SENSE: a Student Performance Quantifier using Sentiment Analysis

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***Abstract*—Academic feedback is essential in secondary schools to keep a rapport between students, teachers, and parents and guardians. There are three main factors that contribute towards a student's progress: attitude, attendance and aptitude. Monitoring their progress is key to a student's development in school and allows both teachers and parents or guardians to support them to a greater extent. Annual reports are sent to a student's home to summarise their performance over the academic year, following set criterion from the government. One aspect of a student's report is the teacher's written comment, providing more details on a student's attitude towards their learning. However, families whose primary language is not English may struggle to interpret this information. Working in schools has demonstrated the diversity of students and their wide range of backgrounds, including – but not limited to – language barriers. This work proposes a system called SENSE (Student pErformance quaNtifier using SEntiment analysis) for improving the information conveyed in secondary school reports through means of natural language processing. By combining the three key features which contribute towards a student's progress, a numerical representation is produced for an easier interpretation. This reduces the likelihood of a tarnished relationship between home and schools through better means of conveying information and maintains communication between students, teachers and parents or guardians.**

***Index Terms*—NLP, student performance, technology social factors, academic reports, artificial intelligence.**

I. Introduction

Monitoring student progress is instrumental to a student's success and keeping them on track to enable them to reach their goals [1]. Results of their progress should be shared with parents or guardians in the form of a formal school report, which gives them context as to what their child is learning and what progress has been made [2]. In the UK, 1 in 5 students comes from aboard [3] and their families barely speak English [4]. Annual reports do not always accommodate to these Black, Asian and Minority Ethnic (BAME) families, as teacher's written reports may not be fully understood by them. Schools are encouraged to write school reports in the student's primary language [2], however this is not always achievable.

There are currently no computer-based methods of translating report data to a qualitative output that considers not just a student's attendance and test scores, but also their attitude. As subject grading is well standardised, achievements may not improve, but a teacher's satisfaction may increase if the student's attitude changes [5]. Typically, there is a positive correlation between students with good attitudes towards their learning and successful exam results; hence, this data should be considered when monitoring a student's performance.

In recent years computationally intelligent techniques (CIT) have been applied to a variety of tasks including biological data mining [6], [7], image analysis [8], financial forecasting [9], anomaly detection [10], disease detection [11], [12], natural language processing (NLP) [13] and strategic game playing [14]. Following this, the automatic analysis of the written human language can be done through means of NLP, a theory-motivated range of computational techniques [15].

Mining opinions and feelings using CIT is a powerful and effective way of studying the interpretation of narratives. However, it is a difficult task, as the model needs a clear understanding of the rules of explicit and implicit, regular and irregular language, and syntactic and semantic language [16]. Currently, the majority of the existing techniques are based on the syntactic representation of text – a process that relies primarily on levels of word co-occurrence.

One of the most commonly used applications of NLP is sentiment analysis, which basic tasks are emotion recognition and polarity detection. While the former emphasises on collecting a set of emotion labels, the latter discovers the targets on which opinions were expressed in a sentence, and then determines whether the opinions are positive, negative or neutral [17]. In our case, the target is the student, and its attributes are the student's behaviour. For example, in the sentence, "John is a cheerful, positive pupil who always gives of her best", the comment is on "John" and the opinion is positive.

This work uses sentiment analysis to analyse and understand the context of teacher's written comments in the school report, turning those comments into quantitative data. Combining this with attendance and attainment, the system determines each student's academic progress from these three factors. This system will allow educational establishments to cope with the demands over a trafficked school network and to be in line with how companies use advanced technology, as schools should not be treated any differently to other business sectors [18].

The rest of the paper is organised as: related research about sentiment analysis is presented in section II. The employed technique and dataset are presented in section III. The results and their discussion are presented in section IV, while conclusions and future work are outlined in section V.

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II. Related Works

Sentiment analysis is being used widely with a lot of applications areas. Cognovi Labs created a tool, 'Twitris', which can interpret several users' comments to calculate a polarity score for future predictions [19]. One case it was used was during the 'Brexit' vote, whereby it collected the view points of Twitter's users to build a bigger picture on the likelihood of leave/remain [20].

Another example is eBay's use of sentiment analysis for their customer feedback. This form of NLP allows for large number of customer feedback to be analysed in a quicker time frame whilst still presenting as accurate and reliable [21].

In the medical field, CITs have been used in medicine to predict the future of a patient's health. They provide creation of a diagnostic system that understands pathology and radiological results, and scanned images to provide a comprehensive report to the user. NLP can predict, for example, the likelihood of a patient receiving successful cancer treatment based on the narratives of their diagnostic results [22].

In the education field, the use of sentiment analysis has mainly been advocated to the evaluation of teachers performance [23]–[28]. Other applications in education include the automatic analysis of feedback of students using support vector machines (SVM) to detect different issues students may have with a lecture [29]; the study of students' learning diaries to track emotion based on Plutchik's eight emotion categories as an informative feedback source for instructors. It considers the student's emotional wellbeing [30], and the analysis of a student's feedback with SVM, for real-time interventions in classrooms, to address problems like confusion and boredom, which affect students engagement [31].

Additionally, Newman et al. used VADER (Valence Aware Dictionary and sEntiment Reasoner) [32] - a parsimonious rule-based model, to analyse Student Evaluations of Teaching (SET) of single-course lessons from three different sources [33]. They contrasted the positive and negative valences of this sources, defined which key words are commonly used in SET comments and assessed the effect on the positivity or negativity of the comments that included them. In the official course SET comments, they determined positive or negative values by question. Results show that the correlation between overall sentiment analysis scores for a review and overall scores given to a class appear to foster legitimacy of sentiment analysis as a measurement.

Rule-based sentiment analysis methods have previously been proven to be highly accurate. For example, the approach of Poria et al. [34], which exploits common-sense knowledge and sentence dependency trees to detect both explicit and implicit aspects, achieved the highest accuracy for two popular review datasets.

The latest trends in sentiment analysis include word representations for sentiment analysis [35], capsule networks for challenging NLP applications, [36] and LSTM language models [37].

III. Methods

Sentiment analysis was used to analyse the context of teacher's written comments. The logical thinking behind sentiment analysis is depicted in Fig. 1 (modified from 38). When performing sentiment analysis, the following assumptions were made: the chosen language for the reports was English, teachers across the country use similar terminology for describing students, comments were in full sentences in a paragraph format, and comments contained no spelling mistakes.

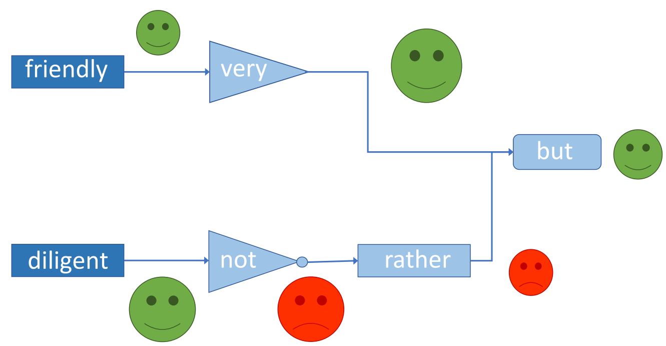

Fig. 1: A diagrammatic representation of sentiment analysis (modified from [38]).

The VADER function from Natural Language Toolkit [39] was used to perform sentiment analysis on the teacher's written comment for a student. VADER does not require training data, yet it was constructed from a generalisable, valence-based, human-curated gold standard sentiment lexicon. It consists of just over $7,500$ lexical features with validated valence scores that indicated both the sentiment polarity (positive or negative), and the sentiment intensity on a scale from –4 to +4.

First, a list of words $W_1, W_2, ..., W_k$ was defined that were either not considered in VADER, or not believed to be fairly represented, and were assigned a score S as shown in Eq. 1.

$$S \in \mathbb{R} : -4 < S < 4 \tag{1}$$

Second, the lexicon file was loaded with the predefined words and their scores from VADER. It was converted to a dictionary and rules were defined to allow for the sentence to be interpreted accurately; for example, if the word 'but' was detected, the system was trained to recognise the next part of the sentence would be a polar opposite to the start. Punctuation was also considered when emphasising a polarity score. The total of negative, neutral and positive polarities were stored as floats to later calculate the compound for an overall sentiment analysis score.

The words $W_1, W_2, ..., W_k$ and their corresponding score S were pushed to a dictionary within VADER. For each sentence in the given text file, sentiment analysis assigned it with a breakdown of the polarity score: negative, neutral, positive and compound. This generated a list of compounds $C_1, C_2, ..., C_n$

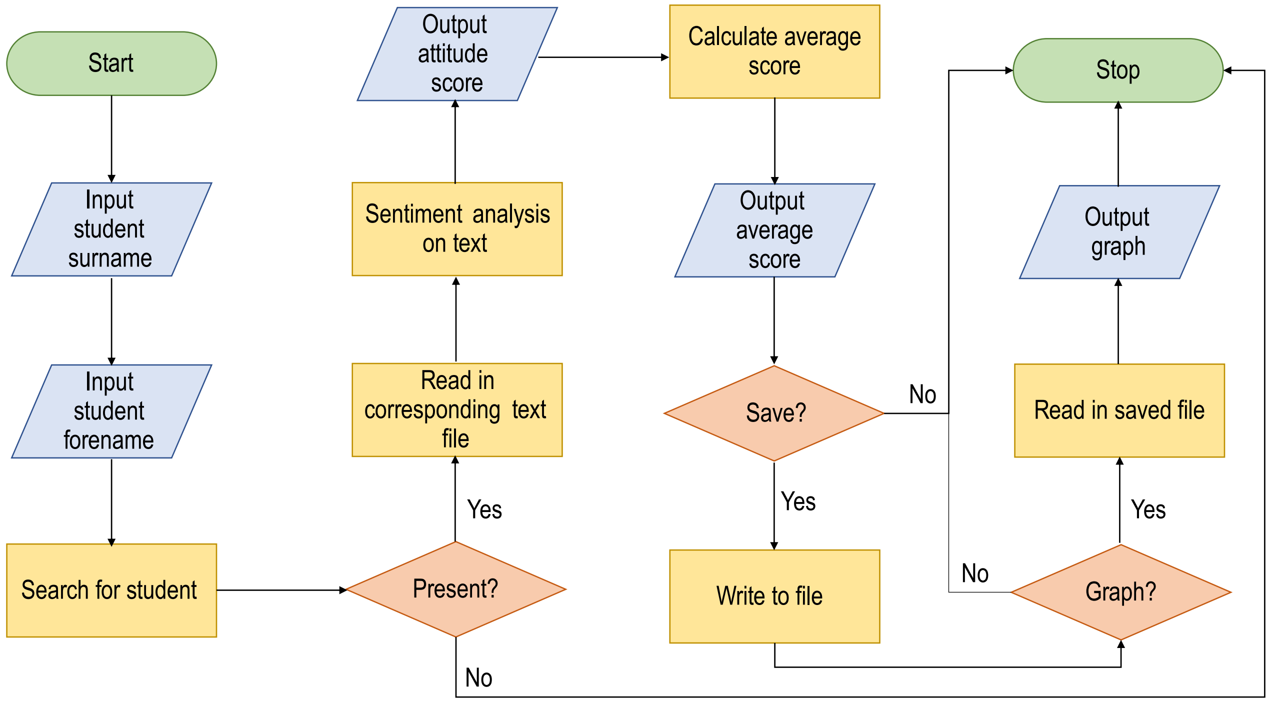

Fig. 2: Flowchart representation of the proposed system.

from each sentiment analysis, so any null values of 0.0 could be removed. Subsequently, the mean of the compounds was calculated as a percentage in the following form:

$$\bar{X} = \frac{\sum_{i=1}^{n} C_i}{n} \times 100 \tag{2}$$

Should the value be less that 0, the student's attitude was scored 0%. With this result, an array containing the average student score, average student attendance and newly calculated student attitude was generated. Finally, the three items in the list were averaged for the overall student performance. This data can be written to a file, so it can later be graphed. The whole process is displayed in Fig. 2, where a flowchart representation of the overall system was used to depict it.

Our testing data was composed of 188 paragraphs of text (i.e. 188 individual teacher's comments), and focuses on the sentiment analysis aspect of the system and the value of average which was produced. The following terminology and scores have been added to better reflect the results: 'sound': 2, 'distracted': -2,'exemplary': 2, 'remarkable': 4,'insufficient': -2, 'outstanding': 4.

IV. Results and Discussion

Table I is representative of the wide range of reports used. Text files 1 to 18 are extracts from real secondary school reports from different students, subjects, teachers and schools. Text files 19 and 20 are controlled paragraphs that were introduced to compare the extremities of the system: one from a 'worst case' student, and one from a 'best case' student. After manually reviewing all 188 text files and building an

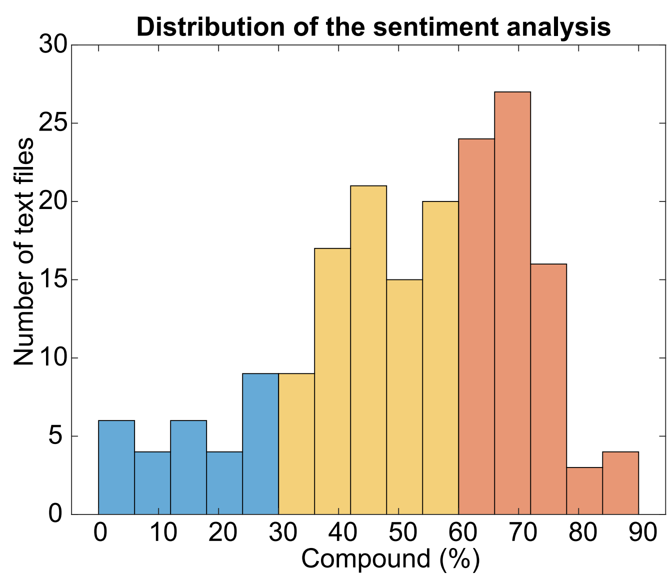

Fig. 3: Distribution of sentiment analysis of the test data. Students with a mostly poor attitude to their learning are coloured blue, students with mixed feedback are coloured yellow and in red students with a mostly positive attitude.

image of the pictured student, the results show to be an accurate representation of the student's attitude in the classroom. VADER has exceeded expectations in accurately performing sentiment analysis whilst allowing for adjustments such that

TABLE I: Results for testing sentiment analysis

Text File	Sentiment Analysis				
	Key words	negative (%)	neutral (%)	positive (%)	average (%)
1	steadily, slightly, well presented, but, more details	0	61	14	35
2	tremendously, bright, well behaved, excellent	0	63	37	73
3	consistently, strong, good	0	53	14	61
4	polite, strong, sound, improved, but, further	0	53	22	68
5	steady, does not, positively, rushed	2	62	22	46
6	enthusiastic, however, off task, distracted, steadily	3	61	20	44
7	excellent, exemplary, enthusiasm, good, outstanding, accurate	1	50	31	68
8	incredible, easily, remarkable, perseverance, talent, hard work	1	57	22	76
9	mixed, keen, intersted, anywhere near, insufficient, issue, long way	1	76	6	20
10	enthusiastic, very good, however, disappointed, lose focus, does not	6	56	17	27
11	greatly improved, very high, very impressed, very skilled	0	49	26	70
12	quite well, relied upon, good, however, focused	0	56	19	53
13	enthusiastic, good, diligent, importantly	2	55	19	64
14	able, conscientious, interest, good, excellent, great, well done	0	46	34	57
15	consistently, capable, effort, focus, improve	0	67	8	52
16	outstanding, delighted, genuine interest, determination	0	55	20	68
17	cheerful, positive, not always, nevertheless, persevered, reasonable, very good, however, disappointing, disappointed	8	57	19	26
18	worked hard, enthusiasm, very well, consistently, high standard, progress, improvement, top marks	2	58	20	65
19	unpleasant, never, awful, do not, will not, extremely disappointed	20	60	0	0
20	amazing, love, incredibly passionate, so determined, great success, remarkably talented, praise, best student, honor, diligent	0	43	37	85

terminology can be redefined when necessary.

It is expected that until introducing the controlled variable in Text file 19, the system is not detecting many negative phrases. Due to the nature of school reports being written to be informative and to refrain from demotivating students, it is normal for them to depict a lower amount of 'negative' comments and many will remain neutral in circumstances of poor attitude. This right-skewed distribution can be seen in Fig. 3, which displays the distribution of the sentiment analysis of the test data.

The system allows the user to personally define their own terminology, particularly if there are differences between educational establishments and their interpretations. For example, a student who is described as 'good' in a grammar school may have the potential for greater improvement, than that of a student in a state secondary school who is outperforming their peers.

It is crucial that VADER performs at a high standard, as to accurately reflect the students' efforts. The larger the data set in the text file, the greater the accuracy of the sentiment analysis. Text files with less content produced expected results, but anomalies were more likely to affect them. For instance, the word 'exceptional' could greatly outweigh other negative terms in a smaller excerpt and affect validity. However, when using real data - some of which included less content - results still were found to fairly represent a student's attitude.

Table II is representative of a selection of students who received different combined averages, where it can be seen the impact of each factor.

TABLE II: Results for calculating overall student performance

Student	attitude (%)	aptitude (%)	attendance (%)	average (%)
1	86	93	100	93
2	0	18	88	35
3	41	53	99	64
4	25	89	96	70
5	74	86	75	78
6	74	42	99	72

- Student 1: This student has a great attitude towards their learning, has achieved a high combined average of their test scores over the academic year, and has full attendance. Their combined average accurately represents the high progress the student has made.
- Student 2: This student received very negative comments about their attitude to learning, has performed badly in class tests as a result, and has a lower attendance record than most students. Their combined average accurately represents the poor progress the student has made.
- Student 3: This student received a mixture of positive and negative comments regarding their learning from the teacher. Their test scores have shown both a good and poor understanding of the subject material, and they have a high attendance. Their combined average accurately represents the academic progress the student has made.
- Student 4: This student has received mostly negative comments regarding their attitude in class, but has achieved very high test scores and has a respectable attendance. The combined average is still representative of their academic progress during the year.
- Student 5: This student demonstrates a mostly positive attitude towards their learning and is achieving above average results in examinations. However, their attendance is far below the average of their peers. The combined average is a fair representation of their progress during the academic year.

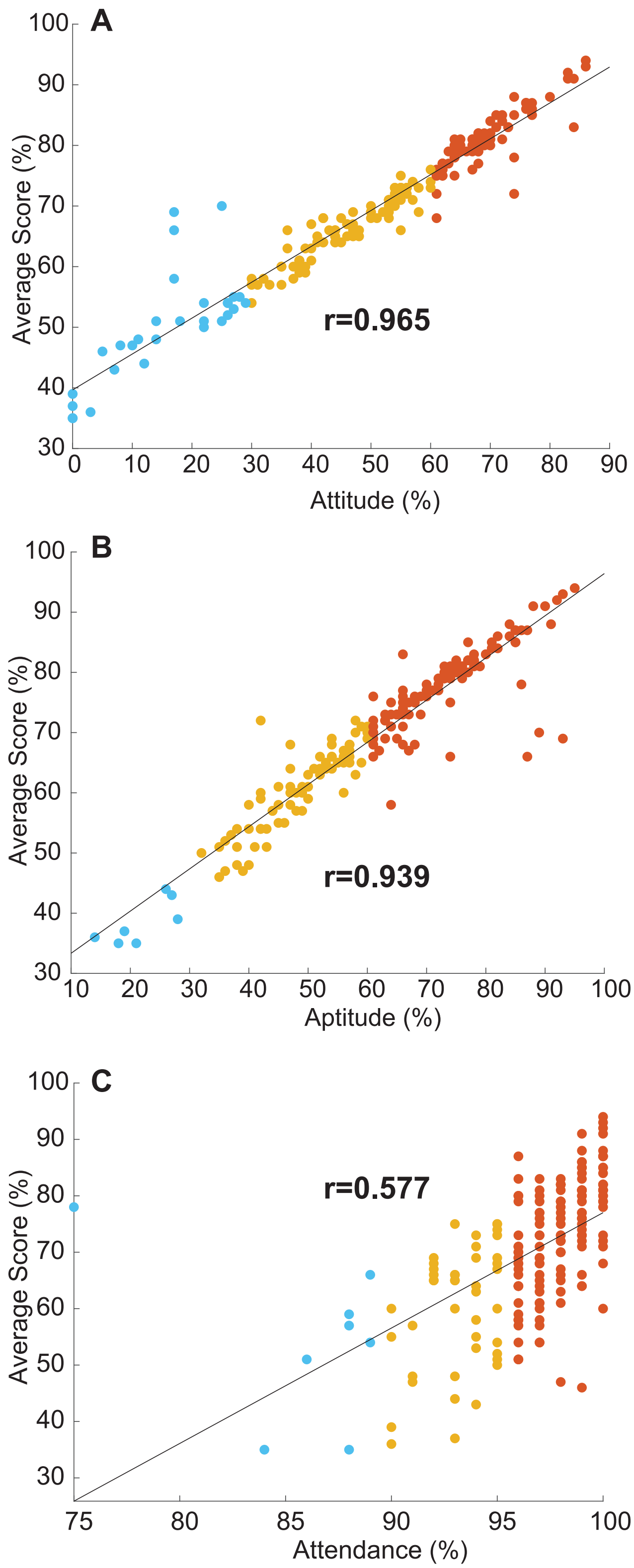

Fig. 4: The behaviour of the the average score in regards to factors Attitude (A), Aptitude (B) and Attendance (C). The colours blue, yellow and red were used to illustrate the students which archive low, average and high values of each factor, respectively.

- Student 6: This student demonstrates a most positive attitude towards their learning and has almost a full attendance record. However, their test scores are below what would be expected of them. The combined average is still representative of their academic progress.

Students 1, 2 and 3 are representative of those that are consistent across the three considerations: attitude, aptitude and attendance. However, there will be inconsistencies in trends, as displayed in Table II.

Student 4 has received poor comments from their teacher regarding their attitude towards their learning, but is still performing exceptionally well and attending the majority of lessons. Students whose capabilities exceed the level of the set work will find themselves getting bored in the classroom as they are not being challenged in their studies. It too is possible for a naturally gifted student to pay little attention in lessons, yet still produce results in examinations. As their attitude can be instrumental to both themselves and their peers' learning, a lower average (despite a high academic score) is still just.

Student 5 has received good results regarding their attitude and examination results, but their attendance appears to be far lower than average. Due to personal circumstances, students can find themselves involuntarily taking more time out of school than they should be. This is not necessarily reflective of their academic ability; consequently, it is pleasing to see the other 2 factors will boost their score and is still representative of their talent.

Student 6 has a good attitude towards their learning - according to their teacher - and has attended the vast majority of sessions, yet appears to have disappointing results in their examinations. Regardless, it is still encouraging to see the commitment the student has to their studies. As schools have a duty of care for their students, efforts can be made to raise these attainment levels and a determined student of this nature still shows potential to improve their test scores; hence, their average is still a fair measure of their academic abilities.

Regardless of differing factors and anomalies across results, (see Fig. 4), we observed a set of accurate results for all three elements that compose the dataset. The regression values calculated using the *lsline()* function of Matlab [40] indicate that two out of three factors are strongly correlated with the average score, i.e., a student's attitude and aptitude both present as high influences towards the student's average score (r values 0.965 and 0.939, respectively). The attendance of the student is limited to a particular range, due to students abiding by the law and attending school (r value 0.577). Despite this increasing the likelihood of more diverse results, and hence a smaller regression value, it still appears to have less of an impact on the average score; as previously stated, it still produces a fair representation of a student's progress. Unexpected outcomes from Table II have also been further explained and justified. The final average score to be printed on school reports is a true reflection on that student's academic progress and can give all parents and guardians a quantitative representation of their child's performance.

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V. Conclusion

The research has successfully found a method to represent a student's attitude to their studies in quantitative means, for an easier analysis and for accommodating the needs of BAME families; VADER has proven to be a good API for the beginnings of this field of research. The system is user-friendly and can be easily adapted for personal use by changing the terminology to analyse. The system shows the need for concentrating on other factors such as attitude. This evidently have a greater impact on a student's educational journey than their attendance, which typically is more closely monitored.

Currently, it is at a stage where it could be used actively within educational establishments. In the future, this project could see aspects of optical character recognition, so sentiment analysis could be applied to a teacher's handwritten comments. This would encompass both handwritten reports and those typed on the computer with the use of comment banks.

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