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SELF-ORGANIZING MAP BASED QUERY REORGANIZATION FOR EFFICIENT INFORMATION FILTERING

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ABSTRACT

Information at World Wide Web (WWW) is retrieved through queries that are submitted by the users to the search engine. For a given query, various techniques are followed to access the WWW to process it and retrieve the most related documents. All techniques retrieve more or less same documents, but vary in time that it consumes to generate such results. Therefore, the best method is needed to reduce the time required for information retrieval. This requirement is focused by enormous researchers to discover and invent many techniques. Though the invented techniques retrieved the documents quickly, they did not concentrate on the relevancy of retrieved documents. Hence, an essential technique that depletes less time and retrieves more accurate document is necessary.In this paper, a new clustering method has proposed for query re-organizationin the information filtering of WWW.

KEYWORDS: World Wide Wide, Information Filtering, Clustering, Query Re-organization

1. INTRODUCTION

Text clustering is a technique used to gather the documents which have similar content [1]. The main objective of text clustering is to divide theunstructured set of objects into clusters. The algorithm can be used torepresent the concept and to measure

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the similarity among the concept presentin the document. The clustering process is widely applied for summarizingthe corpus and document classification [2]. Traditionally, quantitative data arefocused for clustering, which contain numeric data as their attributes.Following this, categorical data are also studied where the attributes hold thenominal values. Nevertheless, these techniques do not work well forclustering the text data. Since the text data has the following uniqueproperties, it requires a specialized algorithm for the task.

1. Dimensionality representation [3] of the text is very large,whereas the underlying data is sparse.

2. The total number of concepts in the data is much smallerthan the feature space, which made the design of clusteringalgorithm very complex.

3. Normalization of document representation is required sincethe word count varies for different documents.

The high dimensional representation and the sparse nature of the documents require the design of text-specific algorithms for documentrepresentation and processing. Many existing clustering algorithms are usedto improve the document representation for clustering. Usually, the vectorspacebased Term Frequency - Inverse Document Frequency (TF-IDF) [4]representation is used for text clustering. In such type of representation, theTerm Frequency (TF) [5] for each word is normalized by Inverse DocumentFrequency (IDF) [6]. In addition to the IDF, term-frequencies are appended withthe sub-linear transformation function. This is carried out to avoid theundesirable dominating effect of any single term that might be frequent in thedocument. The clustering algorithms for text are widely classified into arange of different types. Partitioning algorithm, Agglomerative algorithm,and EM-algorithm are the different types of clustering algorithms. Different tradeoffs exist among the different clustering algorithms in terms of efficiencyand effectiveness.

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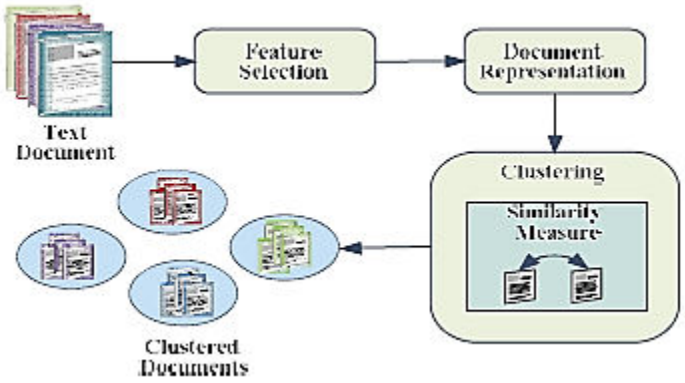

Figure 1: Overall Process of Text clustering for Query Reorganization

2. FEATURE SELECTION

Simple unsupervised methods [7] can also be used for feature selectionin text clustering. Document Frequency-based selection, Term strength,Entropy-based ranking and term contribution are the various populartechniques that are used for feature selection. The descriptions of thesetechniques are presented in the following subsections.

2.1 Document Frequency - Based Selection

The simplest technique [8] for selecting the feature in the document clustering is that of the uses of document frequency to filter out the featuresthat are irrelevant. The words that occur too frequently, i.e. stop words in thecorpus, are removed since they are not discriminative from the clusteringperspective. On the other side, the most infrequent words present in the textare also removed. In addition to this, noisy data are also removed. Someresearch scholars define the document frequency based feature selection aspurely depending on the infrequent terms. This is due to the reason that theseterms contribute the least to the similarity calculations. However, the wordswhich are not discriminative for the clustering process should be removed.

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2.2 Term Strength

This is the most aggressive technique for removing the stop words [9].The strength of the term is computed to detect how informative a word is foridentifying the documents that are related to each other. Consider the tworelated documents x and y , for which the term strength can be computedfrom the following probabilistic equation:

$$s(t) = P(t \in y \mid t \in x)$$

One major advantage of this technique is that there is no need ofinitial supervision or training data for the selection process.

2.3 Entropy - Based Ranking

The quality of the term in the document is measured through this technique [10]. The entropy of a term in the documents can be determined throughthe equation:

$$E(t) = -\sum_{i=1}^{n}\sum_{j=1}^{n}\left(X_{ij}.\log(X_{ij}) + (1-X_{ij}).\log(1-X_{ij})\right)$$

In the above equation, $X_{ij} \in (0,1)$ shows the similarity among i^{th} and j^{th} document in the collection, after the term t is removed. The mathematical representation of$X_{ij}$is represented in equation

$$X_{ij} = 2^{-\frac{d(i,j)}{d}}$$

From the above equation has d(i,j) which denotes the distance between the terms i and j after the term t is removed. The computation of $E\,t$ requires $O\,(n^2)$ operations. With this requirement, it becomes impractical to implementfor the corpus holding many terms.

2.4 Term Contribution

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This method depends on the fact that the clustering of texts is highly dependent on the similarity present in the document. Here, the termcontribution is considered the contribution of document similarity [11].

3. FEATURE REPRESENTATION

Similar to feature selection, feature transformation [12] is a technique that improves the quality of the retrieving process. The transformationtechnique defines the new features as its functional representation of thefeatures in the original data set. The most common method is dimensionalityreduction. In dimensionality reduction, the features are transformed to a newspace of smaller dimensionality. Here, the features are usually thecombination of features in the original data. Non-negative MatrixFactorization, Latent Semantic Indexing and Probabilistic Latent SemanticIndexing are some of the transformation techniques.

4. CLUSTERING TECHNIQUES

The text clustering process [13] is carried out using any one the following five ways: (1) Distance-based text clustering [14], (2) Text clusteringdepending on word patterns and phrases [15], (3) Text clustering using text stream [16],(4) Probabilistic text clustering [17] and (5) Semi-supervised text clustering [18].

Similarity functions are used for designing the distance-based text clustering algorithms that are used to compute the closeness among the textobjects. The most widely implemented technique that is used in the textdomain is the cosine similarity function.

Another way for clustering text is through word patterns and word phrases. If a corpus contains n number of documents and t terms then, aterm-document matrix can be constructed as $n\ d$. The entry at $(i, j)^{th}$is thefrequency of j^{th}term in i^{th}document. This shows the relation amongclustering the row and document clustering.

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Both the clustering techniques are related, as good word clustering may be leveraged to detect an efficient document clustering and vice-versa.Word clustering is related to dimensionality reduction, whereas the clusteringof documents is related to traditional clustering. Clustering with frequentword patterns, leveraging word clusters for document cluster, co-clusteringwords and documents and clustering with frequent phrases are the varioustechniques that deal with the aforesaid dual problem and cluster the documentthrough word phrase and patterns.

Probabilistic clustering is also a way to cluster the document. The most familiar technique for probabilistic document clustering is that of topic modeling. In addition to these techniques, the process of clustering is carriedout using the text stream as well as semi-supervised learning.

Most of the techniques that are discussed so far for clustering the text are based on the statistical analysis of a term in the document. It can beeither phrase or word. Such techniques concentrate only on the termfrequency within a single document. Nevertheless, a document may have twoor more terms with same frequency, but one term contributes more to themeaning of its sentences than the other term. From the above discussion, it isunderstood that the previous approaches were proved as merely extracting thephrases and as not tending to mine well enriched core part of the document.Therefore, there exists a need to indicate the term to capture the semantics ofthe text. With this requirement, a novel method for query re-organization using SOM cluster (QR- C) has developed.

5. PROPOSED QUERY RE-ORGANISATION METHOD USING CLUSTERING

It is essential for the proposed text clustering method to extract the relation between verbs and their associated arguments in the same sentence.This extraction has potential information for analyzing terms within asentence. To identify and clarify the

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contribution of each term of a particular sentence the information about who is doing what to whom should be used.

QR-C technique captures the semantic structure of each term within a sentence and document rather than the frequency of the termfrequency within a document alone. The contexts on three angles dependingon the corpus, document and sentence levels are computed. The contexts canbe either word or phrases and that are entirely dependent on the semanticstructure of the sentence. On arrival of a new document, the contexts from itare extracted and matched with the previously processed documents. Alongwith this, a new similarity measure is proposed to find the similarity betweenthe documents present in a corpus. This depends on the combinationcorpus-based, document-based, and sentence-based context analysis.

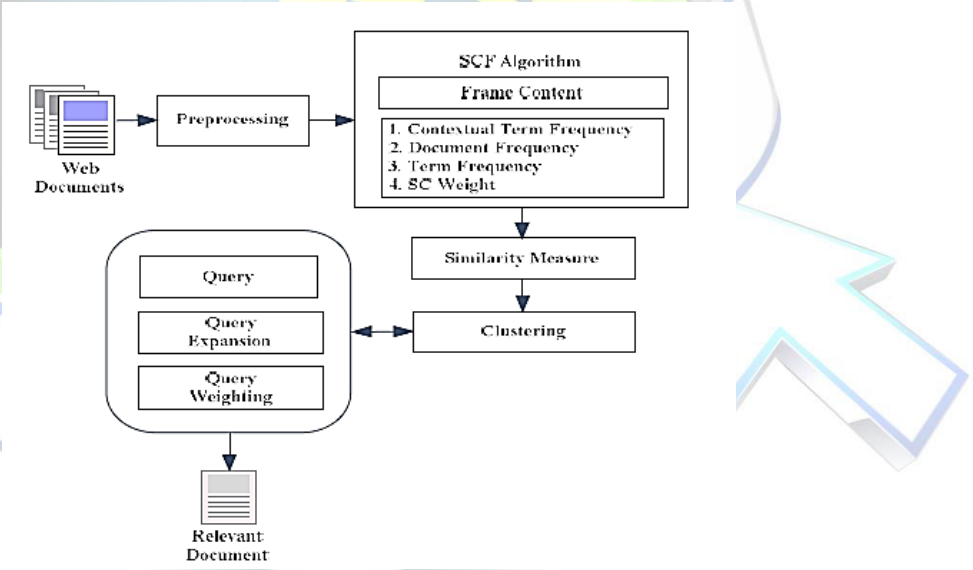

Figure 2: System Architecture

5.1 Steps in Proposed Method

Input to the proposed technique is the raw text document. The input documents are pre-processed through the following steps. Preprocessinghas the following five different steps (1) Document's individualsentences are separated, (2) HTML tags in the

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web document are removed,(3) Stop words are detected, (4) Stemming and (5) POS tagging. Consider anexample to compute the SV parameter. Consider a document that containsthe following sentences.

"The employees must abide by the rules of the company. Billalways abides by his promises. Problems always arise during such protestsfor human rights. Disputes arose whom would be the first to speak".

During pre-processing the above paragraph is separated to sentences as below.

a. The employees must abide by the rules of the company

b. Bill always abides by his promises.

c. Problems always arise during such protests for human rights

d. Disputes arose whom would be the first to speak

Once the lines are separated then, the stop words and other words that are not discriminate are removed. For example after this the firststatement looks as ***"Employees abide Rules Company"***. The parameters andverbs are computed and their results are given below.

Param0: employees, **Verb:** abide, **Param1:** rules company.

Param0: Bill always, **Verb:** abides, **Param1:** his promises.

Param0: Problems always, **Verb:** arise, **Param1:** such protestshuman rights.

Param0: Disputes arose, **Verb:** be, **Param1:** first speak.

Param0: first, **Verb:** speak. While calculating the individual CTFfor the contexts (discussed as follows), the sentences are dissectedinto SV Parameters.

Each sentence will be having conjugation called object that resolves the terms which donate the sentence semantics, associated with their subject verb- argument

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structure. Context is defined to either phrases or words thatdepend on the subjective part of a sentence. This is repeated for a wholedocument and for all documents aggregated on a whole by iterating the abovesteps.

The estimation of similarity is computed for each context x presented in the sentence s , document d and in the corpus. The similarityanalysis part holds three stages.

(a) Computing CTF , TF and DF

(b) Similarity measure

(c) Query weighting based on clusters

5.2 Computing CTF, TF and DF

The value of conceptual term frequency (CTF) denotes the numberof occurrences of c in SV argument structures of sentence s . This shows thelocal measure on the sentence measure. The occurrence of c is measuredsince it has a major role of contributing to the meaning of s . The context $c$has different CTF values for different sentences in a document. Therefore,the CTF value of c in a document d is manipulated through the followingequation.

$$CTF_d = \frac{\sum_{n=1}^{s} CTF_n}{s}$$

In the above equation, s denotes the number of sentences that contain the context c in document d . The average value of CTF_dvalue of the context$c$ in its sentences of document d measures the overall impact of context c toits meaning of the corresponding sentence s in document d . The context thathas higher CTF values in most of the sentences has foremost contribution tothe meaning of its sentence that leads to discover

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the topic of the document.Therefore, the value obtained through the above equation computes the overallimportance of each context to the semantics of a document through thesentences.

Similarly, the term frequency (TF) is computed for the whole documents through counting the number of occurrences of a context c in a document. The corpus may contain a set of documents as$D = \{d_1, d_2, \dots, d_n\}$ and each document contains a set of sentences as$S = \{s_1, s_2, \dots, s_n\}Sayd_i$contains$S = \{s_1, s_2, \dots, s_n\}$, which implies that the document $d_i$contains nnumber of sentences. Algorithm explains the procedure for computing the aforementioned terms in the documentd_i.

I n algorithm, the steps 6-9 are used to compute the*CTF*, *TF* and*DF* values. The weight for the context is computed by using the steps from 11 through 14 and is used to manipulate the weight of each context which iscompared with the other documents. The measuring of context weight isdiscussed in detail in the following subsection. The sentence *CTF* values willbe differing and hence overall *CTF* for *D* is computed through above equation. The *CTF* values are depending on the number of verbs present. If thepredicative part in the sentence follows with more than one verb, then the*CTF* value for the parameters following the verbs will be having higher *CTF*values. The following algorithm QR-C context based analysis.

Step 1:begin

Step 2:Consider a documentd_i

Step 3:Consider a sentence in documentd_i

Step 4:Frame Semantic context by evaluating SV parameter

Step 5:for each contextc_i in d_i do

Step 6: Evaluate CTF_i for a context C in d_i

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Step 7: Evaluate $TF_i$for a context C in d_i

Step 8: Evaluate DF_i for a context C in d_i

Step 9:Frame the context catalogL_k from S_i in S

Step 10:**for** each context$l_j \in L_k$

Step 11: if $l_i == l_j$then

Step 12:updateDF_i ofc_i

Step 13:ComputeCTF_{Weight}= avg (CTF_i, CTF_j)

Step 14: end if

Step 15: end for

Step 16: end for

Step 17: end.

5.3 Similarity Measure

T h e most important and significant part in clustering the text document is measuring the similarity between the set of documents, whichhelps to group the documents effectively. The similarity measure isconsidered as a noteworthy process since the result of similarity processjudges the efficiency of the clustering. The contexts in the document areextracted to determine the semantic structure of each sentence. Theoccurrence of each context is computed to determine the benefaction of aparticular context in the document. The documents are distinguished from theothers existing documents by their availability of the context. The sequentialflow of computing the

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context frequency semantically proceeds according tothe algorithm QR-C Context Frequency Algorithm.

Following factors are considered for measuring the similarity between the documents.

(a) **m:** number of matching context is measured for eachdocument.

(b) n: the total number that contains the matching context $C_i$is computed for all documents.

Along with this, *CTF* for each sentence in a document is computed. The value of *CTF* is computed for all the documents present inthe corpus.The *CTF* computation for each $C_i$in S for each document $d_i$where i 1,2,3,.....,$m$is exported. Similarly, for each document$d_i$the similarity depends on DF_i, the frequency for the documents where $i \in \{1,2,3,\dots,n\}$

The value of *CTF* is the pre-judging factor for evaluating the similarity between documents. The fact lies in frequency of the context lying in the verb SV parametric structure. If the frequency rate is higher, thendocument is also more similar. The similarity measure between twodocuments is estimated by the equation below.

$$Sim(d_1,d_2)=\sum_{i=1}^{n}\max\left(\frac{c1}{C1},\frac{c2}{C2}\right)\times w_i \times w_j$$

$$w_i=(TFw_i+CTFw_i)+\log\left(\frac{N}{DF_i}\right)$$

In the following equation TFw_ivalue denotes the weight of context i in document d

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$$TFw_i = \frac{TF_{ij}}{\sqrt{\sum_{j-1}^{n}(TF_{ij})^2}}$$

The TFw_i(Term Frequency weight) corresponds to its contributionin document level.

$$CTFw_i = \frac{CTF_{ij}}{\sqrt{\sum_{j-1}^{n}(CTF_{ij})^2}}$$

where$CTFw_i$represents the weight of context *i* in document *d* (expressing how far that context is semantically related) and *j*= *{*1,2,....,*n}*. The summation of $TFw_i$and $CTFw_i$represents the effective contribution of the contextproviding semantic meaning to the document. The above equation exemplifies similarity for each context in the verb argument structure in each document *d* ,its length is evaluated which is denoted as *ci* . *Ci*is evaluated on considering each verb agreement structurethat is enclosing a matched context, and total number of documents is denotedas *N* , in the context.

In the equation, $\log\left(\frac{N}{DF_i}\right)$denotes the value the weight of the context i on the extent of context occurrence.The summation of TFw_i ,$CTFw_i$ and$\log\left(\frac{N}{DF_i}\right)$denotes precise dimension of each context with respect to its semantically contributing perspective over the entire context.The above-said steps are conceded for all documents, finally similarity matrix is acquired for all documents. After computing the similarity between each document, the clustering is done. Clustering is carried out by means of the similarity matrix.

5.4 Query Weighting based on Cluster

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Query weighting is the term given when a search engine is adding search terms to a user's weighted search. The goal of query weighting inQR-C mechanism is to improve precision and/or recall. IR is the vitalprocess on the web. The amount of data on the web is always increasing. In1999, a survey report presented that Google had 135 million pages. It nowhas over 3 billion. Search engines follow specific mechanism trends withtheir searches. In the proposed technique, the IR is conceded having WeightedQuerying mechanism.

Cluster is a collection of documents having similar terms. For a given query "*Y*", relevant clusters are extracted through the searchingprocess. Each cluster computes a probability metric (*D*) for*Y*. If the query is related to that cluster then, *D* has the value one, otherwise zero.

$$D = \begin{cases} 1, if\ 'Y' exist \\ 0, otherwise \end{cases}$$

The document that has the term '*Y* ' is extracted. The given query iscompared with the document and depends on the similarity, the query weightis computed. This process is carried for all the documents in the cluster. Thequery weight for a single document can be computed from the equation

$$\sigma = \frac{P\ X\ a^2}{b}$$

where '*a*' indicates the number of query terms in that sentence, *b* is the term used to represent the total number of documents that are extracted. Moreover,coefficient *P* is judged as the Query coefficient. Similarly, the query weightfor the cluster is manipulated through the Equation

$$D_i = \sum_{i=1}^{n} \sigma_i$$

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where, *i* represents the total number of documents in the cluster. The query weight is an important decisive factor to retrieve the relevant documents inthe cluster. From this, one can extract the first *N* number of documents thatare matched with query*Y* . The document extraction is carried out through theequation

$$S = {}^{D_i}/_{N}$$

Here, *S* is the status coefficient. The documents are prioritized and ranked. The relevant documents are retrieved based on their rank.

6. RESULT AND DISCUSSION

The performance of the proposedQR-C text clustering technique is carried out through experiments. Two different datasets are used for theexperiments, namely (1) Reuters and (2) Usenet. Initially, the datasets aretrained in a way to extract and evaluate the right context. Perform POStagging on the trained dataset using the Stanford Log-linear Part-of-SpeechTagger version 3.1.0 to remove the words that are not discriminative.Consider a snippet as below.

> *"To resolve the aforementioned problems, we propose a novel methodnamed Navigation-Pattern-based Relevance Feedback to achieve the highretrieval quality of CBIR with RF by using the discovered navigationpatterns".*

On applying the POS tagging to the above snippet, the following is obtained.

> *To/TO resolve/VB the/DT aforementioned/JJ problems/NNS,/, we/PRPpropose/VBP a/DT novel/NN method/NN named/VBN Navigation-Patternbased/ JJ Relevance/NNP Feedback/NNP to/TO achieve/VB the/DThigh/JJ retrieval/NN quality/NN of/IN CBIR/NNP with/IN RF/NNP by/INusing/VBG the/DT discovered/VBN navigation/NN patterns/NNS ./.*

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With the above POS tagged sentences, the stop words are removed toconstruct a parsed sentence as given below.

Verb: resolve Param1: aforementioned problems novel method namedNavigation-Pattern-based Relevance Feedback achieve high retrievalquality CBIR RF discovered navigation patterns;

Param0: method, Verb: named Param1: Navigation-Pattern-based Relevance Feedback achieve high retrieval quality CBIR RF discovered navigation patterns;

Param0: Feedback, Verb: achieve Param1: high retrieval quality CBIR RF discovered navigation patterns;

Param0: RF, Verb: discovered Param1: navigation patterns.

The tagging of POS is stripped with VBN, VB, VBP that areextracted and the CTF, TF and DF are computed. The result of thiscomputation is shown in Table 1.

SContext	CTF	TF	DF
Resolve	1	1	2
aforementioned problems novel method named Navigation-Pattern-based Relevance Feedback achieve high retrieval quality CBIR RF discovered navigation patterns	1	1	0
method	2	1	2
named	2	1	2
Feedback	3	1	2
high retrieval quality CBIR RF discovered navigation patterns	3	1	2
RF	4	1	2
Discovered	4	1	2

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Navigation patterns	4	1	2
Aforementioned	1	1	2
Problems	1	1	2
Novel	1	1	2
Relevance	2	1	2
High	3	1	2
Retrieval	3	1	2
Quality	3	1	2
CBIR	3	1	2
Navigation	4	1	2
Patterns	4	1	2

With the computation of the above, clustering algorithms areapplied to the documents. The efficiency of both the algorithms such as SOMand Single Pass algorithm is compared. The comparison results are presentedas graph in Figure 3. From Figure 3, SOM algorithm is selected for furtherprocess.

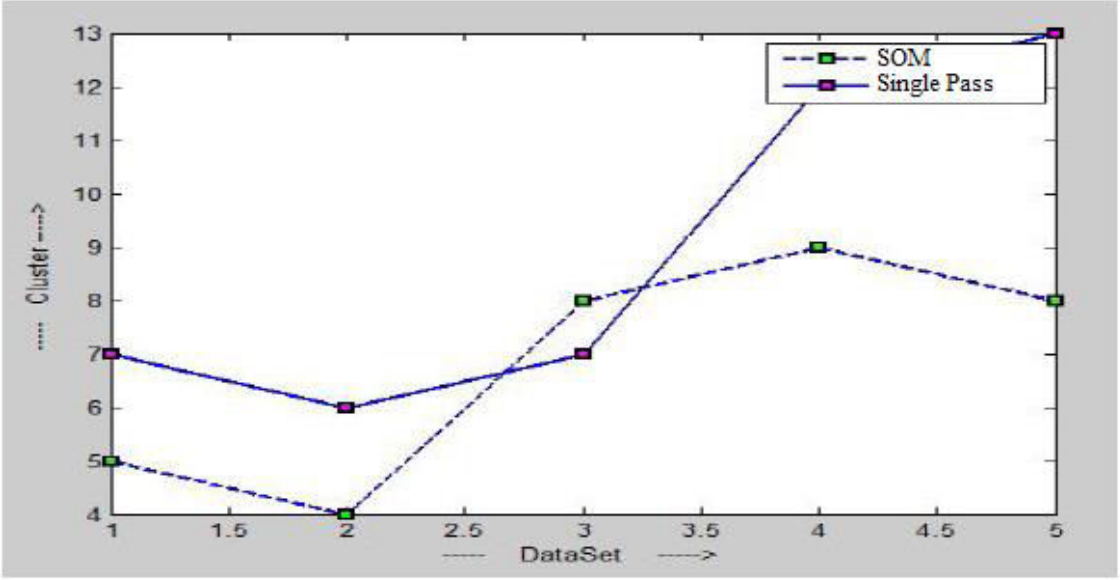

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Figure 3: Comparison between SOM and single pass clustering algorithm

Figure 3 expresses the cluster formation of the correspondingalgorithm. The X-axis represents five datasets (1-5), with increasing numberof documents. Table 2 shows the number of documents present in eachdataset.

Table 2 Dataset and number of documents

Dataset	Number of Documents
1	50
2	60
3	70
4	75
5	90

For the dataset-1, 5 clusters for SOM and 7 for Single Pass are procured. Similarly, for dataset-5, 8 clusters for SOM and 13 for Single Passare evolved. Dataset 4 and 5 comprise of Usenet Dataset. The results are compared with the experimental results of SVM technique presented. The results outperform SVM weighted approach. Theproposed approach QR-C is showing good latency rate in processing time.On experimenting it is predicted that the proposed approach consumes lesstime than the previous SVM approach. Of 50 documents (Dataset 1), QR-Capproach has taken 2 seconds, and for SVM it is 3 seconds. Similarly, theexperiment is repeated for the remaining datasets.

Moreover, Query weighting scheme is applied for IR. Whileperforming the query weighting mechanism, decisive factor value is kept as0.2 and the results are estimated for this value. It is healthier to keep the valueof decisive factor less than 0.25.

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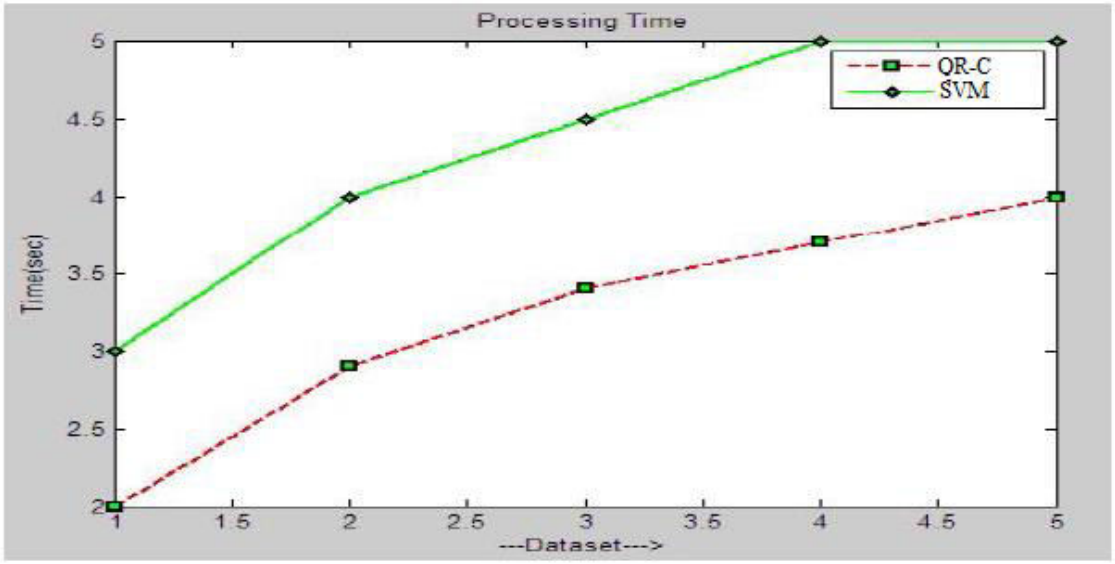

Figure 4: Comparison between two approaches with respect to processing time

Figure 4 represents the time required for the proposed and theexisting technique. It is explicit from the above figure that the time taken bythe SVM technique is much more than the QR-C technique. It is clear fromthis analysis that the proposed technique outperforms the existing techniqueirrespective of the dataset size. The study also shows that the overall timerequired for the proposed technique is less than the existing techniques for allrange of datasets.

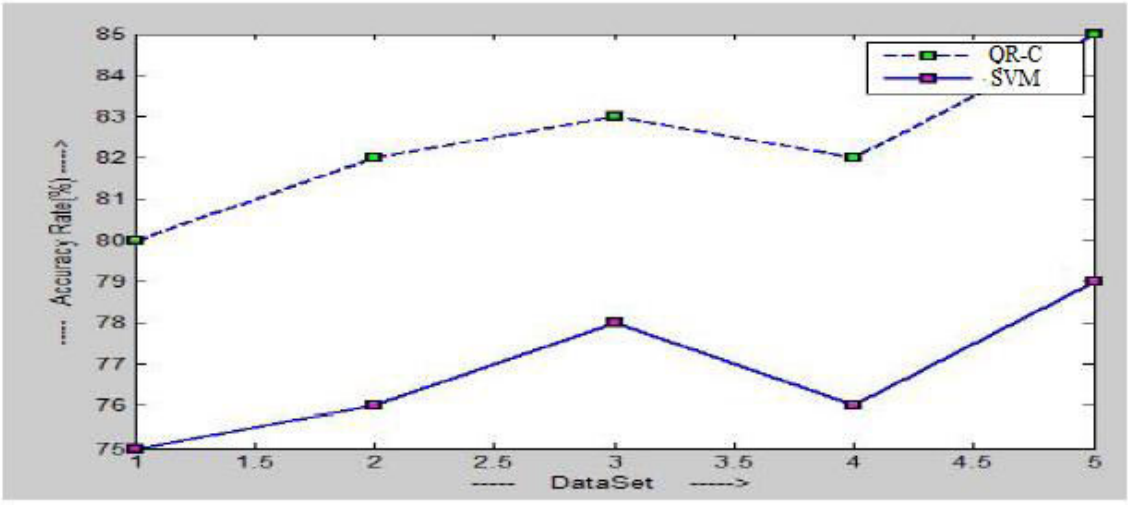

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Figure 5: Comparison between two approaches with respect to accuracy rate

Figure 4.5 portrays that the accuracy value is high for QR-C when compared with SVM approach. The precision is defined as the quantity ofdocuments that are retrieved which are appropriate to the search. The termrecall is presented as quantity of documents that are retrieved successfully andwhich are appropriate to the query.

The *precision P* and *recall R* of a cluster *j* with respect to a class*i* are defined as:

$$P - Precision(i,j) = C_{ij}/C_j$$

$$P - Recall(i,j) = C_{ij}/C_i$$

whereC_{ij}denotes the number of candidates of i and cluster j ,C_j denotes the number of candidates of cluster j ,$C_i$denotes the number of candidates of class i .The *F-measure* of a cluster *i* is defined as in equation

$$F - Measure = \frac{2\ X\ p\ X\ r}{p + r}$$

Two different clustering techniques, namely single pass and SOM have been tested to cluster similar documents. They are evaluated based on three quantifying measures, namely precision, recall and F-Measure. Table 3 represents the performance of both the clustering techniques forSVM and QR-C approaches.

Table 3: Comparison between single pass and SOM clustering techniquebased on qualifying measures

Quantifying Measures	Single Pass		SOM	
	SVM	QR-C	SVM	QR-C
Precision	0.34	**0.45**	0.4	**0.49**
Recall	0.29	**0.37**	0.35	**0.48**
F-measure	0.313	**0.406**	0.36	**0.48**

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On comparing, SOM clustering outperforms the Single Pass clustering. But the quality of clustering depends on the term frequency,context frequency and document frequency. When compared with SOM, thissingle-pass clustering is highly sensitive to noise. From the above discussionthe conclusion is that the proposed technique clusters the documenteffectively than the existing technique.With the help of this technique, the clustered documents are used forinformation retrieval.

7. CONCLUSION

In this chapter a novel strategic approach called QR-C is implemented for information retrieval. On adopting this approach, initially theSV parametric structure is extracted. This investigates similarity based on thesemantic meaning that it affords to the document. The three measures basedon contextual term frequency, term frequency and document frequency areestimated offering their semantic merits to a good extent. As the clustering result primarily depends on the similarity matrix, the proximity of that matrixis quite increased. Moreover, the clustering results are finally processed forquery expansion and query weighting methodologies.The utility of clustering algorithms is enclosed with superior extent. But the query expansion approach should be enhanced further, so thatit should be applied for huge search engine related searches.

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