# Data Dimension Reduction for Clustering Semantic Documents using SVD Fuzzy C-Mean (SVD-FCM)

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**Abstract -** The rapid growth of XML adoption has urged for the need of a proper representation for semi-structured documents, where the document semantic structural information has to be taken into account so as to support more precise document analysis. In order to analyze the information represented in XML documents efficiently, researches on XML document clustering are actively in progress. The key issue is how to devise the similarity measure between XML documents to be used for clustering. In this paper, we introduce data dimension reduction (DDR) based on the SVD factorization (DDR/SVD) for the documents similarity calculating and DDR SVD Fuzzy C-Mean (DDR SVD-FCM) After projecting XML documents to the lower dimensional space obtained from DDR, our proposed method fuzzy c-mean to execute the document-analysis clustering algorithms (SVD-FCM). DDR can substantially reduce the computing time and/or memory requirement of a given document-analysis clustering algorithm, especially when we need to run the document-analysis algorithm many times for estimating parameters or searching for a better solution.

***Key Words*: SVD, DDR, XML, SVD-FCM**

## 1. INTRODUCTION

An XML document, which is semi-structured data, has a hierarchical structure. Therefore, rather than using the similarity measure of the general document clustering techniques as it is, a new similarity measure which considers the semantic and structural information of an XML document must be investigated. However, some XML clustering methods used the similarity measure which only takes the structural information of XML documents into account. Hwang proposes a clustering method which extracts a typical structure of the maximum frequency pattern n using *PrefixSpan* algorithm [1] on XML documents [2, 3]. However, since such a typical structure extracted from XML documents is not the only structure which represents the XML document itself, it cannot be the representative of the whole document corpus, since there is an accuracy issue of similarity. Lian summarizes XML documents into an *S-graph* which is a structural graph, and proposes that the calculation method of the distance between *S-graphs* is used for clustering [4]. However, they do not consider semantic information on XML documents since they only focus on structural information. Since dimension reduction is one of the fundamental methods of data analysis, there have been a great many studies on effective and efficient dimension reduction algorithms. There are linear dimension reduction algorithms including principal component analysis (PCA) [5] and multidimensional scaling (MDS) [6]. There are also nonlinear dimensional reduction algorithms (NLDR) including an Isomap [7], locally linear embedding (LLE) [8], [9], Hessian LLE [10], Laplacian eigenmaps [11], local tangent space alignment (LTSA) [12] and a distance preserving dimension reduction based on a singular value decomposition (DPDR/QR) [13]. These dimensions cover a variety of areas such as biomedical image recognition, biomedical text data mining, and biological data analysis.

The rest of this paper is organized as follows. In Section 2, we introduce the prepared XML documents on a vector space model. In Section 3, we show the DDR based on the SVD decomposition and the DDR SVD-FCM. Section 4 presents the experimental results illustrating properties of the proposed DDR methods. A summary is made in Section 5.

## 2. Preparation of Semantic-based XML Documents

In this section, we first introduce the pre-processing steps for the incorporation of hierarchical information in encoding the XML tree's paths. This is based on the preorder tree representation (PTR) [14] and will be introduced after a brief review of how to generate an XML tree from an XML document.

Chart-1 illustrates an example of structural summary. By applying the phase of the nested reduction on tree $T_1$, we derived tree $T_2$ where there are no nested nodes. By applying the repetition reduction on tree $T_2$, we derived tree $T_3$, which is the structural summary tree without nested and repeated nodes. Once the trees have been compacted using structural summaries, the nesting and repetition are reduced.

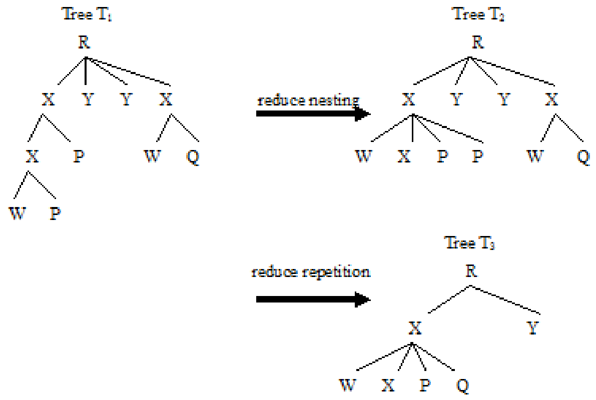



**Chart -1**: nested and repeated nodes extraction

Now the XML document is modeled as a XML tree *T*=(*V*,*E*) where *V*={ $v_1$, $v_2$, ....} as a set of vertices and $v_1 \in V$, $v_2 \in V$, $(v_1, v_2) \in E$ as a set of edges. As an example, Chart-2 depicts a sample XML tree containing some information about the collection of books. The *book* consists of *intro* tags, each comprising *title*, *author* and *date* tags. Each *author* contains *fname* and *lname*, each *date* includes *year* and *month* tags. Chart-2 left shows only the first letter of each tag for simplicity.

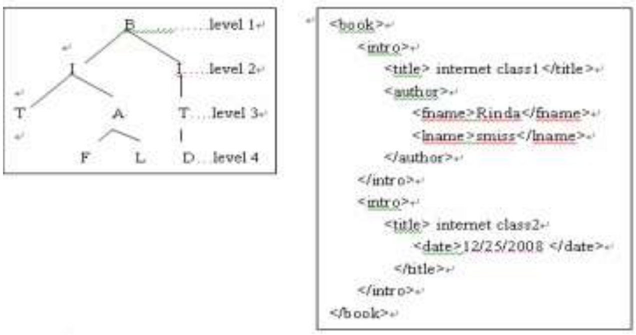



**Chart -2**: Example of XML Document

The XML document has a hierarchical structure and this structure is organized with tag paths, to represent document characteristics which can predict the contents of the XML document. Strictly speaking, this shows the semantic structural characteristics of the XML document. In this paper, we propose a new method for calculating the similarity using all of the tag paths of the XML tree representing the semantic structural information of the XML document. From now on, a tag path is termed *path element*. Table-1 shows path elements obtained from the XML document in Chart-3. The $PE_{L-i}$ represents the extracted path elements on the XML document tree from the i^th^ tree level to the leaf node. For example, the $PE_{L-1}$ means the path element from the root level (level 1) to the leaf node, and $PE_{L-2}$ means the path element from the level 2 to the leaf node respectively.

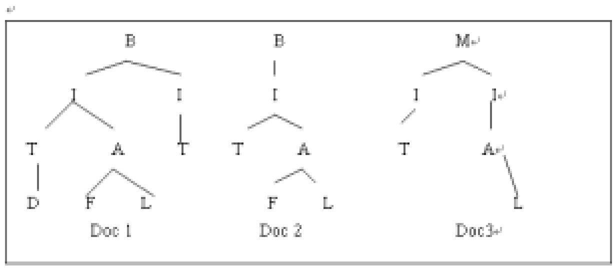



**Chart -3**: XML Documents Example

**Table -1:** Path elements example

| $PE_{L-1}$ | $PE_{L-2}$ | $PE_{L-3}$ | $PE_{L-4}$ |
|---|---|---|---|
| /B/I/T/D | /I/T/D | /T/D | D |
| /B/I/A/F | /I/A/F | /A/F | F |
| /B/I/A/L | /I/A/L | /A/L | L |
| /M/I/A/L | /I/T | /T | |
| /B/I/T/ | /I/A | /A | |
| /B/I/A | /I | | |
| /B/I/ | | | |
| /B | | | |
| /M/I/T | | | |
| /M | | | |
| /M/I | | | |

## 3. Path Element of the Vector Space Model (PEVSM)

Vector model represents a document as a vector whose elements are the weights of the path elements within the document. To calculate the weight of each path element within the document, a Term Frequency and IDF (Inverse Document Frequency) method is used [15]. We define the PESSW (Path Element Structural Semantic Weight) which calculates the weight of the path element in an XML document. The PESSW is PEWF (Path Element Weighted Frequency) multiplied by the PEIDF (Path Element Inverse Document Frequency). The $PESSW_{ij}$ of i^th^ path element in the j^th^ document is shown in equation (1). In this paper, we use the PESSW and $D_{PESSW}$ interchange.

$$PESSW_{ij} = PEWF_{ij} \times PEIDF_{ij} \quad (1)$$

$PEWF_{ij}$ is shown in equation (2).

$$PEWF_{ij} = freq_{ij} \times \frac{1}{x^n} \quad (2)$$

$freq_{ij}$ is a frequency of j-th path element in a i-th document and it is multiplied by level weight $\frac{1}{x^n}$ in order to consider the semantic importance of a path element in a document. X refers to the level number of the highest tag of a tag path. The level number of the root tag is 1, and that of a tag under the root tag is 2, and so on. N is a real number larger than 1, and in this paper, 1 is chosen for the value of n. $PEIDF_{ij}$ is shown in equation (3). $PEIDF_{ij}$ is shown in equation (3).

$$PEIDF_{ij} = \log \frac{N}{DF_j} \qquad (3)$$

where N is the total number of documents and $DF_j$ is the number of documents in which the $j^{th}$ path element appears. The PESSW is prudently calculated to correctly reflect the structural semantic similarity. Table-2 shows the PEWF, PEIDF, and PESSW on sample trees in Chart-3.

**Table-2:** An example of *PTWF*, *PTIDF* and *PESSW*

| Path | PEWF | | | PEIDF | | | PESSW | | |
|---|---|---|---|---|---|---|---|---|---|
| | do | do | do | do | do | do | do | do | do |
| /B/I/T | 1.0 | 0.0 | 0.0 | 1.1 | 0.0 | 0.0 | 1.1 | 0.0 | 0.0 |
| /B/I/A | 1.0 | 1.0 | 0.0 | 0.4 | 0.4 | 0.0 | 0.4 | 0.4 | 0.0 |
| /B/I/A | 1.0 | 1.0 | 0.0 | 0.4 | 0.4 | 0.0 | 0.4 | 0.4 | 0.0 |
| /M/I/ | 0.0 | 0.0 | 1.0 | 0.0 | 0.0 | 1.1 | 0.0 | 0.0 | 1.1 |
| /B/I/T | 2.0 | 1.0 | 0.0 | 0.4 | 0.4 | 0.0 | 0.8 | 0.4 | 0.0 |
| /B/I/A | 1.0 | 1.0 | 0.0 | 0.4 | 0.4 | 0.0 | 0.4 | 0.4 | 0.0 |
| /B/I/ | 2.0 | 1.0 | 0.0 | 0.4 | 0.4 | 0.0 | 0.8 | 0.4 | 0.0 |
| /B | 1.0 | 1.0 | 0.0 | 0.4 | 0.4 | 0.0 | 0.4 | 0.4 | 0.0 |
| /M/I/ | 0.0 | 0.0 | 1.0 | 0.0 | 0.0 | 1.1 | 0.0 | 0.0 | 1.1 |
| /M | 0.0 | 0.0 | 1.0 | 0.0 | 0.0 | 1.1 | 0.0 | 0.0 | 1.1 |
| /M/I | 0.0 | 0.0 | 2.0 | 0.0 | 0.0 | 1.1 | 0.0 | 0.0 | 2.2 |
| /I/T/D | 0.5 | 0.0 | 0.0 | 1.1 | 0.0 | 0.0 | 0.5 | 0.0 | 0.0 |
| /I/A/F | 0.5 | 0.5 | 0.0 | 0.4 | 0.4 | 0.0 | 0.2 | 0.2 | 0.0 |
| /I/A/L | 0.5 | 0.5 | 0.5 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| /I/T | 1.0 | 0.5 | 0.5 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| /I/A | 0.5 | 0.5 | 0.5 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| /I | 1.0 | 0.5 | 1.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| /T/D | 0.3 | 0.0 | 0.0 | 1.1 | 0.0 | 0.0 | 0.3 | 0.0 | 0.0 |
| /A/F | 0.3 | 0.3 | 0.0 | 0.4 | 0.4 | 0.0 | 0.1 | 0.1 | 0.0 |
| /A/L | 0.3 | 0.3 | 0.3 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| /T | 0.6 | 0.3 | 0.3 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| /A | 0.3 | 0.3 | 0.3 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| D | 0.2 | 0.0 | 0.0 | 1.1 | 0.0 | 0.0 | 0.2 | 0.0 | 0.0 |
| F | 0.2 | 0.2 | 0.0 | 0.4 | 0.4 | 0.0 | 0.1 | 0.1 | 0.0 |
| L | 0.2 | 0.2 | 0.2 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |

Let $d_x$ and $d_y$ be two vectors which represent an XML document $doc_x$ and $doc_y$. Cosine similarity is defined as being the angle between two vectors and is quantified by equation (4) and (5).

$$\cos\theta = \frac{d_x \cdot d_y^T}{|d_x| \cdot |d_y|} \text{, that is} \qquad (4)$$

$$sim(doc_x, doc_y) = \frac{d_x \cdot d_y^T}{|d_x| \times |d_y|} = \frac{\sum_{k=1}^{t} w_{kx} \times w_{ky}}{\sqrt{\sum_{k=1}^{t} w_{kx}^2} \times \sqrt{\sum_{k=1}^{t} w_{ky}^2}} \qquad (5)$$

$$d_x = (w_{1x}, w_{2x}, \ldots, w_{tx}) \quad , \quad d_y = (w_{1y}, w_{2y}, \ldots, w_{ty})$$

and $(w_{1x}, w_{2x}, \ldots, w_{tx})$ is weight of $d_x$, $(w_{1y}, w_{2y}, \ldots, w_{ty})$ is weight of document of $d_y$, and t is the total number of path elements in $d_x$, $d_y$ respectively [16].

### 3.1 Singular Value Decomposition (SVD) and DDR SVD

Using $SVD_{LSI}$, the original path element document matrix $PESSW_{mxn}$ is first decomposes into three matrices:

$$PESSW_{mxn} = U_{mxm} \cdot S_{mxn} \cdot V_{nxn}^T$$

where U and V contain orthonormal columns and S is diagonal. By restricting the matrices U, V and S to their first *k* <min(*m*,*n*) columns, one obtains the matrix

$$\hat{D}_{mxn}(PESSW_{mxn}) = \hat{U}_{mxk} \cdot \hat{S}_{kxk} \cdot \hat{V}_{kxn}^T$$

, where $\hat{D}$ is the best square approximation of D by a matrix of rank k. To deal with novel documents not included in the path element-document matrix D, one can project the novel document vector onto the “semantic space” of dimension k and measure distance directly in the semantic space. Thus, an XML document will eventually be represented as a matrix, $d_x \in \Re^{kxm}$, with each column being the projection of the element-specific feature vector on the semantic space. We call this version of PESSW as thin-SVD of the $D_{PESSW}$ in the subsequent sections. In this paper, we focus on DDR based on the SVD (DDR/SVD) for the sake of simple presentation.

The thin SVD of D is

$$D = U_1 S_1 V_1^T,$$

where $U_1 \in \Re^{m \times n}$ has only n basis vectors, $S_1 \in \Re^{n \times n}$ is a diagonal matrix, and $V_1 \in \Re^{n \times n}$ is an orthogonal matrix.

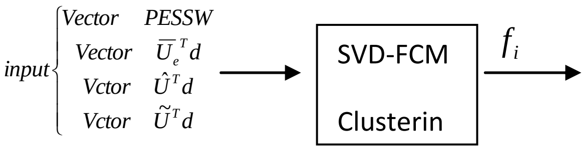
According to the cosine similarities are preserved in the t-dimensional space owing to

$$\cos(d_i, d_j) = \frac{(U_1^T d_i)^T (U_1^T d_j)}{\|U_1^T d_j\|_2 \|U_1^T d_j\|_2} = \frac{y_i^T y_j}{\|y_i\|_2 \|y_j\|_2} = \frac{\hat{y}_i^T \hat{y}_j}{\|\hat{y}_i\|_2 \|\hat{y}_j\|_2}.$$

We refer this method to as DDR SVD is based on the SVD.

### 3.2 Our proposed DDR SVD-FCM Algorithm

As described in the previous section from the DDR SVD decomposition, we have the originated document vector PESSW, document vector $\overline{U}^T D$ (refer to economic SVD decomposition), document vector $\hat{Q}^T D$ (refer to SVD decomposition of rank PESSW), and document vector $\tilde{U}^T D$ (refer to efficient low rank PESSW on SVD decomposition) based on the XML documents, which is taken as the SVD-FCM input data and then goes through the clustering.




F(I)=[f$_1$,f$_2$,.....,f$_c$] , where $f_i = \sum_{j=1}^{N} \mu_{ij} P_j = \frac{1}{N} \sum_{j=1}^{N} \mu_{ij}$ .

This method developed by [17] and improved by [18] [19] is frequently used in pattern recognition. It is based on the minimization of the following objective function:

$$J_m = \sum_{i=1}^{N} \sum_{j=1}^{C} \mu_{ij}^m \times \|d_i - c_j\|^2, \ 1 \le m \le \infty$$

where $m$ is any real number greater than 1, $u_{ij}$ is the degree of membership of $d_i$ in the cluster $j$, $d_i$ is the $i$th of d-dimensional measured data, $c_j$ is the d-dimension center of the cluster, and ||*|| is any norm expressing the dissimilarity between any measured data and the center.

The objective function shown above with the update of membership $u_{ij}$ and the cluster centers $c_j$ by:

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{C} \left( \frac{\|d_i - c_j\|}{\|d_i - c_k\|} \right)^{\frac{2}{m-1}}}, \quad c_j = \frac{\sum_{i=1}^{N} \mu_{ij}^m \times d_i}{\sum_{i=1}^{N} \mu_{ij}^m}$$

This iteration will stop when $\max_{ij} \{ |\mu_{ij}^{(k+1)} - \mu_{ij}^{(k)}| \} < \xi$, where $\xi$ is a termination criterion between 0 and 1, whereas $k$ are the iteration steps.

### 4. Experiment Result

In the Chart-4, we show the occupied space (k) on the variant document vectors D$_{PESSW}$, $\overline{U}^T D$, $\hat{U}^T D$, and $\tilde{U}^T D$ from 400, 800, 1200, 1600, and 2000 XMLs separately. When comparing the D$_{PESSW}$ with the $\tilde{U}^T D$ on 2000 XMLs, we could save a lot of space, and importantly unaffected the clustering result where we used the SVD-FCM would be unaffected. In the Chart-5, we show CPU executing time (ms) to run SVD-FCM on the variant document vectors D$_{PESSW}$ , $\overline{U}^T D$, $\hat{U}^T D$, and $\tilde{U}^T D$ from 400, 800, 1200, 1600, and 2000 XMLs separately. When comparing the D$_{PESSW}$ with the $\tilde{U}^T D$ on 2000 XMLs, we could save a great deal of time, and importantly the clustering result where we used the SVD-FCM still remains the right result.

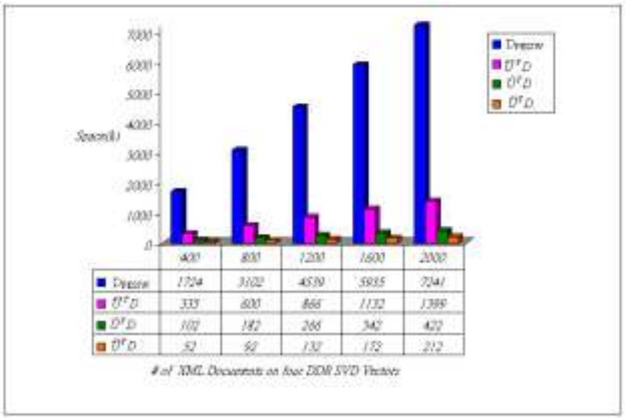



**Chart-4:** Space on the variant vector from different # XMLs

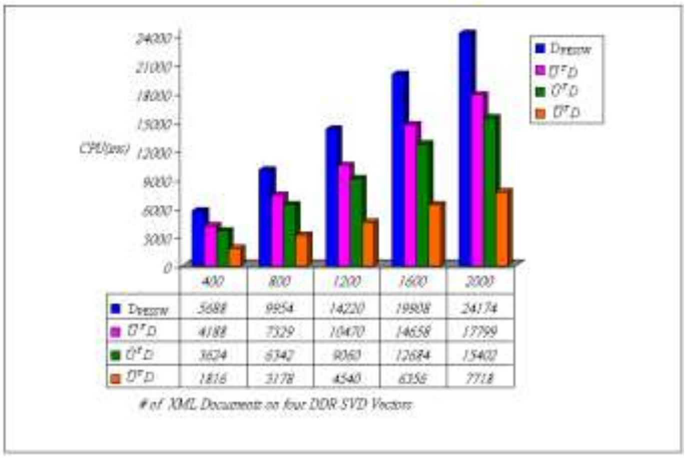



**Chart-5:** CPU (ms) executing SVD-FCM on the variant vector

In the Table-3, we show the percentage of the space saved when comparing $\overline{U}^T D$ with $\hat{U}^T D$ , $\overline{U}^T D$ with $\widetilde{U}^T D$, $\hat{U}^T D$ with $\widetilde{U}^T D$, on running SVD-FCM using 2000 XMLs and 1600 XMLs from 5 DTDs. We also show the percentage of the CPU executing time when comparing $\overline{U}^T D$ with $\widetilde{U}^T D$ , $\overline{U}^T D$ and $\hat{U}^T D$ , $\hat{U}^T D$ with $\widetilde{U}^T D$ , on running SVD-FCM using 2000 XMLs and 1600 XMLs from 5 DTDs. On comparing $\overline{U}^T D$ with $\hat{U}^T D$, we find that using $\hat{U}^T D$ instead of $\overline{U}^T D$ on 2000 XMLs for the SVD-FCM saving 69% of space in k and 13% of CPU time in ms. In the Table-4, we show the percentage of the space saved and CPU time (ms) when comparing original document vector $D_{PESSW}$ with $\overline{U}^T D$, $\hat{U}^T D$, and $\widetilde{U}^T D$ on running SVD-FCM using 2000 XMLs and 1600 XMLs from 5 DTDs. When comparing $D_{PESSW}$ with $\hat{U}^T D$, we find that using $\hat{U}^T D$ instead of $D_{PESSW}$ on 2000 XMLs for the SVD-FCM saving 94% of space in k and 36% of CPU running time in ms.

**Table-3:** Percentage of space and CPU saved in thin-SVD and low rank thin-SVD

| Space(k)/CPU(ns) | 2000 XMLs | 1600 XMLs |
|---|---|---|
| | % saved | % saved |
| $\overline{U}^T D \sim \hat{U}^T D$ | 69% 13% | 69% 14% |
| $\overline{U}^T D \sim \widetilde{U}^T D$ | 84% 57 % | 84% 58% |
| $\hat{U}^T D \sim \widetilde{U}^T D$ | 49% 50% | 49% 51% |

**Table-4:** Percentage of space and CPU saved in $D_{PESSW}$ / thin-SVD

| Space(k)/CPU(ns) | 2000 XMLs | | 1600 XMLs | |
|---|---|---|---|---|
| | % saved | | % saved | |
| Variant Vectors | Space | CPU | Space | CPU |
| $D_{PESSW} \sim \overline{U}^T D$ | 80% | 26 % | 80% 26% | |
| $D_{PESSW} \sim \hat{U}^T D$ | 94% | 36 % | 94% 36% | |
| $D_{PESSW} \sim \widetilde{U}^T D$ | 97% | 68% | 97% | 68 % |

## 5. CONCLUSION

The original XML documents $D_N=[d_1,d_2,..,d_N]$ are modeled on the vector space model according to the path element of each document, that is $D_{PESSW}$ (PESSW), then a SVD was conducted on the $D_{PESSW}$. We derived the $D_{PESSW} = USV^T$, and then took the low-rank on the $\hat{D}_k = U_k S_k V_k^T$ upon the k low-rank from rank ($D_{PESSW}$) to efficient low rank of $D_{PESSW}$. We passed the 4 resulting vectors ($D_{PESSW}$, $\overline{U}^T D$, $\hat{U}^T D$ and $\widetilde{U}^T D$) into the SVD-FCM clustering algorithm to attain the clustering result. In terms of the clustering results of the section experiment, we found the same clustering result as from the variant $D_{PESSW}$, $\overline{U}^T D$, $\hat{U}^T D$, and $\widetilde{U}^T D$ vectors. From the practical experiment results, we conclude that using the low-rank vector $\widetilde{U}^T D$ instead of the original document (PESSW), not only saved the space on the input vector but also took less time to cluster on the documents.

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