Relevance Vector Machine for Summarization

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Abstract. This research aimed at finding relevances Vector Machine for summarization. The need of producing an automatic text summarization create the research of text summarization continues to develop. One way to create an automatic summarization is by choosing the sentences which contain the main topics and reassembled them into a summary. The usage of Supports Vector Machine method (SVM) able to select summary sentences. The Relevance Vector Machine (RVM) appears as a further development of the SVM. This method performs a good result in a classification of Magnetic Resonance Imaging (MRI) data. Therefore, in this research, it examined the ability of RVM in the text summarization. Extracting the sentences used eight features, they are the length of the sentence, the sentence position, the containing of numerical data, the thematic words in the sentence, the similarity of the title, the sentence similarity, the sentence lexical cohesion before and after. There are 1509 training sentences and 214 testing sentences from 100 text documents. The result showed that using Radial Basis Function the accuracy of the RVM reached 63.084%. The RVM performance shows a better result than the SVM, 2% higher than the SVM result and uses fewer vector supports.

1. Introduction

Automatic text summarization is the process of making a summary with the aid of computers from a source of text's digital. The growing of online text causes the need for the automatic text summarization increase. Increasing the number of documents make more effort it takes to read and understand the information. The way to summarize text automatically is by extracting or by selecting sentences which contain the main topic and then rearranged them into a summary. Some research uses machine learning to create a summary. They identify which sentences chosen as the candidate of summary sentences. Hirao's research utilized the Support Vector Machine (SVM) to select summary sentences [1]. Hirao used the dataset from the Text Summarization Challenge (TSC) corpus. The selection of sentence summaries based on the ranking of the SVM decision value function. The test results obtained that the SVM produces a better accuracy of the summary algorithm C4.5 and C5.0 on the decision tree [1].

The SVM method has weaknesses, such as the selection of kernel functions must satisfy the Mercer's condition, the number of support vectors will increase linearly with the increasing amount of training data used [2]. Therefore, Tipping proposed the Relevance Vector Machine (RVM) method to overcome these weaknesses. The RVM algorithm works on the principle of Sparse Bayesian Learning [3]. Xiang-min [4] has compared the performance of both SVM and RVM on the heart scale data classification, breast cancer, Boston, Wdbc. The result shows that RVM requires fewer support vectors.
than SVM. When the testing data added gradually, then the error of the RVM is always smaller than
the SVM. It also shows that the time's requirement of training dataset using SVM is shorter than
RVM. Some studies of RVM were classifying the coffee data [5], detecting arrhythmia [6], epilepsy
[7], and recognizing a silent speech [8]. All these studies have shown that RVM performance is better
than SVM. Matsumoto added that the results obtained RVM better than SVM when the amount of
training data much [8].

This research used the RVM and the feature of a sentence to extract the information of each
sentence. The research about text features was seen in Fattah, Anita and Begum [9, 10, 11]. We used
the same features as Fitriaman's research because he has showed the optimal result for summarization
in Bahasa Indonesia [12]. There are eight features used in this research. That features are the length of
sentences, the position of sentences, numerical data, thematic words in sentences, title word count,
sentence similarities, lexical ties of a sentence before and after. Fitriaman proofed that eight of these
features influence the quality of automatic text summarization. The accuracy of each feature is greater
than 58% [12]. Therefore, this study will measure the summaries resulting from the implementation of
RVM and the usage of extraction features.

2. Method
This research uses a quantitative approach. The stages in the study were:

2.1. Literature study and formulation of a problem
The authors studied papers that relating to problems in automated text summarization, learned the
machine learning methods used in summarization, found the extraction features used in determining
sentence of the summary. At the end of this process was formulating the problems to be resolved in
the study.

2.2. Collecting data set
Testing used 100 documents dataset. The dataset was the introduction of a thesis in .txt format. After
collecting the data set, two of linguists chose the main sentences of each document. This summary
used 50% compression. So, the expert selected half of the document's sentences as the summary
sentences.

2.3. Preprocessing and feature extraction
Two things to do at this stage were performing a preprocessing and extracting feature of sentences.
Preprocessing steps used were case folding, sentence separation, filtering, tokenization, and stopword
removal. Feature extraction used were the length of sentences, the position of sentences, numerical
data, thematic words in sentences, title word count, sentence similarities, lexical ties of a sentence
before and after.

2.4. Learning and testing RVM
After the extraction process, the next step was training data set using RVM. In principle of RVM
training was to find the value of the parameters used in the testing process. From the test results
obtained summary sentences. The results were compared with a summary that made by experts.

2.5. Conclusion
The summary use accuracy to measure how good the result of the summary and compare it with the
SVM result. This part discusses the possibility of kernel function used. The researcher compares the
result with the others.

3. Result and discussion
Based on Fitriaman research [12], there are eight features to be used in the extraction process. The
features are as follows:
3.1. The length of sentence
In selecting of summary sentences process, it considers the length of sentence. Candidates of the summary are the longest sentence. To calculate this feature, it's a result of dividing the number of words in a sentence against the number of words from the longest sentence. How to calculate the length of sentence given to the equation (1).

\[ f_{1j} = \frac{\text{number of word in } j\text{-th sentence}}{\text{number of word in document}} \]  

(1)

3.2. The position of sentence
This feature assumes the first sentence of each paragraph is the most important sentence. The equation (2) shows how to compute the position of the jth sentence.

\[ f_{2j} = \frac{m-j}{m} \]  

(2)

Where m is the number of sentences in each document, j is the index of a sentence. Index of the first sentence is 0.

3.3. Numerical data
Usually, a sentence that contains numerical data is an important sentence. Equation (3) denotes how to calculate that sentence.

\[ f_{3j} = \frac{\text{a lot of numerical data in the } j\text{-th sentence}}{\text{number of words in the } j\text{-th sentence}} \]  

(3)

3.4. Thematic’s words in sentences
This feature calculates the relative appearance of a keyword in a sentence. Usually, a sentence with keywords is a summary sentence. Equation (4) is calculate the value of thematic word feature in the jth sentence.

\[ f_{4j} = \frac{\text{number of thematic words appearing in the } j\text{-th sentence}}{\text{the total number of thematic sentences in the document}} \]  

(4)

3.5. Title word count
A title-like sentence is a sentence that has a vocabulary overlap between sentences with the title. Equation (5) shows how to calculate the resemblance of jth sentence.

\[ f_{5j} = \frac{\text{number of (word in the } j\text{-th sentence } \cap \text{word in title)}}{\text{number of (word in the } j\text{-th sentence } \cup \text{word in title)}} \]  

(5)

3.6. Sentence similarity
The similarity of sentences counts the overlap of vocabulary between sentences with the others. To simplify it, it uses only keywords. Equation (6) shows how to calculate the resemblance of the jth sentence with another sentence:

\[ f_{6j} = \frac{\text{number of (word in the } j\text{-th sentence } \cap \text{word in other sentences)}}{\text{number of word in document}} \]  

(6)

3.7. Lexical ties of a previous sentence
The lexical tie between the sentence and the previous sentence is the word (stem) that appears in both sentences. If the sentence has a lexical relationship then the value of this feature is 1, otherwise is 0.

3.8. Lexical ties of a next sentence
The lexical tied between the sentence and the next sentence is the word (stem) that appears in both sentences. The same previous feature, the value will be 1 if it has a lexical relationship and 0 if it does not have.

After all the documents extracted, the RVM algorithm uses the result of feature extraction to generate summaries. Tipping shows that the detail of Bayesian Sparse Learning and RVM relationship in classification context [13]. It used the library provided by Mike Tipping to apply the RVM algorithm [14]. Dataset used are 100 of the introduction’s part of the thesis. From 100 documents, it
obtains 1723 sentences. The two of linguists asked to summarize the text manually. There are 838 sentences chosen as the sentences of summary and 885 as the sentences that were not summary from 1723 sentences. Table 1 shows the training and the testing data used. There were 1509 sentences used as trainer data. That sentences consist of 733 summary sentences and the other of 776 sentences not selected as summary sentences. The test used 214 sentences. There are 105 sentences of the summary sentences and the other of 109 sentences not selected as summary sentences.

The composition of the data in Table 1 will be used to test the performance of the RVM method in the summary. As a comparison, there is also a summary process using the SVM. The LibSVM package used to implement the SVM method [15]. There are several kernel functions tested in this research, namely: linear, polynomial, Radial Basis Function (RBF), and sigmoid. Performed several tests to obtain the optimal parameter value of each kernel function usage. The optimal value is determined based on the highest accuracy value obtained from the test data. Table 2 shows the details of the optimal parameter values used in each kernel function. The optimal parameter values in the SVM will be used to test the performance of the RVM. Table 2 shows the SVM and the RVM accuracy (See Table 1).

Table 1. Details of training data and tested data.

|                   | Summary Sentences | Non-Summary Sentences | Total Sentences |
|-------------------|-------------------|-----------------------|----------------|
| Training Sentences| 733               | 776                   | 1509           |
| Tested Sentences  | 105               | 109                   | 214            |

Table 2 shows that both the SVM and the RVM get the highest accuracy when it uses Radial Basis Function Kernel. The RVM accuracy is better than the SVM, except for the polynomial kernel function. The number of support vectors required in the RVM is less than the SVM. For the RBF, the number of support vectors in the SVM is 1191 vectors, whereas for the relevance vector on RVM there are only 21 vectors. This result is consistent with what Tipping has said and Xiang-ming’s result [2,4]. The SVM method produces a large support vector when the data is sparse, but not with the RVM method [2,3]. It also indirectly describes the distribution of sentence summaries selected by the expert. The results of this RVM test are same as those done by Lima et. al [7]. They have shown that the use of RBF is suitable for scattered and sparse data.

After comparison of the performance of RVM with SVM for each kernel function is selected, then the next election will be the best parameter values for the use of the RBF. Table 3 showed the rated accuracy of the gamma value changes on the RBF. The highest accuracy reached when gamma was 9. The accuracy of RVM was 63.084% and 27 relevance vectors used. However, the best accuracy shown in table 3 was better than Putra's research [16]. Putra used RVM for the document summary. This study only used TF-IDF in its feature extraction and produce accuracy as much as 53%. While in Arifin's research, multi-documentary summarization using RVM obtained 67% accuracy [17]. Our result is better than Putra’s research but not more than Arifin’s. Arifin used the feature of entity word of the sentences whereas we used the thematic’s word as a feature. This result shows that it needs to evaluate the optimal features of the summary and see the conformity with the RVM method. Although it has yet to show results, this study has shown that the use of RVM allows selecting the sentence of summarization and the performance of RVM consistently better than SVM, especially using RBF Kernel (See Table 2).
Table 2. The performancy result of RVM and SVM.

| Kernel Function | Parameter | SVM  | RVM  |
|-----------------|-----------|------|------|
| $\vec{u} \cdot \vec{v}$ | -         | 52.333 | 58.411 |
| $(\gamma(\vec{u} \cdot \vec{v}) + C)\text{degree}$ | $\gamma = 8, C = 10, \text{degree} = 2$ | 60.280 | 57.009 |
| $\exp(-\gamma \|\vec{u} - \vec{v}\|^2)$ | $\gamma = 8$ | 61.682 | 62.150 |
| $\tanh(\gamma(\vec{u} \cdot \vec{v}) + C)$ | $\gamma = 1/8, C = 0$ | 52.804 | 58.411 |

Table 3. The performancy of RVM using radial basis function kernel

| $\gamma$ | Accuracy (%) | Number of Vector |
|----------|--------------|-----------------|
| 7        | 61.682       | 19              |
| 8        | 62.150       | 21              |
| 9        | 63.084       | 27              |
| 10       | 63.084       | 26              |
| 11       | 63.084       | 26              |

4. Conclusion

This research has shown that RVM allows for use in automated text summarization. The results showed the comparison of accuracy between the RVM and the SVM. Based on the testing, the RVM works better than the SVM. It is seen from the accuracy obtained and from the number of support vectors needed to determine the candidate of sentence summarization. The Radial Basis Function remains the first choice for use in the classification process by the RVM method.

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