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# Implementing Support Vector Machine Sentiment Analysis to Students' Opinion toward Lecturer in an Indonesian Public University

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**Abstract.** Student feedback is an important evaluation tool for quality improvement. Moreover, in Indonesian higher education system, there is an assessment regulation that puts special attention to the availability of the student feedback system. However, parts of the questionnaire are in the form of descriptive text that requires more effort for analysis. This situation leads to a very tiresome work in case of the number of documents reaches several hundred or even thousands. There were some efforts to apply computer-assisted classification by utilizing machine learning, however, most of them only analyzed English documents. Only a handful that studied the classification of documents in Bahasa Indonesia. In reality, we found some cases where the students used mixed languages while filling the evaluation forms. Therefore, in this study, we expand the application of text classification by using Support Vector Machne (SVM) to cases of student feedback in mixed languages. The model was built computationally and from the test, we get 74% accuracy and 0.46 Kappa value.

## 1. Introduction

*Evaluasi Dosen oleh Mahasiswa* (literally: Students Evaluation to the Lecturer, abbreviated as EDOM) is a mandatory element in Indonesia higher education system. Most of the items are in close-ended questions, similar with the Likert-scale. However, there are some descriptive questions where the answers cannot be processed structurally. Therefore, these unstructured answers are manually analyzed. This analysis will become a tiresome tasks when there are hundreds or even thousands of them. To alleviate this problem there are efforts of using computer-assisted classfications, such machine learning, as discussed in [1–4]. However, these studies only incorporated single language. In our case, a higher institution where the students mostly come from the same/similar ethnic group, there are variances in languages used when the students expressing their feelings for the semester that recently passed. Hence, this research aims to analyze the application of sentiment analysis for documents with mixed languages. The Support Vector Machine (SVM) was used as the classification method for it was found to yield more accurate result within this particular field as reported in [2–4].

The remaining work is organized as follows: in section 2 we discuss some of the known works within this field; in Section 3 the methods used are presented; Section 4 presents the results as well as some discussion regarding it; and finally this paper is concluded in Section 5.

## 2. Related Works

Students' satisfaction toward the quality of a lecturer is an important in the tertiary education institution. In Indonesia, this aspect is even included as a mandatory instrument of an academic program assessment as decreed by the National Accreditation Agency for Higher Education [5]. As some parts of the evaluation questionnaire are possibly in forms that require descriptive feedbacks, hence the analysis process could be tiresome when there are several hundreds or even thousands of feedbacks. To alleviate this problem, [1] proposed the use of sentiment analysis techniques to identify the students' feelings. Later, [2–4] also tried to solve the same issue. The work of [3] is the closest to our case in terms of geographic location, language, and regulations of higher education. However, there are some differences in the case we faced. Although the the feedbacks are mostly in Bahasa Indonesia, there are some of them that mixed with local dialect.

## 3. Methodology

In this study, we mainly follow the basic course of sentiment analysis as done in [3, 6, 7] except for the stemming part. Stemming is an effort of finding the root word, but this method was found ineffective for documents in Bahasa Indonesia [8].

## 4. Results and Discussion

The data we used came from the evaluation of the Spring Semester 2019. The feedbacks were collected on-line from May to mid of June. There are 636 feedbacks collected within this period, with 430, 109, 97 of positive, negative, and neutral sentiments, respectively. Figure 1 shows the composition of the sentiments.

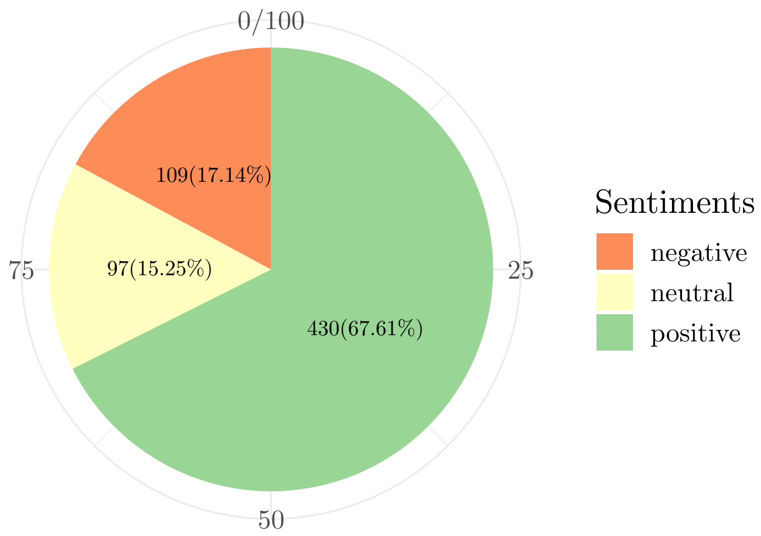
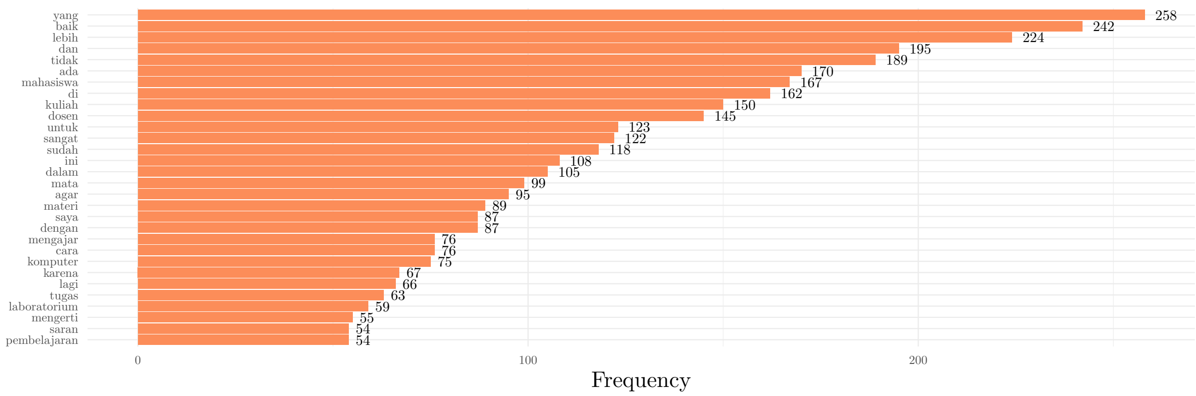


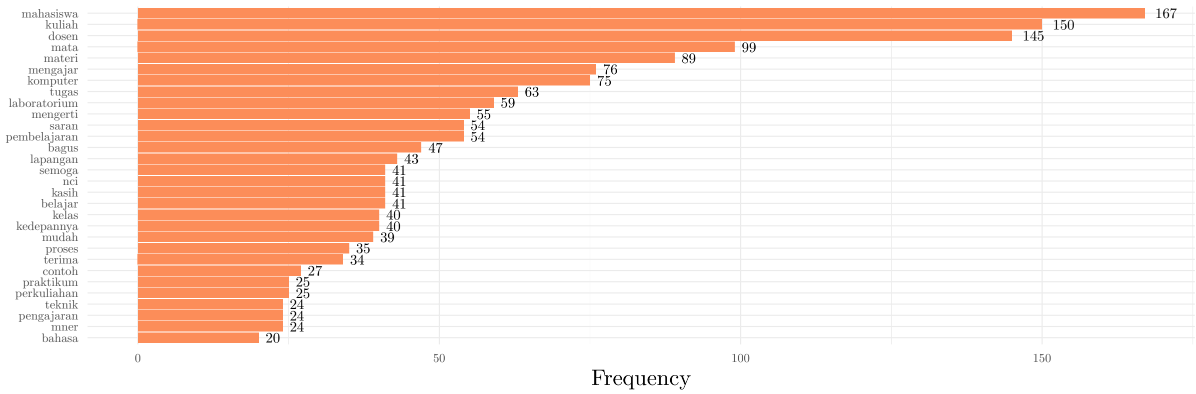

Figure 1: Sentiments composition in the dataset.

*4.1. Preprocessing*

The preprocessing task started with punctuation and number removal, case folding and tokenization. The aim of this process is to remove the punctuations and numbers in the documents and also remove the case differences by transforming all cases to lowercase. These steps were followed by tokenizing the sentences in the documents to tokens. In this study the tokenization process yielded words. The post-tokenizations of the highest 30 words frequency is shown on Figure 2a.




(a) Post tokenization, pre stopwords removal




(b) Post stopwords removal

Figure 2: Top 30 words with the highest frequency.

As shown on Figure 2a, there were documents that contain stopwords. A stopword is a frequent word that has no significant meaning. There were 2 stopwords dictionary that we used: the English stopwords from the Tidytext packet for R [9], and the Bahasa Indonesia stopwords as available on-line in [10, 11]. The result was significant, as shown on Figures 2b and 3. The reduction is more than half of the number of words (49.84 %).

*4.2. Applying Support Vector Machine*

After the data are tidied, the documents are transformed into a DTM (Document Term Matrix) according to the Term Frequency (TF). The DTM then splitted into 478 and 158 of training and testing data, respectively. It means 75% of the documents were used as training dataset and the other 25% as testing dataset. Then, with the training dataset the SVM model was built. To built the SVM model, the SVM function from the e1071 R package [12] with C-classification

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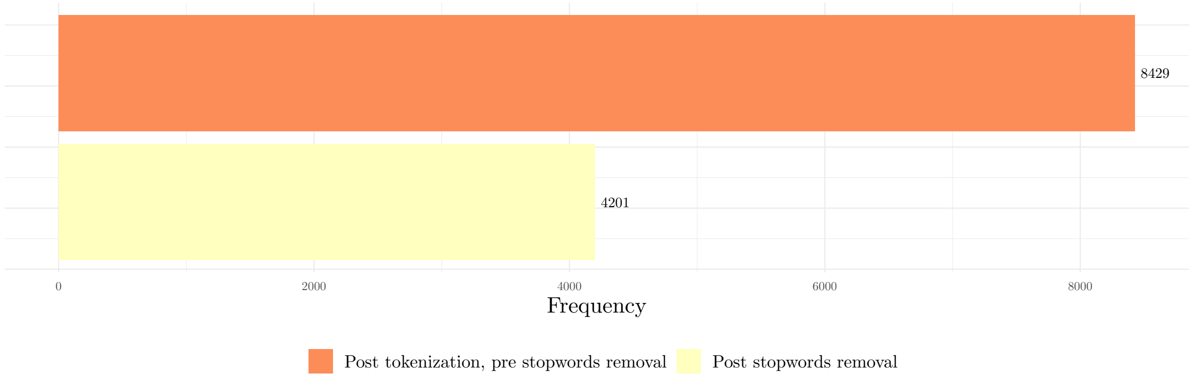


Figure 3: Number of words before and after stopwords removal.

Table 1: Statistics from the confusion matrix

| Statistics | Value |
|---|---|
| Accuracy | 0.7405 |
| Kappa | 0.4607 |
| AccuracyLower | 0.6649 |
| AccuracyUpper | 0.8069 |
| AccuracyNull | 0.6772 |
| AccuracyPValue | 0.0510 |
| McnemarPValue | 0.0001 |

type and the radial kernel were used. The built model then tested against the testing data (25% of the dataset).

The performance of the model was best when predicting positive sentiments, followed by neutral sentiments, and it was performed poorly when predicting negative sentiments, as shown in Figure 4. From the confusion matrix statistics in Tabel 1, our model has 74% accuracy and 0.46 of Kappa value which considerably moderate strength in agreement according to [13].

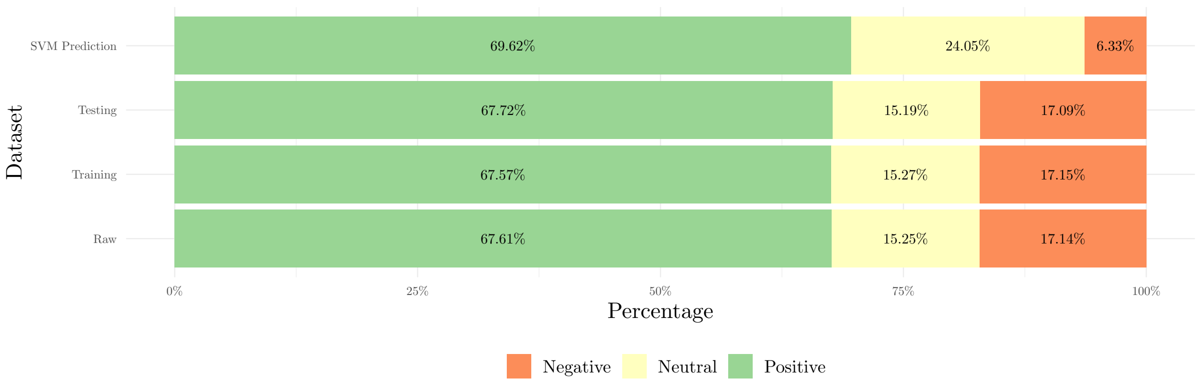


Figure 4: Sentiments composition between datasets.

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## 5. Conclusion and Future Works

In this paper we have observed the utilization of SVM to be used with the students' feedback data that have variations in languages used. The example of this variation can be seen in Figure 2 where some words such as "nci" and "mner" were commonly used. By using this 'noisy' data we tried to apply the SVM to classify the feedbacks. The built model has 74% accuracy with 0.46 Kappa value, which is a considerably moderate value. In the future works, the model must be adjusted to gain higher accuracy. Extending this work with more classification method and preprocessing task should also be considered.

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