

# Latent Semantic Indexing for Indonesian Text Similarity

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**Submission date:** 20-Sep-2018 02:26PM (UTC+0700)

**Submission ID:** 1005208890

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Article · March 2018

DOI: 10.14419/ijet.v7i2.3.12619

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## Latent Semantic Indexing for Indonesian Text Similarity

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### Abstract

Document is a written letter that can be used as evidence of information. Plagiarism is a deliberate or unintentional act of obtaining or attempting to obtain credit or value for a scientific work, citing some or all of the scientific work of another party acknowledged as a scientific work without stating the source properly and adequately. Latent Semantic Indexing method serves to find text that has the same text against from a document. The algorithm used is TF/IDF Algorithm that is the result of multiplication of TF value with IDF for a term in document while Vector Space Model (VSM) is method to see the level of closeness or similarity of word by way of weighting term.

**Keywords :** Similarity, Latent Semantic Indexing, Vector Space Model

### 1. Introduction

Similarity of sentences may occur either accidentally or intentionally (plagiarism), the examination of the resemblance of the current sentence can be done using tools such as Turnitin, iThenticate or PlagiarismCheckerX or can also search directly by search engines like Google by entering the sentence user want to search, the general concept of examination of sentence similarity is to search and compare process[1]–[4] and this process could be done by using algorithm like Boyer-Moore[5], [6], Knuth-Morris-Pratt[7], Breadth-First Search[8], Depth-First Search[9] or any other algorithm.

The publication of scientific papers, academic articles, theses are fragile documents that will result in similarities to the detriment of many parties[10]–[12], to examine the possibilities that can occur in analysis by using Latent Semantic Indexing (LSI) method[13]–[15]. The LSI method is a statistical method that extracts the semantic structure of a word or phrase from a document, if the number of common words in the document is very large then the sentence is semantic. The LSI method will summarize the existing sentence and then calculate to show the calculation of the similarity of words that may be contained in the document[13], [14], as well as the application of the Term Frequency/Inverse Document Frequency algorithm to calculate the frequency of occurrence of term from a document[16]–[20].

The application [21]–[23] of the LSI method of examining the resemblance of sentences may help to avoid accidental or deliberate plagiarism and may be used for some other examinations such as the repetition of words that may be contained in a sentence contained in the document.

### 2. Methodology

Process examination with Latent Semantic Indexing algorithm[10], [13], [14] can be performed in several steps as follows:

- Calculating the value of the term frequency (tf).
- Calculate the value of the document frequency (df).
- Calculating inverse document frequency (idf).
- Calculate the weight of the document (W).
- Calculate the multiplication of the value of the keyword weight (query) of the document (WD) with the weight value of the  $i$  document ( $W_{di}$ ), sum the result of the multiplication of the weight value.
- Calculate the vector length of each document and keyword (query).
- Calculate similarity.

The final result is then calculated the level of similarity with the keyword (query) using vector space model calculation.

### 3. Results and Discussion



Implementation phase Latent Semantic Indexing TF/IDF to be more clearly created examples of keywords (Q = query) and documents (D = 4), as below:

Keyword (Q) = Analisis pada dokumen otomatis menggunakan metode LSI

Document 1 (D1)= Sistem analisis dokumen teks

Document 2 (D2)= Penilaian sistem dokumen teks terhadap dokumen otomatis

Document 3 (D3)= dalam sistem dokumen teks pada algoritma TF/IDF dan LSI

Document 4 (D4)= Analisis sistem pada dokumen otomatis untuk proses clustering dokumen menggunakan LSI dan TF/IDF

Through tokenizing process then entering the filtering process (stopword and stoplist), the word "pada" in Q, the word "terhadap" on D2, the word "dalam", "pada" and the "/" in D3, the word "pada" "untuk" and "dan" on D4 are deleted. Furthermore, a collection of words that have been selected are processed by the weighting of documents through the following calculations.

- a. Calculating the value of term frequency (tf). Table 1 shows TF Value.

**Table 1: TF Value**

| No. | Term        | TF |    |    |    |    |
|-----|-------------|----|----|----|----|----|
|     |             | Q  | D1 | D2 | D3 | D4 |
| 1   | Analisis    | 1  | 1  | 0  | 0  | 1  |
| 2   | Dokumen     | 1  | 1  | 2  | 1  | 2  |
| 3   | Otomatis    | 1  | 0  | 1  | 0  | 1  |
| 4   | Menggunakan | 1  | 0  | 0  | 0  | 1  |
| 5   | LSI         | 1  | 0  | 0  | 1  | 1  |
| 6   | Sistem      | 0  | 1  | 1  | 1  | 1  |
| 7   | Teks        | 0  | 1  | 1  | 1  | 0  |
| 8   | Penilaian   | 0  | 0  | 1  | 0  | 0  |
| 9   | Algoritma   | 0  | 0  | 0  | 1  | 0  |
| 10  | Tf          | 0  | 0  | 0  | 1  | 0  |
| 11  | Idf         | 0  | 0  | 0  | 1  | 0  |
| 12  | Proses      | 0  | 0  | 0  | 0  | 1  |
| 13  | Clustering  | 0  | 0  | 0  | 0  | 1  |

After the tokenizing process is done, it can be the result of the term frequency (TF) value of each word in the sentence and form a matrix on each document. Next calculate the value of the document frequency (DF).

- b. Calculates the value of the document frequency (DF).

Document frequency (DF) is the number of documents in which a word (term) appears. Table 2 shows DF value.

**Table 2: DF Value**

| No. | Term        | DF |
|-----|-------------|----|
| 1   | Analisis    | 2  |
| 2   | Dokumen     | 4  |
| 3   | Otomatis    | 2  |
| 4   | Menggunakan | 1  |
| 5   | LSI         | 2  |
| 6   | Sistem      | 4  |
| 7   | Teks        | 3  |
| 8   | Penilaian   | 1  |
| 9   | Algoritma   | 1  |
| 10  | Tf          | 1  |
| 11  | Idf         | 1  |
| 12  | Proses      | 1  |
| 13  | Clustering  | 1  |

After the calculation results TF and DF obtained, the next step calculation inverse document frequency (IDF) of each word (term) to calculate the weight of the word (term).

- c. Calculate inverse document frequency (IDF)

Formula used:  $IDF = \log \frac{D}{DF}$

Information:

D = number of documents

Through IDF calculation obtained IDF calculation results.

**Table 3: IDF Value**

| Term        | Tf |    |    |    |    | df | D/df | IDF   |
|-------------|----|----|----|----|----|----|------|-------|
|             | Q  | D1 | D2 | D3 | D4 |    |      |       |
| Analisis    | 1  | 1  | 0  | 0  | 1  | 2  | 4/2  | 0,301 |
| Dokumen     | 1  | 1  | 2  | 1  | 2  | 4  | 4/4  | 0     |
| Otomatis    | 1  | 0  | 1  | 0  | 1  | 2  | 4/2  | 0,301 |
| Menggunakan | 1  | 0  | 0  | 0  | 1  | 1  | 4/1  | 0,602 |
| LSI         | 1  | 0  | 0  | 1  | 1  | 2  | 4/2  | 0,301 |
| Sistem      | 0  | 1  | 1  | 1  | 1  | 4  | 4/4  | 0     |
| Teks        | 0  | 1  | 1  | 1  | 0  | 3  | 4/3  | 0,124 |
| Penilaian   | 0  | 0  | 1  | 0  | 0  | 1  | 4/1  | 0,602 |
| Algoritma   | 0  | 0  | 0  | 1  | 0  | 1  | 4/1  | 0,602 |
| Tf          | 0  | 0  | 0  | 1  | 0  | 1  | 4/1  | 0,602 |
| Idf         | 0  | 0  | 0  | 1  | 0  | 1  | 4/1  | 0,602 |
| Proses      | 0  | 0  | 0  | 0  | 1  | 1  | 4/1  | 0,602 |
| Clustering  | 0  | 0  | 0  | 0  | 1  | 1  | 4/1  | 0,602 |

Table 3 is an IDF computation process with different values for every word token in process, where the value 0 is a word token with no resemblance. Furthermore, after the tf and idf values have been obtained, it is then included in the calculation of tf-idf weighting to calculate the weight of the relationship of a term (term) in the document.

- d. Calculates the weight of the document (W)

Formula used:  $W_{d,t} = tf_{d,t} * IDF$

Information:

d=d document

t= the t word of the keyword

W= the weight of the d document against the t-word

**Table 4:** W value (document weight)

| No. | Term        | tf |    |    |    |    | IDF=log<br>(D/df) | W <sub>di</sub> =tf <sub>di</sub> *IDF |       |       |       |       |
|-----|-------------|----|----|----|----|----|-------------------|--|-------|-------|-------|-------|
|     |             | Q  | D1 | D2 | D3 | D4 |                   | Q                                      | D1    | D2    | D3    | D4    |
| 1   | Analisis    | 1  | 1  | 0  | 0  | 1  | 0,301             | 0,301                                  | 0,301 | 0     | 0     | 0,301 |
| 2   | Dokumen     | 1  | 1  | 2  | 1  | 2  | 0                 | 0                                      | 0     | 0     | 0     | 0     |
| 3   | Otomatis    | 1  | 0  | 1  | 0  | 1  | 0,301             | 0,301                                  | 0     | 0,301 | 0     | 0,301 |
| 4   | Menggunakan | 1  | 0  | 0  | 0  | 1  | 0,602             | 0,602                                  | 0     | 0     | 0     | 0,602 |
| 5   | LSI         | 1  | 0  | 0  | 1  | 1  | 0,301             | 0,301                                  | 0     | 0     | 0,301 | 0,301 |
| 6   | Sistem      | 0  | 1  | 1  | 1  | 1  | 0                 | 0                                      | 0     | 0     | 0     | 0     |
| 7   | Teks        | 0  | 1  | 1  | 1  | 0  | 0,124             | 0                                      | 0,124 | 0,124 | 0,124 | 0     |
| 8   | Penilaian   | 0  | 0  | 1  | 0  | 0  | 0,602             | 0                                      | 0     | 0,602 | 0     | 0     |
| 9   | Algoritma   | 0  | 0  | 0  | 1  | 0  | 0,602             | 0                                      | 0     | 0     | 0,602 | 0     |
| 10  | Tf          | 0  | 0  | 0  | 1  | 0  | 0,602             | 0                                      | 0     | 0     | 0,602 | 0     |
| 11  | Idf         | 0  | 0  | 0  | 1  | 0  | 0,602             | 0                                      | 0     | 0     | 0,602 | 0     |
| 12  | Proses      | 0  | 0  | 0  | 0  | 1  | 0,602             | 0                                      | 0     | 0     | 0     | 0,602 |
| 13  | Clustering  | 0  | 0  | 0  | 0  | 1  | 0,602             | 0                                      | 0     | 0     | 0     | 0,602 |

Table 4 is the weighting for each document based on a word token that has been processed by obtaining the IDF value of each word, the weighting is grouped in Q, D1, D2, D3 and D4.

Furthermore, after calculating the multiplication of  $WD * W_{di}$ , the sum of the results of the multiplication of the value of the weight is shown in Table 6.

- e. Calculates the multiplication of the value of the document weight (WD) with the weight value of the  $i$  th document ( $W_{di}$ ) as shown in Table 5.

**Table 5:** Multiplication  $WD * W_{di}$ 

| WD*W <sub>di</sub> |       |       |       |
|--------------------|-------|-------|-------|
| D1                 | D2    | D3    | D4    |
| 0,091              | 0     | 0     | 0,091 |
| 0                  | 0     | 0     | 0     |
| 0                  | 0,091 | 0     | 0,091 |
| 0                  | 0     | 0     | 0,362 |
| 0                  | 0     | 0,091 | 0,091 |
| 0                  | 0     | 0     | 0     |
| 0                  | 0     | 0     | 0     |
| 0                  | 0     | 0     | 0     |
| 0                  | 0     | 0     | 0     |
| 0                  | 0     | 0     | 0     |
| 0                  | 0     | 0     | 0     |
| 0                  | 0     | 0     | 0     |
| 0                  | 0     | 0     | 0     |

**Table 6:**  $WD * W_{di}$  sum

| Document | Function                                      | Result  |
|----------|---|---|
|          | $SUM(WD * Wd_i) = \sum_{j=1}^n WD_j Wd_{i,j}$ |   |
| D1       | $SUM(WD * Wd_1) = \sum_{j=1}^n WD_j Wd_{1,j}$ | 0,091 + 0 + 0 + 0 + 0 + 0 + 0 + 0 + 0 + 0 + 0 + 0 = 0,091             |
| D2       | $SUM(WD * Wd_2) = \sum_{j=1}^n WD_j Wd_{2,j}$ | 0 + 0 + 0,091 + 0 + 0 + 0 + 0 + 0 + 0 + 0 + 0 + 0 = 0,091             |
| D3       | $SUM(WD * Wd_3) = \sum_{j=1}^n WD_j Wd_{3,j}$ | 0 + 0 + 0 + 0 + 0,091 + 0 + 0 + 0 + 0 + 0 + 0 + 0 = 0,091             |
| D4       | $SUM(WD * Wd_4) = \sum_{j=1}^n WD_j Wd_{4,j}$ | 0,091 + 0 + 0,091 + 0,362 + 0,091 + 0 + 0 + 0 + 0 + 0 + 0 + 0 = 0,634 |

After the multiplication of  $WD * W_{di}$  and sum of  $WD * W_{di}$  is obtained, then calculate the length of each document vector and keyword (query).

- f. Calculates the vector length of each document and keyword (query) as shown in Table 7 and Table 8.

**Table 7:** Vector calculation from query

| Table 7: vector calculation from query |                                      |  |
|--|--------------------------------------|--|
| Query                                  | Function                             | Result   |
|  | $ Q  = \sqrt{\sum_i W_{q,i}^2}$      |  |
| Q                                      | $sqr(Q) = \sqrt{\sum_{j=1}^n Q_j^2}$ | $= \sqrt{(0,301)^2 + (0)^2 + (0,301)^2 + (0,602)^2 + (0,301)^2 + (0)^2 + (0)^2 + (0)^2 + (0)^2 + (0)^2 + (0)^2 + (0)^2}$ $= \sqrt{0,091 + 0 + 0,091 + 0,362 + 0,091 + 0 + 0 + 0 + 0 + 0 + 0}$ $= \sqrt{0,635}$ $= 0,796$ |

Table 8: Vector calculation from document

| Document | Function  |  |
|----------|---|--|
|          | $ D_i  = \sqrt{\sum_i W_{i,j}^2}$                                 | Result   |
| D1       | $\text{sqr}(Q) = \text{sqr}\left(\sum_{j=1}^n D_{1,j}^2\right)$   | $= \sqrt{(0,301)^2 + (0)^2 + (0)^2 + (0)^2 + (0)^2 + (0)^2 + (0)^2 + (0)^2 + (0)^2 + (0)^2}$ $= \sqrt{0,091 + 0 + 0 + 0 + 0 + 0 + 0 + 0 + 0 + 0}$ $= \sqrt{0,106}$ $= 0,326$                                 |
| D2       | $\text{sqr}(D_2) = \text{sqr}\left(\sum_{j=1}^n D_{2,j}^2\right)$ | $= \sqrt{(0)^2 + (0)^2 + (0,301)^2 + (0)^2 + (0)^2 + (0)^2 + (0,124)^2 + (0)^2 + (0)^2 + (0)^2}$ $= \sqrt{0 + 0 + 0,091 + 0 + 0 + 0 + 0,015 + 0 + 0 + 0 + 0}$ $= \sqrt{0,468}$ $= 0,684$                     |
| D3       | $\text{sqr}(D_3) = \text{sqr}\left(\sum_{j=1}^n D_{3,j}^2\right)$ | $= \sqrt{(0)^2 + (0)^2 + (0)^2 + (0)^2 + (0,301)^2 + (0)^2 + (0,124)^2 + (0)^2 + (0,602)^2 + (0)^2}$ $= \sqrt{0 + 0 + 0 + 0 + 0,091 + 0 + 0,015 + 0 + 0,362 + 0 + 0 + 0}$ $= \sqrt{1,192}$ $= 1,092$         |
| D4       | $\text{sqr}(D_4) = \text{sqr}\left(\sum_{j=1}^n D_{4,j}^2\right)$ | $= \sqrt{(0,301)^2 + (0)^2 + (0,301)^2 + (0,602)^2 + (0,301)^2 + (0)^2 + (0)^2 + (0)^2 + (0)^2 + (0)^2}$ $= \sqrt{0,091 + 0 + 0,091 + 0,362 + 0,091 + 0 + 0 + 0 + 0,362 + 0,362}$ $= \sqrt{1,359}$ $= 1,166$ |

After the calculation of vector query and document, then get the value of vector length as shown in Table 9.

| Table 9: Vector Length Values |       |       |       |       |
|-------------------------------|-------|-------|-------|-------|
| Vector Length Values          |       |       |       |       |
| Q                             | D1    | D2    | D3    | D4    |
| 0,091                         | 0,091 | 0     | 0     | 0,091 |
| 0                             | 0     | 0     | 0     | 0     |
| 0,091                         | 0     | 0,091 | 0     | 0,091 |
| 0,362                         | 0     | 0     | 0     | 0,362 |
| 0,091                         | 0     | 0     | 0,091 | 0,091 |
| 0                             | 0     | 0     | 0     | 0     |
| 0                             | 0,015 | 0,015 | 0,015 | 0     |
| 0                             | 0     | 0,362 | 0     | 0     |
| 0                             | 0     | 0     | 0,362 | 0     |
| 0                             | 0     | 0     | 0,362 | 0     |
| 0                             | 0     | 0     | 0,362 | 0     |
| 0                             | 0     | 0     | 0     | 0,362 |
| 0                             | 0     | 0     | 0     | 0,362 |

The next step is to calculate the Similarity between the keyword vectors (query) with each document.

g. Counting Similarities is shown in Table 10.

Table 10: Counting Similarities

| Document | Function  |   | Result    |
|----------|---|---|-----------|
|          | $Cosine\theta_{D_i} = \frac{Q, D_i}{ Q  *  D_i }$ |   |           |
|          |   |   |           |
| D1       | $Cosine\theta_{D_1} = \frac{Q, D_1}{ Q  *  D_1 }$ | $= \frac{0,091}{0,796 * 0,326} = \frac{0,091}{0,259}$ | $= 0,349$ |
| D2       | $Cosine\theta_{D_2} = \frac{Q, D_2}{ Q  *  D_2 }$ | $= \frac{0,091}{0,796 * 0,684} = \frac{0,091}{0,545}$ | $= 0,166$ |
| D3       | $Cosine\theta_{D_3} = \frac{Q, D_3}{ Q  *  D_3 }$ | $= \frac{0,091}{0,796 * 1,092} = \frac{0,091}{0,87}$  | $= 0,104$ |
| D4       | $Cosine\theta_{D_4} = \frac{Q, D_4}{ Q  *  D_4 }$ | $= \frac{0,634}{0,796 * 1,166} = \frac{0,634}{0,928}$ | $= 0,683$ |

Cosine calculation results note that Document 4 (D4) has the highest similarity level followed by D1, D2 and D3.

#### 4. Conclusion

Examination of similarity of words or sentences by using Latent Semantic Indexing can be done well, the process of examination similarity done enough detail so that the margin error obtained is also small, the development by combining with other algorithms is possible so that the results obtained will also be better.

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