A STUDY ON THE IMPACT OF DATA SELECTION AND CLEANING TECHNIQUES

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ABSTRACT

Data cleansing offers a better data quality which will be a great help for the organization to make sure their data is ready for the analysing phase. However, the amount of data collected by the organizations has been increasing every year, which is making most of the existing methods no longer suitable for big data. The accuracy and integrity of data are important for the implementation of construction waste treatment. Abnormal detection and incomplete filling occur when traditional cleaning algorithms are used. Data quality affects machine learning (ML) model performances, and data scientists spend considerable amount of time on data cleaning before model training. Data collected from the various resources are dirty and this will affect the accuracy of prediction result. However, to date, there does not exist a rigorous study on how exactly cleaning affects ML — ML community usually focuses on developing ML algorithms that are robust to some particular noise types of certain distributions. To improve the cleaning of construction waste data, a data cleaning algorithm based on multi-type construction waste was presented in this study. Thereafter, a natural language data cleaning model was proposed, and the spatial location data were separated from the general data through the content separation mechanism to effectively frame the area to be cleaned. Data cleansing process mainly consists of identifying the errors, detecting the errors and corrects them.

Keywords: *Data cleansing, Data Integration, Data Mining, machine learning (ML) model, Data collected, ML community.*

INTRODUCTION

Data mining is a process of extraction of useful information and patterns from huge data. It is also called as knowledge discovery process, knowledge mining from data, knowledge extraction or data /pattern analysis. Data Mining is as process developed to explore large amounts of data to discover useful patterns. The goal of data mining is extracting knowledge from large database, which can be used in major decision-making business applications. Below are the steps involved in the knowledge discovery process. Data mining can be defined as the process of extracting Valid, previously unknown and actionable information from large data sets. The purpose of the data mining is to use the extracted information to make crucial business decisions. The tutorial starts off with a basic overview and the terminologies involved in data mining and then gradually moves on to cover topics such as knowledge discovery, query language, classification and prediction, decision tree induction, cluster analysis, and how to mine the Web. There is a huge amount of data available in the Information Industry. This data is of no use until it is converted into useful information. It is necessary to analyze this huge amount of data and extract useful information from it. Extraction of information is not the only process we need to perform; data mining also involves other processes such as Data Cleaning, Data Integration, Data Transformation, Data Mining, Pattern Evaluation and Data Presentation.

LITERATURE REVIEW

Deepa D. Shankar (2024) The world is currently facing the era of Cyber

biosecurity, also known as Bio cybersecurity, or Digital Biosecurity, which poses a few unique security vulnerabilities. A significant percentage of the scientific, agricultural, and health communities are still unaware of the unique security complexities that have resulted from fusion of the supply chain, infrastructure, cyber, and life and medical sciences. Measurement, analysis, and mitigation of cyberattacks on biological systems are the goals of Cyber biosecurity. Data mining is a promising avenue for further investigation as a means of mitigating cyber-attacks for research purposes. Data mining is the process of extracting useful patterns, information, and expertise from massive datasets. In the domain of Cyber-biosecurity, data mining techniques have received little attention. The purpose of this survey on data mining in cybersecurity is to determine the state of the art in cybersecurity issues, including different types of assaults and data mining methods that could be used to address these issues.

Purna Chandra Rao Kandimalla (2024) This research study delves into the extensive exploration of uncovering concealed trends and patterns within healthcare data. The primary objective is to reveal obscured insights present within diverse clinical information reports, including electronic health records, imaging scans, and patient histories. Employing data mining methodologies, this study aims to extract invaluable knowledge with the potential to significantly enhance the efficiency of diagnostic procedures and treatment plans in the healthcare domain. In the current healthcare landscape, a surge in data generation has created an unprecedented opportunity at the crossroads of data mining and machine learning within the healthcare industry. The core purpose of this study is to conduct a comprehensive investigation into the symbiotic relationship between data-driven methodologies and the medical field. Emphasizing the most recent trends and advancements, the research rigorously assesses the potential impact of machine learning techniques.

Johanes Fernandes Andry (2023) Football clubs store a lot of data about their players, Squad, Transfer Market, and Market Value, so Big Data is needed to process this data. This data can be analysed to gain insight into the Club's Market Value. Changes in Player Performance, Age, and Squad Size can be analysed using statistical methods. These digital data will provide information about the Club's Market Value. Data mining is the process of analysing data using various methods to produce useful information. The software application used in this data analysis is RapidMiner Studio, which is one of the best data mining tools. The purpose of this research is to analyse Football Clubs' Market Value according to Squad Size, Players' Value, and League. This study will use the Clustering K-means and Linear Regression methods. The results of this study can be used by those who want to invest money in Football Clubs. An investor can use this data to predict and make decisions about whether to invest in specific clubs and leagues.

David Jacob, Roberto Henriques (2023) Predicting academic success is essential in higher education because it is perceived as a critical driver for scientific and technological advancement and countries' economic and social development. This paper aims to retrieve the most relevant attributes for academic success by applying educational data mining (EDM) techniques to a Portuguese business school bachelor's historical data. We propose two predictive

models to classify each student regarding academic success at enrolment and the end of the first academic year. We implemented a SEMMA methodology and tried several machines learning algorithms, including decision trees, KNN, neural networks, and SVM. The best classifier for academic success at the entry-level reached is a random forest with an accuracy of 69%. At the end of the first academic year, an MLP artificial neural network's best performance was achieved with an accuracy of 85%. The main findings show that at enrolment or the end of the first year, the grades and, thus, the student's previous education and engagement with the school environment are decisive in achieving academic success.

Ashour A N Mostafa (2022) Nowadays, some of the interesting roles of human life are data, information, and knowledge. Analysing and modelling of big data have been required by data massive store houses together with the rapid technologies growth to predict and analyse the future trends of information. Methodologies and techniques, which are employed into diverse information systems scope, are needed for detection of knowing in the databases. The technology which extracts advantageous information to discover knowledge is called Data Mining. Data mining, it has been defined as discovery of knowledge in data (KDD), it is the disclosure of modalities procedures and other valuable information from considerable sets of data. It has been a tremendous progress in machine learning, artificial agent systems, and decision-making in the expert systems. In the last decades, most of the techniques and applications has been surveyed via the researchers.

Data Mining Techniques

Data mining uses algorithms and various other techniques to convert large collections of data into useful output. The most popular types of data mining techniques include association rules, classification, clustering, decision trees, K-Nearest Neighbor, neural networks, and predictive analysis. Association rules, also referred to as market basket analysis, search for relationships between variables. This relationship in itself creates additional value within the data set as it strives to link pieces of data. For example, association rules would search a company's sales history to see which products are most commonly purchased together; with this information, stores can plan, promote, and forecast.

Classification uses predefined classes to assign to objects. These classes describe the characteristics of items or represent what the data points have in common with each other. This data mining technique allows the underlying data to be more neatly categorized and summarized across similar features or product lines.

Why is data mining important?

Data mining is a crucial component of successful analytics initiatives in organizations. Data specialists can use the information it generates in business intelligence (BI) and advanced analytics applications that involve analysis of historical data, as well as real-time analytics applications that examine streaming data as it's created or collected.

Effective data mining aids in various aspects of planning business strategies and managing operations. This includes customer-facing functions, such as marketing, advertising, sales and customer support, as well as manufacturing, supply chain management (SCM), finance and human resources (HR). Data mining

supports fraud detection, risk management, cybersecurity planning and many other critical business use cases. It also plays an important role in other areas, including healthcare, government, scientific research, mathematics and sports.

The data mining process: How does data mining work?

Data scientists and other skilled BI and analytics professionals typically perform data mining. But data-savvy business analysts, executives and workers who function as citizen data scientists in an organization can also perform data mining.

The core elements of data mining include machine learning and statistical analysis, along with data management tasks done to prepare data for analysis. The use of machine learning algorithms and artificial intelligence (AI) tools has automated more of the process. These tools have also made it easier to mine massive data sets, such as customer databases, transaction records and log files from web servers, mobile apps and sensors.

Although the number of stages can differ depending on how granular an organization wants each step to be, the data mining process can generally be broken down into the following four primary stages:

Data gathering: Identify and assemble relevant data for an analytics application. The data might be located in different source systems, a data warehouse or a data lake, an increasingly common repository in big data environments that contain a mix of structured and unstructured data. External data sources can also be used. Wherever the data comes from, a data scientist often moves it to a data lake for the remaining steps in the process.

Data preparation: This stage includes a set of steps to get the data ready to be mined. Data preparation starts with data exploration, profiling and pre-processing, followed by data cleansing work to fix errors and other data quality issues, such as duplicate or missing values. Data transformation is also done to make data sets consistent, unless a data scientist wants to analyze unfiltered raw data for a particular application.

Data mining: Once the data is prepared, a data scientist chooses the appropriate data mining technique and then implements one or more algorithms to do the mining. These techniques, for example, could analyze data relationships and detect patterns, associations and correlations. In machine learning applications, the algorithms typically must be trained on sample data sets to look for the information being sought before they're run against the full set of data.

Data analysis and interpretation: The data mining results are used to create analytical models that can help drive decision-making and other business actions. The data scientist or another member of a data science team must also communicate the findings to business executives and users, often through data visualization and the use of data storytelling techniques.

Data mining vs. data analytics and data warehousing

Data mining is sometimes considered synonymous with data analytics. But it's predominantly seen as a specific aspect of data analytics that automates the analysis of large data sets to discover information that otherwise couldn't be detected. That information can then be used in the data science process and in other BI and analytics applications.

Data warehousing supports data mining efforts by providing repositories for the data sets. Traditionally, historical data has been

stored in enterprise data warehouses or smaller data marts built for individual business units or to hold specific subsets of data. Now, though, data mining applications are often served by data lakes that store both historical and streaming data and are based on big data platforms, like Hadoop and Spark; NoSQL databases; or cloud object storage services.

Data mining history and origins

Data warehousing, BI and analytics technologies began to emerge in the late 1980s and early 1990s, increasing organizations' abilities to analyze the growing amounts of data that they were creating and collecting. The term data mining was first used in 1983 by economist Michael Lovell and saw wider use by 1995 when the First International Conference on Knowledge Discovery and Data Mining was held in Montreal.

The event was sponsored by the Association for the Advancement of Artificial Intelligence, which also held the conference annually for the next three years. Since 1999, the Special Interest Group for Knowledge Discovery and Data Mining within the Association for Computing Machinery has primarily organized the ACM SIGKDD conference.

RESEARCH METHODOLOGY

The association rules that satisfy both the minimum support and minimum confidence are called as interesting association rules. The problem of frequent pattern mining is not limited to static databases, but also extended to dynamic databases and data streams. A data stream is an ordered collection of transactions that arrive in timely order. The data in a stream are usually continuous, unbounded and come at high speed. Thus, data streams have change in data distribution and there are two classifications of stream data, such as online and offline streams. . Concept change is categorized as concept drift and concept shift. Some new patterns may be introduced or some existing patterns become invalid. In online shopping environments, purchasing behaviour of the customers changes over time and affects the set of items frequently purchased together. This study deals with the offline stream where the bulk arrival of data is considered. In general, data stream mining algorithms adapts to changes in the concept due to its changing nature of data. Thus, concept change is the known scenario in data stream processing. The concept refers to the target variable that the model is trying to describe. In the frequent pattern mining scenario, the concept is referred to as the set of frequent patterns that the mining algorithm tries to generate Concept change in data stream processing is treated as a challenging problem than in traditional static databases. Detection of concept changes in data stream mining helps to analyse the amount of changes happened, and helps to find a new set of valid frequent patterns with respect to these changes.

RESULTS AND DISCUSSIONS

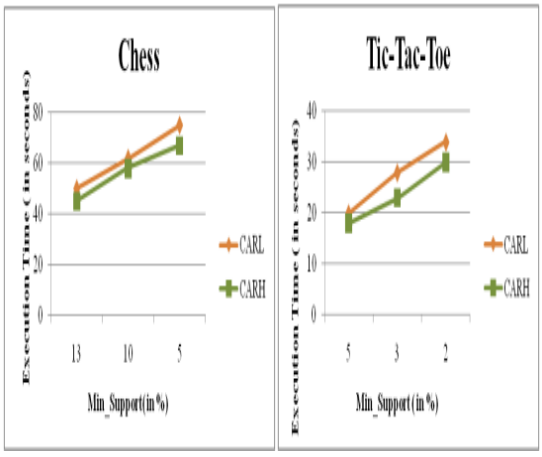
The Tic-Tac-Toe is the smallest dataset containing 958 objects and 10 attributes, whereas Connect is the largest dataset with 67,557 objects. Table 1 shows the characteristics of the experimental datasets.

Table 1: Characteristics of experimental datasets

Data set	# of Attributes	# of Classes	# of Distinct Values	# of Objects
Chess	37	2	73	3196
Tic-	10	2	27	958

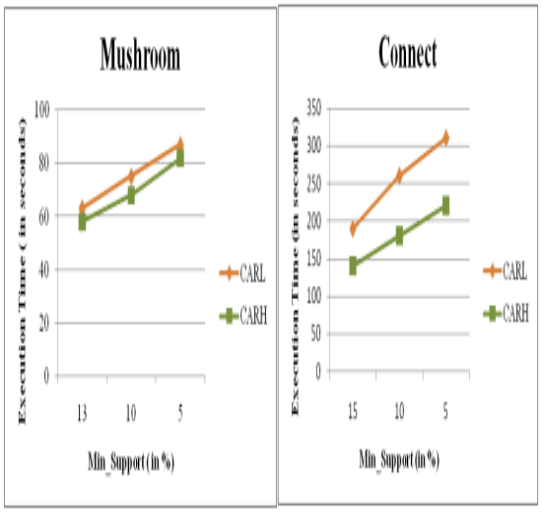
Tac-Toe				
Connect	43	3	126	67557
Mushroom	21	2	115	8124

Experiments are made to compare the execution time of the proposed Class Association Rule mining using Hash (CARH) algorithm with Class Association Rule mining using Lattice (CARL) algorithm for different datasets by varying the support values. A minconf of 50% is used in all the experiments. Graph 1 show the results of the execution time of CARH and CARL algorithms for all the datasets. From the figures, it is observed that CAR mining using hash structure gives the minimal execution time compared to lattice structure. Graph 1 show the results of the execution time of CARH and CARL algorithms for all the datasets. From the figures, it is observed that CAR mining using hash structure gives the minimal execution time compared to lattice structure.



Graph 1: Execution time comparisons of CARH and CARL algorithms in the Chess and Tic-Tac-Toe dataset

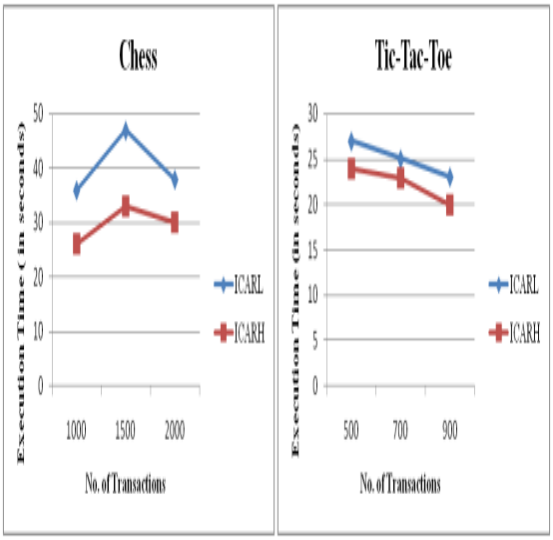
For example, with a minimum support of 5%, for the connect dataset, the CARH algorithm takes 220 seconds for execution, whereas the CARL algorithm requires 310 seconds and for the tic-tac-toe dataset, the CARH algorithm takes 18 seconds of execution while CARL algorithm takes 20 seconds.



Graph 2: Execution time comparisons of CARH and CARL algorithms in the Mushroom and Connect dataset

Results of Incremental Mining of CARs

The upper support threshold is same as minsup and lower support is 3%. To realize the effects of incremental mining, different increment sizes have been used for different datasets and the increment size determines the value of safety threshold measure. For different increment sizes across various datasets, the execution time of ICARH and ICARL is noted and the results are depicted Graph 3. When the original database of size 3000 records are processed, the ICARH algorithm takes 29 seconds for execution, whereas the ICARL algorithm takes 33 seconds.



Graph 3: Execution time comparisons of ICARH and ICARL algorithms in the Chess and Tic-Tac-Toe dataset

When 1500 records are added as the first increment, updating hash structure to generate updated CARs for the entire4500 records requires 32 seconds, whereas updating lattice structure takes 39 seconds. From the experimental results, it is observed that the incremental algorithm using hash structure gives good results compared to the lattice structure with respect to mining time.

CONCLUSIONS

Detecting and repairing dirty data is one of the perennial challenges in data analytics, and failure to do so can result in inaccurate analytics and unreliable decisions. Over the past few years, there has been a surge of interest from both industry and academia on different aspects of this problem including new abstractions, interfaces, and approaches for scalability. This tutorial focused on qualitative data cleaning which uses constraints, rules, or patterns to detect errors. The transformation steps may request user feedback on data instances for which they have no built-in cleaning logic. The correctness and effectiveness of a transformation workflow and the transformation definitions should be tested and evaluated, e.g., on a sample or copy of the source data, to improve the definitions if necessary. In this work, the first phase is used to select the data and it would be selected from the multiple data source, then Schema level problem will be rectified using modified XML constraints, and in the second phase, instance level problem will be rectified using ETL based data cleaning with smart tokens. The results have improved significantly compared to the conventional data cleaning methods. Hence this research work paves way for researchers to create an ECDC data cleaning tool for all the issues of single and multi-data source based on the proposed ECDC framework.

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