PERFORMANCE ANALYSIS OF EDUCATIONAL DATA MINING (EDM) AND SENTIMENT ANALYSIS

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Abstract

The goal of EDM is to create new tools and algorithms for detecting patterns in data. To analyse data acquired during teaching and learning, EDM examines ideas and applies tools from statistics, machine learning, and data mining. EDM is a research project that tests learning theories and has an impact on educational practise. EDM is becoming more popular as a research topic because of a number of computational and psychological tools and research methodologies for determining how children learn. Intelligent tutoring systems, simulations, and games are just a few of the new computer-assisted interactive learning methods and tools that have opened up new opportunities for collecting and analysing student data, identifying patterns and trends in that data, and making new discoveries and testing hypotheses about how students learn. Data from online learning systems can be aggregated across a large number of students and contain a big number of parameters for model construction that can be studied by data mining techniques. It is useful in a variety of sectors, including management and the social sciences, as well as education, where student feedback is crucial for determining the success of learning aids. Many students have been drawn to online learning portals that provide free courses by educational institutions. Each year, thousands of students enrol in these enormous online courses and score their happiness with the material and instructional quality. Additionally, to improve the quality of training, convey positive or negative thoughts in blogs. This study takes a broad look of EDM as a whole, with sentiment Analysis (SA) as a starting point. For the performance research, a paper from a number of regular publications was employed.

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I INTRODUCTION

In order to determine if a sentence is positive or negative, SA is employed as a criterion. For text analysis, natural language processing (NLP) and machine learning (ML) approaches are used to provide weighted sentiment scores to entities, topics, themes and categories inside a sentence or phrase[1]. For better understanding of the social sentiment that surrounding your brand, product, or service while monitoring internet debates, SA is the best way to go. Statistic analysis and count-based metrics make up the bulk of social media stream analysis. SA is used by data analysts at large companies to identify experiences of buyer[2]. As a result of recent advances in deep learning, algorithms' capacity to analyse text has substantially improved. When employed imaginatively, advanced artificial intelligence algorithms may be a fantastic tool for performing in-depth study [3].

When these essential principles are put together, you get a machine that can analyse millions of brand conversations with human-level precision[4]. Humans painstakingly coded vast amounts of adjectives and phrases to construct sentiment libraries (great game, fantastic narrative, poor performance, horrible presentation). Manual sentiment scoring is challenging since everyone involved must agree on the relative strengths and weaknesses of each score.

Furthermore, a multilingual SA engine requires its own library for each language supported. And new scores, phrases, and unrelated concepts must be added to each of these libraries on a regular basis[5].

One of the components of SA is speech tagging. For that, firstly it is important to understand the components that make up a sentence or phrase before you can analyse it for sentiment. One of the sub-functions involved in breaking down a text into its component components is Part of Speech (PoS) tagging. It is possible to recognise structural features by tagging them as part of speech[6].

II ML AND SENTIMENT ANALYSIS

ML is often used to progress and systematize text analytics procedures like Part of Speech tagging. After the prototype has built, the data scientist can use the same training processes to build many models that recognise different bits of speech. As a result, a trustworthy and timely service is delivered. Speech tagging is a text analytics feature that aids in the detection of sentiment-bearing utterances.

ML can also be used by data analysts to overcome challenges provided by language evolution. The term "sick burn," for example, could signify a multitude of things. It's difficult to create a SAruleset that accounts for all possible interpretations. A ML model can learn to distinguish between what "sick burn" means in the domain of video games and what it means in the context of healthcare given a few thousand pre-tagged data sets. Similar training strategies can be used to understand more double meanings[7].

To compensate for the disadvantages of each technique, hybrid SA methods mix ML and classical rules.For example, rules-based SA is a fantastic approach to get started with PoS tagging and sentiment analysis. As we've seen, these rule sets, however, quickly outrun their administration. In this case, ML can help by taking on the burden of difficult natural language processing jobs like double meanings.

According to a Bain & Co. study, effective experiences can increase revenue by 4-8 percent above the competition by increasing customer lifetime by 6-14 times and enhancing retention by up to 55 percent. The key drivers of this rise are automated SA tools. Business analysts acquire vital insights into how customers feel about their brands, commodities, and services by analysing tweets, internet reviews, and news stories at scale. Customer service directors and social media managers identify and address frequent issues before they become widely publicised, as well as educate product managers so they may make informed feature choices. In general, SA is more beneficial for Voice of Customer and Voice of Employee[8].

According to the Center for American Progress, replacing an employee costs 20-30% of their income. SA aids workforce analysts and HR executives in minimising employee churn by monitoring what employees are talking about and how they feel. HR teams may be able to gain the insights they need to proactively address pain spots and raise morale by analysing employee surveys, Slack conversations, emails, and other communications [10].

III EDM

EDM is a new field that combines computational and psychological technologies with research approaches to better understand how students learn and their learning environments [11]. Data from collaborating students, administrative data, demographic data, and data on student affect may be of importance in addition to individual student interactions with an educational institution [12]. EDM can be used to evaluate learning materials and courseware, direct students' learning, provide feedback and change learning recommendations depending on students' learning behaviours, discover anomalous learning behaviours and difficulties, and acquire a deeper knowledge of educational phenomena[13].

Santana presented a comparison of EDMsystems' utility in identifying students who are likely to fail starting programming courses in 2017. Despite the fact that other research have looked into comparable techniques for detecting academic failures in pupils, ours is unique in the following ways: We look into the effectiveness of such techniques in identifying students who are likely to fail early enough to take action[14].The results showed that the techniques we looked into can detect students who are likely to fail early on, that the success of these techniques improves after data pre-processing and/or algorithm fine-tuning, and that the SVM technique statistically outperforms the others.

Z. Kastrati proposed a SAapproach for MOOC student comments based on aspect in 2020. The framework uses a weak supervision technique to forecast the piececlasses that are important in evaluating the effectiveness of online courses in general. The framework then examined how students felt about these attributes as represented in their comments. There are two different kinds of factors that have been discovered. The first focuses on the more general features of MOOCs, while the second focuses on the more specialised aspects. In the ABSA framework, two supervised data types are input into a deep network [15]. The first type comprised a list of keywords connected with each aspect category, while the second included a small number of individually annotated reviews. The suggested method is analysed and validated using two real-world datasets: Coursera student feedback and student input from traditional course settings. The findings showed that the suggested framework is trustworthy and comprehensive, with an F1 score of 86.13 percent for aspect category identification (broader MOOC-related aspects) and 82.10 percent for aspect sentiment classification (CNN+FastText). Furthermore, using a manually labelled dataset, it outperformed the baseline model with an F1 score of 93.3 percent[16].

In order to monitor students' views and sentiments concerning the system, the current study will do a SA(SA) on the collected Turkish tweets on an ODE system. The 63699 tweets about the ODE system are gathered and analysed in the first stage. The dataset is then preprocessed after that. The data is used to perform sentence-based SA. SVM, KNN, LR, and ANN are tested on the dataset, which is vectorized using two vector space models. These classifiers' F-score values are investigated, and the results are presented. For each vector space model, the LR classifier provides the best F-score values, with a percent 75. The university administration will learn immediately about students' unhappiness, appreciation, and worries as a consequence of the SA findings, allowing them to take actions to improve the quality of education and educational services[17].

More input components were acquired for analysis, and the feedback collecting format was changed to match the study's objectives. Sentiment categorization was done using ML methods (NBand SVM), and emotion analysis was done using the NRC Emotion Lexicon, which was built on the Weka 3.7 platform. The outcomes of this round of research aroused strong emotions and feelings. Students were more forthright when it came to offering criticism, as indicated by the results. As a result, the information can be utilised to determine how to improve teaching and learning in order to improve overall student quality[18].

In 2018, Nabeela Altrabsheh, Mohamed Medhat Gaber, and Mihaela Cocea presented an overview of EDMand sentiment analysis, as well as a range of student feedback methodologies. We believe there is a lot of promise in incorporating the burgeoning field of data mining SA into educational systems[19]. After a fast comparison of SA methodologies, it was decided that Naive Bayes and SVM algorithms were the best for educational data. We've also discussed integrating the two for real-time analysis of student input. Systems Analysis for Education, our system architecture, has been revealed (SA-E). The SA-realization E's pave the path for a SA application that could be beneficial. In 2019, Kavitha experimented with EDM. The value of employing SA to improve the teaching-learning process by analysing student replies is discussed in this study. This paper examines the value of analysing student feedback acquired via the use of a Learning Management System. SVM was found to be superior than the other techniques in terms of classification accuracy. In addition, in terms of features, IG has excelled the competition.

In the year 2020, Praveen Kumarv connects learning analytics to grounded theory by analysing students' sentiments and emotions through feedback using a Lexicon-based sentimental analysis technique. The SA method is a computer software that recognises and categorises subjective data from source material into three categories: positive, negative, and neutral. From a phrase fragment, it may extract emotions and sentiments. As a result, the goal of this study is to determine whether students have positive or negative feelings towards online learning, as well as specific emotions. The process is divided into four steps[20]. The first stage is to employ open-ended questions (Text) to extract data from student comments, which is then used as source material and imported into R studio. Data cleaning and pre-processing, as well as the removal of undesirable data and data separation, are all part of the second step. SA is the third phase, which divides the data into three categories: positive, negative, and neutral. According to the sentiment ratings, students had positive sentiments/feelings about online teaching, and emotions varied based on the online class schedule.

Nabeela Altrabsheh conducted a series of tests in 2015 to explore if students' textual classroom comments may predict different learning moods. We focused on Amusement, Anxiety, Boredom, Confusion, Engagement, Enthusiasm, Excitement, and Frustration because they were found to be significant in previous study. To discover what would perform best, we used a range of preprocessing and ML techniques, as well as different n-gram feature combinations. The metrics accuracy, error rate, precision, recall, and F-score were used to test the models' accuracy, error rate, precision, recall, and F-score using 10-fold cross-validation. The best-performing 2-class models for three distinct emotions: amusement, boredom, and excitement were discovered. The best classifier was complement Naive Bayes (CNB). A mixture of n-grams generated the greatest outcomes in most models.

Ref	Year	Methods	Performance	Output
Ref [11]	2020	NRC Emotion lexicon NB, SVM	Accuracy	Efficient than other basic model
Ref[12]	2017	SVM,DT, NB NN	Accuracy	SVM works efficient
Ref [13]	2020	CNN fast text	f-score	93%
Ref[14]	2021	. Sentence-based SA SVM, LR ,KNN,ANN	f-score	75%
Ref [15]	2020	Lexican based	sentiment scores and emotional variance	Higher positive score
Ref [16]	2019	DT, SVM NB , KNN	Precision f-score	SVM produce better results
Ref[17]	2018	SVM, NB	-	-
Ref [18]	2015	ME, CNB	Accuracy Error rate , precision recall	CNB: best result

Table 1. Performance Analysis of Sentiment Analysis over EDM

IV. EDMF or Students' Performance Prediction

In 2019, ref [19] experimented. A number of data mining techniques were applied to the retrieved dataset. The Random Forest (RF) algorithm was found to be the best data mining tool for predicting academic achievement in kids. Student demographics, prior performance information, course and teacher information, and basic information about the student were split into four categories. Instead of wasting time gathering irrelevant data on the students, future study might be based on this set of traits. The findings of this study will aid higher education institutions in identifying defects and variables that influence student performance.

The Bangor Engagement Statistic was established in 2019 as a descriptive metric with good predictive value in ref[20]. This measure was created to help Bangor University improve its present student information systems. We've now demonstrated how ML can help with student retention. To achieve the goal of early detection, we picked a combination of classifiers and measurements based on a series of tests. The precision of this combination is greater than 97 percent. The model, like other ML applications, will not be static, reducing the number of children who are unduly tampered with as well as the number of students who are incorrectly forecast to achieve a favourable result. Students in different cohorts will progress through their courses at varying speeds, necessitating the identification of diverse patterns. This means that the model will be continuously trained as new data is added and old data is deleted. We also recognise that models are only as good as their teachers, thus while this model works for Bangor children, it may not work for students at other schools. On the other hand, the technique, classifier, and attributes employed would be transferable. As a result, long-term research, both within Bangor and in comparison to similar groups at other universities, is required.

Table 2: Performance Analysis of EDM with Machine Learning

Ref	Year	Methods	Performance	Output
Ref[19]	2019	DT, NB, ANN, SVM,LR	Accuracy Recall precision	RF) achieves the best
Ref[20]	2019	Sequential Forward Selection Single neural network	Roc Auc Precision Recal f-measure accuracy	97% accuracy
Ref [21]	2018	ensemble predictive model SVM,RF, NB, ANN	TPR FPR Precision Accuracy	50% more than other
Ref[22]	2017	discriminative and generative SVM, C4.5.CART,BN, NB	Precision Recall f-score	outperforms than basic model
Ref [23]	2018	Linear regression Random forest robust linear regression	RMSE R2 MAE APA	12.28% of RMSE

Ref[24]	2018	Random forest	Accuracy Sensitivity Specificity Roc Auc	an excellent performance in predicting students' dropouts in terms of performance measures for binary classification.
Ref[25]	2018	bidirectional long short -term memory Deep learning GritNet	ROC AUC FPR TPR	outperforms the standard logistic - regression based method
Ref[26]	2017	ensemble predictors latent factor model -based course clustering	MSE	the proposed method achieves superior performance to benchmark approache
Ref[27]	2018	Yet Another Two -Stage Idea Self-training	Accuracy	Accuracy 100
Ref[28]	2018	ANNs, SVM,LR ,NBDT	RMS recall Precision f-score accuracy	ANN and SVM outperforms
Ref[29]	2019	Bp, SVR LSTM, Gradient Boosting Classifier (GBC)	MSE, R2 Score and EV Score, Accuracy	Accuracy 87.78%.

The ensemble predictive model was developed in 2018[21] after comparing the prediction accuracy of various supervised ML classifiers and J48 tree with various k-fold cross-validation. The K-nearest neighbour algorithm is trained using an 8-fold cross-validation data set with various k values (IbK or KNN). Following feature reduction processes, 131 characteristics connected to ICT in education are analysed as a dichotomous variable. According to the outcomes of the study, SVM provides the best prediction (76 percent) at each fold when compared to other approaches. RF detects the total number of accurate females (23535) at a 6-fold level, while SVM detects correct male perdition at a 2-fold level. According to the researchers, the NB classifier had the lowest prediction accuracy at each fold. Finally, in order to accurately identify student gender across the data set. The ensemble confusion matrix shows that the female student has the biggest forecast when compared to the male student's survey response.

In ref [22]2017, generative and discriminative classification models were used to assess the impact of our proposed qualities on student performance prediction. A feature space is created by combining the characteristics of a student'sfamily spending, family income, personal information, and family assets. Because it only shows us a subset of features, we must choose potential/dominant attributes. For our given criteria of family expenditure and student personal information categories, the SVM classifier has proven to be successful. According to intuitive explanations offered in presentations, the results imply that family spending and personal information aspects have a considerable impact on a student's performance.

A number of contributions and their consequences for educational practise were emphasised in 2018 by ref[23]. To begin with, it offers a low-cost model for predicting student accomplishment that does not require active data collecting. Because it is based on data that already exists at institutions, it may be valuable for teachers and educational management. As a result, resources could be diverted from data collection to help at-risk youngsters. Second, incorporating LMS use data resulted in Random Forest, an algorithm that outperformed ordinary LR and RLR to a higher extent. Furthermore, LMS data improved the forecasts of at-risk students more than the forecasts of good and average-performing students. As a result, researchers who want to use more precise prediction models can combine the algorithm above with LMS data and apply it to socio-demographic and academic data. Third, the current study discovered that aggregating LMS usage data produced comparable or better midterm predictions than using all of the semester's data at the conclusion of the semester. As a result, the method could be effective in early detection of at-risk youngsters, allowing for early intervention to prevent student failure. Fourth, these benefits demonstrate how universities should establish specialised analytics departments to monitor and forecast student progress. Instructors, programme coordinators, and learning support specialists may be able to get information from these courses as early as the middle of the semester to help struggling students. Finally, our findings demonstrate that including LMS data improves prediction, which may be an incentive for teachers to use LMS more frequently, especially in schools where teachers have big classes and cannot meet with each student individually.

In 2019, ref [24] considered the use of ML in the building of a predictive model for early detection of students at risk of dropping out. Our prediction method, which utilised random forests, did remarkably well in predicting student dropouts. Despite privacy concerns, our findings imply that in the classroom, merging ML with students' big data could be beneficial. An existing school dropout prediction model might be installed and used within NEIS in Korea's example. NEIS updates student data on a regular basis so that ML can improve the early warning system for dropouts. Homeroom teachers can use the prediction model to minimize risks by offering appropriate interventions and supports, as well as enhancing protective characteristics in the kids' environment.

Deep learning was effectively used to the difficult challenge of predicting student performance in 2018, which has yet to be thoroughly researched, in ref[25]. In contrast to previous research, this one framed the problem as a sequential event prediction problem, suggested a novel algorithm called the GritNet to solve it, and demonstrated the GritNet's superiority using student data from Udacity's Nanodegree programmes. GritNet is unique in two ways: (1) it does not require feature engineering (it can learn from raw data), and (2) it can work with any student event data that has a time stamp (even when highly imbalanced). Present GritNet, a novel deep learning-based technique for recasting the student performance prediction issue as a sequential event prediction problem using bidirectional long short term memory (BLSTM). Our findings, which are based on actual Udacity students' graduation predictions, show that the GritNet not only outperforms the traditional logistic-regression-based approach on a consistent basis, but that the gains are especially noticeable in the first few weeks, when making accurate predictions is most difficult.

In 2017, ref[26] released a new method for forecasting students' future success in degree programmes based on their current and previous performance. To find eligible courses for generating base predictors, a latent component model-based course clustering approach was developed. To incorporate students' changing performance into the forecast, an ensemble-based progressive prediction architecture was constructed. These data-driven strategies can be used in conjunction with other educational approaches to assess students' performance and give critical information for academic advisers to recommend future courses and implement pedagogical intervention measures as needed. This study will have an impact on degree programme curriculum design as well as education policy design in general.

In ref [27] 2018, the utility of two wrapper techniques for semisupervised learning in predicting final exam results of high-school students was investigated. The results of the self-training and YATSI procedures were compared to the most commonly used supervised methods, as well as two semi supervised algorithms. The findings reveal that during the academic year, selected features related to written assignments, oral examinations, short tests, and examinations are marked according to predefined assessment criteria and used to accurately estimate the final grade in exams using semi supervised learning methods. Finally, by combining labelled and unlabeled data to construct reliable prediction models, semi supervised algorithms may increase classification accuracy.

In ref [28] 2018, data gathered by the digital electronics education and design suite, a technology-enhanced learning (TEL) system, is analysed using ML algorithms (DEEDS). ANN(ANNs), SVM (SVMs), logistic regression, NB classifiers, and decision trees were among the ML methods used. The DEEDS system allows students to execute a range of digital design tasks while simultaneously recording their input data. The average duration, total number of activities, average idle time, average number of keystrokes, and total related activity for each exercise during different sessions in the digital design course served as the input variables for this study, with the student(s) grades for each session serving as the output variables. The data from the previous session was then utilised to train ML algorithms, which were then put to the test on data from the next session. The data reveal that ANNs and SVMs outperform other approaches in terms of accuracy. Because ANNs and SVMs are simple to integrate into the TEL system, teachers should expect improved student performance in the next session.

In ref [29] 2019, discuss how analysing educational data is critical for improving educational quality for future generations, particularly the impact of social environment and family on student accomplishment[30]. As a result, a range of datasets must be analysed in order to anticipate and categorise the behaviour of students in related courses, as well as give early intervention to improve performance. For various sorts of tasks, such as prediction and classification, different ML algorithms are advantageous and successful [31,32]. This article employs a total of four ways to address two types of problems: prediction and categorization. Significant results are generated when data is fed into algorithms without using a data selection procedure. SVR has the lowest Mean Square Value and the highest R2 and EV Scores in prediction[33]. Despite having the lowest prediction rates, BP outperformed other classification algorithms by 87.78 percent in classification tests. Our findings demonstrate that ML algorithms can predict or classify any form of educational data, and that the outcomes can be improved as a result[34,35].

V CONCLUSION

SA has some of the same issues as emotion recognition in that it requires us to define "sentiment" before evaluating the sentiment of a text. Is it categorical, with feelings like happiness, sadness, fury, and boredom falling into distinct categories? Is it dimensional, in which case both directions of sentiment must be assessed? Aside from the defining issue, any human-generated statement has numerous degrees of significance[36]. People communicate in a variety of ways, and rhetorical devices such as sarcasm, irony, and implicit meaning can cause SA misinterpretation. The only way to truly grasp these strategies is to examine them in context:

how a paragraph begins can have a significant impact on the tone of subsequent internal sentences[37,38,39].

The majority of modern SA theory is based on a categorical paradigm, which divides sentiment into many buckets with varying degrees of membership. A statement might say 45 percent joyful, 23 percent sad, 89 percent eager, and 55 percent hopeful, for example. These are individual measures of how "X" a statement expresses itself; they don't total up to 100.A lot of SAresearch has focused on feature generation to tackle the context problem. Using context, tone, and past indicators of sentiment as model inputs can assist increase accuracy and give you a better understanding of what the author is attempting to communicate. This research in Knowledge-Based Systems, which creates a framework for this form of contextual attention, is an interesting example. Semantic search, which identifies the intent and context of users' search terms, is also used by search engines[40,41,42].

Finally, determining how to train the model you wish to utilise in SA is difficult. In major Data Science languages, there are a choice of pre-trained models to choose from. TextBlob, for example, is a Python package that implements some of Stanford's NLP Group's research, whereas Syuzhet is a R package that implements part of Stanford's NLP Group's research. These modules can help you get started quickly, but you should train your own models for the greatest long-term outcomes. Although acquiring tagged training data for SA can be challenging, it is required for building models that perform well for your specific use case. You may create a workflow using an application like CrowdFlower to gather, classify, and prepare your private data (ie., customer support chats).

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