The Impact of Social Media Usage on Academic performance: A Survey Paper from a Randomized trial of Nigerian tertiary institution

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ABSTRACT

Social media allow the creation and interaction of user created content. Social medium places include Facebook, Twitter, Whatsapp etc. Students' casual discussion on social media mirror into their educational experience, mind-set, and worry about the learning procedure. Information from such environments can present valuable data to address students' problem. The impact of student's academic performance revealed from social media site requires human analysis or interaction. Several researches postulate that students spend much time on social media than their books. Based on this, a multi-label classification algorithm; the naive Bayes multi-label classifier algorithm is applied to parse data manually in order to determine the number of hours spent by 60 students from five tertiary institutions. This study presents a tactic and outcome that demonstrates how casual social media data can affect positively or negatively a student academic pursuit. It was observed that this is highly distinct, and mirrors well into the academic achievements of the reported students.

Keywords: Social media, Data mining, Social Networking Sites, Bayes Theorem.

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1. INTRODUCTION

Social media is a web-based mobile application that allows people or companies to interact with, and share new user-generated or current material, in digital environment. It is also defined as technologies that makes social communication easy and enable discussions among its participants. However, these media provides undesirables apart from the desirables. Generally, time is used in every human endeavor. So does social media. Time spent here by users can run into several hours if not minutes. And as such, may not be good for people that need such time for other creative ventures. According to a research conducted on Social Network, addiction to social media among Nigerian youths is on the increase. It has been observed that majority of the respondents spend more time on social networking sites, which affects their productivity negatively [2]. The findings of this study also indicate that youths in Nigeria spend too much time on social networking sites, at the detriment of other things. Also another study conducted in 2013 proposed that students use of social media for the purposes like entertainment, pornography, research, games, relaxation and other things [11].

2. DATA MINING

Data mining is a process of discovering useful or actionable knowledge in large-scale data [14]. Data mining also means Knowledge Discovery from Data (KDD) which describes the typical process of extracting useful information from raw Data [9]. The KDD process broadly consists of tasks such as data pre-processing, data mining, and post-processing. These steps need not be separate tasks and can be combined together. Data mining is an integral part of many related fields including statistics, machine learning, pattern recognition, database systems, visualization, data warehouse, and information retrieval [9].

2.1 Data Mining Process

Data mining is used to extract implicit and previously unknown information from data. Data mining is the process which provides a concept to attract attention of users due to high availability of huge amount of data and need to convert such data into useful information. So many people use the term “knowledge discovery device “or KDD for data mining. Knowledge extraction or discovery is done in different sequential steps used in data mining:

i. **Data Collection:** Data collection is the systematic approach to gathering and measuring information from a variety of sources to get a complete and accurate picture of an area of interest. Data collection enables a person or organization to answer relevant questions, evaluate outcomes and make predictions about future probabilities and trends.
ii. **Data Cleaning:** This entails the removal of irrelevant data from collected raw data.
iii. **Data Integration:** This step deals with combining multiple data sources into single data store called target data.
iv. **Data Selection:** Here, data relevant to analysis task are retrieved from data base as pre-processed data.
v. **Data Transformation:** Here, data is consolidating into standard formats appropriate for mining by summarizing and aggregated operations.
vi. **Data Mining:** At this step, various smart techniques and tools are applied in order to extract data pattern or rules.
vii. **Pattern Evaluation:** This step strictly identifies tree patterns representing knowledge.
viii. **Knowledge Representation:** This is the last stage in which, visualization and knowledge representation techniques are used to help users to understand and interpret the data mining knowledge or result. The goal of knowledge discovery and data mining process is to find the patterns that are hidden among the huge set of data and interpret useful knowledge and information.

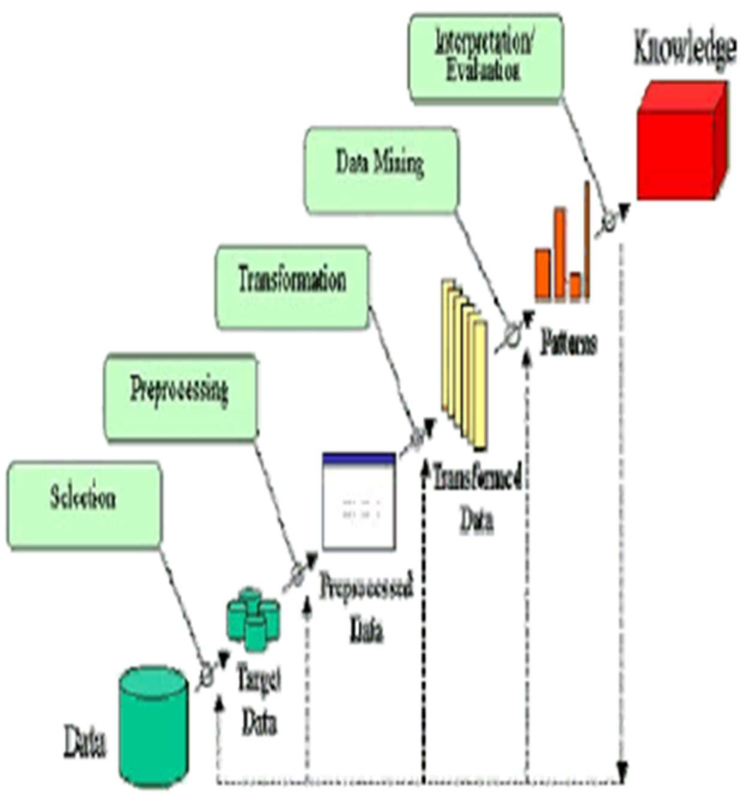

Fig 1. Data Mining Process

2.2 Data Mining Techniques

There are various major data mining techniques that have been developed and used in data mining projects recently. These include association rule classification, clustering, prediction and evaluation pattern which are used for knowledge discovery from database. Data mining algorithms are concepts that deal with data mining. These include: C4.5 Algorithm, K-Means Algorithm, Super Vector Machine Algorithm, AprioriAlgorithm, EM Algorithm, AdaBoost Algorithm, kNN Algorithm, Naïve Bayes Algorithm and CART Algorithm. They are broadly classified into supervised, unsupervised, and semi-supervised learning algorithms. Classification is a common example of supervised learning approach. For supervised learning algorithms, a given data set is typically divided into two parts which are training and testing data sets with known class labels. Supervised algorithms build classification models from the training data and use the learned models for prediction. To evaluate a classification model's performance, the model is applied to the tested data to obtain classification accuracy. Typical supervised learning methods include decision tree induction, k-nearest neighbors, naive Bayes classification, and support vector machines [9].

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Unsupervised learning algorithms are designed for data without class labels. Clustering is a common example of unsupervised learning. For a given task, unsupervised learning algorithms build the model based on the similarity or dissimilarity between data objects. Similarity or dissimilarity between the data objects can be measured using proximity measures including Euclidean distance, Minkowski distance, and Mahalanobis distance. Other proximity measures such as simple matching coefficient, Jaccard coefficient, cosine similarity, and Pearson's correlation can also be used to calculate similarity or dissimilarity between the data objects. K-means, hierarchical clustering (agglomerative or partitional methods), and density-based clustering are typical examples of unsupervised learning [3].

Semi supervised learning algorithms are most applicable where there exist small amounts of labeled data and large amounts of unlabeled data. Two typical types of semi-supervised learning are semi supervised classification and semi supervised clustering. The former uses labeled data to make classification and unlabeled data to refine the classification boundaries further, and the latter uses labeled data to guide clustering. Co-training is a representative semi supervised learning algorithm. Active learning algorithms allow users to play an active role in the learning process via labeling. Typically, users are domain experts and their skills are employed to label some data instances for which a machine learning algorithm are confident about its classification. Minimum marginal hyper plane and maximum curiosity are two popular active learning algorithms [7].

2.3 Educational Data Mining

Educational Data Mining is a promising regulation, concerned with budding techniques for discovering exclusive types of data that come from educational background, and using those techniques to better understand students, and the settings which they study. Learning analytics and educational data mining (EDM) are data-driven approaches emerging in education. These approaches analyze data generated in educational settings to understand students and their learning environments in order to inform institutional decision-making. Educational Data Mining (EDM) is the application of Data Mining (DM) techniques too. Its objective is to examine this type of information in order to determine educational research problems. EDM search for to use these data repositories to better understand learners and learning, and to develop computational approaches that combine data and theory to transform practice to benefit learners [13].

3 NAIVE BAYES CLASSIFIER

The Naive Bayes classifier is a straight forward probabilistic classifier which is based on Bayes theorem with strong and naïve *self-government* assumptions. It is one of the most basic text categorization methods with various applications in email spam exposure, private mail sorting, document categorization, language discovery and sentiment discovery. Naive Bayes executes well in many difficult real-world troubles. Even though it is frequently outperformed by other techniques such as boosted trees, Max Entropy, Support Vector Machines etc, Naive Bayes classifier is extremely efficient since it requires a small amount of preparation information as well as being less computational. One well-liked way to execute multi-label classifier is to convert the multi-label organization problem into multiple single-label categorization problems. Basically, naive Bayes is rated as more than one attribute best classifier because all the attributes coming from a class are independent of each other as they are mined from an online social networking media such as Facebook. Simple Bayesian network can be denoted as naive Bayesian classification assuming all the attributes are independent to each other when represented in Bayesian network.
This classifier offers a simple yet powerful supervised classification technique. The model assumes all input attributes to be of equal importance and independent of one another. Naive Bayes classifier is based on the classical Bayes theorem presented in 1763 which works on the probability theory. In simple terms, a naive Bayes

classifier assumes that the presence (or absence) of a particular feature of a class is unrelated to the presence (or absence) of any other feature. Even though these assumptions are likely to be false, Bayes classifier still works quite well in practice. Depending on the precise nature of the probability model, Naive Bayes classifiers can be trained very efficiently in a supervised learning setting. In many practical applications, parameter estimation for Naive Bayes model uses the method of maximum likelihood. Despite its simplicity, Naive Bayes can often outperform more sophisticated classification methods.

Bayesian Classification is named after Thomas Bayes (1702-1761), who proposed the Bayes Theorem. Bayesian classification provides practical learning algorithms and prior knowledge of observed data which can be combined. Bayesian Classification provides a useful perspective for understanding and evaluating many learning algorithms. It calculates explicit probabilities for hypothesis and it is robust to noise in input data.

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. The classifier is based on Bayes theorem, which is stated as:

$P(A|B) = P(B|A)*P(A)/P(B)$

Where

- P (*A*) is the prior probability or marginal probability of *A*. It is "prior" in the sense that it does not take into account any information about *B*.
- P (A|B) is the conditional probability of A, given B. It is also called the posterior probability because it is derived from or depends upon the specified value of B.
- P (B|A) is the conditional probability of B given A.
- P (B) is the prior or marginal probability of B, and acts as a normalizing constant.

4. DATA PARSING USING NAÏVE BAYES CLASSIFIER

Example: Taking a case study of students in a department, what is the probability of students passing examination?

a) If he/she spend 0.5 hrs on facebook?
b) If he/she spend 1 hrs on facebook?
c) If he/she spend 2 hrs on facebook?
d) If he/she spend 3 hrs on facebook?

Using Bayes Theorem

$$P(A|B) = \frac{P(B|A)*P(A)}{P(B)\,P(A)} \quad X \quad \frac{1}{2}$$

Where P (A) is the marginal probability of event A
P (B) is the marginal probability of event B
P (A|B) is the is the conditional probability of B given A
P (B|A) is the is the conditional probability of A given B

Solution (a)
Let A = 0.5hrs = 30mins = (60*30) seconds=1800sec,
B=total number of hours in a day=24hrs=(3600*24)=86400sec

Calculation in Seconds

$$P(A|B) = \frac{(86400/1800)*\ 1800*0.5}{86400*\ 1800}$$

= 0.0003

Calculation in Hours

$$P(A|B) = \frac{(24/0.5)*\ 0.5}{24 * 0.5}$$

= 1

Inference: This result shows that if a student spends at least 30 minutes on Facebook in a day, the probability of **success** rate is 1

Solution (b)
Let A= 1hr=(60*60)sec=3600sec,B=total number of hours in a day=24hrs=(3600*24)sec=86400sec

Calculation in Seconds

$$P(A|B) = \frac{(86400/3600)* 3600*0.5}{86400* 3600}$$

= 0.00015

Calculation in Hours

$$P(A|B) = \frac{(24/1)* 1*0.5}{24 * 1}$$

= 0.5

Inference: This result shows that if a student spends an hour on Facebook in a day, the probability of **success** rate is 0.5

Solution (c)
Let A= 2hrs=(3600*24)sec=7200sec,
B=total number of hours in a day=24hrs=(3600*24)=86400sec

Calculation in Seconds

$$P(A|B) = \frac{(86400/7200)* 7200*0.5}{86400*7200}$$

= 0.00005

Calculation in Hours

$$P(A|B) = \frac{(24/2)* 2*0.5}{24 * 2}$$

= 0.25

Inference: This result shows that if a student spends 2 hours on Facebook in a day, the probability of **success** rate is 0.25

Solution (d)
Let A= 3hr = (3600*3) sec=10800, B=total number of hours in a day=24hrs= (3600*24)=86400sec

Calculation in Seconds

$$P(A|B) = \frac{(86400/10800)* 10800*0.5}{86400* 10800}$$

= 0.000045

Calculation in Hours

$$P(A|B) = \frac{(24/3)* 3*0.5}{24 * 3}$$

= 0.17

Inference: This result shows that if a student spends3 hours on Facebook in a day, the probability of **success** rate is 0.17

Solution (e)
Let A= 4hr=(3600*4) sec=14400, B=total number of hours in a day=24hrs= (3600*24)=86400sec

Calculation in Seconds

$$P(A|B) = \frac{(86400/14400)* 14400*0.5}{86400* 14400}$$

$$= 0.000035$$

Calculation in Hours

$$P(A|B) = \frac{(24/4)* 4*0.5}{24 * 4}$$

$$= 0.125$$

Inference: This result shows that if a student spends 4 hours on Facebook in a day, the probability of **success** rate is 0.125

5. EVALUATION OF RESULTS

From the data collected using SUS questionnaires, the data were kept and monitored for 8 weeks in order to estimate the number of hours spent by each student on Facebook. The number of hours so observed were recorded and parsed through a multi labeled classifier known as Naïve Bayes. The result so obtained from the Bayesian Theorem revealed that students who spend more than an hour on frivolities on Facebook within 24 hours are likely to perform poorly. This analysis was examined graphically with of the Number of Hours plotted against each result of Bayesian assumption. An automated system was developed which also can handle the analysis and produce a probabilistic result based on Bayes Theorem.

Graphical Solutions
Table of Values

Number of Hours	Probability Rate of Success
0.5	**1**
1	**0.25**
2	**0.17**
3	**0.125**
4	**0.1**
5	**0.083**

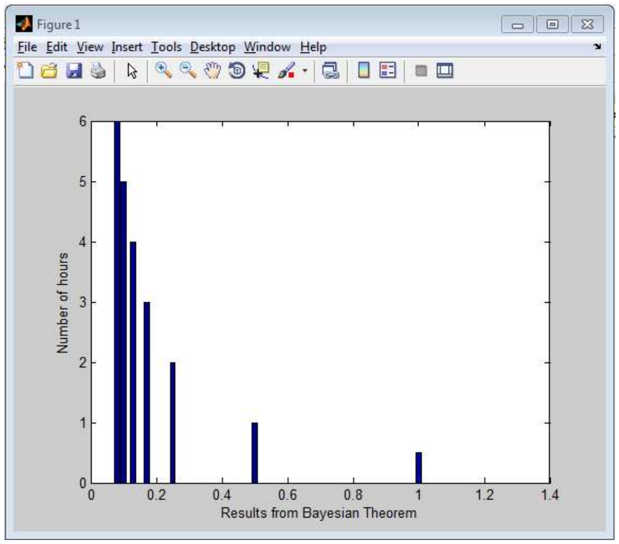

Fig. 2 A bar chart showing the number of hour spent on Facebook plotted against the probability rate of success.

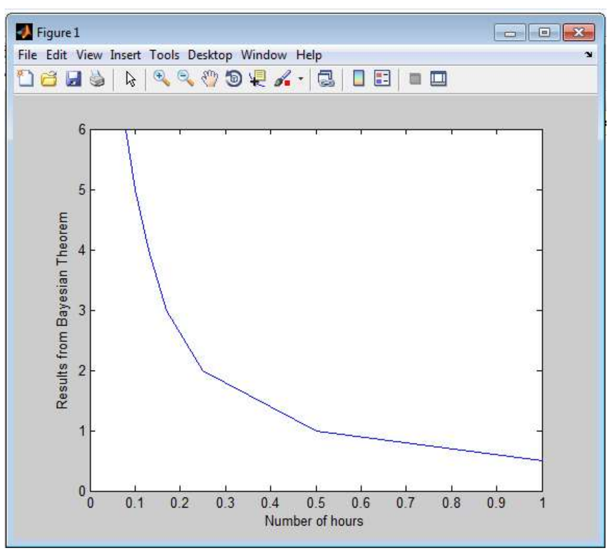

Fig. 3: A graph showing the number of hour spent on Facebook plotted against the probability rate of success.

6. DISCUSSION OF RESULTS

It is pertinent to say that the conditional probability of Bayes Theorem helps to calculate the probability of failure and success both manually and through the use of an automated system. This methodology helps provide values that could be used by future researchers to help ensure that the entire system is totally automated which will in turn contribute more the success rate of this research.
The results of data parsed were 1 at one 30 minutes, 0.5 at one hour, 0.25 at two hours and 0.17 at 3 hours' time duration. It has shown that the probability of success is decreasing with respect to a corresponding increase in hours. This means that there is a tendency of failure if a student spends more than an hour on frivolities on Facebook within 24 hours.

7. CONCLUSION

Mining social media data is helpful to researchers in learning analytics, educational data removal, and learning skill. The Naive Bayes Multi-label Classifier has been a very useful algorithm used for classification and arriving at results which are useful to future researchers.

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