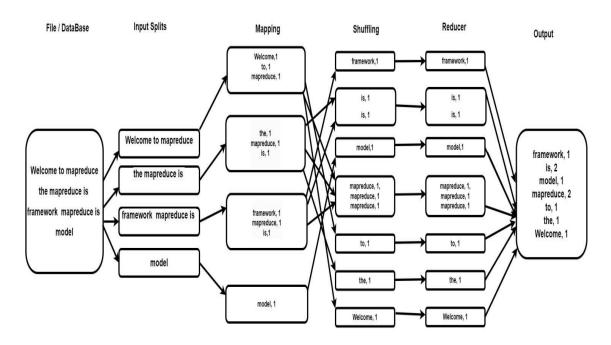


Figure 8. Phases of MapReduce.

MapReduce Work Organization in Hadoop

Jobs are divided into tasks by Hadoop. Tasks are of two types (Map tasks, Reduce tasks) were shown in Table 8 below.

Table 8. MapReduce Tasks.

MapReduce Tasks	Purpose
Map tasks	Splits & Mapping
Reduce tasks	Shuffling, Reducing

Execution Process of MapReduce Programs

Execution Process of MapReduce Programs is controlled by two main components (Job tracker, Multiple Task Trackers). User interacts with the Jobtracker for the completion of their job. MapReduce Execution Process Components are show in Table 9 below and MapReduce Execution Process Components is shown in Figure 9 below.

Table 9. MapReduce Execution Process Components.

MapReduce Execution	Details
Process Components	
Jobtracker	It is a master node which is used to complete execution of submitted job. Jobtracker resides on Namenode.
Multiple Task Trackers	Multiple Task Trackers are the slave machines for performing the job submitted by Jobtracker node. Task Trackers resides on Datanode

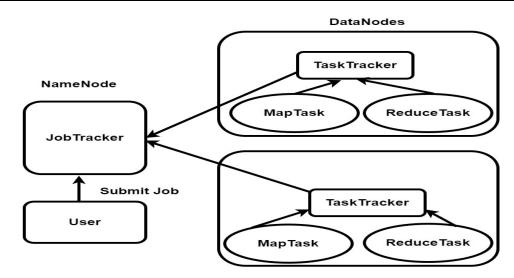


Figure 9. MapReduce Execution Process Components.

4.2. Spark Apache

Spark is used for the data processing framework for parallel processing. Apache Spark consists of two main components. They were single master node (process) and several worker nodes.

Master node assigning tasks Worker nodes and controls the Worker nodes and the resources assigned to the Worker nodes. Apache Spark runs queries, continuous iterative jobs and reduces execution time on big datasets. Apache Spark supports shared variables, resilient distributed datasets (RDDs) and parallel operations. Spark executes the applications as separate sets of processes on a cluster. Apache Spark runs the Driver Program it creates a SparkContext which is used to convert the user program / written code into jobs which runs on the cluster. Spark Driver coordinates the cluster manager to control the jobs execution. Normally jobs are broken down into sub jobs and are distributed to worker nodes. Spark executor runs the jobs and data and cache. Spark executors are registered with the spark context. Spark executor are dynamically created and removed during the running of the tasks [44]. Apache Spark main components are shown in the Figure 10 below.

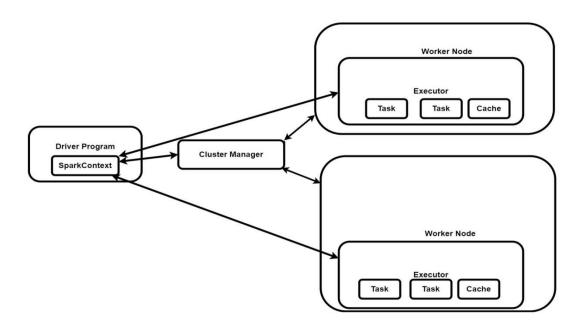


Figure 10. Apache Spark main components.

Spark Apache Execution Modes

Spark Apache runs in three different modes (Cluster mode, Client mode and Local mode) based on where your application resources are located and you're going to run. Spark Apache Execution Modes are shown in the Table 10 below.

Execution Modes

Details

Cluster

It is used to run production jobs where the driver executes under the worker nodes.

application using spark-submit command.

 Table 10. Spark Apache Execution Modes.

Here the driver runs locally from where you are submitting your

It is used to run complete Spark Application on a individual machine.

Cluster Manager Types

Client

Local

The cluster managers supported by the current system which were shown in the Table 11 below and Apache Spark Features are shown in Table 12.

Local mode uses threads instead of parallelized threads.

Table 11. Types of Cluster Managers.

Cluster Manager Types	Details	
Standalone	It is used to set up a cluster and provides a web-based graphical user	
	interface to monitor the cluster.	
Apache Mesos	It is used to run multiple distributed applications on the same cluster	
	resource allocation and scheduling conflicts.	
Hadoop YARN	It is a Hadoop3 resource manager.	
Kubernetes	It an open source system for automatic scaling, management ,	
	deployment applications.	

Table 12. Apache Spark Features.

Apache Spark	Details
Features	
Speed	Applications run on Spark process which is much faster in memory and on disk by reducing number of read and write operations to disk.
Multi-Language Support	Spark uses various APIs like Java, Scala, or Python. So application programs can be written different languages.
Advanced Analytics	For generating analytics spark uses Map, reduce, SQL queries machine learning (ML), and graph algorithms and streaming data

4.3. P2P networks

P2P means Peer-to-peer networks. P2P architecture distributes the divides tasks or workloads among peers. P2P networks not requires server to control the operations (transfer and receiving and data). All the peers are given equal preference in the p2p architecture. P2p networks are used to share files and access to devices among the peers. Nodes of the peer to peer networks can be scalable (Added / Removed). P2P networks are resistant to failures mean one node fails it effects the other nodes. Security wise P2P network are failed and require high bandwidth usage for the data transfer [45]. Typical Peer-to-peer network architecture is shown in the Figure 11 below.

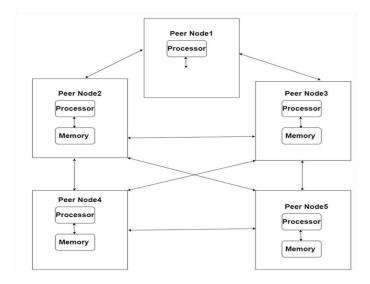


Figure 11. Typical Peer-to-peer network architecture.

Parallel clustering platform: Vertical scaling platforms

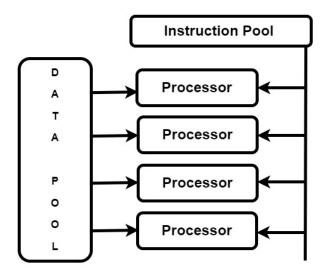
4.4. Graphics processing unit (GPU)

It is a graphics card / single chip microprocessor which is used for processing 2D and 3D Graphics. GPU uses parallel architecture as Single Instruction, Multiple Data (SIMD. Normally the CPU used to process the instruction serially known processing. But the GPU is used for vector processing and parallel computing means the processes are executed simultaneously or parallel. So parallel processing is very fast and efficient. GPUs takes a big problem breaks it into parts called as tasks and work on all these tasks and consolidate it to gets the result for the big problem. GPU parallel computing platform used to do one or more computations or processes are carried out parallel. So GPUs are fast and efficient [46]. Comparison of CPU and GPU are shown in Table 13 below. Graphics processing unit Instruction pooling is shown in the Figure 12 below.

Table 13. Comparison of CPU and GPU.

	CPU(Central processing unit)	Graphics processing unit
No Of Cores	4 to 8	100s Or 1000s
Throughput	Low	High
Instructions Execution	Serial	Parallel
Computing Applications	General purpose	High Performance
Parallel Programming Languages	Java, .net e.t.c	CUDA, Opencl E.T.C

Drawback		Limited Memory Capacity
Memory Management	Easy	Complex



Single Instruction, Multiple Data (SIMD)

Figure 12. Typical Peer-to-peer network architecture.

5.5. Multi-core CPU

It is a single chip an integrated circuit which consists of two or more processor cores. It is used to process of multiple tasks using one of the concepts like multithreading and parallel processing. Multi cores CPU are used due to the increase in performance; reduce power consumption, low heat generation [47]. Typical Multi-core CPU is shown in the Figure 13 below.

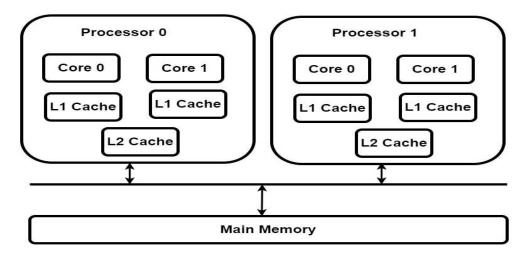


Figure 13. Typical Multi-core CPU.

6.6. Field programmable gate arrays (FPGA)

It is a integrated circuit which can be programmed for doing customized operations for a particular application. FPGA is low cost, flexible, expandable larger and less power consuming [48].

FPGA consists of three main structures. The FPGA structures were shown in the Table 14 below. Typical FPGA architecture is shown in the Figure 14 below.

Table 14. FPGA structure.

FPGA structure	Details
Programmable logic	It consists of collection of CLBs. CLB means configurable logic block
structure	used to implement any
	Boolean function of 4 to 6 variables. One or two flip-flops are used to
	implement one CLB.
Programmable routing	It is used for routing the information. It consists of vertical and
structure	horizontal routing channels, connection boxes and switch boxes.
Programmable Input /	It consists of buffers either which are used as Input buffers or used
Output structure	as output buffers.

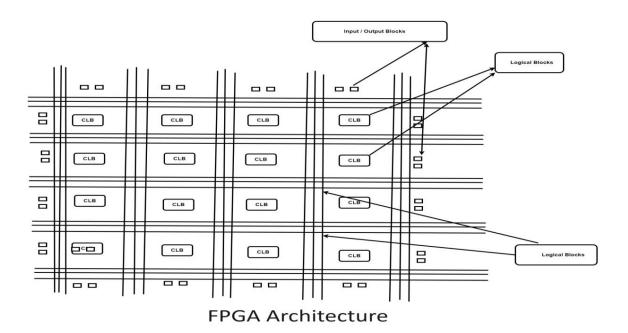


Figure 14. Typical FPGA architecture.

4. Clustering Dependence on parallel clustering platform, clustering Algorithms and clustering Criteria

The research carried out in the context of this survey of parallel clustering platforms, clustering algorithms and clustering algorithms criteria. Clustering algorithms always depends on the clustering criteria and parallel clustering platforms always depends on the clustering algorithms.

Dependency of parallel clustering algorithms on clustering algorithms and clustering Criteria is shown in the Table 15 below.

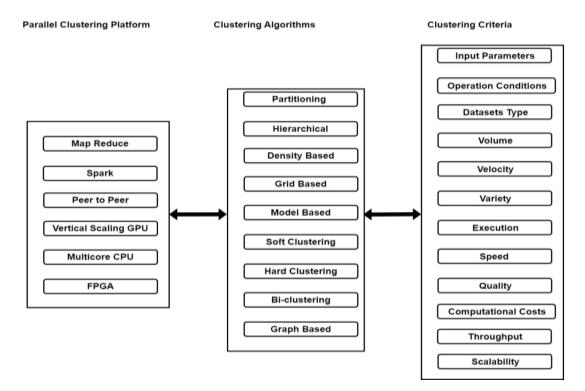


Figure 15. Dependency of parallel clustering algorithms on clustering algorithms and clustering Criteria.

Note:

- 1. Every algorithm uses its own data type to get optimal clusters or results [49].
- 2. Based on patterns, clusters, iterations and Levels Generated, clustering algorithm time and space Complexity of the clustering algorithm will varies [50].
- 3. Clustering method performance based on Data source, Data source size, shape of clusters shape, objective function, and similarity measurement functions [51].
- 4. Clustering methods use different data types like Numerical, categorical, Textual data, Multimedia, Network, Uncertain, Time Series, Discrete data e.t.c [52].
- 5. Similarity functions are used for identify inter and intra clusters similarities in between the clusters. Examples of distance functions are Euclidean Distance Function, Manhattan Distance Function, Chebyshev Distance Function, Davies Bould in Index e.t.c. Distance Function can affect the Performance of the clustering Algorithms [53].
- 6. Clustering algorithm is one of the steps in Knowledge Discovery in Databases (KDD) process [54].
- 7. In the clustering process Uniqueness may or may not be present in the Inter and Intra clustering process [55].
- 8. In any Clustering Algorithm used to differentiate between one cluster group with other cluster group [56].
- 9. Each and every Clustering method will have its own advantages and disadvantages based on the constraints, metrics used in the clustering algorithm [57].
- 10. Each clustering algorithm will have its own sub methods [58].
- 11. Parallel clustering platform is used to run the clustering algorithms in parallel [59].
- 12. Parallel clustering platform depends on clustering algorithm and clustering algorithm depends on clustering criteria [60].

5. Conclusions

This paper is about the performance clustering algorithms always depends on the parallel clustering platforms and the clustering algorithms along with their clustering criteria. Clustering platforms are used for data processing either by using horizontal scaling platforms or vertical scaling platforms. Parallel clustering platforms use MapReduce, Peer-to-Peer networks and Spark. A vertical scaling platform forms with the Multi-core processors, GPU, and FPGA.

Conflicts of Interest: The authors declare that there are no conflicts of interest in connection with the work submitted.

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