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Sentimental Analysis of online study of College and School going Students

Mamta Tiwari[1]*, Swagata Dutta[2]

[1]Assistant Professor, Computer Application UIET,CSJM University,Kanpur, India
[2]MCA 2nd year, CSJM University, Kanpur, India

Corresponding Author: themamta1@gmail.com

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***Abstract*—** Online research opinion mining and sentiment analysis of college and school going students may accurately represent the students learning circumstances, providing the theoretical foundation for further revisions of teaching programmes. Analysis of student learning experiences using data mining and sentiment analysis in online learning community may lay the theoretical groundwork for future changes to teaching programmes. The term "online study" is the study that takes place using the internet. One of the objectives of the project is the creation and assessment of a conceptual model that incorporates students' learning and teaching preferences as well as technological experience, as well as their feelings about how these things impact their learning and teaching. An online survey of college and school going students was performed. It was found that some clusters of students were formed after applying k-means clustering machine learning algorithm which shows us that some changes should be adopted in the current online study scenario. Prediction and visualization of the data is done by seaborn, matplotlib python libraries which helps us to understand the pattern of the data. It is expected that this assessment would create a better system for students to study. Discoveries corroborate hypotheses about the influence of sentiment on factors such as attitude, favorite hobbies, and technological experience.

***Keywords*—** online study, sentiment analysis, python, machine learning, clustering, k-means sert.

I. INTRODUCTION

Analysis of student responses to an online survey using opinion mining and sentiment analysis may provide a more accurate picture of how much online learning should be kept, while the rest have to be offline, establishing the theoretical foundation for future changes to the curriculum. A unique topic sentiment analysis model, which outperforms existing state of the art methods, is presented to increase the exactness of topic sentiment analysis. As a result of emotion and opinion mining in the Online Learning Community, future teaching programme adjustments may be more grounded in theory. A new model that outperforms existing state of the art topic sentiment analysis methods is presented to increase topic sentiment analysis accuracy.

The Internet has transformed today's methods of exchanging ideas and thinking. Currently, the majority of this work has done during the use of various online platforms such as blogs, internet forums, product review websites, and social media. To express their sentiments, debate their ideas, and provide a viewpoint on the world around them, millions of people turn to social networking sites.

SA tells customers whether or not the information they've received about a product is adequate before they buy it. Companies or marketers utilize this data to better understand their products and services so that they can cater to the needs of the customers.

Written report of college education activities, such as papers, statement and phrases, typically hide academic feelings. Sentiment analysis, weight computation and semantic understanding approaches may all be used to explore the emotional connection between learning processes and sentiment. For the development of teaching theories and practices, academic sentiment mining can extract insights from comments in online study college and schools to analyze the elements that influence learning results in this respect.

Using real-world data from the online survey using Google forms was performed, the data was simultaneously collected in Google spreadsheet and was preprocessed before using it for mining. A rating 1-5 is given, where the scale goes from Strongly Disagree to Strongly Agree. Finally, a collection of formal concepts is created and shown, complete with topic-terms and a set of association rules:

The report makes the following recommendations:

- ✓ In an online research, a topic analytics approach is presented for analyzing and extracting possible subjects.
- ✓ A unique technique to identifying subject sentiment by measuring sentiment distance is developed based on feedback from college and school students.

- ✓ Furthermore, the hierarchical & related relationships also the granularity of sentiment data is derived.

	Name	Class	Time commitment of online classes(in hrs)?	Do you dropout frequently in online class?	Do you feel isolated in online classes?	Can you clear your doubts in online classes?	Do you feel any pressure on your eyes?	Are you self motivated to learn?	Do you get distracted easily in online classes?	Is it difficult for you to use the technological instruments / gadgets?	Do you enjoy learning in online class?	Is there a lack of discipline in online classes?	Are there any fraud and privacy issues for conducting online examinations?	Can practical courses be taught online?
0	Aastha Mishra	college	3	3	2	2	4	5	4	1	3	2	3	4
1	Deepanshu Shukla	college	1	4	3	4	5	5	4	2	4	4	2	1
2	Anchal Mishra	college	1	4	4	4	5	5	4	2	2	4	3	4
3	Khushbu	college	4	3	3	4	2	4	4	3	4	2	2	2
4	Shashwat Gupta	college	4	3	4	3	2	4	3	1	4	1	1	1

Figure 1. Sample of our dataset that shows various rating of students.

For textual information retrieval systems, the most important considerations are how to process, locate, and evaluate factual information. Despite the popular belief that facts are immutable, literature contains a significant amount of subjective information. Opinion, feelings, evaluations, attitudes and emotions are among the most common Sentiment Analysis contents SA.

As an illustration, by considering factors such as favourable or negative views, suggestions of things suggested by a recommendation system may be anticipated. By using SA, you may learn more about those products.

II. Related Work

There are several reasons for conducting a thorough investigation of the links between communicative processes, such as eye contact, and linguistic use. A thorough foundation for this study is provided by reviewing the academic literature in three key areas: communication and interaction in learning, communication in online learning contexts, and sentiment analysis. Starting off the chapter is a look at recent research on how people learn to communicate and connect with one another. The next step is to do a complete literature study on online communication and implementation issues. Finally, various research views on sentiment analysis are presented, as well as the effects of sentiment analysis on student understanding.

Opinion mining, also known as sentiment analysis, is a method of studying people's feelings. In computer science as well as artificial intelligence, it's part of Natural Language Processing which deals with the interaction between human and machine language. Sentiment analysis is a science that examines people's feelings, sentiments, assessments, judgments, attitudes, and emotions about products, services, organizations, persons, problems, events, themes, and their characteristics. Subjectivity and Polarity are two components of Sentiment Analysis. Subjectivity is defined as a statement that conveys feelings, views, or beliefs, while polarity is defined as a phrase that expresses emotions, which may be positive or negative in nature.

The findings revealed substantial improvements in student learning outcomes. This study looked at the advantages of giving students proper learning mode both online and offline. Where in case of online visual presentations based on theory saves much effort and time for teachers and gives better understanding to students who can clear their doubts at the same time. And in case of offline study mode practical subjects can be taught more easily, which brings a positive attitude in students. So, online and offline study mode should go hand in hand, where some of its part have to be online and the rest should be offline.

2.1 SENTIMENTAL ANALYSIS:

Sentiment analysis is a fascinating and popular study field that has recently emerged. Sentiment analysis is a technique for reviewing and analyzing the opinions of a large amount of people. Sentiment Analysis is a sub field of (NLP) that uses machine learning methods to recognize and extract opinions from text. This involves assessing the polarity (positive or negative) of a person's or a group's attitude toward a certain topic or organization. Due to its many practical applications, such as product analytics, market research, and market analysis, sentiment analysis has lately aroused the public's attention. Because the quantity of publicly accessible information on the Internet continues to grow, a large number of texts expressing views may be found on review sites and social media platforms such as Face book.

Every day, a great amount of data is generated via social networks, blogs, and other forms of media and disseminated throughout the world over the internet. This massive amount of data provides extremely main opinion-related in order that may be used to help enterprises and other parts of the commercial and scientific industries, as well as the general public. Sentiment analysis is important since manual tracking and extraction of this valuable information is not possible; therefore, it is necessary.

Sentiment identification:

An SSM (Sentiment Scores Matrix) is constructed to hold the distance of semantic similarity between opinion words in order to create sentiment scores. To begin, we use Section 4.3's concept lattice to extract the subject formal concept, which we then use to compile a set of term datasets. Once the sentiment polarity of the phrase has been established, the data from this analysis may be utilized to classify the term's sentiment using the sentiment dictionary's semantic similarity to the positive or negative seed words. First, an initial value is assigned to the seed word and then sentiment weights are added to the modifiers of the sentiment terms. Positive emotion, negative emotion, and neutral sentiment are the three types of seed words in the sentiment lexicon. It serves as the foundation for compiling a collection of emotion terms, which is mostly based on the opinions of domain specialists.

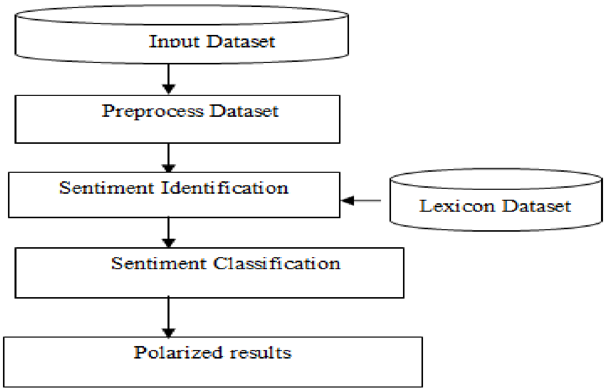


Figure 2

2.2 Sentiment Score calculation:

The SSM must be started in arrange to ascertain a student approach propensity toward a Question. The Sentiment Score is a number that ranges from 1 to 5, with 5 being the best sentiment (very positive). We use the same factors that app shops consider when deciding whether or not your app should be featured or ranked in the app store. These are some of them:

- The total number of reviews within the time period.
- The volume of reviews (whether it's increasing or decreasing).
- Text-based reviews are given a star rating.
- There is a trend in the star rating.
- Positive, neutral, and negative feedback ratio.

2.3 Sentiment Similarity Computing:

After obtaining the mapping associations between the student and the topic, it is possible to compute the emotion value. Its purpose is to turn the entire sentence into an adverb, providing for a more accurate understanding of how the opinions, thoughts, and experiences in the comment text were delivered. Furthermore, the higher the reported emotion polarity, the greater the influence on pupils' ability to grasp and analyze information.

2.4 APPROACHES FOR SENTIMENT ANALYSIS OF ONLINE LEARNING OF COLLEGE AND SCHOOL STUDENTS:

There are basically two techniques to sentiment analysis used by college students while conducting research:

a. Machine Education Approaches:

Machine learning is a learning process of a machine from experiences, which includes not only learning from examples, but also reinforcement learning, learning with a teacher, etc. In machine learning, the learning algorithm takes the dataset and its accompanying information as the input and returns a statement, like a concept representing the results of the learning as output.

Inductive learning through which the system infers knowledge from observing its environment, has two main strategies: supervised learning and unsupervised learning. The future situations can be predicted by the model produced by inductive learning methods. It can be used not only for predicting about the states already encountered but also for unseen states that could occur. Multiple models can be formed from a given set of examples. In such situations, the principle of Occam's Razor must be applied which states that if there are multiple explanations for a particular phenomenon, then the best way is to choose the simplest one because it's more likely to capture the nature of the phenomenon.

Supervised learning Supervised learning involves learning from examples where a training set is given which acts as examples for the classes. The system finds a description of each class and once such description has been formulated, it is used to predict the class of previously unseen objects.

Unsupervised learning In Unsupervised learning, there is no training set or prior knowledge of the classes. The system analyses the given dataset to find out the similarities that exist between the subsets of data. The result of this process includes a subset of class descriptions, one for each class, discovered in the environment. This mode of learning is similar to cluster analysis.

While data mining finds hidden knowledge in the data, machine learning on the other hand is concerned with improving the performance of an intelligent system. When database systems are integrated with machine learning techniques, the databases will need more efficient learning algorithms because realistic databases are normally very large and noisy.

b. Lexicon Based Approaches: In order to detect polarity, a Lexicon-Based method makes use of an opinion dictionary and compares it to the data to find matches. Vocabulary like "positive,""negative," and "objective" are all assigned emotion scores. Word-based approaches like the Opinion Finder lexicon are predicated on an existing sentiment dictionary, which is comprised of commonly used sentiment expressions such as "I agree" and "I disagree," as well as "I disagree."

Two sub classifications for this approach:

1. Dictionary Based: It is built on the procedure of words, which are generally gathered & labeled physically. As a result of a dictionary's synonyms and antonyms search, this collection grows. Senti Word Net, for example, is a thesaurus that was created using WordNet, a dictionary.

2 Corpus Based: The objective of using the corpus-based technique is to generate dictionaries specific to a certain field. To build these dictionaries, researchers start with a small selection of opinion keywords and then use statistical or semantic techniques to discover phrases that are conceptually similar to those keywords.

a. LSA is a type of semantic analysis that looks (LSA).

b. It's also possible that semantic approaches, such as using thesaurus relationships like WordNet or synonyms and antonyms, are a feasible alternative.

2.5 APPLICATIONS OF SENTIMENT ANALYSIS ONLINE STUDY OF COLLEGE STUDENTS:

2.5.1. Applications Reviews from Websites: Almost everything may be found in a review or remark on the internet. This includes, among other things, assessments of products, political criticism, and remarks about service. As a result, a system for extracting feelings regarding a certain product or service is required for sentiment analysis. Our comments and ratings on products, items and additional objects will be automated thanks to this technology. Customers and suppliers would be happy with this solution.

2.5.2 Applications Sub-component Technology: In recommender systems, a sentiment prediction algorithm may prove useful. Many negative comments or low ratings will keep an item from being recommended by the recommender system. When using the internet to communicate, we are frequently subjected to foul language and other obnoxious traits. These are able to be recognized by simply identifying and acting to lessen a strong unpleasant emotion.

2.5.3 Applications in Business Intelligence: Before making a purchase, many people check online evaluations of the items they're considering. Public opinion on the internet determines whether many companies' goods are successful or not. This is why sentiment analysis is so important in business. Online evaluations may also be used by businesses to better their products and, as a result, their reputation and customer satisfaction.

2.5.4 Applications across Domains: Sentiment Analysis has aided recent studies in sociology and other areas such as medicine and sports by revealing patterns in human emotions, particularly on social media..

2.5.5 Applications in Smart Homes: The technology of the future is intended to be smart houses. People will be able to manage any aspect of their house with a tablet device in the future since whole homes will be networked. A lot of study has been done on the Internet of Things (IoT). IoT would also benefit from sentiment analysis. For example, the house may change its ambience to provide a relaxing and tranquil environment depending on the user's present mood or emotion**.**

III. METHDOLOGOY

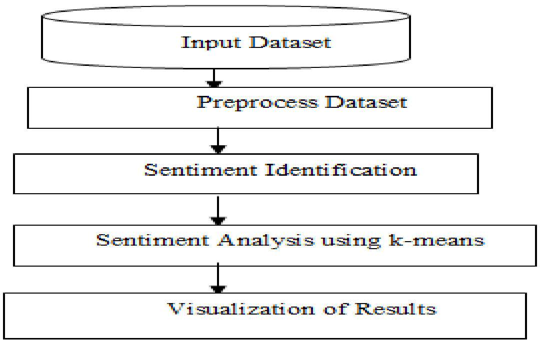


Figure 3 RESEARCH MODEL FLOWCHART

RESEARCH MODEL FLOWCHART

3.1. Clustering Algorithms Used for Research Model: Data mining and analytic methods are used in this study. For all studies, Jupyter Notebook-Python was utilized. The pandas, numpy, matplotlib, seaborn, sklearn, k-means clustering techniques were used to the data set. Pretreatment methods such as Clean Text, were applied to the feedbacks gathered in the data set before they were used in machine learning.

Clustering Approaches

Clustering is a data mining technique that is generally used for the discovery of data distribution and patterns in the underlying data. The technique aims at discovering both the dense and the sparse regions in the dataset.

Partitioning clustering

These algorithms partition the database into a predefined number of clusters (k clusters) that optimizes a certain criterion function. K-means algorithm is an example of partitioning clustering, using which each cluster is represented by the centre of gravity of that cluster.

3.2 K-Means Clustering

The k-means algorithm takes as an input a predefined number of clusters k, Means or averages relate to the common location of all the members of a selected cluster. When addressing clustering techniques, one should adopt a notion of a high dimensional space within which the worth of every attribute of a knowledge record represents a distance of the record from the origin along the attribute axis. However, the values within the dataset must all be numeric (in case the info is categorical, it must be transformed into numeric) and may be normalized. This helps us to compute the general distances in an exceedingly multi-attribute space. K-means algorithm could be a simple, iterative procedure, within which the centroid plays an important role. Many authors have defined the centroid as a synthetic point within the space of records which represents a mean location of the actual cluster. The coordinates of now are averages of attribute values of all datasets that belong to the cluster. The steps of the k-means algorithm are as follows:

1. Select randomly k points or data records to be the seeds for the centroids of k clusters.
2. Assign each data record to the centroid closest to the information record, thereby forming k clusters of information records.
3. Calculate new centroids of the clusters by calculating the typical of all attribute values of the info records belonging to the identical cluster (centroid).
4. Check if there's a change within the centroid of the clusters. If yes, start again from step 2. If no, cluster detection is finished and each record is placed in their respective clusters.

Distance Metrics A distance metric is used to calculate the distance between elements of a set which comprises of non-negative real number. Two elements are equal under a particular metric if the distance between them is zero. Distance functions present a method to measure the closeness of two elements. Here, elements can be matrices, vectors or arbitrary objects and do not necessarily need to be numbered.

Euclidean distance Euclidean distance is used to measure the distance between data points and the centroid in k-means clustering algorithm. The distance between two points in the plane with coordinates (x, y) and (a, b) according to the Euclidean distance formula is given by:
Euclidean dist((x, y), (a, b)) = $\sqrt{(x - a)^2 + (y - b)^2}$
For example, the (Euclidean) distance between points (-2, 2) and (2, -1) is calculated as

$$\begin{aligned} \text{Euclidean dist}((-2, 2), (2, -1)) &= \sqrt{(-2 - (2))^2 + (2 - (-1))^2} \\ &= \sqrt{(-4)^2 + (3)^2} \\ &= \sqrt{16 + 9} \\ &= \sqrt{25} \\ &= 5 \end{aligned}$$

3.3 Data Set: In this study, the words in user comments for the e-campus software were utilized to perform an automated 5-point Likert-type scale. If the remark's content includes words such as strongly disagree are classed as 1. In the text of the comment, if they disagree then it is marked as 2. If they select neutral, then it is classified as 3. If Agree was selected then it is marked as 4. And if they select strongly agree then it is marked as 5. As a consequence of this process, the data set was discovered to be balanced.

3.4 Data Preprocessing: All comments are changed to numbers in this area. The user has to select the rating from the following:

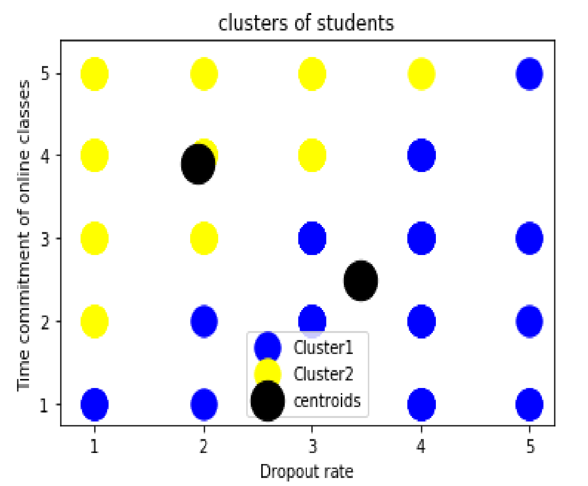
Strongly Disagree - which was converted to a rating of 1
Disagree - which was converted to a rating of 2
Neutral - which was converted to a rating of 3
Agree - which was converted to a rating of 4
Strongly Agree - which was converted to a rating of 5

]:

lame	Class	Time commitment of online classes(in hrs)?	Do you dropout frequently in online class?	Do you feel isolated in online classes?	Can you clear your doubts in online classes?	Do you feel any pressure on your eyes?	Are you self motivated to learn?	Do you get distracted easily in online classes?	Is it difficult for you to use the technological instruments / gadgets?	Do you enjoy learning in online class?	Is there a lack of discipline in online classes?	Are there any fraud and privacy issues for conducting online examinations?	Can practical courses be taught online?	Should there be a small gap between online classes?
astha ishra	college	3	3	2	2	4	5	4	1	3	2	3	4	5
nshu hukla	college	1	4	3	4	5	5	4	2	4	4	2	1	4
nchal ishra	college	1	4	4	4	5	5	4	2	2	4	3	4	4
shbu	college	4	3	3	4	2	4	4	3	4	2	2	2	4
hwat Gupta	college	4	3	4	3	2	4	3	1	4	1	1	1	3
awan Tiwari	college	4	1	2	5	1	5	1	1	5	1	1	5	1
Saini	college	5	1	1	5	2	5	1	1	5	1	1	5	4
a Ali	college	3	3	2	3	5	4	5	2	3	2	3	2	4
Dipali awat	college	1	3	3	2	4	3	4	4	2	4	2	2	4
ishek auria	college	3	2	2	4	3	4	4	1	4	2	3	2	5
weya Gupta	college	4	1	1	4	5	5	1	1	5	1	1	5	5

IV. Implementation and Results

1. The k-means algorithm is implemented using sklearn development environment. sklearn is an open source machine learning library written in python which has collection of all supervised and unsupervised machine learning algorithms like naïve bayes, support vector machine, k-neighbours, random forest algorithms and the numerical and scientific libraries like NumPy and SciPy are also supported by it.



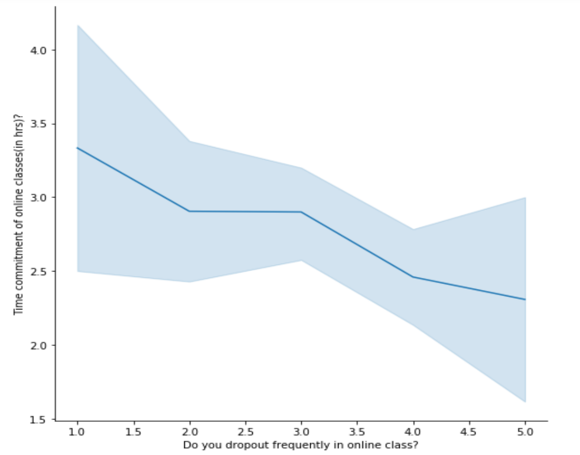
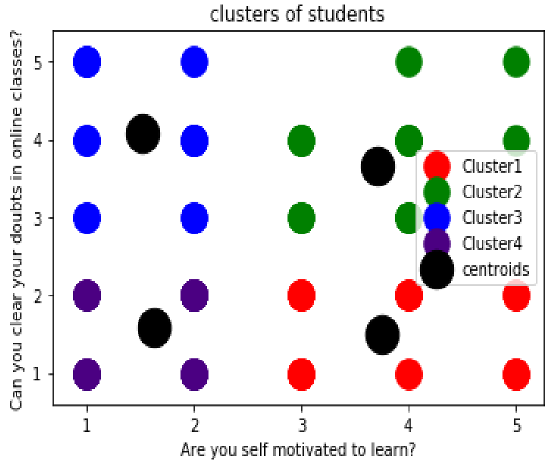


Fig 4.1 shows the relationship between Time commitment of online classes and the dropout rate.

x-axis represents the dropout rate and y-axis represents the time commitment of online classes.
The dense part of the Fig which is represented in blue clusters in downward right side, shows that the average time commitment of online classes is 3(in hrs), and if the time commitment is between 1 to 3 (in hrs) then the dropout rate is between 3 to 5 (neutral to strongly agree) i.e. if the time commitment is less then the dropout rate is more. Hence time commitment of online classes is inversely proportional to the dropout rate.



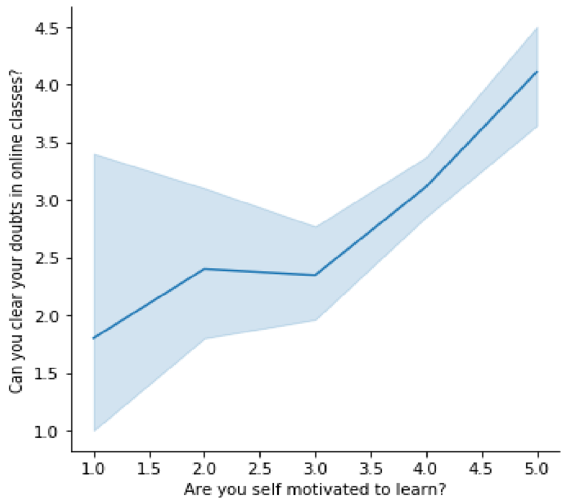
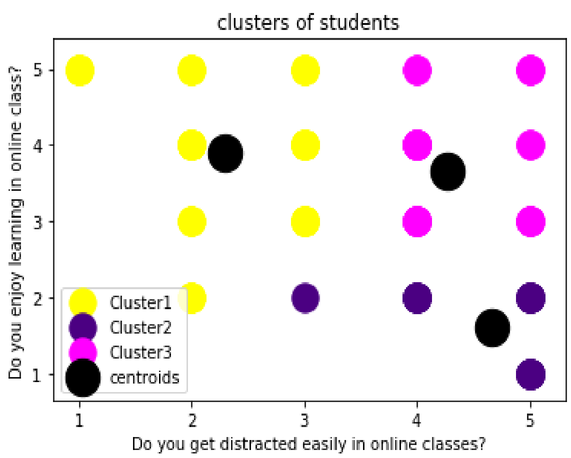


Fig 4.2 shows the relationship between clearing doubts in online class and self motivation to learn. X-axis represents Are they self-motivation to learn? and Y-axis represents Can they clear their doubts in online classes?. In the Fig there are four clusters formed, but the dense part is in green colour which shows self-motivation to learn is 3 to 5 rated (neutral to strongly agree) and clearing the doubts is also 3 to 5 rated (neutral to strongly agree). Hence if the students are self-motivated to learn then the fig shows that they can clear their doubts in online classes. The relationship between the two is directly proportional to each other.



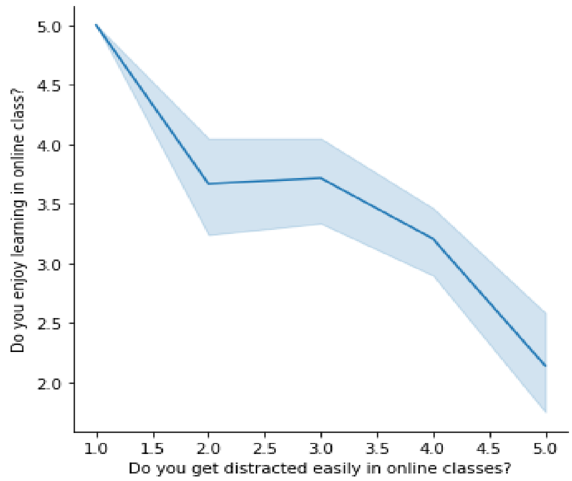
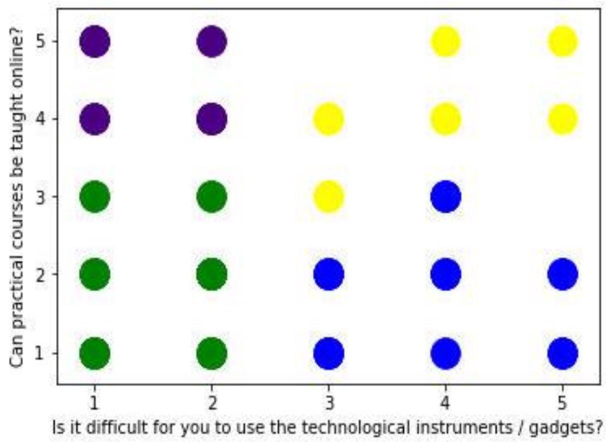


Fig 4.3 shows the relationship between students enjoying learning in online classes but getting easily distracted in them. X-axis represents Do the students get distracted easily in online classes and Y-axis represents Do the students enjoy learning in online classes. The fig shows three cluster formation in three different colours but the dense part of the cluster formation is in yellow colour, which shows that if the students enjoy learning in online classes rated 3 to 5 (neutral to strongly agree) then they don't get distracted easily in online classes rated 1 to 3 (strongly disagree to neutral). Hence the relationship between the two in the fig is inversely proportional to each other.



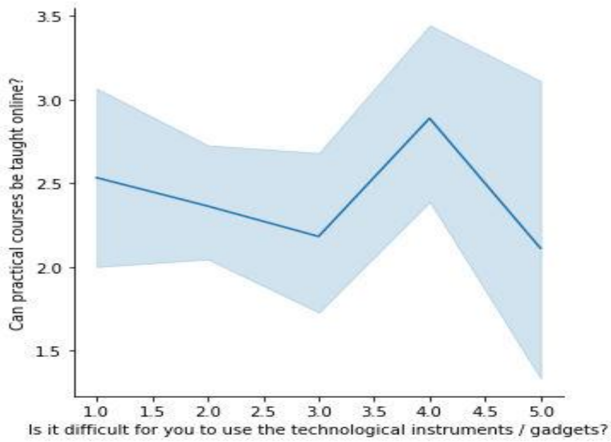


Fig 4.4 shows the relationship between learning practical courses online but difficult to use technological gadgets for that. X-axis represents difficulty to use the technological gadgets and Y-axis shows whether the practical courses can be taught online?. The fig shows four cluster formation but the dense part of cluster formation is blue coloured. Difficulty to use the technological gadgets is rated 3 to 5 (neutral to strongly agree) and whether the practical courses can be taught online is also rated 1 to 3 (strongly disagree to neutral). So , the fig shows that if there is a difficulty in using technological gadgets then the students don't want practical classes to be taught online and vice-versa. Hence the relationship between the two is inversely proportional to each other.

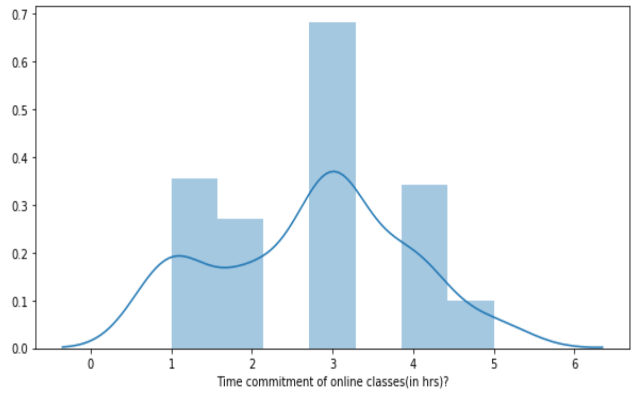


Fig 4.5 shows average Time commitment of online classes (in hrs).

The average time commitment of online classes as shown in the figure is 3 hrs.

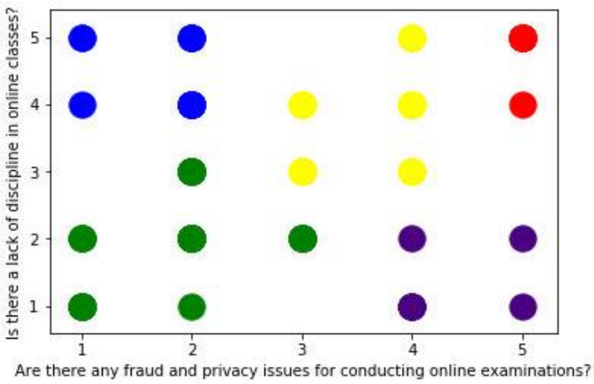
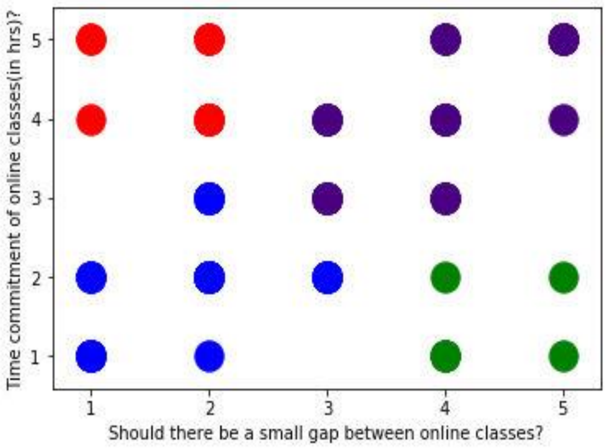


Fig 4.6 shows relationship between fraud and privacy issues for conducting examinations online and no lack of discipline in online classes. Y-axis represents whether there is a lack of discipline in online classes? And Y-axis represents whether there are any fraud privacy issues for conducting online examinations?. There are four cluster formation in the above fig, but the dense part of cluster formation is in green colour, which shows that fraud and privacy issues in online examinations is rated 1 to 3 (strongly disagree to neutral), and lack of discipline is also rated 1 to 3 (strongly disagree to neutral) i.e. that if there is no lack of discipline in online classes then there are no fraud and privacy issues for conducting online examinations. Hence there is a directly proportional relationship between the two.



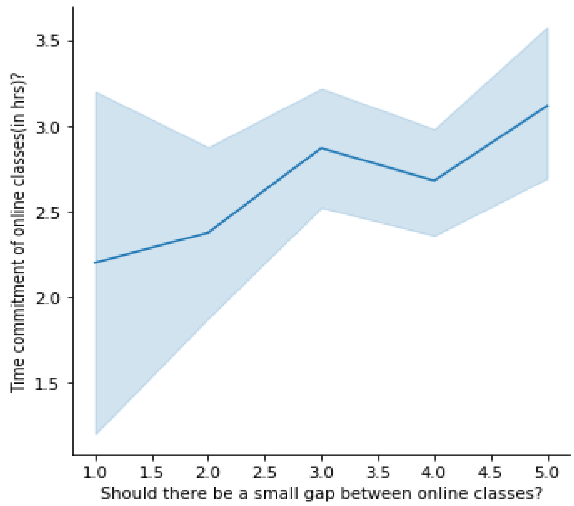


Fig 4.7 shows the relationship between Time commitment of online classes and small gap between the classes. X-axis represents whether there should be gap between online classes? And Y-axis represents the time commitment of online classes. There are 4 cluster formations in the fig but the dense part of the cluster formation is in indigo colour which shows the time commitment of online classes from 3 to 5(in hrs) leads to a short gap between online classes rated 3 to 5 (neutral to strongly agree). Hence there is a directly proportional relationship between the two.

Fig 4.8 shows the correlation values between each and every columns used to visualize the values of the matrix.

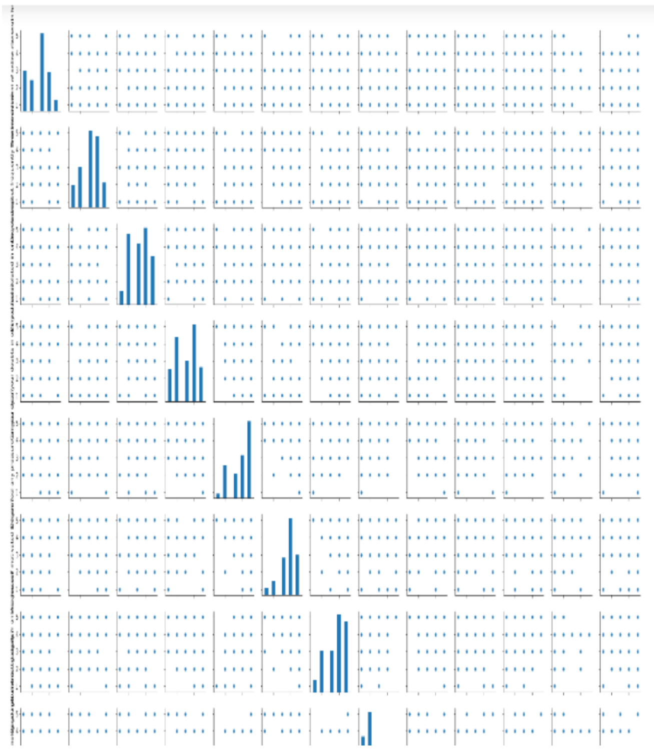


Fig 4.9 Plotting multiple pair wise bivariate distributions in a dataset. This shows the relationship between two variables in theData Frame as a matrix of plots and the diagonal plots are the univariate plots.

V. Conclusion and Future Scope

For a variety of themes, this study provides a framework for analyzing online sentiment among college and school students. Sentiment ratings are analyzed to find out how the participants feel, and a k-means clustering unsupervised machine learning algorithm is applied. The subject sentiment can also be represented using implication and association rules to improve the granularity of sentiment data.

When used as a practical guide, the suggested model can assist teachers better provide proper schedule for both online and offline classes, by detecting students' sentiment patterns. Sentiment analysis was used to determine how individuals felt about online education. Incorporating SA with online survey using Google forms offers a novel approach to discovering public views around online education. According to the findings of this study, online learning has favorable but cautious impressions in public digital media with a low polarity. For many nations, greater extensive distribution in the public media of online learning research is needed to develop strong public opinion and move policy toward online and blended learning as a method of creating a resilient system. This is an excellent place to start.

This paper reviews and compares current opinion mining methodologies, such as machine education and lexicon-based approaches and also includes cross-domain and cross-lingual methods and metrics of evaluation. While SVM and naive Bayes are the most accurate machine learning techniques, lexicon-based approaches have been found to be extremely effective in some cases and to require little effort in texts that have been human-labeled. These lexicon-based approaches can be considered baseline learning methods because of their high accuracy. We also studied the impact of different classifier characteristics. The more precise the findings are, the clearer the data are, and so is the result/prediction.

In this study, we found that dense clusters which represent strong public opinion are formed, which gives following conclusions:-

1. Time commitment of online classes is inversely proportional to the dropout rate of the students.
2. If students are self motivated then they can easily clear their doubts in online classes i.e. directly proportional.
3. Students enjoy learning in online classes and hence they do not get distracted easily i.e. inversely proportional.
4. Students feel it difficult to use the technological gadgets, and hence don't have positive attitude towards having practical courses online.
5. The average Time commitment of online classes for both college and school students is 3hrs.
6. Students feel that there is no lack of discipline in online classes and also there are no fraud and privacy issues if examinations are conducted online.

7. Students don't need a small gap between online classes if the average Time commitment of the online classes is merely up to 3hrs but beyond that they need a small gap between the classes.

So, we can come to a conclusion by the following observations that the students want both online and offline classes. As such for the visual presentations based on theory, the online classes saves a lot of time for teachers to clear the doubts of the students and provide a better understanding of the concepts, whereas the practical courses or subjects can be taught at ease in offline classes where the students can have a positive attitude towards getting hands-on experience in a well interactive classroom.

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AUTHORS PROFILE

Dr.Mamta Tiwari pursed Master of computer application from R.D.V.V Jabalpur, Master of Technoloy(Computer Science)from U.P.Technical University and got her Ph.D in Information Technology from M.G.C.G Vishwavidyalaya M.P. and currently working as Assistant Professor in Department of Computer Application,UIET C.S.J.M. University Kanpursince 2004. Her main research work focuses on Data Analysis, Data Mining and application on agriculture data, Deep Learning algorithims. Swa