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Big Data Learning Analytics for Enhancing Pedagogical Practices

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Abstract: ***There is a rapid expansion of the knowledge in the education system. These systems provide secret information for enhancing student performance. Therefore, to recognize the difference between high-level and low-level students in this academic performance, a predictive data extraction method is important. Educators must recognize the technical tools suitable for fostering creative pedagogical practices. In order to conduct research, communicate and create knowledge, students should use different tools with teachers. Analysis of evaluation data creates new possibilities for improving the educational process by helping teachers and students make intelligent choices in their earlier growth. It also helps teachers in the classroom follow innovative teaching policies in order to access their students ' results. Data analysis thus helps teachers to develop their pedagogical skills. This paper is intended to provide a summary of big data, the techniques used in big data and the relationship between pedagogy and its learning analytical systems.***

Keywords: Education Technology, Big Data, Pedagogy, analytical system**.**

1. Introduction

Educators are now drawing attention in finding methods for making effective learning process, for identifying learner's achievements and weakness, for tracing academic progress and also for predicting future performance. The pedagogical decisions taken by a teacher to measure the student's understanding of the material or to organize a course structure may have the greatest impact on student learning. The aim of Learning Analytics is to collect Big Data in the context of teaching and learning, further to analyze and interpret it to gain new insights and to provide the stakeholders with new models for improving teaching, learning, effective organization, and decision making

1.1. Role of Analysis in Teaching and Learning

Learning that initially started in the class room was based on three models namely behavioral, cognitive and constructivist models. The behavioral models rely on observable changes in the behavior of the student to assess the learning outcome. The cognitive models are based on the active involvement of teacher in the learning which helps in guided learning. In the constructivist models, the students have to learn on their own from the knowledge available to them. Assessment data analysis creates new opportunities to improve the education process by helping teachers and learners make smarter decisions earlier in the learning progression. It is also being effectively used to access the students' performance and helping teachers in the classroom for adopting an adaptive teaching policy for their students. In this manner, Data analytics allows educators to improve their pedagogical skills.

1.2. Importance of big data in modern education system

Big Data and analytics have gained a huge momentum in recent years. Big Data feeds into the field of Learning Analytics (LA) that may allow academic institutions to better understand the learners' needs. Hence, it is important to have an understanding of Big Data and its applications. In the current learning environments, users learn in online communities. Recent learning methods like Flipped Classroom greatly depend on online activities. In addition to the data available from student activities, data are also created by educational institutions which use applications to manage courses, classes and students. The amount of data made available in the above scenarios is so enormous that traditional processing techniques cannot be used to process them. Therefore, its importance is immense in the education system.

1.3. Discovering Pedagogical practices

Today, students need an adaptive set of competences to meet the major challenges of the future. Pedagogy is defined simply as the method, and practice, of teaching. It encompasses teaching styles, feedback and assessment, and teacher theory. When a teacher plans a lesson, they will consider different ways to deliver the content. That decision will be made based on their own teaching preferences, their experience, and the context that they teach in. Teachers will use research from many different academic disciplines to inform their decisions, alongside their experience teaching those age groups. Teachers need the assistance of a learning analytics in this area. A teacher can plan accordingly by analyzing the various kinds of data of each student. This makes adaptive learning easier for teachers. In enhancing the Pedagogical practices, it plays a significant role.

1.4. Analytical Methods

Different analytical methods can be applied for Big Data Analysis. These include but are not limited to Basic Statistical Procedures, Visualization, Classifiers, Cluster Analysis, and Association Rule mining. A short description is given below of these techniques. This gives you a basic idea of the above techniques.

1.4.1. Basic Statistical Procedures

Tremendous amount of data are generated as a result of various transactions. The data may contain information such as interaction identification, session identification, user identification, and student activities. The data could be on different scales such as Nominal, Ordinal, Interval and Ratio. Depending on the goal and data type, one can apply both descriptive and inferential statistical procedures for data analysis. Descriptive statistics can include procedures such as measures of central tendency such as mean, median, mode; dispersion such as range, interquartile range, variance, standard deviation.

1.4.2. Information Visualization

Information Visualization is an area within the field of Human Computer Interaction (HCI). Information Visualization is defined as "computer-generated graphics of complex data that are typically interactive and dynamic". It provides a means of amplifying human cognition, enables them to see patterns, trends, and anomalies in the visualization to gain insight. In educational environments visualization of user data can provide educators insight into the students' activities in an online environment. Additionally, information visualizations can also support student by helping them monitor their own performance so that they can take necessary corrective actions.

1.4.3. Classifiers

Classifiers are a form of data mining technique. A classifier is a "model that predicts that class value from other explanatory attributes". The general idea behind the classifier is a two-step approach. First you must choose a classification method such as Decision Trees, Neural Network or Bayesian Network. Then you select a data set with known class values. The dataset is divided into a training set and test set. The training set develops a classifier based on an algorithm, then the classifier is tested with the test set, however, you would hide the class values. If the classification works accurately on the test set; one can assume that it would work on future data; otherwise, adjustments need to be made

1.4.4. Cluster analysis

Cluster analysis, often used for explanatory analysis, group cases based on a target variable in such a way that the degree of association between the target variable is maximum if they belong to the same group and vice versa. Clustering can be either hierarchical or non-hierarchical.

1.4.5. Association Rule Mining

Association rule mining discovers relationship among various attributes in a database. It produces IF-ELSE statements related to the attribute relationships. The goal is to uncover relations among different variables in a database that may appear to be unrelated. For example you can have a database with the different type of transactions in an online learning environment such as logging information, discussion boards, grades, quizzes, etc. Based on these transactions various rules can be formulated. Then for different cases and combinations of attributes the percentages can be calculated.

Figure 1.3.1: effective teaching and learning

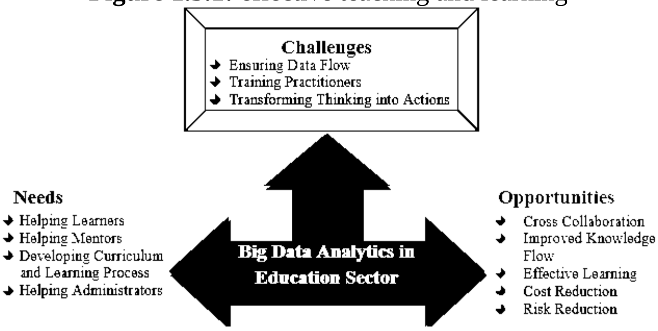

Figure 1.3.2: Big Data analytics in Education Sector

2. Literature Survey

Big Data and Analytics can be applied to various settings within education such as administrative and instructional applications, recruitment, admission processing, financial planning, donor tracking, and student performance monitoring [1].

Many technological innovations are specified, developed, piloted, and honed through partnerships with user communities who have expressed interest in adding an innovation into their existing workflow [22]. When learning technology innovations are introduced to a new audience, the affordances of those innovations may be understandably unclear at first, leading to unintended uses of the innovation [23]. In fact, the innovation may disrupt existing practices while new users learn to adapt new tools into their workflow [24]. This process of appropriation [25] can occur even if the new user community has expressed interest in the tool.

Learning analytics tools are especially susceptible to pushback and unintended uses from new users because they are very new and not well understood by those outside of the learning analytics community [26]. As developers of these learning analytics tools, we feel obligated to confront these challenges, particularly if the rich and massive data sets are to be generalizable and actionable for a broad set of educational audiences.

Authors in paper [2] describe that the aim of Learning Analytics is to collect Big Data in the context of teaching and learning, further to analyze and interpret it to gain new insights and to provide the stakeholders with new models for improving teaching, learning, effective organization, and decision making. Due to its connections with digital teaching and learning, Learning Analytics is an interdisciplinary research field with connections to the field of teaching and learning research, computer science and statistics

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Papamitsiou and Economides [8] did a study on the use of learning analytics and data mining in education. They listed the basic objectives of the major research done between 2008 and 2013 in the field of educational data analysis. Based on these objectives, some tasks techniques have been applied are outlined below.

Mykhaylo Lobur et al [17] provided an insight into the different repositories of information like data warehouses, transactional databases; relational databases etc. Leading to varied approaches for the data mining. They also discussed about the four basic mining approaches supported by different mining technologies: predictive model creation supported by supervised induction techniques, link analysis by association & sequence discovery techniques, DB segmentation supported by clustering techniques, and deviation detection supported by statistical techniques.

2.1. Applications of LA in education

Predicting Student Performance: Realizing the limitations of statistical models in the accurate prediction of student performances, Xing et al. [4] used learning analytics, educational data mining, and human-computer interaction (HCI) theory to develop a model to predict the final performance of the student

Educating Students Using Big Data: The twenty-first century has witnessed the integration of ICT into teaching and learning. Educational big data techniques can be used to create a customized learning environment in which students can be provided personalized learning paths for optimizing their performance [5].

Assessment of Students' Learning: There are several issues with the traditional way of evaluating students' learning. However, the use of big data analysis in the assessment of learning can result in faster progress as EDM can provide a real-time and continuous assessment [6].

Teaching and Research: Big data techniques can be useful to identify the academic resources to increase the awareness of the instructors. The analysis of textual and video data can provide many insights for instructors. For example, after analyzing the video data and performance of the students, researchers discovered that the presentation of the instructor's face in video lectures influences attrition and achievement rates and they found heterogeneous effects on attrition [7].

2.2. Open source tools

Several Open source tools exist which help in taming Big Data [3] . Some of the top tools are listed below.

- MongoDBis a cross platform document oriented database management system
- Hadoop is a framework that allows distributed processing of big datasets across clusters of networked computers using simple programming models.
- MapReduce is a programming model and framework used by Hadoop. It enables processing huge amount of data in parallel on large clusters of compute nodes of add-ons.

Research in education has resulted in several new pedagogical improvements. Community based learning environments have increased in number. Recent learning methods like Flipped Classroom [9] greatly depend on online activities. Several frameworks [10] and models have been proposed for online learning management systems to improve the learning experience. Due to the limitations of the conventional data processing applications, the educational institutions have started exploring "Big Data" technologies to process the educational data.

Lizhu et al [16] described the association rules in the context of data mining concentrating only on improving the efficiency of the algorithm neglecting the users understanding and participation. They revealed the fact that students historical records stored in the university databases could be a data source for mining the students' subjective interest and interest degree so that their performance may be improved through teaching and personal trainings.

2.3. Massive data in the education field

The author in [11] proposed state of art drawing on massive data produced by learning systems, notably the massive data of pedagogical field's which constitute the key elements of the present work. The author in this state of art has developed some methods dedicated to the creation of communication interfaces between a learning system and the new big data architecture. Next, he laid out some techniques and methods of learning analytics for such massive data. Many researchers have worked on the open source HADOOP Ecosystem [12], a system that processes massive data. The said architecture was proposed by the scientific community to give a large coverage of the massive data produced by learner interactions.

2.4. Learning Analytics Methods

Learning analytics is a combination of different disciplines like computer science, statistics, psychology, and education. As a result, we realized different analysis methods that do not only tend to be too technical but rather pedagogical.[13] Before classifying the analysis methods, we have been gravitated towards the beginning topics of the emergence of learning analytics, which briefly described methods and tools for collecting data and analyzing them [14] However, more methods being used to examine learners' data. Main methods categories are: (a) data mining techniques; (b) statistics and mathematics; (c) text mining, semantics and linguistic analysis; (d) visualization; (e) social network analysis; (f) qualitative analysis; and (g) gamification.

2.5. Data Process

Jaya Srivastava et al. in their work [14] stated that The application of data mining is different for educators and students. For students, the goal is to discover activities, resources and learning tasks that improve their learning, based on their attitude and likings while for educators, the goal is to have more feedback from students for evaluating the structure of the course content and its effectiveness on the learning process; to classify students based on their needs; to discover information to improve the adaptation and customization of the course, etc.

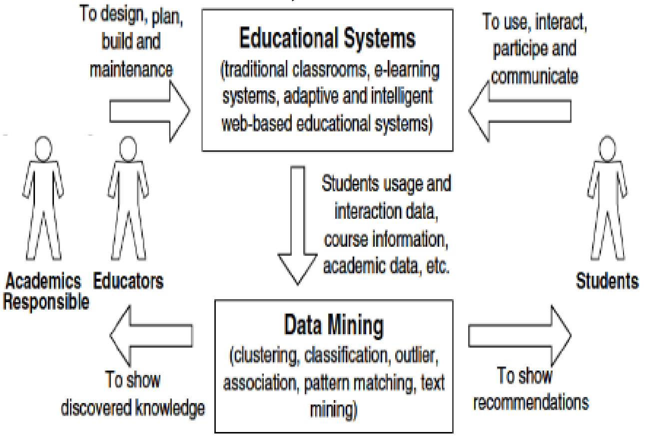

Fig no. 2.5.1: Data Process

Faouzi Mhamdi et al [19] described the Knowledge discovery saying that it provides new concepts or concept relationships hidden in large volumes of raw data which has the capacity to automate complex search and data analysis tasks. They also specified that data mining extracts nuggets of knowledge to be used in verification of hypothesis or the prediction and knowledge explanation and its different phases are data preprocessing, data processing or data mining and data post processing.

Timo Horeis et al [18] described the capability of the conventional systems for knowledge discovery and data mining revealing their ability to extract valid rules from huge data sets. These extracted rules describe the dependencies between attributes and classes in a quantitative way. They also discussed the effect of fusion of this knowledge combined with the qualitative knowledge from several experts' resulting in more comprehensive knowledge about an application area.

Qian Wan et al [20] discussed about the practical usefulness of data mining techniques necessitating an approach which would hope to bring a promising avenue to look at the data from a new angle in order to allow us find new, useful and actionable patterns.

3. Existing System

With the tremendous amount of data that is generated from the Internet, Learning Management Systems and other academic applications, it is very useful to make a decision about the learner. Existing systems are not capable of storing, analyzing and processing large amounts of data very quickly. A teacher can help a learner as a facilitator if they know all the aspects of learning. Existing systems provides an insight to a problem at the small level. However in order to enhance the pedagogy skills, to gain more insight into the data

3.1. Limitation of existing work

The implementation still lacks in adaptive teaching. More optimization is needed.

- More priority in quantitative analysis
- Educators are less likely to perform predictive analyzes because don't have equal importance in quantitative and qualitative assessment.
- Very few disciplines have been covered.
- Decision-making process is not easy, as the data of each area of the learner is not analyzed. Because it only analyzes structured data. There is imperfection in analyzing unstructured data.
- Analyze and process large amount of data at a slow pace as compared to big data processing systems.

4. Proposed system

Students need an adaptive set of competences to meet the major challenges of the future. The magnitude of technology is growing every day in the modern education system. A variety of technological methods are available to be integrated into teaching and learning. However, the inclusion of technology for effective learning can nevertheless be a challenge for educators. It has become important to create a new platform to fulfill the demand of organizations due to the challenges faced by Existing systems.

4.1. System Design and Architecture

The tool consists of three primary parts, two of which, the analysis algorithm and custom visualization. The final and capstone part of the system is a web application that couples the analysis algorithm and visualization platform with a basic web-based interface,
allowing a user to initiate analysis, interact with the data, and interpret the results.

4.2. Overview of System Architecture

The entire tool, from back-end algorithmic analysis to front-end web interface and visualization, is written in the PHP programming language. Adoption of the tool in any number of course, instructor, and institutional settings is dramatically simplified. To optimize compatibility with a variety of different teaching and learning systems, writings can be uploaded to the Point of Originality tool in a simple RSS format that organizes student writings in a standard, chronological, and uniform manner

4.3. Bayes theorem

Various algorithms and techniques like Classification, Clustering, Regression, Artificial Intelligence, Neural Networks, Association Rules, Decision Trees, Genetic Algorithm, Nearest Neighbor method etc., are used for knowledge discovery from databases. It consists of predicting the value of a (categorical) attribute (the class) based on the values of other attributes (the predicting attributes). There are different classification methods. In the present study we use the Bayesian Classification algorithm.

Bayes classification has been proposed that is based on Bayes rule of conditional probability. Bayes rule is a technique to estimate the likelihood of a property given the set of data as evidence or input Bayes rule or Bayes theorem.

The approach is called "naïve" because it assumes the independence between the various attribute values. Naïve Bayes classification can be viewed as both a descriptive and a predictive type of algorithm. The probabilities are descriptive and are then used to predict the class membership for a target tuple. The naïve Bayes approach has several advantages: it is easy to use; unlike other classification approaches only one scan of the training data is required; easily handle mining value by simply omitting that probability . An advantage of the naive Bayes classifier is that it requires a small amount of training data to estimate the parameters (means and variances of the variables) necessary for classification. Because independent variables are assumed, only the variances of the variables for each class need to be determined and not the entire covariance matrix. In spite of their naive design and apparently over-simplified assumptions, naive Bayes classifiers have worked quite well in many complex real-world situations

5. System specifications

5.1. Server Requirements

5.1.1. Hardware

System : 2.7GHz+
Hard Disk : 1 TB+.
Monitor : 15 VGA Colour.
Mouse : Logitech.
Ram : 4GB

5.1.2. Software

Operating system : LINUX Server
Webserver : Apache
Programming Language : PHP 7
Database : Any NoSQL DB

5.2. Client Requirements

System : Pentium IV 2.4 GHz
Hard Disk : 40 GB.
Monitor : 15 VGA Colour.
Mouse : Logitech.
Ram : 512 Mb.
Operating System : Any modern OS
Web browser & Internet Connection

5.3. PHP-ML - Machine learning library for PHP

PHP: Hypertext Preprocessor is a general-purpose programming language originally designed for web development. PHP code may be executed with a command line interface (CLI), embedded into HTML code, or used in combination with various web template systems, web content management systems, and web frameworks. PHP code is usually processed by a PHP interpreter implemented as a module in a web server or as a Common Gateway Interface (CGI) executable. The web server outputs the results of the interpreted and executed PHP code, which may be any type of data, such as generated HTML code or binary image data .

PHP-ML is a Fresh approach to Machine Learning in PHP. Algorithms, Cross Validation, Neural Network, Preprocessing, Feature Extraction and much more in one library. It includes all the features like Association rule Learning, Classification, Regression and Clustering

5.4. Web server and Apache

Web server is the software that receives your request to access a web page. It runs a few security checks on your HTTP request and takes you to the web page. Depending on the page you have requested, the page may ask the server to run a few extra modules while generating the document to serve you. It then serves you the document you requested.

Apache is the most widely used web server and an open source software available for free. It runs on 67% of all webservers in the world. It is fast, reliable, and secure. It can be highly customized to meet the needs of many different environments by using extensions and modules. Its job is to establish a connection between a server and the browsers of website visitors (Firefox, Google Chrome, Safari, etc.) while delivering files back and forth between them (client-server structure). Apache is a cross-platform software, therefore it works on both UNIX and Windows servers.

5.5. NoSQL

A NoSQL (originally referring to "non SQL" or "non-relational") database provides a mechanism for storage and retrieval of data that is modeled in means other than the tabular relations used in relational databases. NoSQL databases are increasingly used in big data and real-time web applications. NoSQL systems are also sometimes called "Not only SQL" to emphasize that they may support SQL-like query languages, or sit alongside SQL databases in polyglot persistent architectures.

NoSQL is a non-relational DMS that does not require a fixed schema, avoids joins, and is easy to scale. NoSQL database is used for distributed data stores with humongous data storage needs. Traditional RDBMS uses SQL syntax to store and retrieve data for further insights. Instead, a NoSQL database system encompasses a wide range of database technologies that can store structured, semi-structured, unstructured and polymorphic data

6. Methodology

6.1. Analytical Engine

The process of methodology Learning Analytics divided into five stages: capture, report, predict, act, and refine. Table 6.1.1 shows a characterization of the five stages by the type of questions.

Table 6.1.1: Questions Considered in each stage

Stage	*Questions*
Capture	• What data is being collected? • How frequently is the data collected? • Where is the data going to be stored? • Which format is going to be used to represent all events? • Are the observations *securely* stored?
Report	• Who will receive the reports? • How frequently? • What kind of information needs to be reported? • How will the reports be accessed?
Predict	• Which aspects of the experience need to be predicted? • Which factors can be used as input for the prediction algorithms? • What kind of prediction technique will be used? • How is the accuracy of the prediction going to be measured? • How are the predictions reported to the stakeholders?
Act	• What actions are considered? • How are the actions deployed in the learning environment?
Refine	• Are the data sources appropriate? Are the storage and access requirements for the • Data appropriate? • Are the produced reports useful? Are they reaching the appropriate stakeholders? • Are the prediction algorithms adequate? Are the predictions useful? Is the accuracy appropriate? • Should the set of actions be revised? Are the actions properly deployed?

6.1.1. Capture

The "capture" stage contains the required measures and techniques to make sure the information about events occurring in a learning environment is stored. This information is likely to be contained in a set of heterogeneous sources and is not directly ready to be processed. The issues present in this stage are related to how this information is centralized, how it is encoded, what issues might be encountered when the amount of data is very large, and how to make sure required security measures are observed.

6.1.2. Report

The "report" stage assumes that the data obtained in the previous stage is processed by an arbitrarily complex method ranging from simple visualizations to more complex algorithms that summarize or combine data. The result is new information that is reported back to the stakeholders. Various aspects need to be taken into account in this phase. The frequency of the reports will be affected by the complexity of the processing applied to the data. For example, if the amount of data captured is very large, a real-time computation of the reports is not feasible, whereas a periodic execution is more feasible. Also, the destination of these reports is important. Students, instructors, and administrators are the three groups that have a direct interest on receiving this information. In the case of students, reporting the data connects their activity with self-reflection on the learning experience. For instructors, receiving the reports directly increases their exposure to the intricacies of the learning process fostering the deployment of adjustments. In the case of an administrator, the received reports may also help to understand other issues in a learning community.

6.1.3. Prediction

The "prediction" stage takes the support for stakeholders further. In this stage the applications are specifically designed to provide answers to previously formulated questions. These predictions are computed using the data previously collected and applying one of the numerous predicting techniques available. From the point of view of information, predictions can be seen as a more sophisticated report and as such, it can be distributed as well among the same stakeholders. Prediction algorithms may help students anticipate difficulties during an experience, help instructors to identify students that are not performing as expected, and help administrators to anticipate complications in a course.

6.1.4. Act

The "act" stage is perhaps one of the most sophisticated and relies on the existence of predictions produced in the previous one. The objective is to generate actions that will change any aspect of the learning activity. For example, if the prediction algorithms report that the probability of a student becoming disengaged from a course is high, the material assigned can be automatically adjusted to include more supporting documents that may help alleviate the situation. The target of the acts included in this stage can be any of the stakeholders. A system may decide to send a notification to the counseling services of an institution after detecting that certain students may require their services. In a broader interpretation of this stage, manually deployed actions would also be included. In other words, an instructor, after reviewing the information reported by the learning analytic application, may decide to take some actions to target certain predicted situation. Thus, the actions considered may range from manually to automatically deploy.

6.1.5. Refinement

The last of the five stages proposed includes the "refinement" of the overall approach. The objective of this stage is to make sure that the previous stages are constantly reviewed and supervised and adjustments are included to improve their suitability. This refinement can be applied to the collection events to improve the quality of the information that is retrieved. The reporting can also be refined by providing more informative information to users. The connection between refinement and prediction algorithms is straightforward as both stages need to reduce the probability of false predictions and increase the accuracy of the results. Finally, the actions that are considered to modify a learning experience can also be the subject of refinement to make sure that they are applied to the right individuals, under the right conditions, and with maximal impact.

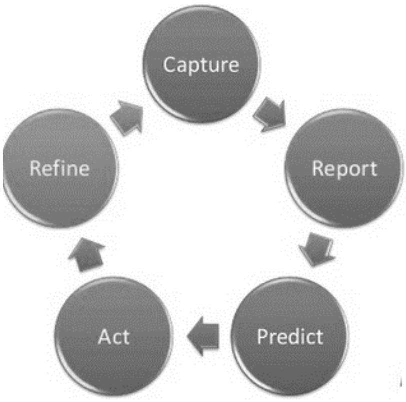

Figure 6.1.1: Analytical methodology

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