SENTIMENT ANALYSIS OF STUDENTS’ OPINION ON PROGRAMMING ASSESSMENT USING NAÏVE BAYES ALGORITHM ON SMALL DATA

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ABSTRACT

Student opinion could be used to facilitate institutions to improve the quality of teaching and learning by delivering the appropriate teaching method based on the student's learning experience. The purpose of this study is to investigate the efficiency of data mining techniques for the sentiment analysis of student opinion on programming subject assessment. Two machine learning algorithms, which are Support Vector Machine (SVM) and Naïve Bayes (NB) have been identified to be the best in sentiment analysis on large data. SVM performs better than NB on big data but the case may not be the same on small dataset. The research aim is to design a framework that will investigate the efficiency of Naïve Bayes algorithm on two sentiment classification classes namely positive and negative on small dataset. A comparative performance measure is done using SVM and lexicon-based approach. Learning programming is considered as a difficult course for the beginners, specifically for the first-year student. The opinions of 175 first-year undergraduate students at School of Computing, Universiti Teknologi Malaysia 2018/2019 session regarding their experience in the assessment of skill-based test 1 and test 2 were collected via an online survey. The result of classifying students' opinions using the NB algorithm had a negative prediction accuracy of 92% and a positive prediction accuracy of 75%. NB had a prediction accuracy of 85% which outperformed both the SVM with 70% and lexicon-based approach with 60% accuracy. The result shows that NB works better than SVM and Lexicon-based approach on small dataset. The findings from the analysis of the survey show that the student's sentiment is classified as negative, which implies that the skill-based test is difficult and gives scary emotions to the students which may further affect students interest in programming assessment. The key finding of this study discovers that the policy of awarding zero scores to students' whose program did not compile successfully, hinders the programming assessment of first-year undergraduate students in the School of Computing, Universiti Teknologi Malaysia.

ABSTRAK

Pendapat pelajar boleh digunakan untuk membantu institusi menambahbaik kualiti pengajaran dan pembelajaran dengan menyesuaikan kaedah pengajaran berdasarkan pengalaman pelajar. Tujuan kajian ini adalah untuk menyiasat keupayaan teknik perlombongan data dalam menganalisa sentimen pelajar mengenai pentaksiran subjek pengaturcaraan. Dua algoritma pembelajaran mesin, iaitu Mesin Sokongan Vektor (SVM) dan Naive Bayes (NB) telah dikenal pasti sebagai teknik yang terbaik dalam analisis sentimen bagi data yang besar. Prestasi SVM lebih baik daripada NB pada data besar, namun prestasinya mungkin berbeza pada data kecil. Matlamat penyelidikan ini adalah untuk merekabentuk satu rangka kerja yang akan menyiasat keupayaan algoritma Naive Bayes dalam pengelasan dua kelasifikasi sentimen iaitu samada positif atau negatif pada set data kecil. Pengukuran prestasi perbandingan dilakukan dengan menggunakan SVM dan pendekatan berasaskan Leksikon. Mempelajari subjek pengaturcaraan dianggap sebagai satu kursus yang sukar bagi mereka yang baru belajar, terutamanya bagi pelajar tahun satu. Pendapat 175 mahasiswa tahun satu dari Sekolah Komputeran, Universiti Teknologi Malaysia sesi 2018/2019 mengenai pengalaman mereka dalam ujian pentaksiran kemahiran 1 dan 2 telah dikumpulkan melalui kajiselidik dalam talian. Keputusan pengelasan pendapat pelajar menggunakan algoritma NB mempunyai ketepatan peramalan negatif sebanyak 92% dan ketepatan peramalan positif sebanyak 75%. NB mempunyai ketepatan ramalan sebanyak 85% yang telah mengatasi pendekatan SVM dengan ketepatan ramalan sebanyak 70% dan Leksikon sebanyak 60%. Keputusan kajian menunjukkan bahawa prestasi NB lebih baik daripada SVM dan kaedah berasaskan Leksikon pada set data kecil. Hasil analisa kajiselidik mendapati bahawa kebanyakan sentimen pelajar adalah negatif, dimana dapatan ini membayangkan bahawa ujian berasaskan kemahiran adalah sukar dan memberi kesan kepada emosi pelajar yang takut dengan cara pentaksiran ini. Ianya mungkin akan menjejaskan minat pelajar dalam penilaian pengaturcaraan. Penemuan utama kajian ini mendapati dasar pemberian markah sifar kepada pelajar yang aturcara mereka tidak berjaya dikompil merupakan halangan kepada pentaksiran kemahiran pengaturcaraan bagi pelajar tahun satu di Sekolah Komputeran, Universiti Teknologi Malaysia.

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LIST OF ABBREVIATIONS

ACT-R	-	Adaptive Control of thought- Rational
AI	-	Artificial Intelligence
API	-	Application Programming Interface
BOW	-	Bag of Words
DTM	-	Document Term Matrix
FN	-	False Negative
FP	-	False Positive
IMDB	-	Internet Movie Dataset
ML	-	Machine Learning
NB	-	Naïve Bayes
NLP	-	Natural Language Processing
Nltk	-	Natural Language Processing Toolkit
NRC	-	National Research Council of Canada
OM	-	Opinion Mining
PBR	-	Polarity Bias Rate
SBT 1	-	Skilled-based test 1
SBT 2	-	Skilled-based Test 2
SVM	-	Support Vector Machine
TN	-	True Negative
TP	-	True Positive
TM	-	Text Mining
UCI	-	Universal Client Identification

LIST OF SYMBOLS

A	-	Length of words
B		Bias
F(x)		Non-linear function
g(x)		Discriminate function
T	-	Term or word
W	-	Loads vector

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CHAPTER 1

INTRODUCTION

1.1 Overview

The advancement in technology has provided several ways of collecting, storing and analysing data in different format such as text, image, audio, video etc. According to Ayala et al., (2014) the data collected requires proper analysis that will help in decision making, future forecasting and knowledge discovery. The idea of discovering knowledge from data gave rise to the research area called data mining (Kumar et al., 2014). The author, further insisted that there is a high demand for the use of data mining techniques to extract useful information from data in education. When students' opinions are collected for analysis, then the application of AI specifically NLP and machine learning is enhanced. In another study by Hanan (2019), the role of data mining techniques in education is increasing as it promotes research in educational data mining and learning analytics. The author also expressed the significance of educational data mining in the enhancement of learning outcomes, instruction and learning effectiveness. Based on these reasons, this study intended to investigate the opinions of the first-year student of School of Computing, Universiti Teknologi Malaysia on programming assessment using Naïve Bayes algorithm.

(Lajis et al., 2018) emphasised on the significance of assessment in any educational institution. The author further mentioned that assessment is a process used to measure student skill and knowledge. A student is said to have acquired skill or knowledge when tested through assignment, test, examination, project or seminar. Computer programming skill assessment differs from other skill assessment because individuals may have a different method of solving a problem in a practical examination and the only way to verify it, is through individual assessment. This type of assessment is stressful and time-consuming. Moreover, the definition of computer programming as "Computer Programming is the process of writing, testing and debugging computer programs using different programming languages “by Rmonal et al., (2009) implies that different measures needed in programming assessment. These include both theoretical knowledge and practical skills. The theoretical knowledge includes; Structure, syntax and semantics of the programming language and its descendants. The practical skill incorporates the used of compiler and text editor for writing, debugging and testing programs. It also includes the necessary skills needed to operate a computer, software installation, configuration and customization. In addition to that, the programming assessment is done as a computer-based test which requires internet for submission of the student project.

Enderson et al., (2014) used data mining technique specifically Naïve Bayes algorithm (machine learning) to conduct sentiment analysis of first-year engineering courses based on student feedback. The study produced a framework that will ease the analysis of the workload of first-year engineering student due to the difficulty and time consumption in the manual analysis of the data from online surveys. However, the scope of the research is wide in scope and not specific in the subject area. For example programming assessment of a course. In my own opinion, specific issues on a course may not be captured in the survey late alone to be addressed. The data used by the author is large. Therefore, the Naïve Bayes algorithm needs to be investigated on small data for performance evaluation.

Universiti Teknologi Malaysia, School of Computing offered programming courses such as programming technique I (SCSJ1013) and programming technique II(SCSJ1023) for the first-year students. The courses provide students with both practical and theoretical knowledge of C++ programming in topics like C++ concepts, association, aggregation and composition. Students from various discipline in the School of Computing register for these courses as part of the requirement for the award of Bachelor of Computer Science, Software engineering and information Security. The students’ performance is measured practically using a skill-based test. The test is conducted on programming technique I and II as skill-based test1 and Skill-based test II respectively. The test is conducted online and last for 1hour 45 minutes. The most important rule regarding the award of the mark is based on program successful compilation. Otherwise, the score is zero. This has been the tradition in the programming assessment of the student. The school of Computing use student evaluation of teachers (SET) as an online survey to assess teacher, course content, teaching aids and teaching methodology of a course. However, the survey is tedious, time-consuming and uniform for all courses. In most cases, student opinions on the survey are not justifiable. Based on these issues, there is a need for short, subject-based, and comprehensive survey that will collect students' opinions on the skill-based test. This will help in the assessment of student performance on learning C++ programming. It will also provide small data for the application of data mining technique specifically Naïve Bayes in the improvement of learning and teaching methodology and assessment. The result of the study would be useful in decision making by the School of Computing. The result obtained is the knowledge contribution to the literature.

Sentiment analysis is a very important data mining technique used in the analysis of student feedback. It is used to classify student opinions as either positive or negative. Positive opinions are words that express good emotions such as like, happiness, courage or recommendation. Negative opinion express bad emotions such as dislike, sadness, discourage or unfairness. Sentiment analysis gives a sentiment score of 1 and -1 for the positive and negative opinions respectively.

According to Ozturk et al., (2017) support vector machine, naïve Bayes classifier and maximum entropy are the sentiment analysis techniques that perform better in the classification of opinions. The author also reports that R and Python programming languages are widely used in the implementation of the sentiment analysis technique.

Altrabsheh et al., (2013) reports that Naïve Bayes and SVM techniques were superior for education data. These two techniques could be combined for the analysis of student's feedback in real-time. The author further concluded that the three classifier commonly used are Naïve Bayes, maximum entropy and SVM. And they had similar performance. And the best result was found with the SVM classifier. The author also used coh-Metrix method to determine if a piece of text from twitter is objective (i.e., is neutral) or subjective (i.e., expresses an opinion); if computers code text as subjective, they then determine whether the opinion expressed is positive or negative.

Archana and Kishore (2017) report that Machine learning, lexicon-based, rule-based are the commonly used techniques to analyze student sentiment from Twitter. The point to consider here is that twitter data is large but not confidential, therefore not suitable for collecting students' opinions.

Ozturk et al., (2017) design a sentiment analysis model for Anadolu University using Naïve Bayes classifier (NBC) specifically Opinion Finder software to analyze student's opinion collected from twitter. The processes of sentiment analysis differ from system to system based on types of the classes to predict (positive or negative, subjective or objective), different levels of classification (sentence, phrase, or document level and language that is processed. It can be observed that the author used opinion finder software as a tool in the sentiment analysis. The issue with this software is that it is a sentiment lexicon used mainly used for subjectivity finding in a sentence. It is a tool used by the lexicon-based approach in sentiment analysis. Therefore, not suitable for the sentiment classification for machine learning. In this study, consider R compiler is a tool selected because it is compatible with all the aspects of sentiment analysis for both the lexicon-based approach and machine learning algorithm, specifically Naïve Bayes.

1.2 Background of the Study

The increase in the application of data mining techniques to address issues in education by the higher institutions is geared by the technological advancement that made an analysis of data fast, easy and accurate. Educational data mining promotes analysis of data for the enhancement of learning and instruction. Nowadays, higher institutions, collect student feedback at the end of every class or examination in order to assess course content, method of teaching, special skill for the effectiveness of the learning process. The data collection is mostly done through the institution's survey. These surveys are characterized as tedious, wide in scope and time-consuming.

Consequently, the justification for the information submitted by the respondents is not guaranteed. Hence there is a need for simple, subject-based and comprehensive survey that will collect student feedback for sentiment analysis to improve learning and teaching.

Since the introduction of Computer programming as coursework at the undergraduate level in the higher institutions, students' understanding of programming has constantly developed obstacles to teachers (Renzella et al., 2019). Since then, the challenges in learning programming language as well as the teaching methodologies have been studied. These methodologies range from complexity related to tool support, educational module, teaching method, and language structure (Pears et al., 2018). In connection to methodology support, there are difficulties with many programming tools as they were initially created for expert or software engineers (Renzella et al., 2019). In this specific situation, the variety of choices given to experts overpower students for whom even the fundamentals of the language become an issue. This shows that there is a need for sufficient literature on student attitudes towards learning programming.

Notwithstanding the difficulties of learning, programming depends on the Language structure and comprehending how programs are executed. A lot of students at first-year finds it difficult to write and execute the program, this is due to the fact that every programming language has its own syntax, semantics and development tool (compiler and editor). Some languages like Java, C and C++ have some syntaxes in common and are an advancement over another. Lack of Background knowledge about one program can affect learning another (Rozali and Zaid, 2017). The student needs to become familiar with an unbending syntax structure and flexible commands that may have apparently subjective or maybe contradictory names.

Programming languages usually can be executed in many compilers (Jones, 2009). Some of these compilers are designed for the professional programmers which may be difficult to use by a beginner. Programming compilers are not an error-free during coding and some languages like Java, C++ is very case sensitive, and the best way a beginner can understand programming easily is to be instructed practically using tools that can detect and alert the user whenever an error occurs. For example, anaconda for python programming. (Pears et al., 2018).

Yang, Tsai, and Ho (2013) conducted research on course assessment on C++ programming. The study aimed at improving learning, student performance and interest to study programming. The issue with the study is that the assessment of the course defends two measurements; the results obtained through competence inventory tests and programming qualify examination but the author concludes on the result from the programming qualify examination with a pass accuracy of 85%. And the data collection is multiple from four sources not centralized on the student. Hence, there is a need for a study that focused on the student as the target respondent in the assessment of C++ programming.

The study by Lajis et al., (2018) shows there is an increase in the number of researches on the application of data mining techniques to analyze student performance. The technique commonly used is Naïve Bayes, random forest, decision tree, neural networks and K-nearest neighbour and many others. The study also shows that machine learning algorithms to be specific support vector machine (SVM) and Naïve Bayes (NB) algorithm are the best in sentiment analysis on large data. SVM outperforms NB because of its ability to analyze non-linear data. This is due to the presence of a kernel that forms a hyperplane from the data. The data to be used in this study is textual which linear. Therefore, the performance of SVM over NB is not guaranteed. In addition to that, SVM outperforms NB because the data is large, the case may be the difference between small data. Since the machine learning algorithms work better on large data, the study also intends to investigate the performance NB on small data. The study also intends to test the result of the investigation using a different approach. The study intends to use the lexicon-based approach to test the performance of NB. SVM is the machine learning algorithm chosen to valid NB because it is found to be the best in sentiment classification.

The main problem to be solved in this study is to design a framework using the Naïve Bayes algorithm that will analyze students' opinions on programming assessment. The algorithm performance will be evaluated specifically on small data.

The programming assessment is on two courses programming technique I and II offered by the School of Computing Universiti Teknologi Malaysia. The course is a core for the first-year undergraduate student of Computer Science, Software Engineering and Information Security. The performance of the student on the programming technique I and II courses is done through Skill-based test1 and 2 respectively. As a result, students' opinions were collected for the sentiment analysis using machine learning algorithm and lexicon-based approach.

(Caitlin et al., 2003) introduced a framework that endeavoured to make programming open in three primary ways in particular, by simplifying the mechanics of programming, by providing support for students and by giving students inspiration to Figure out how to program. The framework consists of pre-processing, feature extraction, feature selection, and classification stages. Most of these frameworks have focused on the mechanics of programming.

1.3 Problem Statement

This study investigates the sentiment analysis techniques in classifying students' opinions on programming assessments. Support vector machines perform better than Naïve Bayes in sentiment classification on large data. The study will investigate the performance of the NB algorithm on small. Students opinions were collected via an online survey from first-year undergraduate students of School of Computing, Universiti Teknologi Malaysia. An online survey that is simple and subject-based is adopted because the institutional survey is characterized as tedious, wide in scope and time-consuming. The subject is a programming technique I and II assessment as a skill-based test I and skilled-based test II on C++ class concept and association, aggregation, composition respectively. The problem to be addressed here is an investigation on the effectiveness of skill-based test on the student. The questions would be extracted based on features of the Skill-based test I and II itemized as follows:

i) Time accuracy -Appropriate or not appropriate

ii) Program output-compile or not compile

iii) Questions Composition -Difficult or simple, scary or motivated

iv) Internet speed- high or low.

The aforementioned are the issues to be responded by the student in the survey. And the responses would be collected as data for sentiment analysis. At the end of the study, the polarity of sentiment analysis is either positive or negative. If positive it means the opinions express good emotions of students on the skilled-based test. Furthermore, the conclusion implies students enjoy the skill-based test and it motivates them to learn the C++ programming language. The teacher will also understand how efficient the skill-based test is in measuring student performance. Negative sentiment score indicates that student finds skill-based test boring and scary, therefore discourage them from learning C++ programming which also implies inefficiency of the skill-based test. This can be used further for decision making by the faculty on whether the use of a Skill-based test to assess student's performance is effective or not.

In a study by Medhat et al., (2014) Learning programming challenges range from a student not having interest in programming, fear of conducting Skill-based test over the written one, difficulty of the test with respect to the time given, environment motivation on learning programming, complexity of the of programming language syntax (e.g. C++), development tools (for example Dev C++) and method of teaching.

Base on the review of the literature, Support vector machines(SVM) and Naïve Base Classifier are the most commonly used techniques in the analysis of student sentiment. (Ozturk et al., 2017) use Naïve Bayes classifier to analyze student sentiment from Twitter on sentence-level SA classification methodology. This study intends to use the Naïve Bayes algorithm (NB), a supervised type of machine learning algorithm to conduct sentiment analysis on document-level classification methodology. The machine learning algorithm is chosen because it overcomes the lexicon-based approach generally in terms of accuracy in the area in which it is trained(Mukhtar et al., 2018). Social media is not chosen for the survey because it is not confidential to collect student opinions.

1.4 Research Question

The main problem to be addressed by this study is to classify students' sentiments on Skill-based test based on the course C++ programming. This requires a lot of review on best sentiment analysis techniques on small and big data, learning programming, programming assessment, the role of student's opinion in education. The algorithm chosen for the analysis is the Naïve Bayes algorithm which is a supervised machine learning type of data mining technique. To be specific, the study tries to provide solutions to the following queries:

i. Is SVM better than Naïve Bayes in sentiment classification? On which entity or Sample size?

ii. What is the result of testing with the lexicon-based approach or using SVM in evaluation?

iii. What validation technique is used to evaluate the performance of the Naïve Bayes classifier (NBC) algorithm?

iv. Can the Skill-based test affect student performance in programming assessment?

Caitlin et al., (2003) introduced a framework that endeavoured to make programming open in three primary ways in particular, by simplifying the mechanics of programming, by providing support for students and by giving learners inspiration to understand out how to program. Most of these frameworks have focused on the mechanics of programming. Plainly, beginners need to feel that they can gain ground in understanding how to program. Be that as it may, unadulterated trouble isn't the main reason that individuals falter to Figure out how to the professional program. There are a variety of sociological variables (counting understudies not seeing the importance of programming or seeing programming just like a socially isolating profession way) that can keep individuals from figuring out how to program. Making environments that address a portion of these sociological hindrances to programming by supporting students or giving intriguing motivations to the program can possibly draw in an increasingly assorted gathering of individuals to the software engineering field. On the off chance that the population of individuals making programming is all the more firmly coordinated to the populace utilizing programming, the product planned and re-rented will likely better match user's needs.

1.5 The aim of the Research

The aim of this research is to study sentiment analysis techniques for the classification of students' opinions on programming assessment. Literature shows that support vector machines (SVM) performs better than Naïve Bayes (NB) in sentiment classification on big data. The study proposed a framework using the Naïve Bayes algorithm to investigate the classification of sentiments on small data. NB and SVM conquer the Lexicon-based methodology in terms of accuracy in the specific area for which it is trained (Kotzias et al., 2015). The Lexicon-based methodology, on the other hand, avoids difficult steps needed to train the classifier (Musto et al., 2014). The study further intends to show the significance of the sentiment polarity (classifying opinions as positive or negative) to improve Skill-based test on C++ programming.

1.6 Research Objectives

In order to achieve the aim of this research, these objectives are in focus:

i. To investigate the sentiment analysis techniques in classifying students' opinions on programming assessment.

ii. To develop a framework using the Naïve Bayes algorithm for the sentiment classification on small data.

iii. To evaluate the framework using a cross-validation technique and comparative measures with the lexicon-based approach and support vector machines.

1.7 Scope and Limitations

The scope of the research focused on sentiment analysis of the first-year student of the School of Computing's opinions on the skill-based test. The opinions would be collected in the English language. Therefore, any data collected in other languages would be translated to English using google translator. The data would be collected via online survey form students. The algorithm chosen is Naïve Bayes algorithm. And student opinion towards C++ programming assessment on document sentiment level classification methodology is the main scope of this study. The data to be collected on the Skill-based test I (C++ class concept) and Skill-based test II (association, aggregation and composition). The sentiment classes considered for the sentiment classification are two: positive or negative. The tools used for all the experiments in this study are; RTool and RStudio compiler for R programming language. Opinion lexicon is the sentiment dictionary selected for the lexicon-based approach.

1.8 Significance of the Research

The research importance is centred on three entities namely: Teacher, Student, faculty and research. The research enables the teacher understands the efficiency of the Skill-based test in assessing student performance. The result of this study is either positive or negative. If found to be positive then, it holds that the Skill-based test encourages the student to learn programming and otherwise, if the result is found to be negative. The student is given a chance to express their challenges with learning programming. The data collected would be served as a sample for testing sentiment analysis algorithms. The result can be used by the faculty for decision making. The report contains research findings which are the contribution to the knowledge to be used by the researchers for further studies.

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