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Enhancing the performance of educational systems using efficient opinion mining techniques

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Abstract

Governments and educational authorities around the world are emphasizing performance evaluation of educational systems. Opinion Mining (OM) has gained acceptance among experts in various regions, including the preparation space. The proposed model involves Two modules: the data preprocessing module and the opinion mining module. The main objective of our article is to enhance educational systems through the analysis of student comments, teacher comments and course comments. Furthermore, the proposed model uses a bundling task to make groups of packs for students from its comments. The datasets were 10,000 instances, 80% of which were for training and 20% for testing. The results showed that K-Means Algorithm had the best accuracy time /Sec of 0.03. The correctly classified 8,000 instances were equal to 96%, and incorrectly classified 2,000 instances were equal to 4%, Accuracy of the model is 95%, Recall is 94.8% and F-Measure is 93.7% between others algorithms. clustering and Association Rule Mining phases Algorithms namely Chi-Square test is good quality than Others Algorithms.

Keywords: Course comments, Educational systems, K-means algorithm, Opinion minning, Student comments, Teacher comments.

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Contents

Contribution of this paper to the literature
The proposed model is about predicting student performance based on the university student feedback/opinion. A hybrid approach (combination of machine learning & opinion mining) was proposed as a new solution for enhancing the performance of educational systems using efficient opinion mining techniques.

1. Introduction

Surveying the teaching and learning process at any preparation establishment isn't simply an imperative, yet the consistent improvement of the said foundation. This is because such analysis helps organizations obtain information about how undergraduates see the topic. It also helps to improve instructors and fosters the appearance framework for future reference. During a day where ends and reactions are thought of as being huge, collecting information through a Likert balance. Thus, one more method ought to be accepted concerning separating student analysis and this should be conceivable using the feelings and feeling assessment methodology. Student analysis is massive considering the way that it can help the instructors with understanding the students learning conduct. Customized systems rely upon artificial intelligence (AI) methodologies to acquire data. Hybrid systems join both rule-based and customized approaches. One endeavor in Sentiment analysis is to manage these sources and accordingly separate these evaluations into different classes like positive appraisal or negative evaluation. Another task is to determine whether a given text is enthusiastic, presenting the writer's perspectives, or objective, conveying essentially real factors (Qin, Wang, & Xu, 2022). These tasks were performed at different levels of examination ranging from the document level to the sentence and articulation level (Shao et al., 2022). Another task is perspective extraction, which started from point-based opinion mining at the state level. This huge number of tasks is under the umbrella of SA. Online information retrieval relies upon methodologies that separate the printed depiction of site pages. These methodologies start by regaining the relevant texts, separating the text into parts, checking the spelling and counting the repeated unequivocal words. Their capacities are known to be well confined concerning translating sentences and removing large amounts of information. Later undertakings in sentiment analysis (SA) go beyond the word level examination of the text and give clever thought level techniques to SA. This allows a more useful passage from (unstructured) scholarly information to (coordinated) machine-process competent data, unbelievably any region. (Shao et al., 2022).

2. Related Works

This segment comprises two sections A. Instructive opinion mining which introduced the new exploration's work concerning or assessment mining in educational data mining (EDM); part. summary of relevant articles introduced the reader to a selection of good-quality articles presented in this survey paper, we further pointed out and nominated 19 journals for articles. In particular, only articles published from 2018 to 2020 in Q1/Q2 level (https://www.scimagojr.com/journalrank.php) journals are in Table 1 (Qin et al., 2022). Concerning previous literature, we found that in the education area concentrated on detecting the methodologies and resources used in SA and identifying the main grants of using SA on education data. Our study is an extended form of this paper; thus a good deal of knowledge is presented from different measurements including bibliographic sources, study trends and patterns, and the latest tools used to perform SA. (Qureshi et al., 2022). In our work, we utilized Learning Information Extracting of information mining that is laid out to zero in on difficulties in schooling. Zeroing in on such difficulties can prompt further developing understudies who need guidance, eliminating and adding data to the unit as per understudies' cognizance, and tracking down viewpoints about the course (Nicoll, Douglas, & Brinton, 2022). The best outcomes were found with the K-Means cluster. The following are a portion of the elements of K-Means clustering processes

Table 1. A summary of relevant articles.

Ref.	Year	Technique used	Approach	Models/ Algorithms	Evaluation metrics	Dataset	Rank
Singh, Jenamani, Thakkar, and Rana (2022)	2020	NLP, DL	LB, Sup	Glove, LSTM	The F1 = 84%, R = 79%, P = 91%,Acc = 88%	16,175 sentences	Q1
Zhang., Liu, Chen, Ye, and Wang (2022)	2020	DL	Sup	LSTM, CNN	F1 = 87.13%	Coursera (104 K reviews)	Q1
Phan, Nguyen, and Hwang (2022)	2020	ML	Sup	NB, SVM, k-NN, GBT	The F1 = 88%	Grade main	Q1
Huang (2022)	2020	NLP	Us	E-LDA, SVM, means, ft*if	F1 = 89%	Questionnaire (10 students)	Q1
NCT05241041 (2022)	2019	DL	LB, Sup	Glove, LSTM	The F1 = 87%, P = 89%, R = 86%, Acc = 94%	Questionnaire 2015 students	Q1

A. Educational Sentiment Analysis

Instructive sentiment analysis is an application area of data mining that is made to choose issues in training. Subsiding such issues can instigate helping students who, the necessitating heading, taking out and adding raw material to the unit according to students' appreciation and finding students' evaluations in regards to the course. Assessment mining in any case called subjectivity evaluation, assessment mining, and examination extraction is the utilization of language the executives and computational (Mondragon-Estrada & Camacho-Zuñiga, 2021). Furthermore, message appraisal to see and recover unequivocal information from the message is done by focusing on the subjectivity of the appraisal. While looking for the achievement of a thing it is important to understand what combinations the client liked or loathed, the term for this is incorporate extraction. In the advancement business field, the get-together issue of dispersed travelers' comments about their various experiences was considered in (Alvarez-Cueva, 2022).

B. Students Feedback

The student's feedback is essential considering the way that it can help educators with understanding the students learning conduct. The assessment ought to be taken to make reinforces in education (Sandra, Gunarso, & Riruma, 2022). Student risk is essential in preparing and one strategy for overseeing and assessing it is through participation (Ezechukwu, 2022). The standard technique for students presenting requests is lifting their hand to ask, yet this way doesn't work for everyone like shy people. Students' nonparticipation is a common concern for educators (Zhou, 2022). In very large classes, it very well may be unfavorable on the off chance that every individual required one. However, at that point not a lot of data will be incorporated (Gravelle, Phillips, Reifler, & Scotto, 2022). A maker endeavored to see what student response systems mean for student learning in immense discussions (Kolano & Sanczyk, 2022) where students have less of an opportunity to present requests by virtue of the class size (Chen, Liu, Zhang, & Al-Qudah, 2022). Lack of interest could be from students not centering. Students can be explicitly due to encountering issues in excess aware of better results than those students who don't.

3. Proposed Model

An efficient sentiment analysis student comment model (SASCM) is proposed to extract the remarks from the free-message remark part of the survey. The proposed model incorporates both the opinion mining area and the irregularity identification space to accomplish its point-gone. Figure 1 explains with a model the different components of the suggested SASCM version beginning with controlling the accessible remarks and finishing with a rundown of extremity student's remarks. The SASCM model comprises three significant modules; information pre-handling module, opinion mining module, and adjusted scorecard (BSC) module. SASCM design shows up in Figure 1. The input dataset is student feedback and courses for all students as datasets, then we aggregated two datasets in one database namely student feedback and courses. We then transferred them to the *data pre-processing module* (Kewsuwun & Kajornkasirat, 2022).

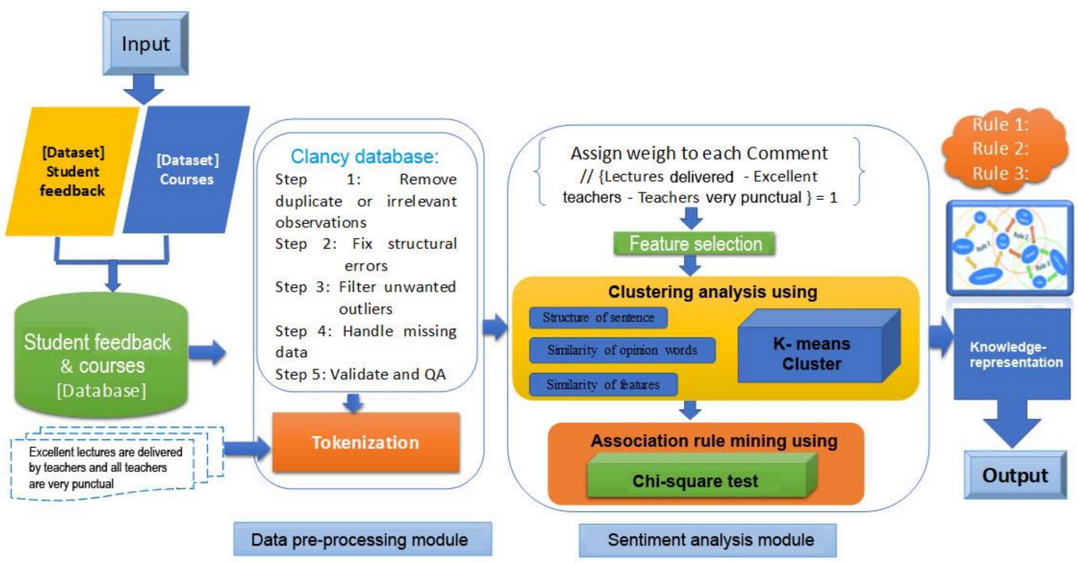

Figure 1. Sentiment analysis student comment model (SASCM).

A. Information Preprocessing Component

Participating in this part, the student's comments were changed and cleaned to be sensibly utilized for dealing with in the accompanying module, the opinion mining module., the attitude mining goes all the way through five natural language processing (NLP) endeavors being in the going with regions. In the main cycle, we use Clancy Database through:

Stage 1: Remove copy or immaterial perceptions, Step 2: Fix underlying mistakes, Step 3: Filter undesirable anomalies Stage 4: Handle missing information, Step 5: Validate and quality assurance (QA) (Salsabila, Pratiwi, Ichsan, & Husna, 2021).

- Tokenization: In the tokenization stage, the giant strings of text are isolated enthused about things that are a little arrangement of articulations. More critical pieces of the message may be divided into choices; choices can get away from phrases, and so forth. The model sentence below shows a depiction of Tokenization and Clancy dataset {Excellent Lectures Are Delivered by Teachers and All Teachers Are Very Punctual}. After tokenization, the resulting message will be: {Excellent Lectures Delivered - Teachers Very Punctual} Advanced managing is regularly determined after a message remark has been appropriately tokenized. Besides, lower packaging: text change into the lower case is a reasonable and solid method for managing to pre-process the text remarks. It is suitable for near issues related to text mining and NLP. Lower packaging is advantageous when the dataset isn't excessively large and assists with making information unsurprising (Utami & Masripah, 2021). The lower packaging is essential to ensure that the word matched separate parts, for instance, "phenomenal" and "eminent" - ought to be changed to "stunning" and stop words taken out. Stop words are a group of words that are reliably utilized in a particular language. For instance, in English a, the, is, her, are, on, of, with, about, what, when, where, that, this, by and be. Similarly, "so forth" is considered as a stop word. The explanation for killing these stop words is that they are futile and shedding them from surveys empowers the model to focus on different words that are generally basic and along these lines, accomplishing a high definite in the far-fetched occasion that the stop words are taken out: (Onan, 2021). {Content of Courses Improves My Knowledge}. Sifting: performing more disinfecting for information is finished by clearing out non-English words and disengaging words by their length, where long words, not short words, will be taken out (Gonzalez-Igual, Corzo Santamaria, & Rua Vieites, 2021) Stemming: stemming is the correspondence used to dispose of the word joins (prefixes) still hanging out there to get the root plan of a word stem.

Stemming systems put word varieties like "amazing", "extraordinarily" and "for the most part basic" to the chance of "mind-blowing" (Zhang, Zhang, Zhang, & Wu, 2021).

B. Sentiment Analysis Module

The opinion extraction technique introduced in this paper depends on a word reference-based strategy for report-level inclination portrayal undertakings. The cleaned studies gained from the past data pre-taking care of module went through three phases; perceive feeling words, remove the limit scores of assessment words, and finally learn the overall advantageousness for each appraisal holder. An organized explanation of every phase is given below (Han, Wu, Huang, Huang, & Zhao, 2020).

- Highlight Selection: this is the best known approach to picking our point of view is worthwhile in our files and can be ignored. This will presumably integrate dispensing with emphasis and stop words, changing words by advancing them lower safeguard, picking how to oversee mistakes or language incorporates, and picking whether to do stemming. What's more, identify feeling words: The identification of feeling words is major to appreciating the presented perspectives in client reviews. Words that are generally used by people to convey their great or melancholy opinions are known as opinion/feeling words. Standard excellent assessment words (fair, shocking, and extraordinary) and gloomy inclination words (dreadful, horrendous, and terrible). Thus, linguistic element (POS) plans are important to eliminate willful words. Linguistic structure naming is "the most well-known approach to arranging a word in the text to its relating tag" (Rao & Palathil, 2020). The essential purpose in doing POS marking is that descriptors and action word modifiers would be strong characteristics of the evaluation of the review, so they help to perform appraisal mining that the most used appraisal words are descriptors and intensifiers (Ezechukwu, 2022). Also, assigning the furthest point and concentrate scores: once After the identification of feeling words in each review record, the ensuing stage is to the limit the strength of every assessment word. Thus, 'SentiWordNet' which is a lexical resource for opinion mining was used. SentiWordNet 'SWN' is appraisal jargon derived from the WordNet informational index and
- The group analysis stage is a multivariate method that intends to organize an illustration of subjects (or things) given a lot of assessed factors into different groups so much that relative subjects are set in a comparable social event. This implies that bunching strategies are used to pack data/discernments in several segments so data inside any part is relative while data across pieces is exceptional. Portraying what we mean when we say "tantamount" or "exceptional" discernments is a basic piece of pack assessment that consistently requires a lot of important data and imagination past what genuine instruments can give. We can do bundling through the going with progress: design of sentence, similarity of evaluation words and similarity of components. We then used four estimations to be clear: two-adventure cluster, hierarchical cluster, frame cluster, and K-means cluster. Finally, we found the best calculation was K-means cluster. The K-implies bunching calculation figures centroids and rehashes until the ideal centroid is found. It is possibly known the number of bunches that are right there. It is otherwise called the level bunching calculation. The quantity of bunches found from information by the strategy is signified by the letter 'K' in K-implies. In this strategy, information focuses are given out in bunches so that the amount of the squared distances between the data of interest and the centroid is almost as little as could be expected. It is vital to note that diminished variety inside groups prompts more indistinguishable data of interest inside a similar bunch. The K-means algorithm in practice; the following stages help us in knowing how the K-means bunched strategy functions: Step 1: we want to define the bunches (K) that this method should create, Step 2: select K arbitrary data of interest and gathering them into groups. Sort the information into classes given the quantity of data of interest, Step 3: ascertain the bunch centroids, Step 4: Repeat stages 1-3 until we distinguish the ideal centroid, which is the designation of information focuses to semi-bunches, 4.1 Calculate the complete of squared distances between data of interest and centroids; and 4.2 (Alfayoumi, Alshraideh, Al-Sharaeh, Leiner, & AlDajani, 2021).
- Association rule mining phase: Affiliation rule mining, as the name suggests, alliance rules are direct If/Then clarifications that help with finding associations between obviously independent social databases or different data vaults. Most AI estimations work with numeric datasets and from now on will commonly be mathematical. Nevertheless, connection rule digging is suitable for non-numeric, straight out data and requires a smidgen of touch more than fundamental counting. Then, dependent upon going with two limits, the critical associations are taken note. Support: Support exhibits how as frequently as conceivable the if/relationship appears in the database. Conviction: Confidence tells about the times these associations have been considered to be self-evident. We used three estimations: Chi-square test, Lambda test, and estimated time of arrival (ETA) test. Finally, we found the best calculation was Chi-square test. In the first place, Chi-square just tests whether two individual factors are free in a paired, "yes" or "no" design. Chi-square testing gives no understanding of the level of distinction between the respondent classifications, implying that scientists can't tell which measurement (a consequence of the Chi-square test) is more prominent or not exactly the other. Second, Chi-square expects scientists to utilize mathematical qualities, otherwise called recurrence counts, rather than utilizing rates or proportions. This can restrict the adaptability that analysts have as far as the cycles that they use. The result was an information portrayal of the data set for deputy criticism and courses as displayed in Figure 1 (Liu & Liu, 2021).

4. Experimental Study

In this section, a preliminary report is unveiled to graph the procedure used for surveying the proposed model. Devices used and dataset: the International Business Machines (IBM) ® Statistical Package for the Social Sciences (SPSS) ® programming stage offers progressed credible evaluation, a tremendous library of AI assessments, message assessment, open-source extensibility, union with enormous information, and unsurprising sending into applications. Its accommodation, adaptability, and flexibility make SPSS available to clients of all levels of ability. Moreover, it's sensible for undertakings of all sizes and levels of multifaceted nature and can help you and your relationship with finding new entryways, further creating capability, and restricting risks. The test is driven on a pc with Microsoft

Windows 10 operating system with Intel® Core™ i7- 7500U central processing unit (CPU) @ 4.0 GHz with 8.00 GB RAM. To endorse the proposed model, the assessment was performed on a certifiable dataset used in this paper of 10,000 comments removed from our enlightening study entrance. The dataset was named with feeling furthest point marks {positive, critical, and neutral} (Ghasiya & Okamura, 2021). Table 2.shows cases of student comments. Our students' feedback data is assembled from the Arab Academy for Science Technology and Maritime Transport (AASTMT) College Management and Technology for four workplaces namely marketing, finance, business information systems (BIS) and political science. Students' reactions are from two years, 2011 and 2021. Right after disposing of all trash, worthless and duplicated sentences, we had more than 10,000 remarks. The data was then remarked on into three imprints: positive (POS), negative (NEG) and fair or neutral (NEU). Table 1 shows real dataset student at AASTMT. Table 2. shows data set in Excel for student feedback represented in Table 3 (Amala & Elizabeth, 2020).

Table 2. Real data set student feedback.

ID	Teaching method	Course content	Examination	Lab work
1	Teacher are punctual but they should also give us the some practical knowledge other than theoretical	Content of courses are average	Examination pattern is good	Not satisfactory, lab work must include latest technologies
2	Good	Not good	Good	Good
3	Excellent lectures are delivered by teachers and all teachers are very punctual.	All courses material provides very good knowledge in depth.	Exam pattern is up to the mark and the Capa depends on the various marks distributions like ca, met etc. which is very nice as compare to other institutions. Paper checking does not depend on length of ques but on the material which is the best part of it.	Lab work is properly covered in the labs by the faculty and evaluations help to learn more practical knowledge in depth.
4	Good	Content of course is perfectly in line with the teaching philosophy that is being perpetuated here i.e. cramming, rote learning.	Again, the university tests students of their ability to memorize stuff. Questions should emphasize more on concepts rather than testing brain's cramming storage house.	Good
5	Teachers give us all the information required to improve the performance.	Content of courses improves my knowledge	Examination pattern is good	Practical work provides detail knowledge of theoretical work
6	Yes	Yes	Yes	Yes
7	Good and punctual	Good	Good	Good
8	It is good	This semester university has provided best teachers	I like the question pattern	Everything is going fine in lab. Learning new things. That is good for us
9	Good	Needs some improvement	Good	Good
10	Good	Content of course is perfectly in line with the teaching philosophy that is being perpetuated here i.e. cramming, rote learning.	Good	Good

A. Data Pre-Handling Module

As were in Table 3. To set up the attempted dataset for the evaluation mining module, the collaboration report from the data overseer whose capacity as a compartment director was used. Tokenize director isolates the text of a review into a gathering of tokens. The non-letter character mode was used, which achieves tokens with a single word. Change cases manager was used to change all characters in a review to cut down a case. Then, the loud deafening words that don't affect the portrayal task were removed from the report by using filtering stop words (English) director which eradicates every token matches the innate stop word list. Channel Token (by length) overseer diverts tokens considering the number of characters they contain. For the proposed model, the minimum number of characters picked two (Pazmiño, Badillo, González, & García-Peñalvo, 2020).

Table 3. The dataset in excel student feedback.

Source text	Sentiment
Teaching method	Positive
Course content	Positive
Examination	Positive
Lab work	Neutral
Teacher are punctual but they should also give us the some practical knowledge other than theoretical	Positive
Content of courses are average	Neutral
Examination pattern is good	Positive
not satisfactory, lab work must include latest technologies	Negative
Good	Positive
Not good	Negative
Good	Positive
Good	Positive
Excellent lectures are delivered by teachers and all teachers are very punctual.	Positive
Lab work is properly covered in the labs by the faculty and evaluations help to learn more practical knowledge in depth.	Negative

B. Sentiment Analysis Module

The examination has applied a word reference-based opinion mining approach. Open WordNet Dictionary manager is liable for partner Rapid Miner with WordNet-3.0 word reference, which was taken care of in a preordained and describing the wordlist. The stem (WordNet) head was used to reduce the length of the words to the base length by applying the Porter stemming computation and the standard-based replacement for word postfixes. Stem WordNet uses WordNet word reference to describe the stem rule. This director uses a WordNet 3.0 delineated in Figure 3 and a SentiWordNet 3.0.0 informational index that is related to Synset identifications to isolate assessments of a data review. This chairman licenses us to perceive the resolute words by picking the kind of words to be used for learning. In the running examination, modifiers and qualifiers are used as assessment words. The head registers the assessment of each word to get the outright feeling of a file, where the primary significance of a word for the most part affects an inclination and each next importance affects an inclination. Energy for each evaluation holder, by and large, is not set in stone as the typical worth of all word sentiments as shown in equation (1). The value of feeling is in the scope (- 1.0 to 1.0]) where - 1.0 means particularly negative and 1.0 means very great (Kovačević, Grljević, Bošnjak, & Svilengaćin, 2020).

5. Results and Discussion

This section looks at the results gained from the past runs of the coordinated investigation. This paper has played out the test evaluation on a moderate assessed certified dataset on bits of students' of feedback data and is collected from the Arab Academy for Science Technology and Maritime Transport (AASTMT) College Management and Technology for four divisions, specifically marketing, finance, BIS and political science. Students' reactions were from two years 2011 and 2021. After removing the trash, worthless and, replicated sentences, we had more than 10,000 unrefined sentences. We used three evaluation estimations. Evaluation of the proposed model was done using a standard appraisal estimation of recall and F-measure. Exactness and audit are described as similar to clear sure (TP), sham positive (POS) and misdirecting negative (NE) as shown in Figure 2.

$$\text{Precision(p)} = \frac{TP}{TP+FP}$$

$$\text{Recall(R)} = \frac{TP}{TP+FN}$$

$$\text{F} - \text{Measure} = \frac{2\,PR}{P+R}$$

Figure 2. Equations used for evaluation metrics.

In this section, the accompanying table shows a correlation between the disarray network and the four models. the proposed combination model is low contrasted with each of the three different models and what the value is. Table 4 shows an illustration of understudy criticism opinion investigation. Figure 3 shows opinion mining for replacement criticism in instructive institutions (Tiwari & Santhi, 2021).

Table 4. Results of student feedback sentiment analyses.

Sentence number	Keyword	Sentiment	Sentiment score
1	Punctual	Positive	0.746
1	Give	Positive	0.725
1	Practical	Neutral	0.247
2	Good	Positive	0.743
3	Latest	Neutral	-0.249
4	Punctual	Positive	0.746
4	Delivered	Neutral	0.25
5	Good	Positive	0.743
5	Provide	Neutral	0.249
6	Depend	Neutral	-0.249
6	Compare	Neutral	-0.249
6	Other	Neutral	-0.249
6	Various	Neutral	-0.25
7	More	Neutral	0.249
7	Practical	Neutral	0.247

Student feedback about teaching methods and learning growth range opinion mining core is illustrated in Figure 4.

Figure 3. Word net student feedback.

The measurements assessment like precision, review and f-measure consume stood cast-off to amount replacement criticism opinion on our models' presentation. The outcomes showed that the K-means algorithm was the most accurate with time/Sec of 0.03 and the accurately characterized 8,000 examples equivalent 96% and mistakenly ordered 2,000 occasions equivalent 4%. Precision was 95%, recall was equivalent to 94.8% and the F-measure was 93.7%. The procedures in the grouping stage are outlined in the table 3. The evaluation for Chi- square algorithm is and Association Rule Mining than the other comparable 0.04 time/Sec and test cluster eminence was 1.0 for self-assurance test as demonstrated in a Table 3.

Figure 4. Score range mining.

In this exploration, we focused on the words that offer viewpoints in each sentence. The way that these expressions constantly contain feeling words was a direct reflection (incredible, great, terrible, and awful). If the sentences contain no feeling phrases, Subsequently, we planned a system to characterize each sentence's perspective in light of its demeanor articulations and their relationship (Cruz, Vargas, Cadena, Carolina, & Delgado, 2021).

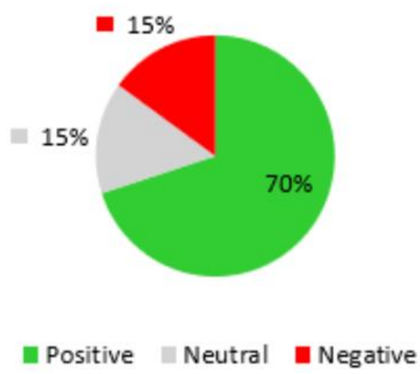

Figure 5. Document sentiment total minning.

Bunching is the act of determining gatherings of information focuses in light of their normalization and reach. It is for the most part utilized for dubious realizing where there is no reliant variable amount. The evaluation measurements which require no ground truth names to work out the proficiency of the grouping calculation could be utilized for the computation of the presentation gauge. In Figure 5 document sentiment divides into three categories where Positive = 70% from all document, negative and neutral = 15%.

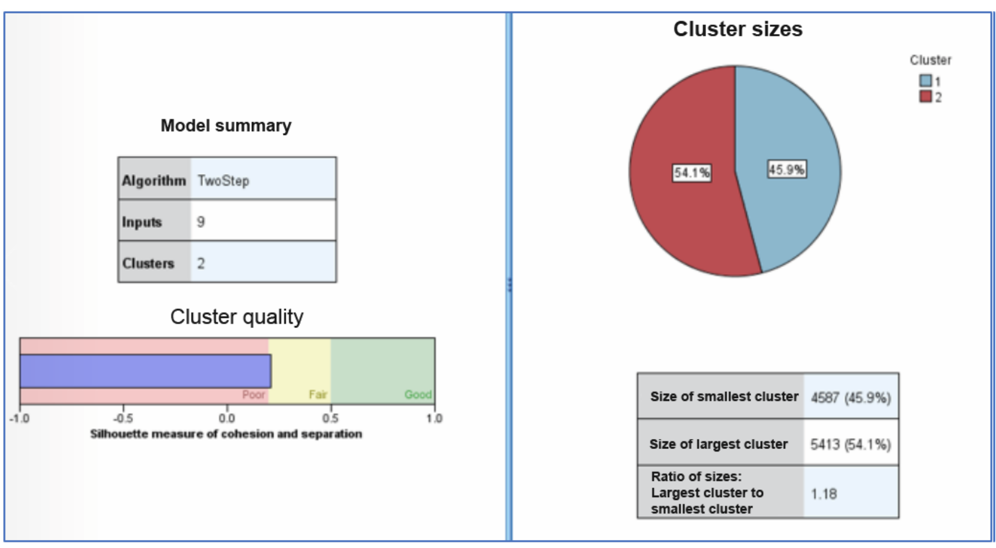

Figure 6. Model cluster summary.

The silhouette factor is determined by utilizing the mean of the distance of the intra-group and nearest bunch for every one of the examples. The silhouette number ranges from [-1, 1]. The better the coefficients (the more like +1), the more is the detachment between bunches. Assuming the value is 0, it suggests that the model is on or extremely near the choice limit between two adjoining bunches while a negative worth shows that those examples might have been moved to some unacceptable cluster (Malhotra & Goyal, 2021).

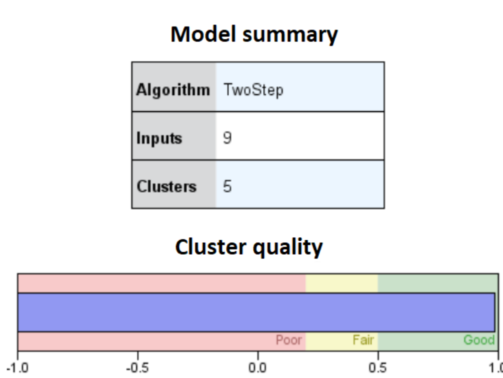

Figure 7. Chi-square test cluster quality.

The chi-square was used to test if an example of information came from occupants with a particular division. Chi-fit test numbers are broadly utilized in the modesty of fit, a trial of consistency and freedom. A chi-square test is a number juggling evaluation used to examine observed results with projected results. The target of this test is to choose if a distinction of assessment between observed information and anticipated information is expected should risk, or on the other hand assuming it is because of a connection between the factors you are considering. In this way, a chi-square test is a very good tool to assist us with better comprehension and decipher the connection between our two unrestricted variable amounts. We utilized a phonetic strategy to decide the assessment and keep track of who's winning every note to classify it as certain, unbiased or negative. Positive words, negative words, modifiers, conjunctions and the names of areas of interest likewise were characterized as corpora. The two feeling corpora, good and pessimistic words, each contain opinion evaluations differing as of - 1 not long before 1. Next are a few instances of our corpora (Almurtadha & Ghaleb, 2021).

Table 5. Relation between sentiment score and each major.

	Major	-0.969	-0.935	-0.826	-0.749	-0.712	-0.553	-0.124	0.000	0.126	0.127	0.147	0.160
Student major	BIS	0	20	0	0	0	0	0	60	0	0	0	0
	Finance	0	447	1	1	1	1	16	1238	0	0	0	1
	Marketing	1	546	0	0	0	0	24	1519	1	1	1	0
	political	0	169	0	0	0	0	0	378	0	0	0	0
Total		1	1182	1	1	1	1	40	3195	1	1	1	1

K-implies a group investigation approach that utilizes a pre-decided number of bunches. It requires earlier information on the letter K's hierarchical gathering, frequently known as various leveled group investigation, is a bunch examination technique that expects to make an order of groups with no set number of groups. The two-Step cluster evaluation stage is an exploratory strategy that aims to uncover regular connections. Inside an informational index, there are groupings (or bunches) that in any case could go undetected.

Table 6. Statistical analysis of clustering analysis using four classifiers.

Algorithm	Time /Sec	Model evaluation						
		Correctly classified		Incorrectly classified		Performance indicator		
		#	%	#	%	Precision (%)	Recall (%)	F-measure (%)
K-means cluster	0.03	8000	96%	2000	4%	95%	94.8%	93.7%
Two-step cluster	0.07	8000	91%	2000	9%	92%	80.4%	86.2%
Silhouette cluster	0.05	8000	89%	2000	11%	89%	82.6%	93.7%
Hierarchical cluster	0.10	8000	84%	2000	16%	84%	88.2%	82.6%

In Table 6, is a statistical analysis of clustering analysis using the four classifiers used in this paper. We used four algorithms namely K-means cluster, two-step cluster, silhouette cluster and hierarchical cluster. W we found that the K-means cluster was a better algorithm than others and delivered 0.0.3 Time /Sec, accuracy was 96%, incorrectly classified 4%, precision (%) was 95%, recall (%) was 94.8% and F-measure (%) was 93.7%.

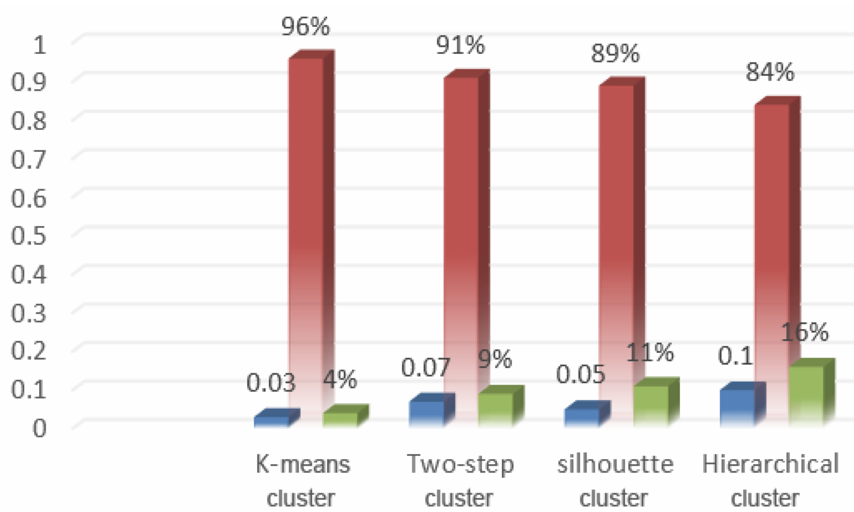

Figure 8. Clustering analysis of four algorithms.

The proposition methodology's calculation. Furthermore, with the capacity to productively examine colossal information records, the silhouette examination can be used to focus on the division distance between the ensuing packs. The framework plot shows the extent of how close each point in one gathering is to centers in the bordering packs and thus gives a strategy for looking over limits like the number of gatherings. In Figure 8 the four algorithms show that K-means algorithm was better than the others with 96% accuracy and 0.03 Time to execute the dataset to build the model.

Table 7. Statistical analysis of three testing association rule mining.

Test association rule mining	Evaluation	
	Time /Sec	Test quality
Chi-square test	0.04	1.0
Lambda test	0.08	0.5
ETA test	0.09	0.2

This action has a scope of [-1, 1]. Silhouette analysis (as these qualities are alluded to as) close to +1 demonstrates that the example is far away from the adjoining bunches. A value of 0 shows that the example is on or extremely near the alternative limit between two adjoining groups, and negative qualities demonstrate that those examples could have been allocated to some unacceptable bunch (Noor, Guo, Shah, Nawaz, & Butt, 2020). In Figure 9 testing the three algorithms that are suitable for association rule mining, the best performing algorithm was the chi-square test, which performed better than Lambada and ETA test. The red line refers to test quality and the blue line refers to time / seconds that each algorithm executed. Finally the best algorithm executed was the chi-square test.

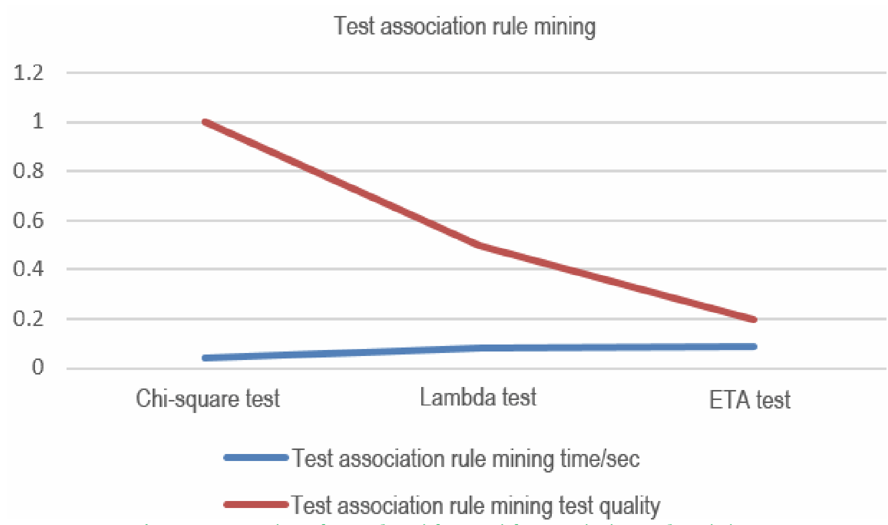

Figure 9. Testing three algorithms with association rule mining.

6. Conclusion and Future Work

As such ends can carry out progressive enhancements in most fields, especially with the development of people's ability to give and disseminate their bits of knowledge straightforwardly at whatever point and any place. The meaning of oddity area is coming from the way that special cases in data are changed over into enormous (and much of the time essential) critical information in a wide combination of use regions. The anomalies in these difficult comments could provoke high mix-ups in data assessment and the unique cycle. Hence, remarkable application regions which use appraisal mining with the oddity ends since they could unfavorably influence their spaces as shown in Figure 6. In this article we proposed a viable sentiment analysis student comment model (SASCM) to mine the student's comments from the free-message comment part of the survey. The proposed model directs both the opinion mining region and the characteristic distinguishing proof space to achieve its fairness. Figure 1 makes sense with a model of the various parts of the proposed SASCM for the model beginning with controlling the open student comments of limited students' comments. SASCM model involves two very large modules: the pre-handling module and the feeling examinations module. SASCM mix appears in Figure 1. Our students' reactions data was assembled from the Arab Academy for Science Technology and Maritime Transport (AASTMT) College Management and Technology for four divisions, namely marketing, finance, and political science. Bits of students' feedback are from two years, 2011 and 2021. After disposing of the trash, silly and replicated sentences, we have more than 10,000 rough sentences. The data was then remarked on into 3 imprints: positive (POS), negative (NEG) and objective (NEU) as shown in Figure 7. Table 1 shows real dataset student feedback at (AASTMT) represented in Table 5. The outcomes showed that the K-means algorithm was the accurate with time/of 0.03 and the accurately characterized 8,000 occasions equivalent to 96% and mistakenly ordered 2,000 examples equivalent to 4%, precision 95%, recall equivalent 94.8% and F-measure 93.7%. In grouping stage delineated in table 3, the Chi-square test was preferable to association rule mining over the extra equivalent 0.04 time/sec and the test cluster quality was 1.0 for certainty test represented in Table 7..

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