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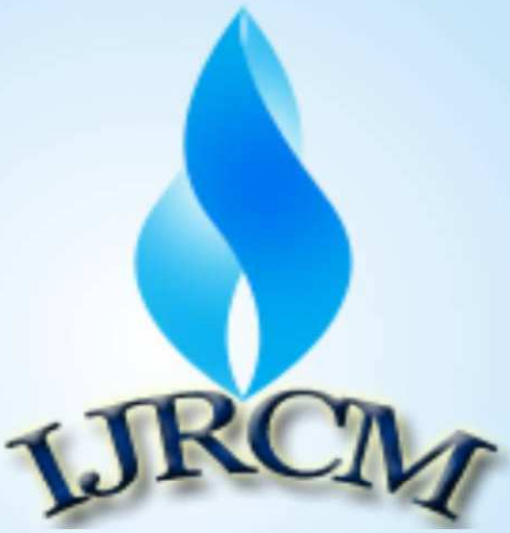

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DYNAMIC RELATIONSHIP TECHNIQUE FOR COMPLICATION REDUCTION IN BIG DATA

SELVARATHI C
ASST.PROFESSOR
COMPUTER SCIENCE & ENGINEERING
M.KUMARASAMY COLLEGE OF ENGINEERING
KARUR

ABSTRACT

Big Data usually includes data sets with sizes beyond the ability of commonly used software tools to capture, curate, manage, and process the data within a tolerable elapsed time. This paper presents a DYNAMIC CORRELATION TECHNIQUE which reduces complexity and characterizes the features of the Big Data revolution, and proposes a Big Data processing model, from the data mining perspective. This DCT model involves demand-driven aggregation of information sources, mining and analysis, user interest modeling, and security and privacy considerations. We analyze the challenging issues in the data-driven model and also in the Big Data revolution.

KEYWORDS
Big Data, data mining, heterogeneity, autonomous sources, complex and evolving associations.

1 INTRODUCTION

The era of Big Data has arrived astonishingly in the past few years. Numerous data are produced in the form of documents, chatting messages, audio, video, and applications and they are spread in the web. It will be more difficult to analyze these enormous data and we need more complicated algorithms and applications for mining these heterogeneous data. Also Big data has property of autonomous sources with complex and evolving relationships.

Mining Complex and Dynamic Data
Mining from Sparse, Uncertain, and Incomplete Data
Local Learning and Model Fusion for Multiple Information Sources

In the internet every day quintillion bytes of data are created and Our capability for data generation has never been so powerful and enormous ever since last few centuries.

The data collection has grown massively and is beyond the ability of commonly used software tools to capture, manage, and process within a "reasonable elapsed time." The most fundamental challenge for Big Data applications is to explore the large volumes of data and extract useful information or knowledge for future actions [40]. In many situations, the knowledge extraction process has to be very efficient and close to real time because storing all observed data is nearly infeasible. As a result, the extraordinary data volumes require an effective data analysis and prediction platform to achieve fast response and real-time classification for such Big Data.

The remainder of the paper is structured as follows: In Section 2, we summarize the key challenges for Big Data mining.. in Section 3 we propose a DCT (DYNAMIC CORRELATION TECHNIQUE) to process mining with Big Data, Related work is discussed in Section 4, and we conclude the paper in Section 5.

2 DATA MINING CHALLENGES WITH BIG DATA

For an intelligent learning database system [52] to handle Big Data, the essential key is to scale up to the exceptionally large volume of data and provide treatments for the characteristics featured by the aforementioned HACE theorem. Fig. 2 shows a conceptual view of the Big Data processing framework, which includes three tiers from inside out with considerations on data accessing and computing (Tier I), data privacy and domain knowledge (Tier II), and Big Data mining algorithms (Tier III).

FIG. 1

TIER III: BIG DATA MINING ALGORITHMS

TIER II: BIG DATA SEMANTICS AND APPLICATION KNOWLEDGE

Information Sharing and Data Privacy
Domain and Application KNOWLEDGE

TIER I: BIG DATA MINING PLATFORM

Clustered nodes
Parallel computing

A Big Data processing framework: The research challenges form a three tier structure and center around the "Big Data mining platform" (Tier I), which focuses on low-level data accessing and computing. Challenges on information sharing and privacy, and Big Data application domains and knowledge form Tier II, which concentrates on high-level semantics, application domain knowledge, and user privacy issues. The outmost circle shows Tier III challenges on actual mining algorithms.

The challenges at Tier I focus on data accessing and Arithmetic computing procedures. Because Big Data are often stored at different locations and data volumes may continuously grow, an effective computing platform will have to take distributed large-scale data storage into consideration for computing. For example, typical data mining algorithms require all data to be loaded into the main memory, this, however, is becoming a clear technical barrier for Big Data because moving data across different locations is expensive (e.g., subject to intensive network communication and other IO costs), even if we do have a super large main memory to hold all data for computing.

The challenges at Tier II center around semantics and domain knowledge for different Big Data applications. Such information can provide additional benefits to the mining process, as well as add technical barriers to the Big Data access (Tier I) and mining algorithms (Tier III). For example, depending on different domain applications, the data privacy and information sharing mechanisms between data producers and data consumers can be significantly differ- ent. Sharing sensor network data for applications like water quality monitoring may not be discouraged, whereas releasing and sharing mobile users' location information is clearly not acceptable for majority, if not all, applications. In addition to the above privacy issues, the application domains can also provide additional information to benefit or guide Big Data mining algorithm designs. For example, in market basket transactions data, each transaction is considered

independent and the discovered knowledge is typically represented by finding highly correlated items, possibly with respect to different temporal and/or spatial restrictions. In a social network, on the other hand, users are linked and share dependency structures. The knowledge is then represented by user communities, leaders in each group, and social influence modeling, and so on. Therefore, understanding semantics and application knowledge is important for both low-level data access and for high-level mining algorithm designs.

At Tier III, the data mining challenges concentrate on algorithm designs in tackling the difficulties raised by the Big Data volumes, distributed data distributions, and by complex and dynamic data characteristics. The circle at Tier III contains three stages. First, sparse, heterogeneous, uncertain, incomplete, and multisource data are prepro- cessed by data fusion techniques. Second, complex and dynamic data are mined after preprocessing. Third, the global knowledge obtained by local learning and model fusion is tested and relevant information is fed back to the preprocessing stage. Then, the model and parameters are adjusted according to the feedback. In the whole process, information sharing is not only a promise of smooth development of each stage, but also a purpose of Big Data processing.

In the following, we elaborate challenges with respect to the three tier framework in Fig. 1.

2.1 TIER I: BIG DATA MINING PLATFORM

In typical data mining systems, the mining procedures require computational intensive computing units for data analysis and comparisons. A computing platform is, therefore, needed to have efficient access to, at least, two types of resources: data and computing processors. For small scale data mining tasks, a single desktop computer, which contains hard disk and CPU processors, is sufficient to fulfill the data mining goals. Indeed, many data mining algorithm are designed for this type of problem settings. For medium scale data mining tasks, data are typically large (and possibly distributed) and cannot be fit into the main memory. Common solutions are to rely on parallel computing [43], [33] or collective mining [12] to sample and aggregate data from different sources and then use parallel computing programming (such as the Message Passing Interface) to carry out the mining process.

For Big Data mining, because data scale is far beyond the capacity that a single personal computer (PC) can handle, a typical Big Data processing framework will rely on cluster computers with a high-performance computing platform, with a data mining task being deployed by running some parallel programming tools, such as MapReduce or Enterprise Control Language (ECL), on a large number of computing nodes (i.e., clusters). The role of the software component is to make sure that a single data mining task, such as finding the best match of a query from a database with billions of records, is split into many small tasks each of which is running on one or multiple computing nodes. For example, as of this writing, the world most powerful super computer Titan, which is deployed at Oak Ridge National Laboratory in Tennessee, contains 18,688 nodes each with a 16-core CPU.

Such a Big Data system, which blends both hardware and software components, is hardly available without key industrial stockholders' support. In fact, for decades, companies have been making business decisions based on transactional data stored in relational databases. Big Data mining offers opportunities to go beyond traditional relational databases to rely on less structured data: weblogs, social media, e-mail, sensors, and photographs that can be mined for useful information. Major business intelligence companies, such IBM, Oracle, Teradata, and so on, have all featured their own products to help customers acquire and organize these diverse data sources and coordinate with customers' existing data to find new insights and capitalize on hidden relationships.

2.2 TIER II: BIG DATA SEMANTICS AND APPLICATION KNOWLEDGE

Semantics and application knowledge in Big Data refer to numerous aspects related to the regulations, policies, user knowledge, and domain information. The two most important issues at this tier include 1) data sharing and privacy; and 2) domain and application knowledge. The former provides answers to resolve concerns on how data are maintained, accessed, and shared; whereas the latter focuses on answering questions like "what are the under- lying applications ?" and "what are the knowledge or patterns users intend to discover from the data?"

2.2.1 INFORMATION SHARING AND DATA PRIVACY

Information sharing is an ultimate goal for all systems involving multiple parties [24]. While the motivation for sharing is clear, a real-world concern is that Big Data applications are related to sensitive information, such as banking transactions and medical records. Simple data exchanges or transmissions do not resolve privacy con- cerns [19], [25], [42]. For example, knowing people's locations and their preferences, one can enable a variety of useful location-based services, but public disclosure of an individual's locations/movements over time can have serious consequences for privacy. To protect privacy, two common approaches are to 1) restrict access to the data, such as adding certification or access control to the data entries, so sensitive information is accessible by a limited group of users only, and 2) anonymize data fields such that sensitive information cannot be pinpointed to an indivi- dual record [15]. For the first approach, common chal- lenges are to design secured certification or access control mechanisms, such that no sensitive information can be misconducted by unauthorized individuals. For data anonymization, the main objective is to inject randomness into the data to ensure a number of privacy goals. For example, the most common k-anonymity privacy measure is to ensure that each individual in the database must be indistinguishable from k — 1 others. Common anonymiza- tion approaches are to use suppression, generalization, perturbation, and permutation to generate an altered version of the data, which is, in fact, some uncertain data.

One of the major benefits of the data annomization-based information sharing approaches is that, once anonymized, data can be freely shared across different parties without involving restrictive access controls. This naturally leads to another research area namely privacy preserving data mining [30], where multiple parties, each holding some sensitive data, are trying to achieve a common data mining goal without sharing any sensitive information inside the data. This privacy preserving mining goal, in practice, can be solved through two types of approaches including 1) using special communication protocols, such as Yao's protocol [54], to request the distributions of the whole data set, rather than requesting the actual values of each record, or 2) designing special data mining methods to derive knowledge from anonymized data (this is inherently similar to the uncertain data mining methods).

2.2.2 DOMAIN AND APPLICATION KNOWLEDGE

Domain and application knowledge [28] provides essential information for designing Big Data mining algorithms and systems. In a simple case, domain knowledge can help identify right features for modeling the underlying data (e.g., blood glucose level is clearly a better feature than body mass in diagnosing Type II diabetes). The domain and application knowledge can also help design achievable business objectives by using Big Data analytical techniques. For example, stock market data are a typical domain that constantly generates a large quantity of information, such as bids, buys, and puts, in every single second. The market continuously evolves and is impacted by different factors, such as domestic and international news, government reports, and natural disasters, and so on. An appealing Big Data mining task is to design a Big Data mining system to predict the movement of the market in the next one or two minutes. Such systems, even if the prediction accuracy is just slightly better than random guess, will bring significant business values to the developers [9]. Without correct domain knowledge, it is a clear challenge to find effective matrices/measures to characterize the market movement, and such knowledge is often beyond the mind of the data miners, although some recent research has shown that using social networks, such as Twitter, it is possible to predict the stock market upward/downward trends [7] with good accuracies.

2.3 TIER III: BIG DATA MINING ALGORITHMS

2.3.1 LOCAL LEARNING AND MODEL FUSION FOR MULTIPLE INFORMATION SOURCES

As Big Data applications are featured with autonomous sources and decentralized controls, aggregating distributed data sources to a centralized site for mining is system- atically prohibitive due to the potential transmission cost and privacy concerns. On the other hand, although we can always carry out mining activities at each distributed site, the biased view of the data collected at each site often leads to biased decisions or models, just like the elephant and blind men case. Under such a circumstance, a Big Data mining system has to enable an information exchange and fusion mechanism to ensure that all distributed sites (or information sources) can work together to achieve a global optimization goal. Model mining and correlations are the key steps to ensure that models or patterns discovered from multiple information sources can be consolidated to meet the global mining objective. More specifically, the global mining can be featured with a two-step (local mining and global correlation) process, at data, model, and at knowledge levels. At the data level, each local site can calculate the data statistics based on the local data sources and exchange the statistics between sites to achieve a global data distribution view. At the model or pattern level, each site can carry out local mining activities, with respect to the localized data, to discover local patterns. By exchanging patterns between multiple sources, new global patterns can be synthetized by aggregating patterns across all sites [50]. At the

knowledge level, model correlation analysis investigates the relevance between models gener- ated from different data sources to determine how relevant the data sources are correlated with each other, and how to form accurate decisions based on models built from autonomous sources.

2.3.2 MINING FROM SPARSE, UNCERTAIN, AND INCOMPLETE DATA

Spare, uncertain, and incomplete data are defining features for Big Data applications. Being sparse, the number of data points is too few for drawing reliable conclusions. This is normally a complication of the data dimensionality issues, where data in a high-dimensional space (such as more than 1,000 dimensions) do not show clear trends or distribu- tions. For most machine learning and data mining algorithms, high-dimensional spare data significantly de- teriorate the reliability of the models derived from the data. Common approaches are to employ dimension reduction or feature selection [48] to reduce the data dimensions or to carefully include additional samples to alleviate the data scarcity, such as generic unsupervised learning methods in data mining. Uncertain data are a special type of data reality where each data field is no longer deterministic but is subject to some random/error distributions. This is mainly linked to domain specific applications with inaccurate data readings and collections. For example, data produced from GPS equipment are inherently uncertain, mainly because the technology barrier of the device limits the precision of the data to certain levels (such as 1 meter). As a result, each recording location is represented by a mean value plus a variance to indicate expected errors. For data privacy- related applications [36], users may intentionally inject randomness/errors into the data to remain anonymous. This is similar to the situation that an individual may not feel comfortable to let you know his/her exact income, but will be fine to provide a rough range like [120k, 160k]. For uncertain data, the major challenge is that each data item is represented as sample distributions but not as a single value, so most existing data mining algorithms cannot be directly applied. Common solutions are to take the data distributions into consideration to estimate model parameters. For example, error aware data mining [49] utilizes the mean and the variance values with respect to each single data item to build a Na¨ıve Bayes model for classification. Similar approaches have also been applied for decision trees or database queries. Incomplete data refer to the missing of data field values for some samples. The missing values can be caused by different realities, such as the malfunction of a sensor node, or some systematic policies to intentionally skip some values (e.g., dropping some sensor node readings to save power for transmission). While most modern data mining algorithms have in-built solutions to handle missing values (such as ignoring data fields with missing values), data imputation is an estab- lished research field that seeks to impute missing values to produce improved models (compared to the ones built from the original data). Many imputation methods [20] exist for this purpose, and the major approaches are to fill most frequently observed values or to build learning models to predict possible values for each data field, based on the observed values of a given instance.

2.3.3 MINING COMPLEX AND DYNAMIC DATA

The rise of Big Data is driven by the rapid increasing of complex data and their changes in volumes and in nature [6]. Documents posted on WWW servers, Internet back- bones, social networks, communication networks, and transportation networks, and so on are all featured with complex data. While complex dependency structures underneath the data raise the difficulty for our learning systems, they also offer exciting opportunities that simple data representations are incapable of achieving. For example, researchers have successfully used Twitter, a well-known social networking site, to detect events such as earthquakes and major social activities, with nearly real- time speed and very high accuracy. In addition, by summarizing the queries users submitted to the search engines, which are all over the world, it is now possible to build an early warning system for detecting fast spreading flu outbreaks [23]. Making use of complex data is a major challenge for Big Data applications, because any two parties in a complex network are potentially interested to each other with a social connection. Such a connection is quadratic with respect to the number of nodes in the network, so a million node network may be subject to one trillion connections. For a large social network site, like Facebook, the number of active users has already reached 1 billion, and analyzing such an enormous network is a big challenge for Big Data mining. If we take daily user actions/interactions into consideration, the scale of diffi- culty will be even more astonishing.

Inspired by the above challenges, many data mining methods have been developed to find interesting knowl- edge from Big Data with complex relationships and dynamically changing volumes. For example, finding communities and tracing their dynamically evolving rela- tionships are essential for understanding and managing complex systems [3], [10]. Discovering outliers in a social network [8] is the first step to identify spammers and provide safe networking environments to our society.

If only facing with huge amounts of structured data, users can solve the problem simply by purchasing more storage or improving storage efficiency. However, Big Data complexity is represented in many aspects, including complex heterogeneous data types, complex intrinsic semantic associations in data, and complex relationship networks among data. That is to say, the value of Big Data is in its complexity.

Complex heterogeneous data types. In Big Data, data types include structured data, unstructured data, and semistruc- tured data, and so on. Specifically, there are tabular data (relational databases), text, hyper-text, image, audio and video data, and so on. The existing data models include key-value stores, bigtable clones, document databases, and graph databases, which are listed in an ascending order of the complexity of these data models. Traditional data models are incapable of handling complex data in the context of Big Data. Currently, there is no acknowledged effective and efficient data model to handle Big Data.

Complex intrinsic semantic associations in data. News on the web, comments on Twitter, pictures on Flicker, and clips of video on YouTube may discuss about an academic award- winning event at the same time. There is no doubt that there are strong semantic associations in these data. Mining complex semantic associations from "text-image-video" data will significantly help improve application system performance such as search engines or recommendation systems. However, in the context of Big Data, it is a great challenge to efficiently describe semantic features and to build semantic association models to bridge the semantic Complex relationship networks in data. In the context of Big Data, there exist relationships between individuals. On the Internet, individuals are web pages and the pages linking to each other via hyperlinks form a complex network. There also exist social relationships between individuals forming complex social networks, such as big relationship data from Face book, Twitter, LinkedIn, and other social media [5], [13], [56], including call detail records (CDR), devices and sensors information [1], [44], GPS and geocoded map data, massive image files transferred by the Manage File Transfer protocol, web text and click-stream data [2], scientific information, e-mail [31], and so on. To deal with complex relationship networks, emerging research efforts have begun to address the issues of structure-and-evolution, crowds-and-interaction, and information-and-communication. The emergence of Big Data has also spawned new computer architectures for real-time data-intensive process- sing, such as the open source Apache Hadoop project that runs on high-performance clusters. The size or complexity of the Big Data, including transaction and interaction data sets, exceeds a regular technical capability in capturing, managing, and processing these data within reasonable cost and time limits. In the context of Big Data, real-time processing for complex data is a very challenging task.

3 RELATED WORK

3.1 BIG DATA MINING PLATFORMS (TIER I)

Due to the multisource, massive, heterogeneous, and dynamic characteristics of application data involved in a distributed environment, one of the most important characteristics of Big Data is to carry out computing on the petabyte (PB), even the exabyte (EB)-level data with a complex computing process. Therefore, utilizing a parallel computing infrastructure, its corresponding programming language support, and software models to efficiently analyze and mine the distributed data are the critical goals for Big Data processing to change from "quantity" to "quality."

Currently, Big Data processing mainly depends on parallel programming models like MapReduce, as well as providing a cloud computing platform of Big Data services for the public. MapReduce is a batch-oriented parallel computing model. There is still a certain gap in perfor- mance with relational databases. Improving the perfor- mance of MapReduce and enhancing the real-time nature of large-scale data processing have received a significant amount of attention, with MapReduce parallel program- ming being applied to many machine learning and data mining algorithms. Data mining algorithms usually need to scan through the training data for obtaining the statistics to solve or optimize model parameters. It calls for intensive computing to access the large-scale data frequently. To improve the efficiency of algorithms, Chu et al. proposed a general-purpose parallel programming method, which is applicable to a large number of machine learning algo- rithms based on the simple MapReduce programming model on multicore processors. Ten classical data mining

algorithms are realized in the framework, including locally weighted linear regression, k-Means, logistic regression, naive Bayes, linear support vector machines, the indepen- dent variable analysis, Gaussian discriminant analysis, expectation maximization, and back-propagation neural networks [14]. With the analysis of these classical machine learning algorithms, we argue that the computational operations in the algorithm learning process could be transformed into a summation operation on a number of training data sets. Summation operations could be per- formed on different subsets independently and achieve penalization executed easily on the MapReduce program- ming platform. Therefore, a large-scale data set could be divided into several subsets and assigned to multiple Mapper nodes. Then, various summation operations could be performed on the Mapper nodes to collect intermediate results. Finally, learning algorithms are executed in parallel through merging summation on Reduce nodes. Ranger et al. [39] proposed a MapReduce-based application programming interface Phoenix, which supports parallel programming in the environment of multi core and multi- processor systems, and realized three data mining algo- rithms including k-Means, principal component analysis, and linear regression. Gillick et al. [22] improved the MapReduce's implementation mechanism in Hadoop, evaluated the algorithms' performance of single-pass learning, iterative learning, and query-based learning in the MapReduce framework, studied data sharing between computing nodes involved in parallel learning algorithms, distributed data storage, and then showed that the MapReduce mechanisms suitable for large-scale data mining by testing series of standard data mining tasks on medium-size clusters. Papadimitriou and Sun [38] pro- posed a distributed collaborative aggregation (DisCo) framework using practical distributed data preprocessing and collaborative aggregation techniques. The implementa- tion on Hadoop in an open source MapReduce project showed that DisCo has perfect scalability and can process and analyze massive data sets (with hundreds of GB).

To improve the weak scalability of traditional analysis software and poor analysis capabilities of Hadoop systems, Das et al. [16] conducted a study of the integration of R (open source statistical analysis software) and Hadoop. The in-depth integration pushes data computation to parallel processing, which enables powerful deep analysis capabil- ities for Hadoop. Wegener et al. [47] achieved the integration of Weka (an open-source machine learning and data mining software tool) and MapReduce. Standard Weka tools can only run on a single machine, with a limitation of 1-GB memory. After algorithm parallelization, Weka breaks through the limitations and improves performance by taking the advantage of parallel computing to handle more than 100-GB data on MapReduce clusters. Ghoting et al. [21] proposed Hadoop-ML, on which developers can easily build task-parallel or data-parallel machine learning and data mining algorithms on program blocks under the language runtime environment.

3.2 BIG DATA SEMANTICS AND APPLICATION KNOWLEDGE (TIER II)

In privacy protection of massive data, Ye et al. [55] proposed a multilayer rough set model, which can accurately describe the granularity change produced by different levels of generalization and provide a theoretical foundation for measuring the data effectiveness criteria in the anonymization process, and designed a dynamic mechanism for balancing privacy and data utility, to solve the optimal generalization/refinement order for classifica- tion. A recent paper on confidentiality protection in Big Data [4] summarizes a number of methods for protecting public release data, including aggregation (such as k-anonymity, l-diversity, etc.), suppression (i.e., deleting sensitive values), data swapping (i.e., switching values of sensitive data records to prevent users from matching), adding random noise, or simply replacing the whole original data values at a high risk of disclosure with values synthetically generated from simulated distributions.

For applications involving Big Data and tremendous data volumes, it is often the case that data are physically distributed at different locations, which means that users no longer physically possess the storage of their data. To carry out Big Data mining, having an efficient and effective data access mechanism is vital, especially for users who intend to hire a third party (such as data miners or data auditors) to process their data. Under such a circumstance, users' privacy restrictions may include 1) no local data copies or downloading, 2) all analysis must be deployed based on the existing data storage systems without violating existing privacy settings, and many others. In Wang et al. [48], a privacy-preserving public auditing mechanism for large scale data storage (such as cloud computing systems) has been proposed. The public key-based mechanism is used to enable third-party auditing (TPA), so users can safely allow a third party to analyze their data without breaching the security settings or compromising the data privacy.

For most Big Data applications, privacy concerns focus on excluding the third party (such as data miners) from directly accessing the original data. Common solutions are to rely on some privacy-preserving approaches or encryp- tion mechanisms to protect the data. A recent effort by Lorch et al. [32] indicates that users' "data access patterns" can also have severe data privacy issues and lead to disclosures of geographically co-located users or users with common interests (e.g., two users searching for the same map locations are likely to be geographically colocated). In their system, namely Shround, users' data access patterns from the servers are hidden by using virtual disks. As a result, it can support a variety of Big Data applications, such as microblog search and social network queries, without compromising the user privacy.

3.3 BIG DATA MINING ALGORITHMS (TIER III)

To adapt to the multisource, massive, dynamic Big Data, researchers have expanded existing data mining methods in many ways, including the efficiency improvement of single-source knowledge discovery methods [11], designing a data mining mechanism from a multisource perspective [50], [51], as well as the study of dynamic data mining methods and the analysis of stream data [18], [12]. The main motivation for discovering knowledge from massive data is improving the efficiency of single-source mining methods. On the basis of gradual improvement of computer hardware functions, researchers continue to explore ways to improve the efficiency of knowledge discovery algo- rithms to make them better for massive data. Because massive data are typically collected from different data sources, the knowledge discovery of the massive data must be performed using a multisource mining mechanism. As real-world data often come as a data stream or a characteristic flow, a well-established mechanism is needed to discover knowledge and master the evolution of knowl- edge in the dynamic data source. Therefore, the massive, heterogeneous and real-time characteristics of multisource data provide essential differences between single-source knowledge discovery and multisource data mining.

Wu et al. [50], [51], [45] proposed and established the theory of local pattern analysis, which has laid a foundation for global knowledge discovery in multisource data mining. This theory provides a solution not only for the problem of full search, but also for finding global models that traditional mining methods cannot find. Local pattern analysis of data processing can avoid putting different data sources together to carry out centralized computing.

Data streams are widely used in financial analysis, online trading, medical testing, and so on. Static knowledge discovery methods cannot adapt to the characteristics of dynamic data streams, such as continuity, variability, rapidity, and infinity, and can easily lead to the loss of useful information. Therefore, effective theoretical and technical frameworks are needed to support data stream mining [18], [57].

Knowledge evolution is a common phenomenon in real- world systems. For example, the clinician's treatment programs will constantly adjust with the conditions of the patient, such as family economic status, health insurance, the course of treatment, treatment effects, and distribution of cardiovascular and other chronic epidemiological changes with the passage of time. In the knowledge discovery process, concept drifting aims to analyze the phenomenon of implicit target concept changes or even fundamental changes triggered by dynamics and context in data streams. According to different types of concept drifts, knowledge evolution can take forms of mutation drift, progressive drift, and data distribution drift, based on single features, multiple features, and streaming features [53].

4 CONCLUSIONS

Driven by real-world applications and key industrial stakeholders and initialized by national funding agencies, managing and mining Big Data have shown to be a challenging yet very compelling task. While the term Big Data literally concerns about data volumes, our HACE theorem suggests that the key characteristics of the Big Data are 1) huge with heterogeneous and diverse data sources, 2) Autonomous with distributed and decentralized control, and 3) complex nd evolving in data and knowledge association Such combined characteristics suggest that Big Data require a "big mind" to consolidate data for maximum values [27]. To explore Big Data, we have analyzed several challenges at the data, model, and system levels. To support Big Data mining, high-performance computing platforms are required, which impose systematic designs to unleash the full power of the Big Data. At the data level, the autonomous information sources and the variety of the data collection environments, often result in data with complicated conditions, such as missing/uncertain values. In other situations, privacy concerns, noise, and errors can be introduced into the data, to produce altered data copies. Developing

a safe and sound information sharing protocol is a major challenge. At the model level, the key challenge is to generate global models by combining locally discovered patterns to form a unifying view. This requires carefully designed algorithms to analyze model correlations between distributed sites, and fuse decisions from multiple sources to gain a best model out of the Big Data. At the system level, the essential challenge is that a Big Data mining framework needs to consider complex relationships between samples, models, and data sources, along with their evolving changes with time and other possible factors. A system needs to be carefully designed so that unstructured data can be linked through their complex relationships to form useful patterns, and the growth of data volumes and item relationships should help form legitimate patterns to predict the trend and future.

We regard Big Data as an emerging trend and the need for Big Data mining is arising in all science and engineering domains. With Big Data technologies, we will hopefully be able to provide most relevant and most accurate social sensing feedback to better understand our society at real- time. We can further stimulate the participation of the public audiences in the data production circle for societal and economical events. The era of Big Data has arrived.

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