



Understanding Big Data Framework Related to a Data Mining Technique

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ABSTRACT

The computing and communication power in the cyber-physical world is expanding greatly. As a result, a lot of data is generated to manage these activities. Big data has four primary challenges: volume, variety, velocity, and authenticity. Some storage-based data processing systems, like Hadoop, manage volume and variety. However, the speed and accuracy of processing such a vast volume of data require an overly complicated process. In this paper, we'll put into practice a system that can deal with huge volumes, varied patterns, and the speed of data. To extract valuable information from the data stream, we'll use correlation analytics and data mining. The system must be able to process data in real time, using an event processing engine like Esper that can generate various events using different language queries. Storm, which uses topology, is used to capture real-time data and for straightforward filtering of that data stream. Apriori and FP-Growth are two separate algorithms that are used for correlation and mining. Data centers all across the world are now using Apache Hadoop. The common programmer can now use parallel processing. It is essential to convert current data mining methods to the Hadoop platform as more data centers support it to maximize the effectiveness of parallel processing. The tendency of moving current data mining algorithms to the Hadoop platform has grown widespread with the advent of big data analytics. We examine the present migration activities and problems in this survey research. The reader's suggestions for solutions to the present migration difficulties will be guided by this essay.

Keywords: NoSQL database, Hadoop, Apriori Algorithm, Data Mining, FP-Growth, Esper, Big Data, Big Data Analytics

1. Introduction

Big data sizes are constantly reaching their pinnacle as they currently range from a few megabytes to several terabytes in a single data storage unit. A significant portion of this data explosion is the consequence of a sharp rise in peripheral devices, such as embedded sensors, smart phones, and tablet computers. Therefore, with resources expanding quickly, obtaining the core data from big data is also a major difficulty for today's cyber-physical systems. Big data presents numerous difficulties in terms of its reliability, scale, accuracy, hardness, and security. The difficulties start as soon as the data is collected, forcing us to make decisions about which data should be kept and which should be thrown away, as well as how to store the data in accordance with its pattern that are neither logically nor practically sound [1] [3] [5]. The format of data nowadays is poorly structured; for instance, tweets and blogs are made up of loosely connected textual fragments, while photos and videos are arranged for storage and display but aren't used for search or semantic content; structuring such content is the biggest difficulty. Integrations of computing and physical processes are known as cyber-physical systems. Since it transfers data from sensors to controllers, the infrastructure's architecture for communication in this system is crucial. The amount of data gathered about cyber-physical systems has increased dramatically along with their utilization. Because we already understand the nature of the data stream at each point in time, offline operations on cyberphysical data are not particularly challenging. But when real-time data is manipulated, the largest issue arises.

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2. Review of Literature

Data Mining Techniques and Big Data

"Big data" refers to areas with high volumes of high-speed data being transacted upon, as well as areas with sufficient computing power to enable precise and prompt decision-making. Since it transfers data from sensors to controllers, the infrastructure's architecture for communication in this system is crucial. The raw data from many sources is stored in storage where terabytes of data are already saved, so handling such data and extracting valuable information from it is the key challenge. To solve this, data stream analytics and mining for cyber-physical systems must be implemented. Numerous significant cyber-physical systems are currently in use, including the smart grid and networks for unmanned aerial vehicles. Knowledge, data, and information play a big part in human activity [2] [6]. Data mining is the process of elaborating knowledge by analyzing vast amounts of data from multiple angles and condensing it into helpful knowledge. And analytics is the process of breaking down ideas or substances into smaller parts in order to comprehend how they function. In the past, big data storage was used to store data that came from many sources. The entire data mining and analytics process happens here. As big data now contains terabytes of data, conducting analytics and mining in storage is time-consuming and prone to several difficulties [4]. Due to the fact that it is already aware that the data is coming from significant sources and is moving at a very high volume and velocity, these issues are not easily overcome. Analyzing and mining such data is a complicated process. Additionally, the cost of doing all these operations on the data after it has been stored in storage is very expensive.

Data mining techniques have been created for continuous files as well as where data is stored in table format. Initially, data mining algorithms worked best for numerical data obtained from a single data source [7][8]. In the early days of data mining, the majority of algorithms used just statistical methods. Due to the highly dynamic nature of data streams, the process must design quick mining techniques for them and must be able to detect rapidly changing concepts and data distribution in real time. Because many real data streams have irregular arrival rates and fluctuate in arrival rates over time, memory management is a major difficulty in stream processing. The use of stream mining techniques with high memory requirements is not appropriate in many applications, such as sensor networks. As a result, synthesis techniques must be developed in order to extract useful information from data streams. It is crucial to have a perfect data structure for storage, regular improvement, and access to the stored information [2] because of the size of memory and the enormous volume of data stream that continuously enters the system. The quality of employing the mining algorithm will significantly decline without this framework. Some classic mining techniques are cumbersome and ineffective for processing internet data. The algorithms used for analytics and mining must take into account all the elements that have an impact on the significance of the system and the value of the data [9][18]. The quantity of data sources and variations in data quality are additional issues with online data processing. Streaming data from numerous sources can occasionally cause a variety of issues, one of which is the tuple being missing or being out of order when the data is sent to storage. Sometimes incorrect values are sent to operations, producing inaccurate results. Energy costs are significant, as is the need to minimize unneeded data in order to save more CPU. The main problem is putting both stream correlation and rule mining on the same system so that rule mining can work on the online data stream and new data mining rules can be made and saved on the same system so they can be used in the future.

3. Framework and Methodology

The data stream management system, the sophisticated event processing engine, and finally business process management and visualization make up the system architecture of data stream analytics. Architecture for data mining and stream analytics The data stream management is first applied to the raw material or row data [10] [11] [12]. Thus, a data stream management system is a pipeline structure whose primary function is to remove unnecessary row data so that it won't later interfere with stream analytics and mining operations, consume less CPU, and reduce storage and memory costs. In order to prevent traffic or data tuple collisions, data stream management systems also offer scheduling and correct maintenance of the data stream. Thus, before the actual sophisticated processing begins, the data stream management system offers all necessary pre-processing. Additionally, it shrinks the amount of the data into rows and columns. The complicated event processing engine, which is employed either offline or online depending on the needs of the system, is the next component included in it. This section also includes a crucial component, a database management system with No SQL queries that are employed in the statistical analysis.

By addressing numerous No SQL queries, the basic filter data in the complicated event processing engine is connected with the standard data that is already recorded in the DBMS system to extract the knowledge-based data needed for a particular application [18]. Although SQL queries are not at all similar to structured query language, they do offer some additional opportunities. Combining these two structures—DSMS and the tool for processing complex events—creates the main filtering tool, which will function as follows. The process of making a correlation between raw data and the standard data whose values are already kept in the database system is known as stream analytics. hence using Row data stream Pearson product moment correlation. Big data is analyzed using stream analytics to uncover links and patterns that can be used to give actionable intelligence and obtain business insight. Every industry is experiencing a large influx of big data, and organizations are working to understand it as well as create analytical platforms that can combine structured data with unstructured and semi-structured data [13] [14] [15]. If big data is handled and managed effectively, it can provide invaluable information about market-related concerns, equipment damage, purchasing trends, maintenance cycles, and many other company issues, as well as a decrease in expenses and the ability to make more creative business decisions. Big data requires a comprehensive set of solutions for gathering, processing, and analyzing the data. These solutions should cover everything from data collection and new insight discovery to decision-making and scaling the related information systems. In reality, correlation is the product of the covariance of two variables and the standard deviation of each. As a

result, it means to take the input data as a variable for an example or application, to calculate the covariance by comparing the current values to one another, and to divide that result by the standard value, which has already been stored after researching all the patterns and conditions related to the data stream. Correlation is used to obtain statistical analysis results that fall within a certain range (-1 to 1). Consider that a high positive correlation will result in a value of +1, a low positive correlation will yield a value of 0 and a large negative correlation will yield a value of -1. The purpose of the application is to research bus transportation's daily routes. This program displays the bus's actual position along its daily route and evaluates its characteristics in relation to other vehicles and itself. Standard bus transportation data must already be stored in a database management system in order for the statistical correlation of buses to maintain proper parameterization. In order to find their analytics, for instance, the correlation of two buses operating on different routes is used. Sliding windows can be used to conduct this analysis. If the window is too small, there won't be as many results to compare and extremely brief faults or errors will trigger an alarm [16] [17] [18] [19]. Large windows will therefore give large results to compare, allowing small flaws to be overlooked. This is helpful for bus applications since buses will eventually catch their flaws. We could use tumbling windows, which only publish results at the conclusion of a time or count period, to reduce the amount of processing and output generated. Because all the data gathered up until the end of a time interval is analyzed at once, the latency for tumbling windows grows with window size.

3.3 Mining Rules

The composition of Data streams in a real-time system are vast, potentially limitless, frequently changing, and organized for a specific time. It is necessary to use semi-automatic interactional techniques to extract embedded knowledge from data due to the high volume and rapidity of input data. The primary algorithm is association rule mining, which employs the Apriori and FPGrowth algorithms. These algorithms are used for rule mining in a variety of applications. The frequent item sets are denoted by X and Y in an association rule denoted by XY (S,C), and S is support, which is the proportion of records that contain item sets from either X or Y or both. C stands for confidence and represents the proportion of records that contain both X and Y. Data stream mining in general Because there are continuous, infinite, and extremely fast fluctuating data streams in both offline and online conditions, there is already a very big quantity of data stored in the data set. As a result, employing typical data mining techniques to repeatedly scan the data is inefficient. It is therefore best to use an algorithm like Apriori, which counts frequently occurring item sets, generates candidate item sets using the minimal support value, prunes the infrequent ones, calculates confidence on all permutations of frequently occurring item sets, and selects those above the specified Confidence threshold. The FP-Growth algorithm follows [20][21]. The FP-Growth algorithm creates a frequency-sorted database of items from the transactions in its first pass, leaves out the less frequent items, and then produces an FP-tree. By avoiding iterative candidate generations, it performs better than Apriori-based algorithms. Data Stream, which are the straightforward tuples with a fixed number of fields that originate from various sources, is then used as the messaging structure in Apache Kafka before being sent to Storm, which has components like spouts and bolts. Before being sent to SPOUTS (data emitters), data streams are first brought into SPOUTS, which then retrieve the streams and send them to storm clusters. This information is entered into BOLTS (data processor), which executes some initial processing operations before emitting the information into one or more streams. Storm data streams are imported into Esper, where complex event processing is carried out using the CEP engine. Complex event processing involves filtering the data using NoSQL queries that are fired continuously, followed by the application of Apriori & FP-Growth for stream mining, which requires some sort of threshold data to be present in the system for association.

4. Summary

The ability to gather data, sort it, and analyze it so that it yields useful business insight is what truly adds value in today's era of data-rich enterprises (BI). Traditional data mining techniques, such as clustering and classification, are the foundation for machine learning operations in business intelligence support systems. Data migration via the network for the purpose of transformation or analysis has become impossible as organizations have started utilizing bigger amounts of data. It makes more sense to push the processing to the data rather than moving terabytes of data between systems on a daily basis, which could earn a programmer the fury of the network administrator. With large data volumes, moving all the big data to a single storage area network (SAN) or ETL server becomes impossible. Even if you can relocate the data, batch processing windows are frequently missed since processing is slow and limited to SAN bandwidth. The main goal is to develop a system or to achieve a specific result that will enable proper data stream mining and analysis in real time. It offers the previous method for analytics and mining. It compares its operation to past techniques and demonstrates how this system has largely overcome their drawbacks. The crucial aspect is that it offers the analytics and mining structure on the same system, making it possible to carry out this operation online because it offers a sliding-window application. The main finding of this system is that it can manage the data stream using a variety of tools, including Esper and Storm, a tool for data stream management systems. This implementation includes several algorithms being researched, including association rule mining, Apriori, and FPGrowth.

REFERENCES

- [1] Abramova, V., & Bernardino, J. (2013, July). NoSQL databases: MongoDB vs Cassandra. In Proceedings of the international C* conference on computer science and software engineering (pp. 14-22).
- [2] Ali, W., Shafique, M. U., Majeed, M. A., & Raza, A. (2019). Comparison between SQL and NoSQL Databases and Their Relationship with Big Data Analytics. *Asian Journal of Research in Computer Science*, 4(2), 1-10
- [3] Becker, M. Y., & Sewell, P. (2004, June). Cassandra: Flexible trust management, applied to electronic health records. In Proceedings. 17th IEEE Computer Security Foundations Workshop, 2004. (pp. 139-154). IEEE.
- [4] Berg, K. L., Seymour, T., & Goel, R. (2013). History of databases. *International Journal of Management & Information Systems (IJMIS)*, 17(1), 29-36.

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- [5] Bjeladinovic, S., Marjanovic, Z., & Babarogic, S. (2020). A proposal of architecture for integration and uniform use of hybrid SQL/NoSQL database components. *Journal of Systems and Software*, 168, 110633.
- [6] Chandra, D. G. (2015). BASE analysis of NoSQL database. *Future Generation Computer Systems*, 52, 13-21.
- [7] Chen, J. K., & Lee, W. Z. (2019). An introduction of NoSQL databases based on their categories and application industries. *Algorithms*, 12(5), 106.
- [8] Cuzzocrea, A., & Shahriar, H. (2017, December). Data masking techniques for NoSQL database security: A systematic review. In *2017 IEEE International Conference on Big Data (Big Data)* (pp. 4467-4473). IEEE.
- [9] de Oliveira, V. F., Pessoa, M. A. D. O., Junqueira, F., & Miyagi, P. E. (2021). SQL and NoSQL Databases in the Context of Industry 4.0. *Machines*, 10(1), 20.
- [10] Deka, G. C. (2013). A survey of cloud database systems. *IT Professional*, 16(2), 50-57. IEEE.
- [11] Di Martino, S., Fiadone, L., Peron, A., Riccabone, A., & Vitale, V. N. (2019, June). Industrial Internet of Things: Persistence for Time Series with NoSQL Databases. In *2019 IEEE 28th International Conference on Enabling Technologies: Infrastructure for Collaborative Enterprises (WETICE)* (pp. 340-345). IEEE.
- [12] dos Santos Ferreira, G., Calil, A., & dos Santos Mello, R. (2013, December). On providing DDL support for a relational layer over a document NoSQL database. In *Proceedings of International Conference on Information Integration and Web-based Applications & Services* (pp. 125-132).
- [13] Gessert, F., Wingerath, W., Friedrich, S., & Ritter, N. (2017). NoSQL database systems: a survey and decision guidance. *Computer Science-Research and Development*, 32(3), 353-365.
- [14] Guimaraes, V., Hondo, F., Almeida, R., Vera, H., Holanda, M., Araujo, A., ... & Lifschitz, S. (2015, November). A study of genomic data provenance in NoSQL document-oriented database systems. In *2015 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)* (pp. 1525-1531). IEEE.
- [15] Rodriguez, K. M., Reddy, R. S., Barreiros, A. Q., & Zehtab, M. (2012, June). Optimizing Program Operations: Creating a Web-Based Application to Assign and Monitor Patient Outcomes, Educator Productivity and Service Reimbursement. In *DIABETES* (Vol. 61, pp. A631-A631). 1701 N BEAUREGARD ST, ALEXANDRIA, VA 22311-1717 USA: AMER DIABETES ASSOC.
- [16] Kwon, D., Reddy, R., & Reis, I. M. (2021). ABCMETAapp: R shiny application for simulation-based estimation of mean and standard deviation for meta-analysis via approximate Bayesian computation. *Research synthesis methods*, 12(6), 842-848. <https://doi.org/10.1002/jrsm.1505>
- [17] Reddy, H. B. S., Reddy, R. R. S., Jonnalagadda, R., Singh, P., & Gogineni, A. (2022). Usability Evaluation of an Unpopular Restaurant Recommender Web Application Zomato. *Asian Journal of Research in Computer Science*, 13(4), 12-33.
- [18] Reddy, H. B. S., Reddy, R. R. S., Jonnalagadda, R., Singh, P., & Gogineni, A. (2022). Analysis of the Unexplored Security Issues Common to All Types of NoSQL Databases. *Asian Journal of Research in Computer Science*, 14(1), 1-12.
- [19] Singh, P., Williams, K., Jonnalagadda, R., Gogineni, A., & Reddy, R. R. (2022). International students: What's missing and what matters. *Open Journal of Social Sciences*, 10(02),
- [20] Jonnalagadda, R., Singh, P., Gogineni, A., Reddy, R. R., & Reddy, H. B. (2022). Developing, implementing and evaluating training for online graduate teaching assistants based on Addie Model. *Asian Journal of Education and Social Studies*, 1-10.
- [21] Sarmiento, J. M., Gogineni, A., Bernstein, J. N., Lee, C., Lineen, E. B., Pust, G. D., & Byers, P. M. (2020). Alcohol/illicit substance use in fatal motorcycle crashes. *Journal of surgical research*, 256, 243-250.
- [22] Brown, M. E., Rizzuto, T., & Singh, P. (2019). Strategic compatibility, collaboration and collective impact for community change. *Leadership & Organization Development Journal*.
- [23] Sprague-Jones, J., Singh, P., Rousseau, M., Counts, J., & Firman, C. (2020). The Protective Factors Survey: Establishing validity and reliability of a self-report measure of protective factors against child maltreatment. *Children and Youth Services Review*, 111, 104868