Clustering Short Text using a Centroid-Based Lexical Clustering Algorithm

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***Abstract*—Traditional lexical clustering methods process text as a bag of words, with similarity between two text-fragments measured on the basis of word co-occurrence. While this approach is suitable for clustering large fragments of text (e.g., documents), it performs poorly when clustering smaller text fragments such as sentences (e.g., short text or quotes). This is because two sentences may be semantically similar while containing no common words. This paper proposes a new variant of the standard *k*-means algorithm for short text clustering that is based on the notion of synonym expansion semantic vectors. These vectors represent short text using semantic information derived from a lexical database constructed to identify the correct meaning to a word, based on the context in which it appears. Thus, whereas conventional *k*-means algorithm application is based on measuring the distance between patterns, the proposed approach is based on measuring semantic similarity between patterns (e, g., sentences). This enables it to utilise a higher degree of semantic information available within the clustered sentences. Empirical results show that the proposed variant method performs favorably against other clustering technique on two specially constructed datasets of famous quotations, benchmark datasets in several other domains, and that its incorporation as a short text similarity using synonym expansion leads to a significant improvement in the centroid-based clustering performance. Therefore, it is potential use in a variety of knowledge discovery processing tasks including text summarisation and text mining.**

***Index Terms*—WordNet, semantic similarity measure, short text clustering, and word sense identification**

I. Introduction

ALTHOUGH text clustering at the long-text level (e.g., document) is well-established in the natural language processing (NLP) and knowledge discovery literature, clustering at the short-text level (e.g., quotes or sentences) is challenged by the fact that word co-occurrence—possible frequent occurrence of words from text corpus—, on which most text similarity measures are based, may be rare or even absent between two semantically related text fragments. To overcome this issue, several short text similarity measures have recently been proposed [1]- [13], [39].

The methods proposed by Li *et al*. (2006) [1], Mihalcea *et al*. (2006) [2] and Wang *et al*. (2008) [14] have two important features in common. Firstly, rather than representing sentences in a vector space model [15] using the full set of features from some corpora, only the words appearing in the two sentences are used, thus overcoming the problem of data sparseness (i.e., high dimensionally) arising from a full bag of words representation. Secondly, they use semantic information derived from external sources to overcome the problem of lack of word co-occurrence.

Short text similarity measures such as described in Abdalgader & Skabar (2011) [10] (the latter of which we use in this paper, and described later in Section II), depend in some way on a measure of semantic similarity between words. Unlike existing measures, which use the set of exact words that appear in the sentences, this method constructs an expansion word set for each sentence using synonyms of the sense-disambiguated words in that sentence. This way leads to provide a richer semantic context to measure sentence similarity through better utilising the semantic information available from lexical resources such as WordNet [16], [52]. For each of the sentences being compared, a *word sense disambiguation* step is first applied in order to identify the sense in which words are being used within the sentence [17]. A synonym expansion step is then applied, resulting in a richer semantic context from which to estimate semantic vectors. The similarity between semantic vectors can then be calculated using a standard vector space similarity measure such as cosine similarity.

Clustering of smaller text fragments plays a significant role in many natural language processing activities (i.e. knowledge discovery). These include, for example, documents summarisation where it is help to avoid problems of content overlap, which leading to better coverage [18]- [21], [57], and text mining where the main objective might be to find out a new knowledge from a collection of texts initially retrieved in response to some query [22], [23]. By clustering the smaller text fragments such as quotes or sentences, we would naturally expect at least one of the clusters to be semantically related to the concepts described by the query terms; however, the remaining clusters still interesting in which may contain knowledge relating to the query in some way hitherto unknown to us, and in such a case we would have successfully retrieved a novel knowledge.

Various clustering algorithms have been proposed in recent years [14], [24]- [32], [53]- [55] and many of them do take as input only a matrix of pairwise similarities. The simplest of these is the *k*-medoids algorithm [25], [26], which is a variant of *k*-means in which centroids are restricted to being data points. However, a problem with the *k*-medoid algorithm is that it is very sensitive to the initial (random) selection of centroids, and in practice it is often necessary to run the algorithm several times with different initializations.

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To overcome this problem with *k*-medoids, Frey & Dueck (2007) [30] proposed *Affinity Propagation*, a graph-based technique which simultaneously considers all data points as exemplars (i.e., possible centroids). Treating each data point as a node in a network or graph, affinity propagation recursively transmits real-valued messages along the edges of the graph until a good set of exemplars (and corresponding clusters) emerges. These messages are then updated using simple formulas that minimize an energy function based on a probability model. Frey & Dueck (2007) [30] have applied affinity propagation to the problem of extracting descriptive summary from text.

Spectral clustering [14], [31], [32], [54] is another graph-based clustering technique that based on matrix decomposition techniques from the linear algebra theories. Rather than clustering data points in the original vector space, spectral clustering algorithms map data points onto the space defined by the eigen-vectors associated with the top eigen-values, and then perform clustering in this transformed space, typically using a *k*-means algorithm. One of the advantages of spectral clustering algorithms is that they are able to identify non-convex clusters, which is not possible when clustering in the original feature space (using *k*-means). Since they are based on established linear algebra techniques, the algorithms can be easily implemented in a language such as MATLAB[1] or NLTK[2] under Python, and since they require as input only a matrix containing pairwise similarity measures or values (together with a specification of the number of clusters to be used), it is straightforward to apply spectral clustering to the short text clustering task.

The application of spectral clustering to short-level text clustering was recently reported in [14], [24], and is, to our knowledge, the first such application of spectral clustering in this area. Note, however, that the short text representation used by Wang *et al*. [14] is different to that which we have described in Section II, and essentially is based on a vector space model.

The idea of applying PageRank [33] as a centrality measure has been used by both Erkan & Radev (2004) [34], Mihalcea & Tarau (2004) [35] and Fang *et al*. (2017) [57] in the context of document summarisation, in which the objective is to rank text-fragments according to their importance in the document or documents being summarized (i.e., sentence scoring task). However, in each of these cases PageRank is applied to only a single cluster; that is, the entire collection of text-fragments being summarized. Interestingly, Skabar & Abdalgader (2013) [24] show how the use of PageRank as a centrality measure can be extended to multiple clusters, and present a full fuzzy relational clustering algorithm. This algorithm allows sentences to belong to all clusters with different degrees of semantic similarity. This is important in the case of text summarisation and text mining, in which a text-fragment may be semantically related to more than one theme or topic. However, fuzzy clustering of short-text level is complicated by the computational difficulties inherent in defining cluster centroids using conventional cluster centrality measures.

The contribution of this paper is a new variant of the standard *k*-means algorithm for short text clustering that is based on the notion of synonym expansion semantic vectors. These vectors represent short text using semantic information derived from a lexical database constructed to identify the correct meaning to a word, based on the context in which it appears. Thus, whereas conventional *k*-means algorithm application is based on measuring the distance between patterns (e, g., sentences), the proposed approach is based on measuring semantic similarity between patterns. This enables it to utilize a higher degree of semantic information available within the clustered sentences. The result is a centroid-based lexical clustering algorithm which is generic in nature, and can be applied to any domain in which the relationship between objects is expressed in terms of pairwise semantic similarities. We apply the algorithm to two datasets of famous quotations, benchmark datasets in several other domains and compare its performance with that of well-known clustering algorithms (i.e., *Spectral Clustering* [31], *Affinity Propagation* [30], *k-medoids* [25], [26], *STC-LE* [54] and *k-means(TF-IDF)* [55]). We argue that the superior performance of our new variation of the centroid-based lexical algorithm (variant of the standard *k*-means algorithm) is due to its capacity to better utilise the available semantic information available in used lexical database. Therefore, it is potential use in a variety of knowledge discovery processing tasks including text summarisation (see Section IV.I) and text mining of more general nature.

The remainder of the paper is structured as follows. Section II describes a text representation scheme for measuring short text similarity. Section III presents our new variation of standard *k*-means clustering (centroid-based) algorithm. Empirical results are presented in Section IV, and Section V concludes the paper.

II. Text Representation Scheme for Measuring Short Text Similarity

Activities typically performed in knowledge discovery processing (e.g., text mining), as our activity focused, include classifying a fragments of the text as belonging to one or more pre-known classes or categories [36], and clustering fragments of the text according to their degree of semantic similarity [37], [20]. These activities are not independent, for example, may involve sub-tasks involving the measurement of semantic similarity between sentence pairs [38], [39], [11]- [13].

One approach to text mining is to identify the main themes or topics which characterise a text, and to then extract useful information by appending, in a coherent manner, a description or an abstraction of each of those themes. Presumably, fragments of text that are similar to each other are more likely to relate to the same theme than fragments that are less similar. Thus, clustering, using both an appropriate similarity measure and an appropriate text representation scheme should provide a useful technique in allowing us to identify those themes.

By far the most common text representation scheme that has been used in the text processing activities is the vector space model (VSM), in which a document (or some other fragment of text) is represented as a point in a high-dimensional (N_i) input space in which each dimension corresponds to a unique word [15]. That is, a document d_j is represented as a vector $\mathbf{x}_j = (w_{1j}, w_{2j}, w_{3j}, ...)$, where w_{ij} is a weight that represents in some way the importance of word

[1] http://www.mathworks.com/products/matlab
[2] http://www.nltk.org

w_i in d_j, and is based, at least in part, on the frequency of occurrence of w_i in d_j (term frequency). The similarity between two documents is then calculated using the corresponding vectors and, since text data is directional in nature, a commonly used measure is the cosine of the angle between the two vectors. Figure 1 illustrates the basic concept of the documents representation in VSM.

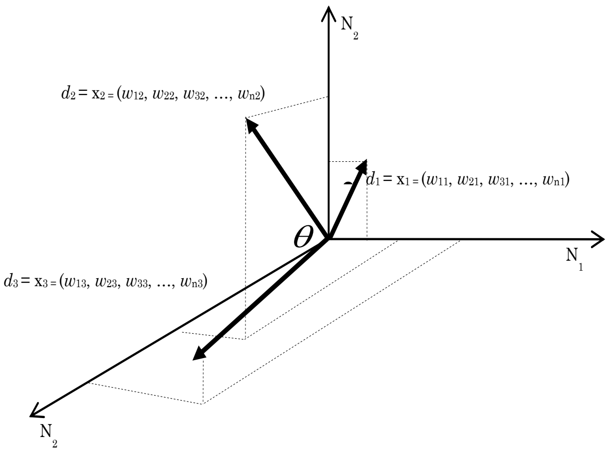


Fig.1. Basic concept of the documents representation in VSM.

The vector space model has been successful in information retrieval process because it is able to adequately capture much of the semantic content of large documents. This is due to large documents may contain many words in common with each other, and thus be found to be similar according to common vector space similarity measures such as the cosine measure. However, in the case of smaller-sized text fragments such as sentences or quotes, this is not the case, since two sentences may be semantically very similar while containing no common words. For example, consider the sentences "*Some places in the world are now in flood disaster*" and "*The current torrent crisis affects the particular states*". Clearly these sentences have similar meaning, yet the only word they have in common is the stopword *the*, which is considered as stop-words and they contain no semantic information. The reason why word co-occurrence may be rare or even absent in natural language arises out of the characteristic flexibility of natural language that enables humans to express similar meanings using quite different sentences in terms of structure and length [40]. At the short text level, therefore, we require a representation scheme which is better able to capture the semantic content of sentences, thus enabling a more appropriate similarity measure to be defined.

A. Measuring Short Text Similarity

To measure short text similarity we use sentence similarity measure that reported in Abdalgader & Skabar (2011) [10]. This measure operates by expanding the semantic context in the direction indicated by the sense-assigned meanings of the original words in the sentence, thereby creating an enriched semantic context, and enabling a more accurate estimate of semantic similarity.

Assume that S_1 and S_2 are the two sentences being compared, W_1 and W_2 are the sets of sense-assigned words contained in S_1 and S_2 respectively, s_1 and s_2 are the sets of synonym expansion contained in W_1 and W_2, and $U = W_1 \cup W_2$. Then a semantic vectors $\mathbf{v}_1$ and $\mathbf{v}_2$ have been constructed, corresponding to s_1 and s_2.

Let v_{ij} be the j^{th} element of v_i, and let w_j be the corresponding sense-assigned word from U. There are two cases to consider, depending on whether w_j appears in s_i:

Case 1: If w_j appears in s_i, set v_{ij} equal to 1, this is because the semantic similarity for same words in the WordNet-based is equal to 1.

Case 2: If w_j does not appear in s_i, calculate a word-word semantic similarity (we use the J&C word-to-word similarity measure [41] score between w_j and each synonym word in s_i, and set v_{ij} to the highest of these similarity scores.

Once $\mathbf{v}_1$ and $\mathbf{v}_2$ have been determined, the semantic similarity between s_1 and s_2 can be defined using a standard measure such as the Cosine similarity between $\mathbf{v}_1$ and $\mathbf{v}_2$, and can be calculated as:

$$Similarity(S_1, S_2) = (\mathbf{v}_1.\mathbf{v}_2)/(|\mathbf{v}_1||\mathbf{v}_2|) \qquad (1)$$

This short text similarity measure relies on a word-to-word similarity measure. A large number of such measures have been proposed, most of these relying on semantic relations expressed in resources such as dictionaries, thesauri, or lexical knowledge-bases such as WordNet [16], [52]. In this paper we use the J&C word-to-word similarity measure [41] which is based on the concept that the similarity degree to which two words are similar is relative to the amount of information they share. The similarity between two words is calculated by:

$$Sim_{J\&C}(w_1, w_2) = \frac{1}{IC(w_1) + IC(w_2) - 2 \times IC(LCS(w_1, w_2))} \qquad (2)$$

where $LCS(w_1, w_2)$ is the word that is the deepest common ancestor of w_1 and w_2, $IC(w)$ is the information content of word w, and defined as $IC(w) = -\log P(w)$, where $P(w)$ is the probability that word w appears in a large textual corpus such as Brown corpus.

III. Clustering Algorithm

This section presents the proposed centroid-based lexical clustering algorithm. We first describe our variation of standard *k*-means clustering algorithm. We then describe how a cluster centroid can be defined. The final subsections discuss measuring similarity between short text and clustering centroid and the issues relating to implementation and computation complexity. Since the proposed algorithm can be viewed as a variant of the standard *k*-means algorithm for short text clustering, we name the algorithm as a Centroid-Based Lexical Clustering (*CBLC*).

A. Centroid-Based Lexical Clustering

Given a number *k*, separate all short text (e.g., sentences) randomly in a given partition into *k* separate clusters (i.e., initialisation), each with a *mean* (centroid) that acts a representative. There are iterations that reset these means then re-assign each sentence to the cluster corresponding to the mean which it is semantically similar to (i.e., by measuring the semantic similarity). Re-compute the determined centroids based on the sentences assigned to them. Then the next iteration that repeats until the centroids do not move. The algorithm is as follows:

ALGORITHM 1. Centroid-Based Lexical Clustering (CBLC)

Input: Sentences to be clustered $S = \{S_i \mid i = 1 \ldots N\}$

Number of clusters k

Output: Cluster membership values $\{\pi_i^j \mid i=1..N,\ j=1..k\}$ where π_i^j is the membership of sentences i to cluster j.

1. // *Partition the sentences into k sets (clusters), randomly (initialisation)*
2. **for** i = 1 to N
3. **if** $i \le k$
4. j +=1
5. π_i^j = sentence(S_i)
6. **else**
7. j=1
8. π_i^j = sentence(S_i)
9. **end**
10. **repeat until convergence** *(no further change in clusters)*
11. // *Find the mean (centroid) for each cluster*
12. **for** j = 1 to k
13. M_j =*union-set{all synonym words appearing in the cluster* $_j$*}*
14. **end**
15. // *calculate the semantic similarity of each sentence* (S_i) *to each of the cluster centroid using the synonym expansion similarity measure described in Section II.A*
16. **for** j = 1 to k
17. *similarity*(M_j, S_m) // S_m *is sentences belong to cluster j, {m=1.. n} where n is the number of sentences in cluster j.*
18. **end**
19. //Re-assign each sentences to the cluster corresponding to the cluster centroid to which it is closest (semantically similar to).
20. re-*assign*(S_i, M_j)
21. **End**

We first describe how a cluster centroid may be represented; we then describe how the similarity measure between and each sentence and a cluster centroid may be defined. The final subsection discusses various other implementation issues.

B. Defining a Clustering Centroid

In the conventional vector space approach, in which a long-text fragment (e.g., document) is represented as a vector of real values (e.g., *tf-idf* scores), a cluster centroid can be found by simply taking the vector average over all text fragments belonging to that cluster. This is clearly not possible using the representation scheme described in Section II, since the semantic vector for a sentence is not unique (i.e., short text), but relies on the context provided by the sentence with which it is being compared. However, just as a context may be defined by a pair of sentences, it is straightforward to extend this idea to defining the context over a larger collection of sentences. Since a cluster is just such a collection, we can define the centroid of a cluster simply as the *union set* of all synonyms of sense-assigned words appearing in the sentences belonging to that cluster. Thus, if S_1, S_2, ... S_N are sentences belonging to some cluster, the centroid of the cluster, which we denote as M_j, is just the union-set $\{w_1, w_2, ..\ w_n\}$, where n is the number of distinct synonyms words (s_i) in $s_1 \cup s_2 \cup ... \cup s_N$. This is illustrated by Figure 2.

C. Measuring Similarity between Short Text and Cluster Centroid

There are two cases to consider in similarity calculation of the above algorithm: (i) the case in which the sentence does not belong to the cluster; and (ii) the case in which the sentence does belong to the cluster. The first case is straightforward. Since cluster centroids are represented in the same way as sentences or quotes (i.e., as a union synonym-set), the similarity between a sentence and a cluster centroid can be calculated as per the similarity between two sentences, as described in Section II. However, there is a subtlety in the second case which is not immediately apparent.

In order to demonstrate this, suppose that two sentences $S_1 = \{w_1,w_2,w_3\}$ and $S_2 = \{w_4,w_5\}$ have absolutely no

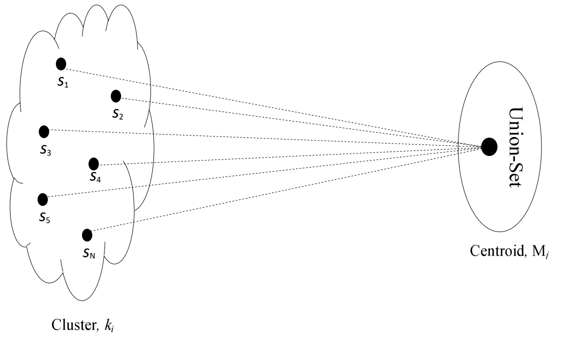


Fig.2. Clustering Centroid, where s_i is set of synonym words corresponding to Si..

semantic similarity. Comparing these sentences, we obtain the semantic vectors $\mathbf{s}_1 = \{1,1,1,0,0\}$ and $\mathbf{s}_2 = \{0,0,0,1,1\}$ which clearly have a cosine value of 0, and is consistent with the fact that they are semantically unrelated. But now suppose that S_1 and S_2 are in the same cluster. If we construct the cluster union-set as described above (i.e., by taking the union of all synonym words appearing in all sentences in that cluster), we obtain $M_j = \{w_1,w_2,w_3,w_4,w_5\}$. If we now calculate the cosine similarity between M_j and S_1, we obtain the semantic vectors $\mathbf{s}_j = \{1,1,1,1,1\}$ and $\mathbf{s}_1 = \{1,1,1,0,0\}$, which have a cosine similarity value of 0.77. Clearly there is a problem here, since if S_1 and S_2 are semantically unrelated, then their centroid would effectively be meaningless, and we would certainly not expect a similarity of 0.77. The above problem has occurred because all of the words of S_1 already appear in the cluster centroid M_j. We can avoid this problem by constructing the centroid using all sentences in the cluster except for the sentence with which the cluster centroid is being compared. Thus, assuming that we have a cluster containing sentences $S_1 \ldots S_N$, and we want the similarity between this cluster and a sentence SG appearing in the cluster, we would determine the cluster centroid using only the words appearing in $s_1 \cup s_2 \cup ... \cup s_{G-1} \cup_{G+1} \cup ... \cup s_N$; that is, we omit SG in calculating the cluster centroid.

D. Short Text Similarity and Thresholding Values

In the case of short text clustering, the similarity scores s_{ij} between two sentences can be calculated using an appropriate short text similarity measure such as described in Section II. In most cases the similarity scores will be non-zero, leading to a heavily connected graph, which means mostly similar. Also, many of the similarity scores will be very small, arising from incidental similarities between words in sentences which are in fact not semantically related. In practice, we have found that the clustering performance of the algorithm can be improved by thresholding these similarity scores such that all scores below the threshold are converted to zero. All datasets clustering results reported in this paper are based on thresholding similarity scores such that 50% of the scores in the similarity matrix are zero (i.e., other threshold values were investigated e.g., between 20% and 80%, but it was found that performance was not highly sensitive to this).

E. Clustering Membership

Unlike soft clustering in which sentences belong to all clusters with differing degrees of membership [24], hard clustering algorithm allows sentences to belong to a single cluster only. This can be trivially achieved in CBLC by assigning a sentence to the particular cluster for which semantic similarity value is highest.

C. Convergence and Complexity

With regard to space complexity, the CBLC algorithm is no more expensive than either the Spectral Clustering [32], [14] or basic *k*-Means [42] families of algorithms, since all require the storage of the same, potentially large, sentence similarity scores. However, the time complexity of CBLC far exceeds that of both Spectral Clustering and basic *k*-Means. Moreover, complexities arise in step of calculating the semantic similarity of each sentence to each cluster centroid, due to the particular representation and associated similarity measure that we use (e.g., synonym expansion similarity measure). Assume that unit operation time for calculating semantic similarity between each sentence and cluster centroid (i.e., cosine similarity) is S, unit operation time for re-compute cluster centroids is M, number of sentences in the dataset is n, number of clusters is k and iteration count of CBLC loop is I. Therefore, essentially the following computations are performed for each and every CBLC iteration: (i) $n.k$ times sentence to cluster centroid semantic similarity calculation; (ii) k times for re-compute cluster centroid. As a result, time complexity of CBLC can be calculated as:

$$T_{CBLC} = (S \,.\, n \,.\, k + M \,.\, k) \,.\, I \qquad (3)$$

Since, $n>>k$ and $S>>M$, overall time complexity of CBLC algorithm is found $O(n)$, which means that computational complexity is relative to number of sentences to be clustered (i.e., size of the dataset). Note that CBLC algorithm adds one extra step to the basic steps in basic *k*-means algorithm. before the semantic similarity calculation of each sentence to all cluster centroids, a word sense identification step is applied.

An alternative to random initialization is to initialize cluster membership values with values found by first applying a computationally inexpensive hard clustering algorithm such as Spectral Clustering or *k*-Medoids. This will result in each object having an initial membership value of either 0 or 1 to each cluster. In practice we have found this to have a significant effect on the rate of convergence, with convergence typically achieved in 20 to 70 cycles—approximately 50 trial of iterations applied when using random initialization. However, care should be taken that the hard clustering algorithm is not itself highly sensitive to initialization, and for this reason we prefer Spectral Clustering and Affinity Propagation. We note, however, that initialization does not affect the final membership values at convergence; that is, on all datasets tested, the algorithm converged to the same solution, irrespective of initialization.

IV. Experiments and Results

This section reports on the application of the algorithm to two specially constructed datasets of famous quotations and seven benchmark datasets in several other domains. We then initially evaluate the CBLC algorithm on end-to-end (*in vivo*) tasks, involving document summarisation. The performance of the CBLC algorithm is compared as stand-alone (*in vitro*) with that of other well-known clustering algorithms; Spectral Clustering [14], [31], Affinity Propagation [30], *k*-medoids algorithm [25], [26], STC-LE [54] and *k*-means(TF-IDF) [55], and performance under synonym expansion sentence similarity measure (which we described it in Section II) is compared against that resulting from other modified sentence similarity measures [10]. We first describe the famous quotation datasets and the seven benchmark datasets. We then discuss cluster evaluation criteria and modified short text similarity measures for comparing performance purposes. The final subsections present a preliminary test of the algorithm to text summarisation task and results discussion.

TABLE I
50-Qoutes Dataset

50-Qoutes Dataset
Knowledge
1. Our knowledge can only be finite, while our ignorance must necessarily be infinite.
2. Everybody gets so much common information all day long that they lose their commonsense.
3. Little minds are interested in the extraordinary; great minds in the commonplace.
…
Marriage
11. A husband is what is left of a lover, after the nerve has been extracted.
12. Marriage has many pains, but celibacy has no pleasures.
13. The woman cries before the wedding; the man afterward.
…
Nature
21. I have called this principle, by which each slight variation, if useful, is preserved, by the term natural selection.
22. Nature is reckless of the individual; when she has points to carry, she carries them.
23. I wanted to say something about the universe; there's God, angels, plants and horseshit.
…
Peace
31. There is no such thing as inner peace, there is only nervousness and death.
32. Once you hear the details of victory, it is hard to distinguish it from a defeat.
33. Peace is a virtual, mute, sustained victory of potential powers against probable greeds.
…
Food
41. Food is an important part of a balanced diet.
42. To eat well in England you should have breakfast three times a day.
43. Dinner, a time when one should eat wisely but not too well, and talk well but not too wisely.
…

TABLE II
211-Qoutes Dataset

211-Qoutes Dataset
1. The fact that a reactionary can sometimes be right is a little less recognized that the fact that a liberal can be ...
2. Any woman who understands the problems of running a home will be nearer to understanding the problems of running a country.
…
47. The secret of all victory lies in the organization of the non obvious.
48. The conditions of conquest are always easy. We have but to toil awhile, endure awhile, believe always, and never turn back.
49. The very first step towards success in any occupation is to become interested in it.
50. Four steps to achievement: plan purposefully, prepare prayerfully, proceed positively, pursue persistently.
…
210. All lasting business is built on friendship..
211. If you can count your money you do not have a billion dollars.

A. Famous Quotation Datasets

We believe that quotations provide a rich context for evaluation of lexical clustering techniques because they often contain a lot of semantic information (i.e., wisdom packed into a small message), and are often couched in a poetic use of language. Two quotations datasets have been constructed: the *50-Quotes* dataset, and the *211-Quotes* dataset. The first dataset contains 50 quotes from 5 different classes (*knowledge, marriage, nature, peace, food*). The quotations are equally distributed among classes; i.e., ten quotes from each class. The second dataset contains 211 quotes from 15 different classes (*politics, music, education, success, work, forgiveness, experience, health, law, spirituality, marriage, food, intelligence, peace, money*). In this case the quotes are not equally distributed amongst classes. Quotes in the 211-Quotes dataset were deliberately selected to display a lower degree of word co-occurrence than those in the 50-Quotes dataset, and can thus be expected to be more difficult to cluster. Extracts from the 50-Quotes and 211-Quotes datasets are shown in Tables I and II respectively [43]. Full datasets are taken from the Famous Quotes and Authors website (http://www.famousquotesandauthors.com/, accessed 12 March 2016).

B. Benchmark Datasets

While CBLC algorithm is clearly applicable to tasks involving sentence clustering, the algorithm is generic in nature and can in principal be applied to any lexical clustering domain. In this section we also apply the algorithm to clustering several datasets: *Reuters-21578* dataset[3] [24], *Aural Sonar* dataset [44], [24], *Protein* dataset [45], [24], *Voting* dataset [46], [24], *SearchSnippets* [53], [56], *StackOverflow* [53] and *Biomedical* [53].

The Reuters-21578 dataset is the most widely used dataset for text classification activities. It contains more than twenty thousand documents from over 600 classes. The 50% percent of the documents are assigned labels, and around 17% percent of the labeled documents are belonging to more than one class. In this paper, we experimented with a subset consisting of 1833 documents, each labeled as belonging to one of ten different classes. The number of documents in each of the ten classes is respectively 355, 334, 259, 211, 156, 135, 114, 99, 97, and 73.

The Aural Sonar dataset was originally founded by Philips *et al*. (2006) [44] who investigated the ability of humans to distinguish between types of sonar signals by ear. Two randomly selected participants were asked to assign a similarity score between 1 and 5 to all pairs of signals returned from a broadband active sonar system. The signals consisted of 50 target-of-interest signals and 50 noise signals. Participants were unaware of the true labels. The two scores were added to produce a 100 × 100 similarity matrix with values ranging from 2 to 10.

The Protein dataset was initially described in [45], and consists of dissimilarity values for 226 samples over 9 classes. We use the dataset described in [47] which uses the reduced set of 213 proteins from 4 classes that result from removing classes with fewer than 7 samples.

The Voting dataset is a two class classification task with around 435 samples, where each sample is a categorical feature vector with sixteen components and three options for each component. Similarity matrix values were calculated from the categorical data using the value difference metric, which achieves maximum class separation by using the class labels to weight different components differently.

The SearchSnippets dataset is predefined phrases of eight different domains (i.e., classes), which was selected from the results of web search transaction.

The StackOverflow is a challenge dataset published in (https//:www.kaggle.com), and we use the dataset consists 3,370,528 samples through July 31st, 2012 to August 14th, 2012. In this paper, we randomly select 20,000 question titles from 20 different domains.

The Biomedical is also challenge dataset published in BioASQ's official website. We randomly select 20,000 paper titles from 20 different MeSH major domains.

C. Clustering Evaluation Criteria

Since *homogeneous* cluster (i.e., each cluster contains only objects from a single class) and *complete* cluster (i.e., all objects from a single class are assigned to a single cluster) are rarely achieved, we are usually interested in achieving an acceptable balance between the two. Therefore, we use only five of external clustering measures, which are: *Purity*, *Entropy* [48], *V-measure* [49], *Rand Index* and *F-measure*.

Entropy and *Purity*. Entropy measures how the classes of objects are distributed within each single cluster. It is defined as weighted average of the individual cluster entropy over all clusters C = {$c_1, c_2, c_3, \dots c_n$}:

$$Entropy = \sum_{j=1}^{|L|} \frac{|w_j|}{N} \left(-\frac{1}{\log|C|} \sum_{i=1}^{|C|} \frac{|w_j \cap c_i|}{|w_j|} \log \frac{|w_j \cap c_i|}{|w_j|} \right) \quad (4)$$

The purity of a cluster is the fraction of the cluster size that the largest class of objects assigned to that cluster represents; i.e.,

$$P_j = \frac{1}{|w_j|} \max_i \left(|w_j \cap c_i| \right) \quad (5)$$

Overall purity is the weighted sum of the individual cluster purities and is given by

$$Purity = \frac{1}{N} \sum_{j=1}^{|L|} \left(|w_j| \times P_j \right) \quad (6)$$

Due to entropy and purity operate on how the classes of objects are distributed within each single cluster, and this will result in homogeneity case. Great values of purity and low values of entropy are normally easy to achieve when the number of clusters is large, but this will result in low completeness. Consequently, while purity and entropy are useful for comparing clusterings with the same number of clusters, they are not reliable when comparing clusterings with different numbers of clusters. The next measure we describe explicitly takes into account homogeneity and completeness.

V-measure. The *V*-measure is defined as the harmonic mean of homogeneity (h) and completeness (c); i.e., $V = hc / (h + c)$, where h and c are defined as:

$$h = 1 - \frac{H(C|L)}{H(C)} \text{ and } c = 1 - \frac{H(L|C)}{H(L)} \quad (7)$$

where

[3] http://www.daviddlewis.com/resources/testcollections/reuters21578

$$H(C) = -\sum_{i=1}^{|C|} \frac{|c_i|}{N} \log \frac{|c_i|}{N}, \quad H(L) = -\sum_{j=1}^{|L|} \frac{|w_j|}{N} \log \frac{|w_j|}{N},$$

$$H(C\,|\,L) = -\sum_{j=1}^{|L|} \sum_{i=1}^{|C|} \frac{|w_j \cap c_i|}{N} \log \frac{|w_j \cap c_i|}{|w_j|}, \text{ and}$$

$$H(L\,|\,C) = -\sum_{i=1}^{|C|} \sum_{j=1}^{|L|} \frac{|w_j \cap c_i|}{N} \log \frac{|w_j \cap c_i|}{|c_i|}.$$

Rand Index and *F-measure*. Unlike purity, entropy and V-measure, which are based on statistics, *Rand Index* and *F-measure* are based on a combinatorial approach which considers each possible pair of objects. Each pair can fall into one of four groups: if both objects belong to the same class and same cluster, then the pair is a true positive (TP); if objects belong to the same cluster but different classes, the pair is a false positive (FP); if objects belong to the same class but different clusters, the pair is a false negative (FN); otherwise the objects must belong to different classes and different clusters, in which case the pair is a true negative (TN). The Rand index is simply the accuracy; i.e., $RI = (TP + FP)/(TP + FP + FN + TN)$. The F-measure is another measure commonly used in the IR literature, and is defined as the harmonic mean of precision and recall; i.e., F-measure = $2PR/(P+R)$, where $P = TP/(TP + FP)$ and $R = TP/(TP + FN)$.

D. Modified Short Text Similarity Measures

In order to compare the performance of synonym expansion similarity measure, we use a modified version of measures proposed by [1], [2], which is reported in [50], [51].

For the Li *et al*. (2006) [1] short-text similarity measure, the only modification required is in determining the components of the semantic vectors. This can be done as; if w_j appears in S_i, set v_{ij} equal to $PR_{w_j}^{S_i}$ (i.e., the PageRank score for w_j in S_i), otherwise set v_{ij} equal to the highest similarity score between w_j and the words in S_i; i.e., $v_{ij} = \arg\max_{x \in \{S_i\}} \left(sim(w_j, x) \times PR_{w_j}^{S_i} \right)$.

The short-text similarity measure proposed by Mihalcea *et al*. (2006) [2] can be modified as follows:

$$sim(S_1,S_2) = \frac{1}{2} \sum_{w \in \{S_1\}} \left(sim\left(w, \arg\max_{x \in \{S_2\}} \left(sim(w,x) \times PR_x^{S_2} \right) \right) \times PR_w^{S_1} \right) \Big/ \sum_{w \in \{S_1\}} PR_w^{S_1}$$
$$\frac{1}{2} \sum_{w \in \{S_2\}} \left(sim\left(w, \arg\max_{x \in \{S_1\}} \left(sim(w,x) \times PR_x^{S_1} \right) \right) \times PR_w^{S_2} \right) \Big/ \sum_{w \in \{S_2\}} PR_w^{S} \quad (8)$$

where PR_x^S is the PageRank score of word x in quote S. Note that for more detailed, see [50].

E. Results

In this section we present the results of applying the CBLC algorithm to 50-Quotes, 211-Quotes, Reuters-21578, Aural Sonar, Protein, Voting, SearchSnippets, StackOverflow and Biomedical datasets, and compare its performance with that of Spectral Clustering, Affinity Propagation, k-medoids, STC-LE and k-means(TF-IDF) algorithms.

F. Clustering the 50-Quotes Dataset

Tables III, and IV show the results of applying the CBLC, Spectral Clustering, Affinity Propagation, k-medoids, STC-LE and k-means(TF-IDF) algorithms respectively to the 50-Quotes dataset and evaluating using the Purity, Entropy, V-measure, Rand Index and F-measure measures. In order to compare the effect of the short text similarity measures, the first section of table III shows performance with the use of the synonym expansion similarity measure (described above in Section II, here after we will call it as synonym expansion similarity measure), the second shows performance with the use of modified Li *et al*. (2006) [1], [50] measure, and the third shows performance with the use of modified Mihalcea *et al*. (2006) [2], [50] measure. The spectral clustering, Affinity Propagation, k-medoids, STC-LE and k-means(TF-IDF) algorithms used are that due to [31], [30], [26], [54], [55] respectively. Note that, the performance shown in table IV is only with the use of the synonym expansion similarity measure.

TABLE III
CBLC ALGORITHM PERFORMANCE ON 50-QUOTES DATASET

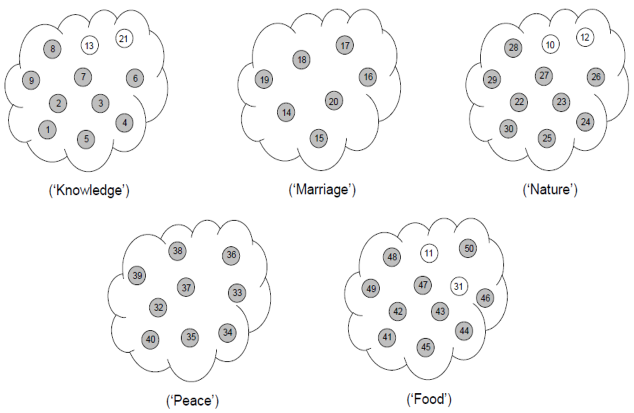
N_clust (k)	Purity	Entropy	V-meas.	Rand	F-meas.
Synonym Expansion Similarity Measure					
3	0.478	0.774	0.335	0.652	0.598
4	0.651	0.497	0.560	0.711	0.632
5	**0.860**	**0.240**	**0.775**	**0.868**	**0.756**
6	0.812	0.275	0.697	0.805	0.695
7	0.719	0.350	0.580	0.799	0.612
Modified Li *et al*. Similarity Measure					
3	0.490	0.785	0.310	0.601	0.580
4	0.610	0.525	0.590	0.687	0.625
5	**0.830**	**0.260**	**0.700**	**0.788**	**0.654**
6	0.790	0.298	0.650	0.732	0.620
7	0.680	0.380	0.553	0.696	0.580
Modified Mihalcea *et al*. Similarity Measure					
3	0.480	0.800	0.299	0.499	0.455
4	0.600	0.550	0.589	0.655	0.584
5	**0.752**	**0.311**	**0.650**	**0.724**	**0.622**
6	0.740	0.320	0.642	0.674	0.578
7	0.729	0.358	0.680	0.590	0.501

TABLE IV
SPECTRAL CLUSTERING, AFFINITY PROPAGATION AND K-MEDOIDS ALGORITHMS PERFORMANCE ON 50-QUOTES DATASET

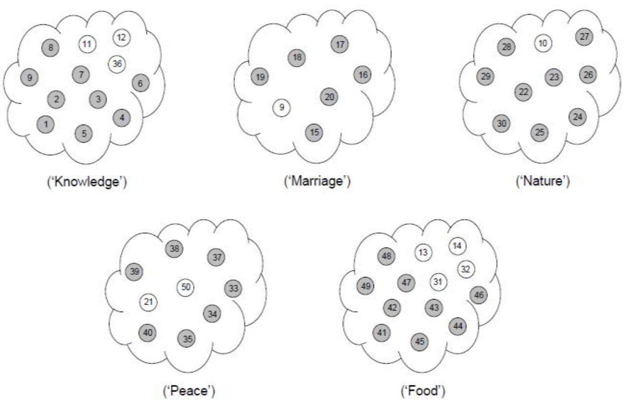
N_clust (k)	Purity	Entropy	V-meas.	Rand	F-meas.
Spectral Clustering					
3	0.740	0.394	0.616	0.735	0.495
4	0.760	0.309	0.667	0.750	0.524
5	**0.810**	**0.291**	**0.698**	**0.808**	**0.585**
6	0.700	0.401	0.666	0.675	0.430
7	0.620	0.540	0.563	0.603	0.392
Affinity Propagation					
4	0.780	0.331	0.629	0.713	0.401
5	**0.800**	**0.298**	**0.646**	**0.748**	**0.480**
6	0.690	0.460	0.545	0.668	0.376
7	0.650	0.490	0.565	0.589	0.305
k-medoids					
3	0.580	0.498	0.425	0.498	0.320
4	0.602	0.411	0.541	0.575	0.391
5	0.650	0.365	0.596	0.612	0.402
6	**0.788**	**0.294**	**0.656**	**0.717**	**0.550**
7	0.710	0.313	0.601	0.689	0.480
STC-LE					
3	0.641	0.412	0.541	0.622	0.430
4	0.687	0.389	0.584	0.676	0.477
5	**0.797**	**0.301**	**0.658**	**0.725**	**0.545**
6	0.748	0.355	0.613	0.700	0.502
7	0.606	0.465	0.521	0.588	0.390
k-means(TF-IDF)					
3	0.402	0.601	0.322	0.362	0.320
4	0.433	0.566	0.366	0.388	0.354
5	0.487	0.524	0.409	0.401	0.398
6	0.510	0.505	0.464	0.456	0.420
7	**0.578**	**0.490**	**0.511**	**0.498**	**0.487**

CBLC algorithm requires that an initial number of clusters in which we specified before the algorithm start. This number was varied from 1 to 10. Interestingly, only 5 unique clusterings were found in the case of using the CBLC, Spectral Clustering, *k*-medoids, STC-LE and *k*-means(TF-IDF) algorithms and only 4 unique clusterings were found in case of using the Affinity Propagation algorithm, each containing a different number of clusters, which ranged from 3 to 7 and 4 to 7 respectively. Note that, values in the tables are averaged over 100 trials.

Since the five evaluation measures performance are not always consistent as to which algorithm achieves best performance for a given number of clusters, we indicate in boldface the value corresponding to the best value for that measure; i.e., the maximum column value in the case of Purity, V-measure, Rand Index and F-measure, the minimum column value in the case of Entropy. In the table III, therefore, it can clearly be seen that use of the synonym expansion similarity measure consistently leads to better clustering performance over that of the modified Li *et al.* and Modified Mihalcea *et al.* similarity measures. That is, the synonym expansion similarity measure leads to better performance across all five algorithms.



(a). Quotes belonging to each of the five clusters using synonym expansion similarity measure



(b). Quotes belonging to each of the five clusters using Li *et al*. similarity measure

Fig. 3. Centroid-based clustering for 50-quotes. Graph (a) and (b) show the quotes belonging to each of the five clusters using both synonym expansion and modified Li *et al*. similarity measures respectively. Open circles represent the quote(s) not belong to the right cluster and the circles colored by gray represent quote(s) belong to the right cluster.

Comparing the first section of Table III, and first and second sections in Table IV (i.e., performance % of the five algorithms using the synonym expansion similarity measure) shows that the CBLC algorithm outperforms the Spectral Clustering, Affinity Propagation, *k*-medoids, STC-LE and *k*-means(TF-IDF) algorithms. The CBLC algorithm also achieves superior results to that of the other algorithms when using the modified Li *et al*. measure, as can be seen by comparing the first and second sections of the table IV.

Best performance in terms of overall purity, entropy, V-measure, Rand Index, F-measure (86.0%, 24.0%, 77.5%, 86.8% and 75.6% respectively), was achieved using CBLC with synonym expansion similarity measure. Interestingly, note that this best performance occurs when the number of clusters is five, which happens to be the actual number of clusters in the 50-quotes dataset.

In order to gauge the significance of the results, this can be gained by examining the quotations assigned to the various clusters. Figure 3 shows the 5-clustering, where the figure (a) shows the results of clustering using CBLC with the synonym expansion measure; the figure (b) shows the results of clustering using CBLC with the modified Li *et al*. measure. In the figure (a), Clusters ('Marriage') and ('Peace') are completely homogenous, since they contain quotes from only a single class. Each of the other clusters (e.g., knowledge, nature and food) contains two quotes not belonging to the class of the majority of quotes in the cluster. In the figure (b), there are no perfectly homogeneous clusters, and in one case ('Food') cluster there are four quotes not belonging to the majority class. In regard to completeness, there is little difference between the two clusterings. This is indicating that the incorporation of synonym expansion similarity measure in the CBLC algorithm leads to a significant improvement in clustering performance.

G. *Clustering the 211-Quotes Dataset*

Tables V and VI show the results of applying the CBLC, Spectral Clustering, Affinity Propagation, *k*-medoids, STC-LE and *k*-means(TF-IDF) algorithms respectively to the 211-Quotes dataset. We follow the same evaluation setting as per the 50-Quotes dataset, with the exception that the initial number of clusters was varied from 13 to 17. This is because where we found a proper clustering performance.

TABLE V
CBLC ALGORITHM PERFORMANCE ON 211-QUOTES DATASET

N_clust (*k*)	Purity	Entropy	*V*-meas.	Rand	*F*-meas.
Synonym Expansion Similarity Measure					
13	0.376	0.654	0.362	0.330	0.298
14	0.396	0.623	0.378	0.365	0.302
15	0.400	0.605	0.397	0.389	0.360
16	**0.485**	**0.531**	**0.426**	**0.434**	**0.398**
17	0.414	0.587	0.400	0.399	0.378
Basic Li *et al.* (6006) Similarity Measure					
13	0.290	0.718	0.284	0.226	0.200
14	0.300	0.687	0.316	0.265	0.213
15	0.319	0.662	0.336	0.279	0.254
16	0.314	0.664	0.332	0.301	0.293
17	**0.347**	**0.628**	**0.361**	**0.320**	**0.325**
Basic Mihalcea *et al.* (6006) Similarity Measure					
13	0.256	0.758	0.234	0.204	0.182
14	0.269	0.742	0.240	0.215	0.212
15	0.310	0.679	0.263	0.245	0.236
16	0.330	0.615	0.345	0.278	0.265
17	**0.350**	**0.589**	**0.369**	**0.301**	**0.295**

TABLE VI
SPECTRAL CLUSTERING AND AFFINITY PROPAGATION ALGORITHMS PERFORMANCE ON 211-QUOTES DATASET

N_clust (*k*)	Purity	Entropy	*V*-meas.	Rand	*F*-meas.
		Spectral Clustering			
13	0.304	0.735	0.279	0.255	0.181
14	0.295	0.746	0.275	0.274	0.193
15	0.300	0.742	0.288	0.298	0.202
16	**0.342**	0.693	0.325	**0.322**	**0.213**
17	0.328	**0.670**	**0.340**	0.320	0.201
		Affinity Propagation			
13	0.242	0.769	0.237	0.180	0.120
14	0.271	0.728	0.276	0.203	0.143
15	0.290	0.706	0.295	0.228	0.152
16	0.295	0.702	0.295	0.259	0.182
17	**0.304**	**0.694**	**0.302**	**0.280**	**0.197**
		k-medoids			
13	0.266	0.752	0.262	0.232	0.161
14	0.273	0.732	0.269	0.251	0.183
15	0.298	0.721	0.290	0.284	0.192
16	**0.315**	0.695	0.305	**0.319**	**0.203**
17	0.301	**0.685**	**0.324**	0.315	0.200
		STC-LE			
13	0.287	0.812	0.233	0.264	0.190
14	0.301	0.787	0.285	0.289	0.254
15	0.321	0.724	0.311	0.310	0.287
16	**0.336**	**0.689**	**0.329**	**0.351**	**0.310**
17	0.312	0.735	0.301	0.320	0.291
		k-means(TF-IDF)			
13	0.102	0.981	0.110	0.100	0.106
14	0.120	0.950	0.121	0.121	0.140
15	0.155	0.912	0.145	0.146	0.151
16	0.194	0.898	0.197	0.189	0.174
17	**0.203**	**0.811**	**0.202**	**0.215**	**0.198**

Best performance in terms of overall purity, entropy, V-measure, Rand Index, F-measure (48.5%, 53.1%, 42.6%, 43.4% and 39.8% respectively), was achieved using CBLC with synonym expansion similarity measure. Importantly, note that this best performance occurs when the number of clusters is sixteen, which happens to be close to the actual number of clusters (fifteen) in the 211-quotes dataset. The values of the performance measures clearly indicate that the 211-Quotes dataset is a much more challenging dataset of quotes (i.e., short text and mostly absent of word co-occurrence) to cluster that is the 50-Quotes dataset. The same conclusions, therefore, can be concluded as was the case for the 50-Quotes dataset. Note that CBLC, Spectral Clustering, Affinity Propagation, *k*-medoids, STC-LE and *k*-means(TF-IDF) algorithms achieve better performance with the use of synonym expansion similarity measure, and the CBLC algorithm performs better than other five algorithms, irrespective of which similarity measure is used.

A more intuitive appreciation of the CBLC algorithm performance on 211-Quotes dataset can be gained by using two benchmarks: (i) a random cluster assignment (CBLC clustering algorithm), and (ii) human clusterings. In the first case, quotes were randomly assigned an integer value between 1 and 15 inclusive, indicating the cluster. Averaged over 50 trials, this results in a purity of 48.5.0%, entropy of 53.1%, *V*-measure of 42.6% and a *F*-measure value of 39.8% (here we only use three clustering evaluation measures as shown in Table V). For human-assigned clusterings, we provided 30 university undergraduate students with the 211 quotes and asked them to cluster the quotes into fifteen groups. Purity of the results ranged from a minimum of 50.0% to a maximum of 100%, with a mean of 65.7%. This is shown in the Figure 4 with the other evaluation measures.

The better performance achieved using the synonym expansion similarity measure is most likely due its ability to capture more semantic information than the modified Li *et al*. and modified Mihalcea *et al*. measures. To illustrate that, consider Quotation 36 in the 50-Quotes dataset: "*We are each gifted in a unique and important way, it is our privilege and our adventure to discover our own special light*", which belongs to the actual class *Peace*. When clustered using the modified Li *et al*. measure, this quote is clustered with quotes belonging predominantly to class *knowledge*, probably due to the presence of the word 'adventure', which might be considered a type of investigation, and also possibly due to the presence of the word 'discover' (used for find out knowledge). However, when clustered using synonym expansion similarity, the quote is clustered into the same cluster as almost all other quotes belonging to class *Peace*, most likely due to the presence of the word 'privilege'. The most likely explanation for this is that the synonym expansion for short-text similarity measure, because it uses an expanded semantic context, is better able to make a stronger connection between 'privilege' and peace-related words appearing in other quotes belonging to Class *Peace*.

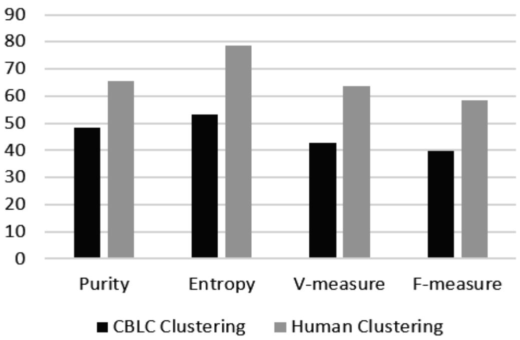


Fig.4. Human Clustering vs. CBLC algorithm clustering performance on 211-quotes dataset

As expected, the purity, entropy, *V*-measure, Rand Index and *F*-measure values on 211-Quotes dataset are lower than those on 50-Quotes dataset. However, the results are still clearly significant when compared against the random benchmark, and comparable to the performance of some human participants, who had the advantage of being told the number of clusters. In regard to short text similarity measures, in the case of 50-Quotes dataset equal-best performance is achieved using the synonym expansion measures under the centroid-based lexical clustering algorithm (CBLC), and this performance is better than the best results for Spectral Clustering and STC-LE algorithms, achieved under the synonym expansion measure. The important result from these experiments is that they support the claim that our variation of centroid-based lexical clustering (variation of standard *k*-means) algorithm with using synonym expansion similarity measure (described in Section II) utilises more of the available semantic information than is utilised by other compared approaches.

H. Clustering the Reuters-21578, Aural Sonar, Protein, Voting, SearchSnippets, StackOverflow and Biomedical Datasets

While CBLC is clearly applicable to tasks involving sentence clustering, the algorithm is generic in nature and can in principal be applied to any lexical semantic clustering domain. In this section we apply the algorithm to clustering several datasets in different domains.

Table VII shows the results of applying the CBLC algorithm to the *Reuters-21578*, *Aural Sonar*, *Protein*, *Voting*, *SearchSnippets*, *StackOverflow* and *Biomedical* datasets respectively. We follow the same evaluation setting as per the 50-Quotes and 211-Quotes datasets, with the exception that the initial number of clusters was varied from 7 to 12 for Reuters-21578, Aural Sonar, Protein, Voting and SearchSnippets datasets, and from 17 to 23 for StackOverflow and Biomedical datasets. This is because where we found a proper clustering performance. Note that the best performance according to each measure depicted in boldface.

TABLE VII
CBLC ALGORITHM PERFORMANCE ON REUTERS-21578, AURAL SONAR, PROTEIN AND VOTING DATASETS WITH THE USE OF THE SYNONYM EXPANSION SENTENCE SIMILARITY MEASURE

N_clust (*k*)	Purity	Entropy	*V*-meas.	Rand	*F*-meas.
Reuters-21578 Dataset					
7	0.571	0.659	0.423	0.584	0.565
8	0.620	0.523	0.498	0.611	0.579
9	0.645	0.409	0.557	0.623	0.602
10	**0.721**	**0.318**	**0.655**	**0.707**	**0.622**
11	0.688	0.361	0.630	0.682	0.587
12	0.670	0.435	0.621	0.673	0.569
Aural Sonar Dataset					
7	0.790	**0.431**	0.538	0.786	0.674
8	**0.820**	0.436	**0.541**	**0.804**	**0.720**
9	0.802	0.492	0.499	0.789	0.646
10	0.778	0.524	0.445	0.768	0.621
11	0.754	0.591	0.401	0.745	0.597
12	0.703	0.611	0.379	0.731	0.569
Protein Dataset					
7	0.719	0.279	0.490	0.776	0.671
8	0.769	0.274	0.523	**0.798**	**0.681**
9	**0.898**	**0.259**	**0.604**	0.781	0.636
10	0.839	0.265	0.601	0.765	0.601
11	0.790	0.316	0.598	0.735	0.587
12	0.749	0.320	0.588	0.701	0.549
Voting Dataset					
7	0.770	**0.421**	0.530	0.768	0.665
8	**0.871**	0.446	**0.545**	**0.812**	**0.717**
9	0.792	0.496	0.490	0.779	0.636
10	0.771	0.534	0.435	0.758	0.615
11	0.750	0.581	0.419	0.734	0.593
12	0.733	0.612	0.389	0.722	0.559
SearchSnippets					
7	0.802	0.462	0.594	0.754	0.643
8	**0.845**	**0.401**	**0.613**	**0.801**	**0.689**
9	0.788	0.478	0.588	0.765	0.624
10	0.741	0.512	0.522	0.732	0.603
11	0.687	0.565	0.479	0.697	0.587
12	0.625	0.577	0.413	0.651	0.526
StackOverflow					
17	0.545	0.488	0.455	0.542	0.465
18	0.599	0.456	0.487	0.596	0.501
19	0.621	0.411	0.501	0.610	0.555
20	**0.681**	**0.354**	**0.520**	**0.623**	**0.597**
21	0.635	0.311	0.512	0.615	0.562
22	0.603	0.401	0.474	0.597	0.510
23	0.574	0.498	0.420	0.566	0.479
Biomedical					
17	0.404	0.395	0.355	0.378	0.451
18	0.436	0.374	0.395	0.410	0.465
19	0.495	0.314	0.421	0.435	0.487
20	**0.521**	**0.254**	**0.461**	**0.489**	**0.501**
21	0.513	0.296	0.432	0.448	0.494
22	0.479	0.333	0.413	0.406	0.456
23	0.422	0.384	0.387	0.378	0.424

Best performance in terms of overall purity, entropy, V-measure, Rand Index, F-measure for the seven datasets, was achieved using CBLC with synonym expansion similarity measure. Interestingly, note that this best performance occurs when the number of clusters is eight-to-teen, which happens to be very close to the actual number of clusters in the Reuters-21578, Aural Sonar, Protein, Voting and SearchSnippets datasets, and nineteen-to-twenty-one in the StackOverflow and Biomedical datasets. By considering all evaluation criteria applied in all datasets, the best overall performance of the six clustering algorithms is achieved by CBLC in conjunction with the synonym expansion measure.

TABLE VIII
SPECTRAL CLUSTERING, AFFINITY PROPAGATION AND K-MEDOIDS ALGORITHMS PERFORMANCE ON REUTERS-21578, AURAL SONAR, PROTEIN AND VOTING DATASETS WITH THE USE OF THE SYNONYM EXPANSION SIMILARITY MEASURE

Algorithm	Purity	Entropy	*V*-meas.	Rand	*F*-meas.
Reuters-21578 Dataset					
CBLC Algorithm	**0.721**	**0.318**	**0.655**	**0.707**	**0.622**
Spectral Clustering	0.669	0.395	0.604	0.674	0.542
Affinity Propagation	0.611	0.465	0.525	0.668	0.537
k-medoids	0.608	0.456	0.520	0.646	0.504
STC-LE	0.650	0.403	0.587	0.687	0.551
k-means(TF-IDF)	0.492	0.741	0.365	0.411	0.374
Aural Sonar Dataset					
CBLC Algorithm	**0.820**	**0.431**	**0.541**	**0.804**	**0.720**
Spectral Clustering	0.780	0.523	0.498	0.745	0.712
Affinity Propagation	0.740	0.535	0.451	0.717	0.695
k-medoids	0.720	0.583	0.426	0.697	0.676
STC-LE	0.801	0.491	0.515	0.764	0.704
k-means(TF-IDF)	0.502	0.789	0.288	0.464	0.422
Protein Dataset					
CBLC Algorithm	**0.898**	**0.259**	**0.604**	**0.798**	**0.681**
Spectral Clustering	0.832	0.289	0.587	0.733	0.614
Affinity Propagation	0.709	0.314	0.531	0.691	0.604
k-medoids	0.713	0.307	0.523	0.626	0.592
STC-LE	0.849	0.261	0.600	0.745	0.622
k-means(TF-IDF)	0.601	0.436	0.466	0.512	0.497
Voting Dataset					
CBLC Algorithm	**0.871**	**0.421**	**0.545**	**0.812**	**0.717**
Spectral Clustering	0.808	0.501	0.509	0.785	0.708
Affinity Propagation	0.780	0.545	0.478	0.715	0.690
k-medoids	0.775	0.589	0.436	0.689	0.643
STC-LE	0.820	0.495	0.519	0.801	0.710
k-means(TF-IDF)	0.490	0.764	0.344	0.394	0.481
SearchSnippets					
CBLC Algorithm	**0.845**	**0.401**	**0.613**	**0.801**	**0.689**
Spectral Clustering	0.741	0.456	0.587	0.788	0.620
Affinity Propagation	0.723	0.479	0.564	0.736	0.601
k-medoids	0.701	0.498	0.531	0.712	0.595
STC-LE	0.780	0.420	0.601	0.798	0.654
k-means(TF-IDF)	0.350	0.786	0.255	0.314	0.264
StackOverflow					
CBLC Algorithm	**0.681**	**0.354**	**0.520**	**0.623**	**0.597**
Spectral Clustering	0.614	0.396	0.510	0.611	0.545
Affinity Propagation	0.580	0.460	0.502	0.591	0.521
k-medoids	0.502	0.487	0.490	0.579	0.501
STC-LE	0.522	0.478	0.500	0.619	0.565
k-means(TF-IDF)	0.231	0.718	0.203	0.221	0.189
Biomedical					
CBLC Algorithm	**0.521**	**0.254**	**0.461**	**0.489**	**0.501**
Spectral Clustering	0.462	0.269	0.443	0.451	0.488
Affinity Propagation	0.422	0.284	0.423	0.436	0.465
k-medoids	0.412	0.940	0.419	0.424	0.433
STC-LE	0.450	0.256	0.451	0.441	0.469
k-means(TF-IDF)	0.300	0.784	0.264	0.287	0.280

Table VIII compares the clustering performance of CBLC algorithm with that of Spectral Clustering, Affinity Propagation, *k*-medoids, STC-LE and *k*-means(TF-IDF) using the five cluster quality measures described earlier. For the compared algorithms, the overall purity, entropy, V-measure, Rand Index and F-measure values was in each case selected by trialling a range of values (number of clusters from 7 to 23), and selecting that which results in the best overall quality clustering evaluation performance. The tabulated results for CBLC, Spectral Clustering, Affinity Propagation, *k*-medoids, STC-LE and *k*-means(TF-IDF) algorithms correspond the best performance obtained from 200 time runs.

The results show that CBLC significantly outperforms the other compared algorithms on all datasets. This is consistent with our observations in Sections IV.F and IV.G, and suggests that CBLC may be intrinsically better able to identify significantly overlapping clusters, while at the same time achieving good performance as measured by above defined clustering criteria. In this experiment, however, we knew *a priori* what the actual number of classes (clusters) was. In general, we would not have this information, and would hope that the algorithm could automatically determine an appropriate number of clusters. Even when run with a high initial number of clusters, CBLC algorithm was able to converge to a solution containing not more than five clusters (e.g., in case of 50-Quotes dataset) and seven clusters (e.g., in case of Reuters-21578 dataset), and from the tables it can be again seen that the evaluation of these clusterings is better than that for the other compared clustering algorithms.

I. *Application to Text Summarisation*

Although we have been primarily concerned with sentence clustering as a generic activity, sentence clustering will often be performed within some other text-processing task such as extractive text (article) summarisation, where the objective is to extract a (usually small) subset of sentences to include in a produced summary.

Table IX shows the sentences from an article about political science that has been chosen because it was topical and our interesting at the time of conducting this study, and that it is typical in terms of length and breadth of content to the type of texts to which text processing activities such as text summarisation are commonly applied. Figure 5 shows the results of applying the CBLC algorithm to this political science article. Sentences in dark-boldface are those that the CBLC algorithm identified as being central to each of the identified four clusters (i.e., *k*=4).

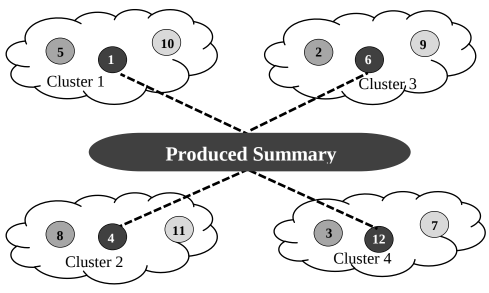


Fig. 5. CBLC algorithm performance on political science article

An obvious way to use the clustering results to produce an extractive summary is to select from each cluster the sentence most central to that cluster. This is interesting in the case of CBLC, and amounts to simply selecting the centroid from each cluster; i.e., sentences **1**, **4**, **6**, and **12** as shown in Figure 5. Note that these sentences tend to be distributed around the perimeter of the denser inner region of the document, as can be seen clearly from Table IX.

TABLE IX
POLITICAL SCIENCE ARTICLE DATASET

Political Science Article Dataset
1. Political science is a social science which deals with systems of governments, and the analysis of political activities, political thoughts and political behavior.
2. It deals extensively with the theory and practice of politics which is commonly thought of as determining of the distribution of power and resources.
3. Political scientists "see themselves engaged in revealing the relationships underlying political events and conditions, and from these revelations they attempt to construct general principles about the way the world of politics works."
4. Political science comprises numerous subfields, including comparative politics, political economy, international relations, political theory, public administration, public policy and political methodology.
5. Furthermore, political science is related to, and draws upon, the fields of economics, law, sociology, history, philosophy, geography, psychology, and anthropology.
6. As a social science, contemporary political science started to take shape in the latter half of the 19th century when it began to separate itself from political philosophy which traces its roots back to the works of Aristotle, Plato, and Chanakya which were written nearly 2,500 years ago.
7. Comparative politics is the science of comparison and teaching of different types of constitutions, political actors, legislature and associated fields, all of them from an intrastate perspective.
8. International relations deals with the interaction between nation-states as well as intergovernmental and transnational organizations.
9. Political theory is more concerned with contributions of various classical and contemporary thinkers and philosophers.
10. Political science is methodologically diverse and appropriates many methods originating in social research.
11. Approaches include positivism, interpretivism, rational choice theory, behaviouralism, structuralism, poststructuralism, realism, institution alism, and pluralism.
12. Political science, as one of the social sciences, uses methods and techniques that relate to the kinds of inquiries sought: primary sources such as historical documents and official records, secondary sources such as scholarly journal articles, survey research, statistical analysis, case studies, experimental research and model building.

Depending on the number of clusters that have been identified (i.e., *k* value), selecting the cluster centroids may result in either too few or too many sentences, and we may wish to either add or delete sentences from this produced summary. There are various approaches we could take. For example, if we wish to include more sentences, we could select additional sentences from each cluster, but this may result in an overly large summary, with possibly some duplication in content. A better approach would be to supplement the summary with sentences which are important globally within the document, and these sentences can be easily identified by their ranking score (i.e., sentence scoring techniques). The next four sentences to be added according to this procedure (obviously not adding duplicates) would be Sentences 5, 8, 2, 3, sorted according to their scoring. It is interesting to note that two of these additional sentences appear very close to the beginning of the article, and intuitively, we would expect the first few sentences of a news article to capture the main content. Indeed, simply selecting the first few sentences in a document is a commonly used benchmark for text summarisation. Should the initial summary contain too many sentences, the rank scores could likewise be used to remove sentences.

A more intuitive appreciation of the CBLC algorithm performance on text summarisation task can be gained by applying it on standard dataset. For this occasion, we use *Opinosis* dataset containing short user reviews in 51 different topics (i.e., 51 clusters) [58]. Each of these topics contains approximately 100 sentences (on the average) and is a collection of different user reviews obtained from various sources such as Amazon.com (electronics), TripAdvisor (hotels) and etc. The dataset contains between 4 and 5 ground-truth summaries (i.e., sentences) generated by human authors for each topic. The length of the ground-truth summaries is around two sentences (i.e., k=2).

We also use *precision*, *recall* and *F-measure* as external validation measure to evaluate the quality of produced summary at the *sentence* level only (i.e., here we do not interest at this time to use the *ROUGE-N* measure to evaluate the produced summary at the *word* level). Precision measure ($TP/(TP + FP)$) is a fraction of the produced summary that is in the ground-truth and recall measure ($TP/(TP + FN)$) is a fraction of a human made ground-truth summary that is generated, with TP being the number of sentences included by both produced and ground-truth summary, FP being the number of sentences appearing in ground-truth summary yet not in produced summary, and FN being the number of sentences appearing in produced summary but not in ground-truth summary. F-measure is a well-known method to combine recall and precision and it can be calculated as ($2PR/(P+R)$). Note that all the values are averages of individual topic (single document).

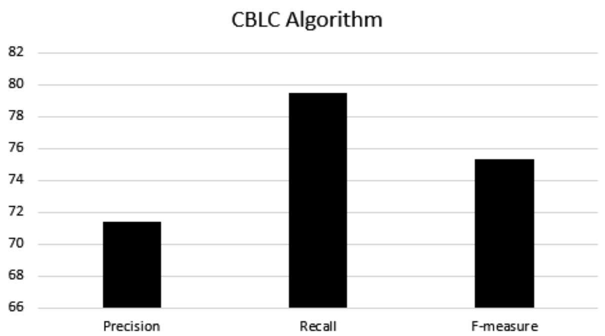


Fig.6. CBLC algorithm performance on Opinosis dataset by using external validation measures

As can be seen from Figure 6, CBLC algorithm achieved a quite satisfactory performance on Opinosis dataset. These results demonstrate the effectiveness of the synonym expansion approach incorporated in CBLC algorithm. The important result from these experiments is that they support the claim that our centroid-based clustering algorithm in conjunction with synonym expansion similarity measure utilises more of the available semantic information available at the sentence level.

V. Discussion and Conclusion

This paper has presented a variant of the standard k-means algorithm for short text clustering that is based on the notion of synonym expansion semantic vectors. These vectors represent sentences using semantic information derived from a lexical database constructed to identify the correct meaning to a word, based on the context in which it appears. Our empirical results have shown the method to achieve satisfactory performance against the Spectral Clustering Affinity Propagation, k-medoids, STC-LE and k-means(TF-IDF) algorithms, as evaluated on two specially constructed datasets of famous quotations, benchmark datasets in several other domains, and that its incorporation as a short text similarity using synonym expansion leads to a significant improvement in the centroid-based lexical clustering performance.

An obvious application of the algorithm is to knowledge discovery processing; however, the algorithm can also be used within more general knowledge discovery settings such as text summarisation or query-directed opinion mining. Like any clustering algorithm, the performance of CBLC will ultimately depend on the quality of the input data (text similarity values), and in the case of sentence clustering this performance may be improved through development of better short text similarity measures, which may in turn be based on improved word sense disambiguation, etc. Any such improvements are orthogonal to the clustering model, and can be easily integrated into it.

Considering all evaluation criteria into account, by far the best overall performance of the six clustering algorithms is achieved by CBLC in conjunction with the synonym expansion measure. In the experiment process, however, we know an advance what the real number of classes (clusters) was. This is for example such a case for 5-classes in case of 50-Quotes dataset, and 15-classes in case of 211-Quotes dataset. In general, we would not have this information, and would hope that the algorithm could automatically determine an appropriate number of clusters. This will be our primary interest in the future work.

The major disadvantage of the algorithm is its time complexity. As previously discussed in, semantic similarity measurement must be applied to each sentence in each cluster centroid, and this can lead to long convergence times if the problem involves a large number of sentences and/or clusters.

Short text clustering is an exciting area of research within the text mining activities, and this paper has introduced a variation of standard k-means clustering which are able to cluster short text fragments such as sentences or quotes based on available semantic information. We have already mentioned some of the new work we are conducting in this area; however, what we are most excited about is extending the cluster technique to perform text mining. The concepts present in natural language documents usually buried interesting information inside it, whereas the techniques we have presented in this paper clusters only sentences and other short text fragmentations. Our other future work is to apply these ideas of short text clustering to the development of complete techniques for text sentiment analysis or opinion miming.

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