A Study on Big Data Analytics and Data Sciences: Challenges, Research Issues and Platforms

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Abstract- **The amount of data produced by mankind is very vast due to the arrival of new technologies, devices, and communication means. A huge repository of terabytes of data is generated each day from modern information systems and digital technologies such as Internet of Things and cloud computing. Analysis of this large data requires a lot of efforts at multiple levels to extract knowledge for decision making. Therefore, big data analysis is a current area of research and development. The main objective of this paper is to explore the potential impact of big data challenges, open research issues and provides an in-depth analysis of different platforms available for performing big data analytics.**

Index Terms- Big data, Data analytics, Data mining, Hadoop, Datasets.

1. INTRODUCTION

In today's world, due to the advancement of technology huge amount of data is being generated from various sources which led to the growth of big data[1]. The term big data is used as it goes beyond the processing power of traditional database systems .It provides evolutionary advances in many fields with collection of large datasets. It generally refers to the collection of large and complex datasets which are difficult to process using traditional database management tools or data processing applications. These are available in structured, semi-structured, and unstructured format in petabytes and beyond.

Big data has three characteristics data volume, velocity, and variety which is referred as 3V. Large amount of data that is being generated every day is referred as Volume whereas velocity is the rate of growth and how fast the data is gathered for analysis. Variety provides information about the types of data such as structured, unstructured, semistructured etc. Apart from these 3V there is another characteristics called veracity. It refers to availability and accountability[2]. The prime objective of big data analysis is to process data of high volume, velocity, variety, and veracity using various traditional and computational intelligent techniques.

Generally, Data warehouses have been used to manage the large dataset. In this case extracting the precise knowledge from the available big data is a critical issue. The present approaches in data mining are not suitable to handle the large datasets successfully[1]. The key problem in the analysis of big data is the lack of coordination between database systems as well as with analysis tools such as data mining and statistical analysis. These challenges generally arise when we wish to perform knowledge discovery and representation for its practical applications.

2. CHALLENGES OF BIG DATA

Recent years big data has been accumulated in several domains like health care, public administration, retail, biochemistry, and other interdisciplinary scientific researches. Web-based applications encounter big data frequently, such as social computing, internet text and documents, and internet search indexing. Considering this advantages of big data it provides a new opportunities in the knowledge processing tasks for the upcoming researchers. However opportunities always follow some challenges[3].

To handle the challenges we need to know various computational complexities, information security, and computational method, to analyze big data. For example, many statistical methods that perform well for small data size do not scale to voluminous data.

Here the challenges of big data analytics are classified into four broad categories namely data storage and analysis, knowledge discovery and computational complexities, scalability and

visualization of data and information security. We discuss these issues briefly in the following subsections.

2.1 Data Storage and Analysis

In recent years the size of data has grown exponentially by various means. These data are stored on spending much cost whereas they ignored or deleted finally because there is no enough space to store them. Therefore, the first challenge for big data analysis is storage mediums and higher input/output speed. In such cases, the data accessibility must be on the top priority for the knowledge discovery and representation. In past decades, analyst use hard disk drives to store data but, it slower random input/output performance than sequential input/output[6]. To overcome this limitation, the concept of solid state drive (SSD) and phrase change memory (PCM) was introduced. However the available storage technologies cannot possess the required performance for processing big data.

Another challenge with Big Data analysis is attributed to diversity of data with the ever growing of datasets, data mining tasks has significantly increased[3]. Additionally data reduction, data selection, feature selection is an essential task especially when dealing with large datasets. This presents an unprecedented challenge for researchers. It is because, existing algorithms may not always respond in an adequate time when dealing with these high dimensional data. Automation of this process and developing new machine learning algorithms to ensure consistency is a major challenge in recent years. Recent technologies such as hadoop and mapReduce make it possible to collect large amount of semi structured and unstructured data in a reasonable amount of time. The key engineering challenge is how to effectively analyze these data for obtaining better knowledge. A standard process to this end is to transform the semi structured or unstructured data into structured data and then apply data mining algorithms to extract knowledge.

The major challenge in this case is to pay more attention for designing storage sytems and to elevate efficient data analysis tool that provide guarantees on the output when the data comes from different sources. Furthermore, design of machine learning algorithms to analyze data is essential for improving efficiency and scalability.

2.2 Knowledge Discovery and Computational Complexities

Knowledge discovery and representation is a prime issue in big data. It includes a number of sub fields such as authentication, archiving, management, preservation, information retrieval, and representation. There are several tools for knowledge discovery and representation. Additionally many hybridized techniques are also developed to process real life problems[4]. All these techniques are problem dependent. Further some of these techniques may not be suitable for large datasets in a sequential computer. At the same time some of the techniques has good characteristics of scalability over parallel computer. Since the size of big data keeps increasing exponentially, the available tools may not be efficient to process these data for obtaining meaningful information. The most popular approach in case of large dataset management is data warehouses and data marts. Datawarehouse is mainly responsible to store data that are sourced from operational systems whereas data mart is based on a data warehouse and facilitates analysis.

Analysis of large dataset requires more computational complexities. The major issue is to handle inconsistencies and uncertainty present in the datasets. In general, systematic modeling of the computational complexity is used. It may be difficult to establish a comprehensive mathematical system that is broadly applicable to Big Data. But a domain specific data analytics can be done easily by understanding the particular complexities. A series of such development could simulate big data analytics for different areas. Much research and survey has been carried out in this direction using machine learning techniques with the least memory requirements. The basic objective in these researches is to minimize computational cost processing and complexities.

However, current big data analysis tools have poor performance in handling computational complexities, uncertainty, techniques and technologies that can deal computational complexity, uncertainty, and inconsistencies in an effective manner.

2.3 Scalability and Visualization of Data

The most important challenge for big data analysis techniques is its scalability and security. In the last decades researchers have paid attentions to accelerate

data analysis and its speed up processors followed by Moore's Law. For the former, it is necessary to develop sampling, on-line, and multiresolution analysis techniques. Incremental techniques have good scalability property in the aspect of big data analysis[5]. As the data size is scaling much faster than CPU speeds, there is a natural dramatic shift in processor technology being embedded with increasing number of cores. This shift in processors leads to the development of parallel computing. Real time applications like navigation, social networks, finance, internet search, timeliness etc. requires parallel computing.

The objective of visualizing data is to present them more adequately using some techniques of graph theory. Graphical visualization provides the link between data with proper interpretation.

However, online marketplace like flipkart, amazon, e-bay have millions of users and billions of goods to be sold every month. This generates a lot of data. To this end, some company uses a tool Tableau for big data visualization. It has capability to transform large and complex data into intuitive pictures. This help employee of a company to visualize search relevance, monitor latest customer feeback, and their sentiment analysis.

However, current big data visualization tools mostly have poor performances in functionalities, scalability, and response in time.

2.4 Information Security

In big data analysis massive amount of data are correlated, analyzed[7], and mined for meaningful patterns. All organizations have different policies to safe guard their sensitive information. Preserving sensitive information is a major issue in big data analysis. There is a huge security risk associated with big data. Therefore, information security is becoming a big data analytics problem. Security of big data can be enhanced by using the techniques of authentication, authorization, and encryption.

Various security measures that big data applications face are scale of network, variety of different devices, real time security monitoring, and lack of intrusion system. The security challenge caused by big data has attracted the attention of information security. Therefore, attention has to be given to develop a multi level security policy model and prevention system. Although much research has been carried out

to secure big data but it requires lot of improvement. The major challenge is to develop a multi-level security, privacy preserved data model for big data.

3. OPEN RESEARCH ISSUES IN BIG DATA ANALYTICS

Big data analytics and data science are becoming the research focal point in industries and academia. Data science aims at researching big data and knowledge extraction from data[8,9]. Applications of big data and data science include information science, uncertainty modeling, uncertain data analysis, machine learning, statistical learning, pattern recognition, data warehousing, and signal processing. Effective integration of technologies and analysis will result in predicting the future drift of events. The research issues pertaining to big data analysis are classified into three broad categories namely internet of things (IoT), cloud computing, bio inspired computing, and quantum computing. However it is not limited to these issues. More research issues related to health care big data can be found.

3.1 IoT for Big Data Analytics

Internet has restructured global interrelations, the art of businesses, cultural revolutions and an unbelievable number of personal characteristics. Currently, machines are getting in on the act to control innumerable autonomous gadgets via internet and create Internet of Things (IoT). Thus, appliances are becoming the user of the internet, just like humans with the web browsers. Internet of Things is attracting the attention of recent researchers for its most promising opportunities and challenges. It has an imperative economic and societal impact for the future construction of information, network and communication technology. The new regulation of future will be eventually; everything will be connected and intelligently controlled. The concept of IoT is becoming more pertinent to the realistic world due to the development of mobile devices, embedded and ubiquitous communication technologies, cloud computing, and data analytics. Moreover, IoT presents challenges in combinations of volume, velocity and variety.

In a broader sense, just like the internet, Internet of Things enables the devices to exist in a myriad of places and facilitates applications ranging from trivial

to the crucial. Conversely, it is still mystifying to understand IoT well, including definitions, content and differences from other similar concepts. Several diversified technologies such as computational intelligence, and big-data can be incorporated together to improve the data management and knowledge discovery of large scale automation applications. Knowledge acquisition from IoT data is the biggest challenge that big data professional are facing[10]. Therefore, it is essential to develop infrastructure to analyze the IoT data. An IoT device generates continuous streams of data and the researchers can develop tools to extract meaningful information from these data using machine learning techniques. Understanding these streams of data generated from IoT devices and analysing them to get meaningful information is a challenging issue and it leads to big data analytics. Machine learning algorithms and computational intelligence techniques is the only solution to handle big data from IoT prospective.

In knowledge acquisition phase, knowledge is discovered by using various traditional and computational intelligence techniques. The discovered knowledge is stored in knowledge bases and expert systems are generally designed based on the discovered knowledge[8]. Knowledge dissemination is important for obtaining meaningful information from the knowledge base. Knowledge extraction is a process that searches documents, knowledge within documents as well as knowledge bases. The final phase is to apply discovered knowledge in various applications. It is the ultimate goal of knowledge discovery. The knowledge exploration system is necessarily iterative with the judgement of knowledge application. There are many issues, discussions, and researches in this area of knowledge exploration.

3.2 Cloud Computing for Big Data Analytics
The development of virtualization technologies have made supercomputing more accessible and affordable. Computing infrastructures that are hidden in virtualization software make systems to behave like a true computer, but with the flexibility of specification details such as number of processors, disk space, memory, and operating system. The use of these virtual computers is known as cloud computing which has been one of the most robust big

data technique [11]. Big Data and cloud computing technologies are developed with the importance of developing a scalable and on demand availability of resources and data. Cloud computing harmonize massive data by on demand access to configurable computing resources through virtualization techniques. The benefits of utilizing the Cloud computing include offering resources when there is a demand and pay only for the resources which is needed to develop the product. Simultaneously, it improves availability and cost reduction. Open challenges and research issues of big data and cloud computing are discussed in detail by many researchers which highlights the challenges in data management, data variety and velocity, data storage, data processing, and resource management. So Cloud computing helps in developing a business model for all varieties of applications with infrastructure and tools.

Big data application using cloud computing should support data analytic and development. The cloud environment should provide tools that allow data scientists and business analysts to interactively and collaboratively explore knowledge acquisition data for further processing and extracting fruitful results. This can help to solve large applications that may arise in various domains. In addition to this, cloud computing should also enable scaling of tools from virtual technologies into new technologies like spark, R, and other types of big data processing techniques.

3.3 Bio-inspired Computing for Big Data Analytics
Bio-inspired computing is a technique inspired by nature to address complex real world problems. Biological systems are self-organized without a central control. A bio-inspired cost minimization mechanism search and find the optimal data service solution on considering cost of data management and service maintenance. These techniques are developed by biological molecules such as DNA and proteins to conduct computational calculations involving storing, retrieving, and processing of data. A significant feature of such computing is that it integrates biologically derived materials to perform computational functions and receive intelligent performance[7].
These systems are more suitable for big data applications. Huge amount of data are generated from variety of resources across the web since the

digitization. Analyzing these data and categorizing into text, image and video etc will require lot of intelligent analytics from data scientists and big data professionals. Proliferations of technologies are emerging like big data, IoT, cloud computing, bio inspired computing etc whereas equilibrium of data can be done only by selecting right platform to analyze large and furnish cost effective results.

Bio-inspired computing techniques serve as a key role in intelligent data analysis and its application to big data. These algorithms help in performing data mining for large datasets due to its optimization application. The most advantage is its simplicity and their rapid convergence to optimal solution while solving service provision problems.

From the discussions, we can observe that the bio-inspired computing models provide smarter interactions, inevitable data losses, and help is handling ambiguities. Hence, it is believed that in future bio-inspired computing may help in handling big data to a large extent.

3.4 Quantum Computing for Big Data Analysis

A quantum computer has memory that is exponentially larger than its physical size and can manipulate an exponential set of inputs simultaneously. This exponential improvement in computer systems might be possible. If a real quantum computer is available now, it could have solved problems that are exceptionally difficult on recent computers, of course today's big data problems. The main technical difficulty in building quantum computer could soon be possible. Quantum computing provides a way to merge the quantum mechanics to process the information. In traditional computer, information is presented by long strings of bits which encode either a zero or a one[13]. On the other hand a quantum computer uses quantum bits or qubits. The difference between qubit and bit is that, a qubit is a quantum system that encodes the zero and the one into two distinguishable quantum states. Therefore, it can be capitalized on the phenomena of superposition and entanglement. It is because qubits behave quantumly. For example, 100 qubits in quantum systems require 2100 complex values to be stored in a classic computer system. It means that many big data problems can be solved much faster by larger scale quantum computers compared with classical computers.

Hence it is a challenge for this generation to built a quantum computer and facilitate quantum computing to solve big data problems.

4. PLATFORMS

4.1 Horizontal scaling platforms

Some of the prominent horizontal scale out platforms include peer-to-peer networks and Apache Hadoop. Recently, researchers have also been working on developing the next generation of horizontal scale out tools such as Spark to overcome the limitations of other platforms. We will now discuss each of these platforms in more detail in this section.

4.1.1. Peer-to-peer networks

Peer-to-Peer networks involve millions of machines connected in a network. It is a decentralized and distributed network architecture where the nodes in the networks (known as peers) serve as well as consume resources. It is one of the oldest distributed computing platforms in existence[15]. Typically, Message Passing Interface (MPI) is the communication scheme used in such a setup to communicate and exchange the data between peers. Each node can store the data instances and the scale out is practically unlimited (can be millions of nodes).

The major bottleneck in such a setup arises in the communication between different nodes. Broadcasting messages in a peer-to-peer network is cheaper but the aggregation of data/results is much more expensive. In addition, the messages are sent over the network in the form of a spanning tree with an arbitrary node as the root where the broadcasting is initiated.

MPI, which is the standard software communication paradigm used in this network, has been in use for several years and is well-established and thoroughly debugged. One of the main features of MPI includes the state preserving process i.e., processes can live as long as the system runs and there is no need to read the same data again and again as in the case of other frameworks such as MapReduce (explained in section "Apachehadoop"). All the parameters can be preserved locally. Hence, unlike MapReduce, MPI is well suited for iterative processing. Another feature of MPI is the hierarchical master/slave paradigm. When MPI is deployed in the master–slave model,

the slave machine can become the master for other processes. This can be extremely useful for dynamic resource allocation where the slaves have large amounts of data to process.

MPI is available for many programming languages. It includes methods to send and receive messages and data. Some other methods available with MPI are 'Broadcast', which is used to broadcast the data or messages over all the nodes and 'Barrier', which is another method that can put a barrier and allows all the processes to synchronize and reach up to a certain point before proceeding further.

Although MPI appears to be perfect for developing algorithms[14] for big data analytics, it has some major drawbacks. One of the primary drawbacks is the fault intolerance since MPI has no mechanism to handle faults. When used on top of peer-to-peer networks, which is a completely unreliable hardware, a single node failure can cause the entire system to shut down. Users have to implement some kind of fault tolerance mechanism within the program to avoid such unfortunate situations. With other frameworks such as Hadoop (that are robust to fault tolerance) becoming widely popular, MPI is not being widely used anymore.

4.1.2. Apache Hadoop

Apache Hadoop is an open source framework[12] for storing and processing large datasets using clusters of commodity hardware. Hadoop is designed to scale up to hundreds and even thousands of nodes and is also highly fault tolerant. The Hadoop platform contains the following two important components:

i) Distributed File System (HDFS) is a distributed file system that is used to store data across cluster of commodity machines while providing high availability and fault tolerance.

ii) Hadoop YARN is a resource management layer and schedules the jobs across the cluster.

4.1.3. Spark: next generation data analysis paradigm

The major feature of Spark that makes it unique is its ability to perform in-memory computations. It allows the data to be cached in memory, thus eliminating the Hadoop's disk overhead limitation for iterative tasks. Spark is a general engine for large-scale data processing that supports Java, Scala and Python and for certain tasks it is tested to be up to 100× faster than Hadoop MapReduce when the data can fit in the memory, and up to 10× faster when data resides on the disk. It can run on Hadoop Yarn manager and can read data from HDFS. This makes it extremely versatile to run
on different systems.

4.2. Vertical scaling platforms

The most popular vertical scale up paradigms are High Performance Computing Clusters(HPC)[10], Multicore processors, Graphics Processing Unit (GPU) and Field Programmable Gate Arrays (FPGA). We describe
each of these platforms and their capabilities in the following sections.

4.2.1. High performance computing (HPC) clusters

HPC clusters, also called as blades or supercomputers, are machines with thousands of cores. They can have a different variety of disk organization, cache, communication mechanism etc. depending upon the user requirement. These systems use well built powerful hardware which is optimized for speed and throughput. Because of the top quality high-end hardware, fault tolerance in such systems is not problematic since hardware failures are extremely rare. The initial cost of deploying such a system can be very high because of the use of the high-end hardware. They are not as scalable as Hadoop or Spark clusters but they are still capable of processing terabytes of data. The cost of scaling up such a system is much higher compared to Hadoop or Spark clusters. The communication scheme used for such platforms is typically MPI. We already discussed about MPI in the peer-to-peer systems (see section "Peer-to-peer networks").

Since fault tolerance is not an important issue in this case, MPIs' lack of fault tolerance mechanism does not come as a significant drawback here.

4.2.2. Multicore CPU

Multicore refers to one machine having dozens of processing cores. They usually have shared memory but only one disk. Over the past few years, CPUs have gained internal parallelism. More recently, the number of cores per chip and the number of operations that a core can perform has increased significantly[15]. Newer breeds of motherboards allow multiple CPUs within a single machine thereby increasing the parallelism. Until the last few years,

CPUs were mainly responsible for accelerating the algorithms for big data analytics.

The parallelism in CPUs is mainly achieved through multithreading. All the cores share the same memory. The task has to be broken down into threads. Each thread is executed in parallel on different CPU cores. Most of the programming languages provide libraries to create threads and use CPU parallelism. The most popular choice of such programming languages is Java. Since multicore CPUs have been around for several years, a large number of software applications and programming environments are well developed for this platform. The developments in CPUs are not at the same pace compared to GPUs. The number of cores per CPU is still in double digits with the processing power close to 10Gflops while a single GPU has more than 2500 processing cores with 1000Tflops of processing power. This massive parallelism in GPU makes it a more appealing option for parallel computing applications.

The drawback of CPUs is their limited number of processing cores and their primary dependence on the system memory for data access. System memory is limited to a few hundred gigabytes and this limits the size of the data that a CPU can process efficiently.

Once the data size exceeds the system memory, disk access becomes a huge bottleneck. Even if the data fits into the system memory, CPU can process data at a much faster rate than the memory access speed which makes memory access a bottleneck. GPU avoids this by making use of DDR5 memory compared to a slower DDR3 memory used in a system. Also, GPU has high speed cache for each multiprocessor which speeds up the data access.

4.2.3. Graphics processing unit (GPU)

Graphics Processing Unit (GPUs) is a specialized hardware designed to accelerate the creation of images in a frame buffer intended for display output. Until the past few years, GPUs were primarily used for graphical operations such as video and image editing, accelerating graphics-related processing etc. However, due to their massively parallel architecture, recent developments in GPU hardware and related programming frameworks have given rise to GPGPU (general-purpose computing on graphics processing units). GPU has large number of processing cores as compared to a multicore CPU. In addition to the processing cores, GPU has its own high throughput

DDR5 memory which is many times faster than a typical DDR3 memory. GPU performance has increased significantly in the past few years compared to that of CPU. Recently, Nvidia has launched Tesla series of GPUs which are specifically designed for high performance computing. Nvidia has released the CUDA framework which made GPU programming accessible to all programmers without delving into the hardware details. These developments suggest that GPGPU is indeed gaining more popularity.

It usually has two levels of parallelism. At the first level, there are several multiprocessors (MPs) and within each multiprocessor there are several streaming processors (SPs). To use this setup, GPU program is broken down into threads which execute on SPs and these threads are grouped together to form thread blocks which run on a multiprocessor. Each thread within a block can communicate with each other and synchronize with other threads in the same block. Each of these threads has access to small but extremely fast shared cache memory and larger global main memory.

Threads in one block cannot communicate with the threads in the other block as they may be scheduled at different times. This architecture implies that for any job to be run on GPU, it has to be broken into blocks of computation that can run independently without communicating with each other [32]. These blocks will have to be further broken down into smaller tasks that execute on an individual thread that may communicate with other threads in the same block.

GPUs have been used in the development of faster machine learning algorithms. Some libraries such as GPUMiner implement few machine learning algorithms on GPU using the CUDA framework. Experiments have shown many folds speedup using the GPU compared to a multicore CPU.

GPU has its own drawbacks. The primary drawback is the limited memory that it contains. With a maximum of 12GB memory per GPU (as of current generation), it is not suitable to handle terabyte scale data. Once the data size is more than the size of the GPU memory[14], the performance decreases significantly as the disk access becomes the primary bottleneck. Another drawback is the limited amount of software and algorithms that are available for GPUs. Because of the way in which the task

breakdown is required for GPUs, not many existing analytical algorithms are easily portable to GPUs.

4.2.4. Field programmable gate arrays (FPGA)
FPGAs are highly specialized hardware units which are custom-built for specific applications. FPGAs can be highly optimized for speed and can be orders of magnitude faster compared to other platforms for certain applications. They are programmed using Hardware descriptive language (HDL). Due to customized hardware, the development cost is typically much higher compared to other platforms. On the software side, coding has to be done in HDL with a low-level knowledge of the hardware which increases the algorithm development cost[6]. User has to carefully investigate the suitability of a particular application for FPGA as they are effective only for a certain set of applications.

FPGAs are used in a variety of real-world applications .One example where FPGA was successfully deployed is in the network security applications. In one such application, FPGA is used as a hardware firewall and is much faster than the software firewalls in scanning large amounts of network data. In the recent years, the speed of multicore processors is reaching closer to that of FPGAs.

5. CONCLUSION

This paper surveys about big data and its challenges. It also focuses on open issues in big data analytics and the platforms in big data analytics. This paper deals with different issues its advantages and disadvantages. The various platforms and its pros and cons have been discussed in detail.

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