

# Comparison of Multinomial Naïve Bayes and Bernoulli Naïve Bayes on Sentiment Analysis of Kurikulum Merdeka with Query Expansion Ranking

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## Abstract

Social media is one of the public services for conveying or obtaining news, opinions and comments on an issue. One of the social media that is in great demand by the people of Indonesia is Twitter. Kurikulum merdeka is one of the most discussed issues currently on Twitter. Kurikulum merdeka is a curriculum that incorporates varied intra-curricular learning with more optimal content to provide students adequate time to investigate ideas and build expertise. Until now, kurikulum merdeka still reaps the pros and cons. To process and analyze further regarding opinions on the kurikulum merdeka, it can be done using sentiment analysis. Sentiment analysis faces challenges due to the large dimension of features in the classification process, which results in inefficient classification and feature selection is needed to solve this problem. The purpose of this study was to obtain the results of the classification of kurikulum merdeka sentiments using the multinomial naïve bayes and bernoulli naïve Bayes, as well as query expansion rankings for feature selection and to compare the performance of the two classifications. Multinomial naïve bayes classification produces 106 tweets with positive sentiment and 164 tweets with negative sentiment with accuracy, recall, precision and f-measure respectively 98.889%, 98.131%, 99.057% and 98.591%, while bernoulli naïve bayes produces 95 tweets with positive sentiment and 175 tweets with negative sentiment with accuracy, recall, precision and f-measure respectively 94.815%, 87.850%, 98.947% and 93.069% respectively. Therefore, multinomial naïve bayes classifies the kurikulum merdeka sentiment better than bernoulli naïve bayes.

**Keywords:** Sentiment Analysis, Multinomial Naïve Bayes, Bernoulli Naïve Bayes, Query Expansion Ranking, Kurikulum Merdeka.

## 1 Introduction

Development of information technology, particularly social media, has altered how people connect with one another. [1]. Social media is one of the public services to convey or obtain news, opinions and comments on an issue. One of the social media that is in great demand by the people of Indonesia is Twitter [2]. Twitter users can express their opinions through posts called tweets. User opinions posted via tweets can come in the form of remarks, advice, or critiques about certain topics [3]. One of the topics that is currently being debated on social media, particularly Twitter, is kurikulum merdeka.

Kurikulum merdeka is a curriculum that incorporates varied intra-curricular learning with more optimal content to provide students adequate time to investigate ideas and build expertise [4]. Teachers in the kurikulum merdeka have the freedom to select different teaching strategies so that lessons can be tailored to the interests and learning needs of the pupils. Projects to improve the success of pancasila student profiles are created based on a number of predetermined government-set themes.

Kurikulum Merdeka is a program that aims to facilitate learning recovery. It has three features: project-based learning; development of soft skills and character in accordance with the pancasila student profile; learning of core subjects; and a more flexible curriculum structure. Additionally, Kurikulum Merdeka seeks to develop a discovery that bridges gaps in various scientific domains. Kurikulum merdeka was implemented in a number of driving schools in the first year quite successfully, but this year it was developed in a number of schools so that when it was implemented the kurikulum merdeka after analysis was better and more in line with Indonesian culture than the kurikulum 2013 [5]. Until

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now, kurikulum merdeka as a new curriculum launched by the Minister of Education, Culture, Research and Technology to overcome the learning crisis still reaps pros and cons. To process and analyze further about opinions on the kurikulum merdeka, it can be done using sentiment analysis.

Sentiment analysis is a branch of research to evaluate the benefits and drawbacks of opinions about things like goods, services, organizations, people, problems, themes, and events. Processing multiple answers from the public or experts through various media outlets is the fundamental work of sentiment analysis in order to extract sentiment information from an opinion [6]. Analysis of a person's feelings, whether they are favorable or negative, is the focus of sentiment analysis [7]. Therefore, in sentiment analysis it is necessary to have a classification used to classify responses into positive or negative sentiments [8]. Support Vector Machine, K-Nearest Neighbor and Naïve Bayes are a few techniques frequently utilized in the classification stage of sentiment analysis. [9]. Naïve bayes classification has several variations that can be used in sentiment analysis, including Multinomial Naïve Bayes and Bernoulli Naïve Bayes.

Sentiment analysis divides opinions into positive and negative categories by evaluating the value of each feature. As a result, sentiment analysis now faces challenges due to the large dimension of features in the classification process, which leads to ineffective classification [10]. Based on this, it is necessary to use feature selection to cut down on the amount of features used in the classification process. Additionally, feature selection can raise the method's classification accuracy [11]. One of the feature selection methods in sentiment analysis is Query Expansion Ranking (QER) [12].

Based on this description, this research will focus on conducting sentiment analysis related to the implementation of kurikulum merdeka on twitter using variations of naïve bayes classification, namely multinomial naïve bayes and bernoulli naïve bayes combined with feature selection query expansion ranking. The purpose of this study is to examine the performance outcomes of the two classes utilized for kurikulum merdeka sentiment classification utilizing multinomial naïve bayes and bernoulli naïve bayes with feature selection query expansion ranking. This research can be useful to provide an overview of public opinion regarding kurikulum merdeka and become a reference for the government, especially the Ministry of Education, Culture, Research and Technology in taking the direction of education policy in Indonesia.

## 2 Literature Review

Naïve bayes classification is a classification technique based on statistics and probability utilizing the bayes theorem with an assumption that every feature is independent [13]. Previous research has been performed with naive bayes classification on sentiment analysis and comparing it with other classification methods. Research on the comparison of naïve bayes and SVM on twitter sentiment analysis was done by Fikri et al in 2020. The research resulted that naïve bayes accuracy is 73.65% better than SVM which has an accuracy of 70.20% [14]. Other related research has also been conducted by Surohman et al in 2020 regarding sentiment analysis of fintech reviews applying naïve bayes which produces 84.76% accuracy value and KNN method which produces 82.92% accuracy value. Based on this, it can be concluded that the naïve bayes is better than the KNN method in classifying sentiments.

Multinomial naïve bayes method was used by Hamzah (2021) in his research with an accuracy of 87.74% [15] and the bernoulli naïve bayes method used in a study conducted by Pavitha et al (2022) with an accuracy of 87.5% [16]. Other related research was conducted by Wardani et al (2020) regarding the sentiment analysis of moving the national capital. Classification using bernoulli naïve bayes produces performance with a sensitivity level of 90.19%, while multinomial naïve bayes produces performance with a sensitivity level of 93.45% [17]. Thus, both Bernoulli and multinomial methods have good performance in classifying sentiment.

Feature selection query expansion ranking was first proposed by Parlar et al. Parlar dkk. (2018) as a new selection feature to assess the words needed and give weight to words to find information in documents. According to the study's results, QER is more accurate than other feature selection methods for sentiment analysis, such as optimal orthogonal centroid, chi-square, information gain and document frequency difference [12]. Research conducted by Fanissa et al (2018) also shows that naïve bayes with QER produces an accuracy value of 86.6% for tourism in Malang City sentiment analysis [10]. This shows that QER feature selection works well with the naïve bayes method.

### 3 Research Method

In this section, will discussed about data and methods used in the research, namely data text preprocessing, feature Selection using QER, classification using multinomial and bernoulli naïve bayes, and model evaluation using a confusion matrix.

#### 3.1 Data

Data used in this research were obtained from Twitter. Data is in the form of tweets in Indonesian Language with the keyword "Kurikulum Merdeka" from 21 July 2022 to 17 November 2022 as much as 15,000 tweets in the form of text. Python programming language's snsrape library is used to collect data from Twitter, which is subsequently saved in csv format. Next, each tweet is manually labeled into two classes (positive and negative) for the purpose of classifying sentiment. Tweets that don't fit into either of these two categories will be ignored, with the exception of those labeled as sentiment-neutral.

#### 3.2 Data Text Preprocessing

Preprocessing is the process of preparing the data used into a format that is easier to process. Preprocessing of text data changes an unstructured text into a more structured one so that it is easier to process [18]. This stage consists of:

1. Data cleaning, namely cleaning noise from data, such as usernames, URLs, hashtags, emoticons, numbers and punctuation marks [19].
2. Case folding, namely is the conversion of letter shapes to lowercase [20].
3. Spelling normalization, namely refinement and substitution of misspelled words, non-standard words, or abbreviations in a certain form [21].
4. Stemming, namely the step of removing affixes (prefixes, suffixes, or a combination of both) to turn words into basic words [22].
5. Stopword removal, namely the removal of common and frequently appearing words but not having significant meaning in text or sentences [23].
6. Tokenizing, namely the process of dividing documents or text into groups of words by separating them using spaces [24].

#### 3.3 Feature Selection Query Expansion Ranking

Based on the query expansion method, which enhances query quality, QER combines it with the probabilistic weighting model method, which is subsequently employed to score sentiment analysis features [25]. Equation (1) is used to calculate the QER score for each word with  $Score_f$  being the QER score for feature  $f$ ,  $p_f$  ratio of documents with positive class containing  $f$  feature  $f$  and  $q_f$  the ratio of documents with negative class containing  $f$  feature. The value of  $p_f$  and  $q_f$  is calculated using Equation (2) and Equation (3) respectively with  $DF_+^f$  and  $DF_-^f$  is the quantity of documents containing  $f$  features in positive and negative classes,  $N^+$  and  $N^-$  the quantity of documents in the positive class and negative class. Features with low QER scores are used for classification [12].

$$Score_f = \frac{|p_f + q_f|}{|p_f - q_f|} \quad (1)$$

$$p_f = \frac{DF_+^f + 0.5}{N^+ + 1.0} \quad (2)$$

$$q_f = \frac{DF_-^f + 0.5}{N^- + 1.0} \quad (3)$$

#### 3.4 Multinomial Naïve Bayes Classification

Multinomial naïve bayes is a variation of naïve bayes which in the process calculates the each word's occurrences in a document [10]. Equation (4) is used to calculate the probability that text  $d$  is in class  $c$  where  $P(c)$  is the probability that a document appears in class  $c$ ,  $P(t_k|c)$  is the probability that the word  $t_k$  is in a class  $c$  document, and  $n_d$  is the number of words on text  $d$ .

$$P(c|d) \propto P(c) \prod_{1 \leq k \leq n_d} P(t_k|c) \quad (4)$$

Equation (5) is used to calculate the value of  $P(c)$  and Equation (6) is used to calculate the value of  $P(t_k|c)$  where  $N_c$  is the quantity of documents with class  $c$  in the training data,  $N$  is the total quantity of documents in training data,  $T_{ct}$  is the quantity the appearance of the word (term)  $t$  in training data in class  $c$ ,  $\sum_{t' \in V} T_{ct'}$  is the total number of terms contained in all training data documents in class  $c$  and  $B$  is the total number of words [26]

$$P(c) = \frac{N_c}{N} \quad (5)$$

$$P(t_k|c) = \frac{T_{ct}+1}{(\sum_{t' \in V} T_{ct'})+B} \quad (6)$$

### 3.5 Bernoulli Naïve Bayes Classification

Bernoulli naïve bayes is a variation of naïve Bayes where a binary vector is used to represent a document indicating whether or not a word appears in the document [17]. Equation (7) is used to calculate the probability that text  $d$  is in class  $c$  where  $P(t_i|c)$  is the probability that the  $i$ -th word appears in a class  $c$  document,  $P(c)$  is the probability that a document appears in class  $c$  and  $M$  is many features [26].

$$P(c|d) \propto P(c) \prod_{\substack{1 \leq i \leq M \\ e_i=1}} P(t_i|c) \prod_{\substack{1 \leq i \leq M \\ e_i=0}} (1 - P(t_i|c)) \quad (7)$$

$P(c)$  is calculated by Equation (5) and  $P(t_i|c)$  is calculated by Equation (8) where  $N_{ct}$  is the quantity of documents containing the word  $t$  in class  $c$  documents in the training data.

$$P(t_i|c) = \frac{N_{ct}+1}{N_c+2} \quad (8)$$

### 3.6 Confusion Matrix

The important thing in classification is to measure the performance of the classification carried out. Classification performance evaluation is carried out using confusion matrix shown in Table 1 with attention to accuracy, recall, precision and f-measure values as in Equation (9) to Equation (12).

**Table 1. Confusion Matrix**

Actual Class	Prediction Class	
	Positive	Negative
Positive	$TP$	$FN$
Negative	$FP$	$TN$

$$Accuracy = \frac{TP+TN}{TP+FN+FP+TN} \quad (9)$$

$$Recall = \frac{TP}{TP+FN} \quad (10)$$

$$Precision = \frac{TP}{TP+FP} \quad (11)$$

$$F - measure = \frac{2 \times Recall \times Precision}{Recall + Precision} \quad (12)$$

## 4 Result and Analysis

In this section, will discussed about the result of data collection, data text preprocessing, visualization of data text that has been collected, feature selection using QER, classification with

multinomial and bernoulli naïve bayes, evaluation of the two models and comparison between each other.

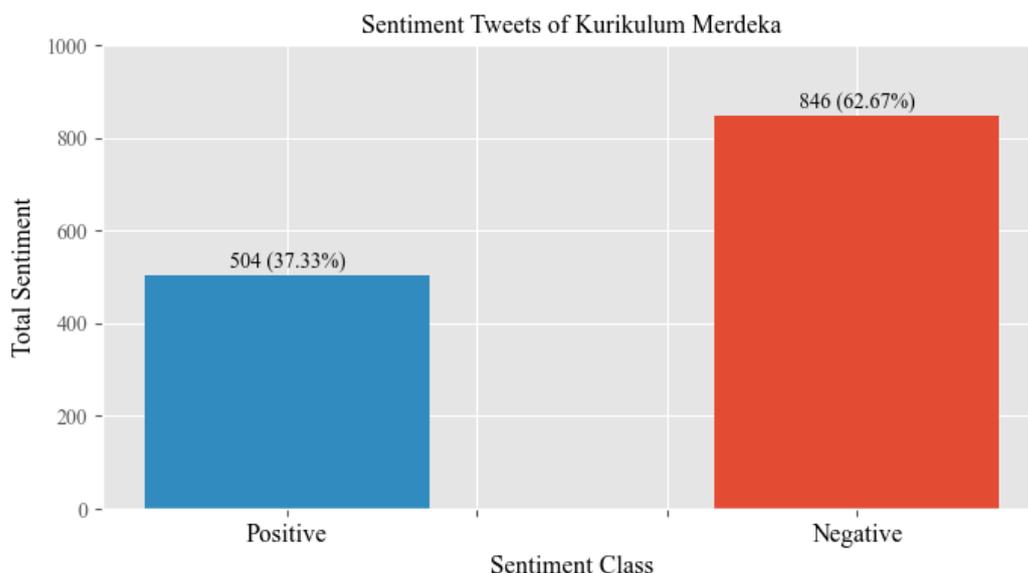
#### 4.1 Data Collection

Data was obtained from the data mining process on Twitter using the keyword "Kurikulum Merdeka" in the form of tweets uploaded on July 21, 2022 to November 17, 2022. Amount of data obtained from this data mining was 15,000 Indonesian language tweets. The outcomes of the data mining are displayed in Table 2.

**Table 2. Data Mining Result**

Date	Username	Tweets
2022-11-17	sakumapulang	meninggal dibantai kurikulum merdeka
2022-11-17	mediaindonesia	Kurikulum Merdeka Diharapkan Menjadikan Siswa Berkarakter Sesuai Nilai Pancasila. <a href="https://t.co/gFBDXabqOv">https://t.co/gFBDXabqOv</a>
2022-11-17	gustisaputr	Jatim Targetkan Seluruh Sekolah Terapkan Kurikulum Merdeka pada 2023 / 2024
2022-11-16	albiziard	@acturusj stres tpi tdk ap" hrs semangat ngerjain proyek kurikulum merdeka aku psti bisa
2022-11-16	scaabi6	Melarikan diri seru juga, ikut kurikulum merdeka
⋮	⋮	⋮
2022-07-21	cadeblury	semangat kurikulum merdeka

The tweets data from data mining are then labeled manually and divided into positive and negative class. Positive sentiment includes the superiority and support of an kurikulum merdeka, while negative sentiment includes dissatisfaction and rejection of an kurikulum merdeka. Based on the results of manual labeling, 1350 labeled data and 13650 data will be ignored because they cannot be classified into the two sentiment classes used, in the sense that they are classified as tweets with neutral sentiment. Figure 1 displays a bar graph of the sentiment class tweets from the kurikulum merdeka that were manually labeled.



**Figure 1. Sentiment Data Class Bar Graph**

Figure 1 demonstrates that the amount of data on sentiment is more negative than positive, which implies that there are more tweets containing dissatisfaction or rejection compared to tweets containing support and advantages of the kurikulum merdeka.





#### 4.6 Multinomial Naïve Bayes Classification

Multinomial naïve bayes classification classifies tweets into a class based on the probability values of words in tweets by paying attention to the number of occurrences of words in tweets. The first step is to calculate the probability for each class using Equation (5).

$$\hat{P}(\text{positive}) = \frac{N_{\text{positive}}}{N} = \frac{397}{1080} = 0.36759$$

$$\hat{P}(\text{negative}) = \frac{N_{\text{negative}}}{N} = \frac{683}{1080} = 0.63241$$

Furthermore, the probability that each word  $t_k$  is in each class  $c$  is calculated using Equation (6) and shown in Table 6.

**Table 6. Probability  $P(t_k|c)$  for Each Word**

Word	$T_{\text{positive};t}$	$T_{\text{negative};t}$	$P(t_k \text{positive})$	$P(t_k \text{negative})$
stres	0	133	0.00044	0.10412
potensi	27	0	0.01232	0.00078
milik	25	0	0.01144	0.00078
seru	23	0	0.01056	0.00078
pilih	22	0	0.01012	0.00078
⋮	⋮	⋮	⋮	⋮
profil	10	1	0.00484	0.00155

Classification of test data based on previously obtained opportunity values using multinomial naïve bayes is displayed using the confusion matrix in Table 7 will then be utilized to assess how well the classification model is performing.

**Table 7. Confusion Matrix Multinomial Naive Bayes**

Actual Class	Prediction Class	
	Positive	Negative
Positive	105	2
Negative	1	162

According to these values, using Equations (9) to Equations (12) the performance values of the naïve Bayes multinomial classification are obtained as follows:

$$\text{Accuracy} = 98.889\%$$

$$\text{Recall} = 98.131\%$$

$$\text{Precision} = 99.057\%$$

$$F - \text{measure} = 98.592\%$$

#### 4.7 Bernoulli Naïve Bayes Classification

Bernoulli naïve bayes classification classifies tweets into a class based on the probability values of words in tweets by focusing solely on the words that appear in tweets and ignoring the number of occurrences. The first step is to calculate the probability for each class using Equation (5).

$$\hat{P}(\text{positive}) = \frac{N_{\text{positive}}}{N} = \frac{397}{1080} = 0.36759$$

$$\hat{P}(\text{negative}) = \frac{N_{\text{negative}}}{N} = \frac{683}{1080} = 0.63241$$

Furthermore, the probability that each word  $t_i$  is present in each class  $c$  is calculated using Equation (8) shown in Table 8.

**Table 8. Probability  $P(t_i|c)$  for Each Word**

Kata	$N_{positif;t}$	$N_{negatif;t}$	$\hat{P}(t_i positif)$	$\hat{P}(t_i negatif)$
stres	0	126	0.00251	0.18540
potensi	24	0	0.06266	0.00146
milik	24	0	0.06266	0.00146
seru	23	0	0.06015	0.00146
pilih	21	0	0.05514	0.00146
⋮	⋮	⋮	⋮	⋮
profil	8	1	0.02256	0.00292

Classification of test data based on opportunity values that have been previously obtained using bernoulli naïve bayes is displayed using the confusion matrix in Table 9 will then be utilized to assess how well the classification model is performing.

**Table 9. Confusion Matrix Bernoulli Naive Bayes**

Actual Class	Prediction Class	
	Positive	Negative
Positive	94	13
Negative	1	162

According to these values, using Equations (9) to Equations (12) the performance values of the naïve bayes multinomial classification are obtained as follows:

$$\begin{aligned}
 \text{Accuracy} &= 94.815\% \\
 \text{Recall} &= 87.850\% \\
 \text{Precision} &= 98.947\% \\
 F - \text{measure} &= 93.069\%
 \end{aligned}$$

#### 4.8 Comparison of Classification Performance

Table 10 shows a comparison of the classification performance between the two methods.

**Table 10. Comparison of Classification Performance**

Classification Method	Classification Performance Measurement Values			
	Accuracy	Recall	Precision	F-Measure
Multinomial Naïve Bayes	98.889%	98.131%	99.057%	98.591%
Bernoulli Naïve Bayes	94.815%	87.850%	98.947%	93.069%

Table 10 shows that the performance values for both classification methods have shown very high scores, which means that both classification methods are very good at classifying kurikulum merdeka sentiments (excellent classification). Performance values of the multinomial naïve bayes classification are greater than the performance values of the bernoulli naïve bayes classification.

## 5 Conclusion

Considering the results of the analysis that was carried out, it can be concluded that the classification of sentiments in the kurikulum merdeka uses multinomial naïve bayes with QER obtain 106 positive sentiment tweets and 164 negative sentiment tweets, while using bernoulli naïve bayes with QER obtain

95 positive sentiment tweets and 175 negative sentiment tweets. Based on the classification performance value, multinomial naive bayes outperformed bernoulli naive bayes in classifying kurikulum merdeka sentiments, namely multinomial naive bayes accuracy of 98.889% compared to bernoulli naive bayes accuracy of 94.815%, multinomial naive bayes recall of 98.131% compared to bernoulli naive recall bayes of 87.850%, precision multinomial naive bayes of 99.057% compared to precision bernoulli naive bayes of 98.947%, and f-measure multinomial naive bayes of 98.591% compared to f-measure bernoulli naive bayes of 93.069%.

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