Discovering Latent Semantics in Web Documents Using Fuzzy Clustering

I-Jen Chiang, Member, IEEE, Charles Chih-Ho Liu, Yi-Hsin Tsai, and Ajit Kumar

Abstract—Web documents are heterogeneous and complex. There exists complicated associations within one web document and linking to the others. The high interactions between terms in documents demonstrate vague and ambiguous meanings. Efficient and effective clustering methods to discover latent and coherent meanings in context are necessary. This paper presents a fuzzy linguistic topological space along with a fuzzy clustering algorithm to discover the contextual meaning in the web documents. The proposed algorithm extracts features from the web documents using conditional random field methods and builds a fuzzy linguistic topological space based on the associations of features. The associations of cooccurring features organize a hierarchy of connected semantic complexes called “CONCEPTS,” wherein a fuzzy linguistic measure is applied on each complex to evaluate 1) the relevance of a document belonging to a topic, and 2) the difference between the other topics. Web contents are able to be clustered into topics in the hierarchy depending on their fuzzy linguistic measures; web users can further explore the CONCEPTS of web contents accordingly. Besides the algorithm applicability in web text domains, it can be extended to other applications, such as data mining, bioinformatics, content-based, or collaborative information filtering, etc.

Index Terms—Fuzzy aggregation algorithm, fuzzy linguistic topological space, fuzzy semantic topology, fuzzy web hierarchical clustering, named entity recognition (NER).

I. INTRODUCTION

SEARCH engines are indispensable tools to find, filter, and extract the desired information, which attempt to aid users in gathering relevant contents from web. Lawrence et al. [1] and Henzinger [2] surveyed and compared search engines, such as AltaVista, Excite, HotBot, Infoseek, Lycos, Northern Light, and Google. Both studies have shown the weaknesses of these search engines and proposed some solutions to overcome some of the weaknesses. A sophisticated mechanisms to recognize the latent semantics in the returned search results is crucial to enhance comprehensiveness of a search engine. The complex and high interactions between terms in documents demonstrates vague and ambiguous meanings. Polysemies, synonyms, homonyms, phrases, dependence, and spams limit the capabilities of search technologies and strongly diminish the comprehensiveness of the results returned from the search engines [3].

Web document clustering is one of the indispensable techniques [4], [5] to discover contextual meaning (hereinafter called semantics) from the returned heterogeneous web pages [6], [7]. Consider users’ queries are also vague and unconscious [8]. Numerous document clustering methods have been proposed; some are based on probabilistic models equipped with distance and similarity measures [9], and others use matrix factorization [10], and data mining techniques, such as SOM [11]. A document is usually represented as a feature vector, which can be viewed as a point in the multidimensional space, to match users’ queries. Many methods, including k-means, hierarchical clustering [13], and nearest-neighbor clustering [14], select a set of key terms or phrases to organize the feature vectors depending on the differences between documents to capture semantics in order to fit users’ intents. Suffix-tree clustering [15] is a phrase-based approach, which carries out document clustering depending on the similarities between documents.

When the documents provide imprecise information, the use of fuzzy set theory is advisable. Fuzzy c-means and fuzzy hierarchical clustering algorithms were deployed for document clustering [16]–[18]. Fuzzy c-means and fuzzy hierarchical clustering need prior knowledge about “number of clusters” and “initial cluster centroids,” which are considered to be serious drawbacks of these approaches. To address these drawbacks, ant-based fuzzy clustering algorithms [19]–[21] and fuzzy k-means clustering algorithms [22] were proposed that can deal with unknown number of clusters. Moreover, the similarity measures and bag of words [23] were the main limitation of those methods to capture the semantics in the collection of documents. Based on Vector Space Model [24], the similarity between two documents is measured with vector distance, such as Euclidean distance, Manhattan distance, etc. These methods do not take contextual meaning into consideration. Ontology-based fuzzy document clustering schemes [25], [26] were used to cluster documents with a limited subsets of selected terms based on the defined ontology. Those methods restrict the application domains, which makes them difficult to be generalized if the domain does not have a proper ontology.

Some approaches consider the cooccurrence of terms, but neglect whether terms cooccur in the same context. For example, two terms “Wall” and “Street” do not represent a meaningful theme, say “Wall Street” if these are located at different places in a document. Moreover, polysemy and other important issues are also ignored. Lin and Chiang [27] pictured the geometric aspect of latent semantics from the given set of documents. Basically, features (keywords or noun phrases) are taken as vertices and the associations (frequent co-occurring features)
among those features are taken as links to represent semantic clusters, which are simplicial complexes in geometry. Chen et al. [28] proposed a fuzzy hierarchical clustering approach to discover a set of highly related fuzzy frequent itemsets to represent the candidate clusters. Zaidi and Melancon [29] presented a decomposition technique by breaking the network organized by cooccurrence keywords with the centroids, that is, the nodes with the maximum degree, and a cutoff threshold into several clusters. Song et al. [30] advocated using part-of-speech and WordNet lexicon to keep the terms in accordance to document subjects or titles, and then perform document clustering using WordNet hierarchical structures.

Most of the subsequent methods have tried to resolve the semantic clustering problem without much consideration to the semantic hierarchy in documents. A fuzzy linguistic measure is given to evaluate a set of features in a document on both “the relevance of the document belonging to a topic” and “the differentials between the other topics” in order to facilitate and enhance relevant information access for the web users. Furthermore, the fuzzy clustering algorithm clusters those documents into homogeneous semantic topics to discover latent semantics in returned documents. Each semantic cluster represents an individual “topic” that indicates the essence or summary from the subset of returned documents. Users can identify topics that are relevant to their intents. For instance, a query term “jaguar” can be classified into the “animal” topic or “automobile” topic according to the semantics of the returned documents, and users can explore their favorite topics from the classified semantic clusters. As another example, let us consider a simple query, “network,” which can yield different topics depending on if it appears close to a term, such as “computer,” “traffic,” “artificial neural,” or “biological neural” in significant fragments of the returned documents. A fuzzy estimate is applied to reveal the uncertainty and vagueness between a term and its adjacent terms in context. Besides, the fuzzy estimates can capture linguistic aspects, such as synonyms and polysemy. Therefore, the aim of this study is to develop a novel fuzzy hierarchical clustering algorithm based on the concepts of fuzzy linguistic topological spaces [31], which can discover the latent semantics in text corpora.

In Section II, we introduce NERs and fuzzy linguistic measures of entities to represent term level semantics. Section III defines and illustrates the fuzzy semantics in a collection of documents from geometric points of view. Building the hierarchical semantic architectures from the collection of named entities is described in Section IV. Section V presents the clustering algorithm for aggregating semantics into several semantic units, each of which represents a concept in the document collection. Documents can then be clustered based on the concepts identified by the algorithm. Experimental results obtained from three different data sets are described in Section VI, which is followed by the conclusion section.

II. FUZZY LINGUISTIC ASPECT

This paper addresses a novel clustering algorithm to discover the latent semantics in a text corpus from a fuzzy linguistic perspective. Besides the applicability in text domains, it can be extended to the applications, such as data mining, bioinformatics, content-based or collaborative information filtering, etc.

As shown in Fig. 1, web documents can constitute several latent semantic topics equipped with numerical coefficients (fuzzy linguistic coefficients) that indicate the significance levels of these inherent situations. A collection of documents X and its corresponding fuzzy linguistic topological space L are two finite and discrete topological spaces, where \( L = \{C_1, C_2, \ldots, C_n\} \) and \( C_i \) denotes a semantic topological category. A discrete topological category is composed of all discrete features, that is, attribute-value pairs. The features in a document are extracted by using semisupervised learning schemes [32] called named entities.

Named entity recognition (NER) can identify one item from a set of features that have similar attributes, i.e., named categories. Examples of named categories are person, affiliations, location, etc. Consider the polysemy like the term “jaguar” can be classified as “animal,” “vehicle,” etc. If the term “jaguar” is associated with the items, such as “cat,” “tiger,” and “feline,” the term “jaguar” is more possible to be classified into the named category “animal.” Fuzzy linguistic coefficient is given to measure the possibilities of a term belonging to every category, where the term is associated with other cooccurring terms.

The general framework of our clustering method consists of two phases. The first phase, feature extraction, is to extract key named entities from a collection of “indexed” documents; the second phase, fuzzy clustering, is to determine relations between features and identify their linguistic categories.

The kernel of the first phase is to identify the key features and their named categories. In order to identify features in documents, we deployed the NER method. From a given sentence, NER method first finds out the segmented entities composed of a sequence of words, and then classify the entities by a type or named category, such as person, organization, location, etc.

This paper considers only noun entities, especially some representative entities. Therefore, discriminative linear chain
conditional random field (CRF) [33]–[35] was used to choose the particular features in the corpus. A CRF is a simple framework for labeling and segmenting data that models a conditional distribution $P(z|x)$ by selecting the label sequence $z$ to label a novel observation sequence $x$ with an associated undirected graph structure [36] that obeys the Markov property [37]. When conditioned on the observations that are given in a particular observation sequence, the CRF defines a single log-linear distribution over the labeled sequence. CRF model does not need to explicitly present the dependence of input variables $x$ affording the use of rich and global features of the input; thus, allows relaxation of the strong independent assumptions made by HMMs.

Definition 1: Let $W = \{x_1, x_2, \ldots, x_n\}$ denote features extracted from documents, and $\Theta = \{z_1, z_2, \ldots, z_m\}$ be the named category set. A membership function for $z_j$ is represented as $\rho_j$, that the value $\rho_j(x_i) = P(z_j|x_i)$ evaluates the membership degree of $x_i$ belonging to named category $z_j$.

Based on the membership function $\rho_j(x)$, we then need to evaluate the possibility of a feature $x$ in a document that could be classified into the named category $z$. In our case, the value of $\rho_j(x)$ is normalized to the real unit interval $[0, 1]$ for the sake of simplification and uniform. Generally, few words other than functional words are more frequent in a document; moreover, some keywords may occur frequently across documents. Therefore, simple frequency of the occurrence of words is not adequate.

Techniques, such as TFIDF [38], have been proposed to deal with some of these problems. The TFIDF value is the weight of features in each document. While considering relevant documents to a search query, if the TFIDF value of a feature is large, it will pull more weight than features with lesser TFIDF values.

The TFIDF value is obtained from two functions $tf$ and $idf$ [38], where $tf$ denotes term frequency that appears in a document, and $idf$ denotes inverse document frequency, where document frequency is the number of documents that contain the feature.

Moffat and Zobel [39] points out that $tf \times idf$ function demonstrates: 1) rare features are no less important than frequent features according to their $idf$ values. 2) multiple appearances of a feature in a document are no less important than single appearances according to their $tf$ values. Based on these two criteria, the membership of a feature belonging to a named category, which can be defined as follows.

Definition 2: The term frequency of a feature in a document belonging to a named category is written as $tf_z$, and the inverse document frequency of a feature in a document belonging to a named category is written as $idf_z$, which are

$$tf_z(x) = tf(x) \times \rho_z(x)$$

and

$$idf_z(x) = idf(x) \times \rho_z(x).$$

Definition 3: The membership of a feature $x$ of a document belonging to a named category $z$ is defined as follows:

$$\mu_z(x) = tf_z(x) \otimes idf_z(x)$$

where $tf_z(x)$ denotes the number of feature $x$ in a document being classified into $z$, $idf_z(x)$ denotes inverse document frequency where document frequency is the number of documents that contain the feature $x$ in category $z$, and $\otimes$ is a fuzzy operator as shown in Fig. 2, where $\alpha$ and $\beta$ are two thresholds respectively for term frequency and inverse document frequency:

$$\mu_z(x) = \begin{cases} 
1 & tf_z(x) \leq \alpha \text{ or } idf_z(x) \geq \beta \\
(tf_z(x) - \alpha) \times (idf_z(x) - \beta) & \text{otherwise}
\end{cases}$$

The membership was defined under the assumption that a feature occurring frequently in a document is more likely to be an interesting feature, a set of features that only occur in a large number of documents are more likely to be associated with a uncommon category among those documents, and as such the thresholds $\alpha$ and $\beta$ should be given a higher score. Consider the phrase “the ferocious jaguar.” Because the term “the” is so common, term frequency trend to incorrectly emphasize the returned documents used the word “the” more frequently, without giving enough weight to the meaningful terms “ferocious” and “jaguar” by using high score $\alpha$. Hence, the threshold $\beta$ incorporated with the $idf$ is set to high score that diminishes the weights of the memberships of the features that occur very frequently and increases the weights of the memberships of features that occur rarely in the returned documents.

Semantics is shown in the relationship between features and their named categories. At the second phase, discovering the underlying connections and interactions between named entities is crucial to understand semantics. Except the word level information, the associations existed between two (or more) named entities show the semantic level relationships, such as synonym, antonym, homonym, polysemy, and metonym. We can use a fuzzy linguistic measure defined for each document to evaluate both: 1) the relevance of the document belonging to a topic, and 2) the difference between the other topics.
Those cooccurring named entities in context along with fuzzy linguistic estimates can capture not only semantic level relationships, but can reveal uncertainty and vagueness among them as well. A more complicated situation arises when users search an unfamiliar field with rapidly evolving themes and nonuniform terminology. In such situations, the problem of semantic level relationships becomes more significant. For example, someone performs research on applications of stem cells. The “Endothelial Progenitor Cell (EPC)” plays a key role in the pathogenesis of two major diseases, tumor vasculogenesis and myocardial repair; and new paradigm of therapeutic modalities are rapidly developing. EPCs are highly related to mesenchymal stromal cells and very small embryonic-like cells, and all belong to a higher class of bone marrow-derived stem and progenitor cells by which different authors can refer by various terminologies. Supposedly, a researcher who is unfamiliar to this domain may start the query with “stem cell” and add a new term, such as “pluripotent,” perhaps a little later. The relevance between these terms can help to clarify such new topics that are uncovered in the current ontology. The underlying cooccurring associations may also discriminate the difference between different trends, “embryonic” and “mesenchymal” stem cells, and even between the pathogenesis of “vasculogenesis” and “angiogenesis” that provides new insight to the literature survey.

Based on membership functions, the other fuzzy linguistic measure, which is the so-called fuzzy latent relational measure, is used to perform context-based segmentation on a set of cooccurring terms. This measure is used to generate the longest semantic phrases instead of single terms.

**Definition 4:** Let \( S = \{x_1, x_2, \ldots, x_n\} \) be a set of terms, in which each \( x_i \) can be a single word or multiword, for instance, “school,” “age” or “school age.” The fuzzy latent relational measure \( \mu_z \) denotes the significance of the associations of \( S \) in a document belonging to a named category \( z \), that is,
\[
\mu_z(S) = \mu_z(x_1) \land \mu_z(x_2) \land \cdots \land \mu_z(x_n) = \min_{x \in S} \mu_z(x)
\]
where \( \land \) is a fuzzy intersection operator.

A minimal threshold \( \theta \) is imposed to filter out the associations and terms that their significance values are small, that is, if \( \mu_z(S) \leq \theta \), \( \mu_z(S) \) will be set to 0. The elements in the set \( S \) will be ignored to be considered in the category \( z \).

### III. Hierarchical Fuzzy Linguistic Topological Spaces

This section introduces a novel hierarchical fuzzy linguistic topological space model, which is based on the concept of fuzzy linguistic topological spaces [31] and combinatorial topology [41]. This model can discover the hierarchy of semantics from a collection of documents.

Before explaining the algorithm, let us define some basic notions of the hierarchical model. The central notion is \( n \)-simplex.

**Definition 5:** A fuzzy semantic \( n \)-simplex, or simple \( n \)-simplex, is a set of independent abstract vertices \( \{v_0, \ldots, v_{n+1}\} \), in which each vertex is a categorized named entity. An \( r \)-face of an \( n \)-simplex \( \{v_0, \ldots, v_{n+1}\} \) is an \( r \)-simplex \( \{v_{i_0}, \ldots, v_{i_r}\} \) whose vertices are a subset of \( \{v_0, \ldots, v_{n+1}\} \) with cardinality \( r + 1 \).

The dominance function is illustrated in Fig. 3. When the peak in \( \mu_z(x|A) \) coincides with the peak in \( \mu_z(x|B) \), we have \( \delta(A, B) = 1 - \sigma(A, B) \). Notice that while \( \delta(A, A) = 1; \delta(A, B) \neq \delta(B, A) \), in general. The dominance function is a fuzzy linguistic function that demonstrates the consensus state between two groups, that is, two simplexes. Two simplexes can be merged into one if their dominance value is bigger than a threshold, and their separation value is less than a threshold. We will set the fuzzy latent relational measure of every element in the simplex to be 1, that means they are coincident with their respective motifs.

![Diagram](image-url)
corresponding named categories after two simplexes have been merged.

These fuzzy linguistic functions satisfy the Apriori condition [43]. If a set cannot be classified into a semantic category, that means the dominance function of the set belonging to the category should be not bigger than a threshold and the separation function of the set not belonging to the category should be not less than a threshold. Both the domination function and the separation function are commonly derived from the minimum operation of all the fuzzy latent relational measure of each feature in the set. According to the minimum operation of all supersets is not bigger than the minimum operation of the original set, it induces that the domination function of its supremum is not bigger than a threshold and the separate function of its supremum is not less than a threshold. Therefore, if a set cannot be merged into a semantic category, neither can its superset. Vice versa, if a set can be merged into a semantic category, so can its subsets.

Based on the fuzzy linguistic functions, a hierarchical agglomeration algorithm is addressed to cluster documents from 0-simplexes to the semantic hierarchy. Geometrically, 0-simplex is a vertex; 1-simplex is an open segment \((v_0, v_1)\) that does not include its end points; 2-simplex is an open triangle \((v_0, v_1, v_2)\) that does not include its edges and vertices; 3-simplex is an open tetrahedron \((v_0, v_1, v_2, v_3)\) that does not include all the boundaries. For each simplex, all its proper faces (boundaries) are not included. An \(n\)-simplex is the high-dimensional analogy of those low-dimensional simplexes (segment, triangle, and tetrahedron) in \(n\)-space. Geometrically, an \(n\)-simplex uniquely determines a set of \(n+1\) linearly independent vertices, and vice versa. An \(n\)-simplex is the smallest convex set in a euclidean space \(\mathbb{R}^n\) that contains \(n+1\) points \(v_0, \ldots, v_n\) that do not lie in a hyperplane of dimension less than \(n\). For example, there is the standard \(n\)-simplex

\[
\delta^n = \left\{ (t_0, t_1, \ldots, t_{n+1}) \in \mathbb{R}^{n+1} \mid \sum_i t_i = 1, t_i \geq 0 \right\}.
\]

The convex hull of any \(m\) vertices of the \(n\)-simplex is called an \(m\)-face. The 0-faces are the vertices, the 1-faces are the edges, the 2-faces are the triangles, and the single \(n\)-face is the whole \(n\)-simplex itself. Formally,

**Definition 8:** A fuzzy semantic simplicial complex, or simple complex is a finite set of simplexes that satisfies the following two conditions:

1) Any set consisting of one vertex is a simplex.
2) Any face of a simplex from a complex is also in this complex.

The vertices of the complex \(v_0, v_1, \ldots, v_n\) is the union of all vertices of those simplexes ([44, pp. 108])

If the maximal dimension of the constituting simplexes is \(n\), then the complex is called \(n\)-complex. An \(n\)-complex is closed set of all \(m\)-simplexes, where \(m \leq n\). All semantics from returned documents becomes simplexes in the complex.

To discover all simplexes in the complex is able to discover all semantics in the returned documents. The corresponding notion of combinatorial \(n\)-complex can be defined by (combinatorial)

\[r\text{-simplexes}.
\]

We need much more precise notions. A \((n, r)\)-skeleton (denoted by \(S^n_r\)) of \(n\)-complex is an \(n\)-complex, in which all \(k\)-simplexes \((k \leq r)\) have been removed. Two simplexes in a complex are said to be **directly connected** if the intersection of them is a nonempty face. Two simplexes in a complex are said to be **connected** if there is a finite sequence of directly connected simplexes connecting them. For any nonempty two simplexes \(A, B\) are said to be **\(r\)-connected** if there exists a sequence of \(k\)-simplexes \(A = S_0, S_1, \ldots, S_m = B\) such that \(S_j\) and \(S_{j+1}\) has an \(h\)-common face for \(j = 0, 1, 2, \ldots, m-1\); where \(r \leq h \leq k \leq n\).

The maximal \(r\)-connected subcomplex is called a **\(r\)-connected component**. Note that an \(r\)-connected component implies that there does not exist any \(r\)-connected component that is a subset of it. A maximal \(r\)-connected subcomplexes of \(n\)-complex is called \(r\)-connected component. A maximal \(r\)-connected component of \(n\)-complex is called connected component, if \(r = 0\).

**IV. SEMANTIC STRUCTURE**

From a collection of documents, a complex of co-occurring named entity associations can be generated. Obviously, a simplicial complex is a certain concept. The 0-simplex (Network) represents a vague CONCEPT. It can be combined into many different concepts. For example, in the following 1-simplexes (computer, network), (traffic, network), (neural, network), (communication, network), etc., express further and richer semantic than their individual 0-simplexes. Of course, the 1-simplex (neural, network) is not conspicuous than the 2-simplexes (artificial neural network) and (biology, neural network).

A collection of documents may carry a set of distinct CONCEPTS. Each concept, we believe, is carried by a connected component of the complex of semantic simplexes.

1) An IDEA (in the forms of complex of cooccurring named entity associations) may consist of many CONCEPTS (in the form of connected components) that consists of PRIMITIVITE CONCEPTS (in the form of simplexes). The maximal simplexes of highest dimension is called MAXIMAL PRIMITIVITE CONCEPT. A simplex is said to be a maximal if no other simplex in the complex is a superset of it. Intuitively, the geometric dimension represents the degree of preciseness or depth of the latent semantics that are represented by simplexes.

**Example 1:** In Fig. 4, an IDEA comprises twelve terms that are organized in the forms of 3-complex, denoted by \(S^3\) [44]. Simplex(a, b, c, d) and Simplex(w, x, y, z) are two maximal simplexes of 3, the highest dimension. That is, the \((3, 3)\)-skeleton \(S^3_3\) consists of two non-connected 3-simplexes or two MAXIMAL PRIMITIVITE CONCEPTS.

Next, let us consider the \((3, 2)\)-skeleton \(S^3_2\), by removing all 0-simplexes and 1-simplexes from \(S^3_3\):

1) Simplex(a, b, c, d) and its four faces:
   a) Simplex(a, b, c),
   b) Simplex(a, b, d),
   c) Simplex(a, c, d),
   d) Simplex(b, c, d).
2) Simplex(a, c, h).
3) \begin{align*} & \text{Simplex}(c, h, e). \\
& \text{Simplex}(h, e, f). \\
& \text{Simplex}(e, f, x). \\
& \text{Simplex}(f, g, x). \\
& \text{Simplex}(g, x, y). \\
& \text{Simplex}(w, x, y, z) \text{ and its four faces:} \\
& \quad a) \ \text{Simplex}(w, x, y), \\
& \quad b) \ \text{Simplex}(w, x, z), \\
& \quad c) \ \text{Simplex}(w, y, z), \\
& \quad d) \ \text{Simplex}(x, y, z). \\
\end{align*}

There are no common faces between any two simplexes; therefore, \( S_2 \) has eight connected components, or eight CONCEPTS.

Consider the \((3, 1)\)-skeleton \( S_1 \). After removing all 0-simplexes from \( S^0 \), the simplexes \( \text{Simplex}(a, c), \text{Simplex}(c, h), \text{Simplex}(h, e), \text{Simplex}(e, f), \text{Simplex}(f, x), \text{Simplex}(g, x), \text{Simplex}(x, y), \) all are common faces among the CONCEPTS generated from \( S_2 \). These simplexes also make \( S_1 \) to be connected. See Appendix for more details.

A complex connected component or simplex of a skeleton represent a more technically refined IDEA, CONCEPT or PRIMITIVE CONCEPT. If a maximal connected component of a skeleton contains only one simplex, this component is said to organize a primitive concept.

Based on the hierarchies of primitive CONCEPTS, we can define the notion of layered clustering. As can be seen in Example 1, connected components in \( S^0 \) are contained in that of \( S^r \), where \( k \geq r \).

**Example 2:** Fig. 5 is 2-complex composed of the term set \( V = \{ t_A, t_B, t_C \} \) in a collection of documents. It is a closed 2-simplex; we recall here that a closed simplex is a complex that consists of one simplex and all its faces. In the skeleton \( S^2 \), all 0-simplexes are ignored, that is, the terms depicted in dashed lines. The simplex set \( S = \{ \text{Simplex}_2, \text{Simplex}_3, \text{Simplex}_4 \} \) is the closed 2-simplex that consists of one 2-simplex and three 1-faces. \( \text{Simplex}_2 \), \( \text{Simplex}_3 \), and \( \text{Simplex}_4 \) (0-faces are ignored). These \( r \)-simplexes \((0 \leq r \leq 2)\) represents frequent itemsets (term-associations) from \( V \), where \( W = \{ w_{A,B}, w_{C,A}, w_{B,C}, w_{A,B,C} \} \) denote their corresponding supports. The lines connecting \( \text{Simplex}_1 \) and three vertices represent the incidences of 2-simplex and 0-simplex; the incidences with 1-simplexes are not shown to avoid overcrowding in the figure.

According to Example 1, it is obvious that simplexes within the higher level skeleton \( S^0 \) is contained in the lower level skeleton \( S^r \) within the same n-complex, \( R \geq k \). Fig. 6 shows the hierarchy, wherein each skeleton is represented as a layer. For the purpose of simplicity, we skip the middle layer, namely, \( S^0, 0 \leq r < 3 \), and is not shown.

By considering different skeletons, we can draw distinct layer of CONCEPTS:

1) In full complex \( S = S^0 \), in this example, only has one CONCEPT (one connected component).
2) In \( S_1 \), this complex still has only one CONCEPT.
3) In \( S_2 \), this complex has eight CONCEPTS.
4) In \( S_3 \), this complex has two CONCEPTS; they are two MAXIMAL PRIMITIVE CONCEPTS.
For each choice, say $S^0$, we have, in this case, eight CONCEPTS to label the documents (or cluster the documents). A document is labeled CONCEPT from the set of all CONCEPTS induced by (lower dimensional) common faces between them; this phenomenon is illustrated here. To handle such a situation properly, we need to ignore the lower dimensional simplexes. By doing so, the overlapping will disappear (not shown).

In general, the simplexes at the lower layers could have common faces between them. Therefore, using all layers of CONCEPTS at the same time will produce vague discrimination as shown in Fig. 7, in which an overlapped CONCEPTS induced by (lower dimensional) common faces could exist. As seen in the skeleton $S^1$, the maximal connected components generated from simplexes Simplex(a, b, c, d) and Simplex(a, c, h) have a common face Simplex(a, c) that makes some documents unable to get properly discriminated in accordance with the generated association rules from term a and term c, so are the other maximal connected components in the skeleton. Because of the intersection produced by such faces, a proper way is to ignore the lower dimensional skeleton, as much as application can tolerate.

V. FUZZY HIERARCHICAL AGGREGATION ALGORITHM

Web documents can be clustered based on maximal simplexes of any dimension (CONCEPTS). Note that web documents clustered by CONCEPTS contains common lower dimensional faces (low dimension simplex, in particular a 0-simplexes), which is a consequence of Apriori property. In this sense, the methodology provides a soft approach; wherein we allow lower dimension to overlap with CONCEPTS existing across different clusters. The fuzzy hierarchical aggregation algorithm is divided into three phases.

**Phase 1:** Perform feature extractions using CRF methods to generate named entities.

**Phase 2:** Calculate the fuzzy linguistic value of every named entity to every named category.

**Phase 3:** Perform hierarchical aggregation clustering in order to generate the semantic hierarchy from the set of coincident named entities.

The algorithm that generates hierarchical aggregation clustering based on fuzzy linguistic memberships is mentioned as below.

The algorithm starts from the set of all 0-simplexes, that is, all single named entities. The algorithm hence aggregates web documents into several different categories to be the PRIMITIVE CONCEPTS. If a web document contains a PRIMITIVE CONCEPT, it means that web document highly equates to such concept. According to the Apriori property, all the subclusters in the concept are also contained in this web document. The algorithm can classify web document into the category identified with such concept. Generally, a web document consisting of more than one PRIMITIVE CONCEPTS, in that case, it can be classified into multicategories.

VI. EXPERIMENTAL RESULTS

Fuzzy latent semantic clustering (FLSC) organizes the returned web documents hierarchically.

A. System

As we know, Google provides a flat list of search result snippets, and PubMed returns a summarized list of the abstracts of medical literatures associated with MeSH terms. Starting from a user query on-the-fly over two remote search engines (PubMed and Google), our system hierarchically generates all the CONCEPTS. A semantic tree represents the CONCEPT hierarchy in which the root is the user query. Except the root, all terms on the other nodes can be considered to be advanced search queries. A query of a node is then aggregated with other co-occurring entities to become more primitive on its branches of the hierarchy.
Fig. 8. Clustering result of the query term “NOD2” retrieved from PubMed.

Fig. 9. FLSC System over search engine Google.

tree. Since the simplexes of the higher dimension are aggregated with several IDEA and the lower dimensions are uncertain, the lower dimensions the CONCEPTS are put near to the root of hierarchy, and vice versa in the system.

The system depicted in Fig. 8 demonstrates the search results from PubMed, for a search query “nod2.” A hierarchy of clusters is built on the return results. The abstract (unstructured) and MeSH terms (semi-structured) are in use to cluster them. The same term “pain” has been taken to retrieve information from Google. The returned result snippets are grouped into several clusters as shown in Fig. 9.

B. Results

The experimental evaluation of document clustering approaches usually measures their effectiveness than their efficiency [45]. In other words, to measure the ability of an approach is to make a right categorization. Entropy estimates the clustering performance [46] based on the human expert’s decisions. An expert submit hundreds of medical queries form our system to evaluate the clustering results returned from PubMed and Google, respectively. More than 200 000 web pages or snippets have been returned. In general, the average entropy is around $0.14 \pm 0.06$ for PubMed, and $0.27 \pm 0.08$ for Google. PubMed has defined metadata of various medical literature with the help of human experts. Without using these metadata, the average entropy was estimated to be $0.21 \pm 0.09$. Accordingly, we can courageously suggest that the CONCEPTS organized by FLSC can generate semantic concept clustering of web pages.

Considering the contingency table for a topic of a category (see Table I); recall, precision, and $F_\beta$ [47] are three direct measures of the effectiveness of a NER method. Precision and recall with respect to a topic are respectively defined as follows:

\[
\text{Precision}_i = \frac{\text{TP}_i}{\text{TP}_i + \text{FP}_i}, \quad \text{Recall}_i = \frac{\text{TP}_i}{\text{TP}_i + \text{FN}_i}
\]

The $F_\beta$ introduced by van Rijsbergen [48] combines precision and recall by the following formula:

\[
F_\beta = \frac{(\beta^2 + 1) \times \text{Precision}_i \times \text{Recall}_i}{\beta^2 \times \text{Precision}_i + \text{Recall}_i}
\]

$F_1$ measure used in this paper was obtained when $\beta$ is set to be 1, which means precision and recall are equally weighted for evaluating the performance of clustering. Because many categories would be generated and need to be compared, the overall precision and recall were calculated as the average of all precisions and recalls belonging to categories, respectively. $F_1$ is calculated as the mean of individual results. It is a macroaverage of the categories.

In a nonoverlapping scenario, each document belongs to exactly one cluster. Three validation metrics: precision, recall, and $F$-measure, are proper to evaluate the performance of crisp clustering algorithms. The overlapping clustering schemes has been involved in a widely variety of application domains because many real problems are naturally overlapped, for example, in social network analysis, computational biology, recommendation systems, etc. Information theoretic measures [49], [50], such as entropy and mutual information, hence have been used to estimate how much information is shared from the labeled instances in a cluster, especially, for a hierarchical clustering schemes [51]. Mutual information is defined extendedly from entropy. In order to compare effectiveness with other methods, two different evaluation metrics, normalized mutual information [49], [52], [53] and overall F-measure [54], [55], were also used.
Given the two sets of topics $C$ and $C'$, let $C$ denote the topic set defined by experts, $C'$ denote the topic set generated by a clustering method, and both derived from the same corpora $X$. Let $N(X)$ denote the total number of documents, $N(z, X)$ denotes the number of documents in a topic $z$, and $N(z', X)$ denotes the number of documents both in topic $z$ and topic $z'$, for any topics in $C$. The normalized mutual information (NMI) metric $\text{MI}(C, C')$ is defined as follows:

$$\text{MI}(C, C') = \sum_{z \in C, z' \in C'} P(z, z') \log_2 \left( \frac{P(z, z')}{P(z)P(z')} \right)$$

where $P(z) = N(z, X)/N(X)$, $P(z') = N(z', X)/N(X)$, and $P(z, z') = N(z, z', X)/N(X)$. The normalized mutual information metric $\text{MI}(C, C')$ will return a value between zero and $\max(H(C), H(C'))$ where $H(C)$ and $H(C')$ define the entropies of $C$ and $C'$, respectively. The higher $\text{MI}(C, C')$ value means that two topics are almost identical, otherwise more independent. The normalized mutual information metric $\tilde{\text{MI}}(C, C')$ is therefore transferred to be

$$\tilde{\text{MI}}(C, C') = \frac{\text{MI}(C, C')}{\max(H(C), H(C'))}.$$

Let $F_z$ be an F-measure for each cluster $z$ defined above. The overall F-measure can be defined as follows:

$$F^* = \sum_{z \in C'} F(z', z') \times \max_{z \in C} F(z, z')$$

where $F(z, z')$ calculates the F-measure between $z$ and $z'$.

“Reuters-21578, Distribution 1” collection consisted of newswire articles. The articles are assigned into 135 so-called topics that are in use to affirm the clustering results. In our test, the documents with multiple topics (category labels) and with single topic were separated, and the topics with less than five documents were removed. Table II shows the summary of the “Reuters-21578, Distribution 1” collection. Two to ten topics had been randomly selected to evaluate FLSC and other methods. For each clustering method, each test run was conducted on a selected topic and calculated the normalized mutual information of the topic and its corresponding cluster accordingly. After conducting 50 test runs on a fixed number of $k$ topics where $2 \leq k \leq 10$, the final performance scores were obtained by averaging mutual information measures from these 50 test runs [53].

The mutual information are used to compare the fuzzy latent semantic clustering method with the other methods as listed in [53], ant-fuzzy clustering algorithm [21], hierarchical-hyperspherical divisive fuzzy $c$-means [22], ontology-based fuzzy document clustering algorithm [26], and $k$-clique-community finding algorithm [56] is shown in Table III: FLSC = Fuzzy Latent Semantic Clustering; AFC = ant-fuzzy clustering algorithm; H2D-FCM = hierarchical-hyperspherical divisive fuzzy $c$-means; OBFDCC = ontology based fuzzy document clustering; GMM = Gaussian mixture model; NB = naive Bayes clustering; KM = traditional k-means; GMM + DFM = Gaussian mixture model followed by the iterative cluster refinement method; NC = spectral clustering algorithm based on normalized cut criterion; RC = spectral clustering based on ratio cut criterion; BP = spectral clustering-based bipartite normalized cut; NMF = nonnegative matrix factorization; CF = concept factorization; NCW = normalized-cut weighted form; CCF = $k$-clique-community finding algorithm. Two statistical testing methods, Kruskal–Wallis $H$-test [57] and the Bonferroni–Dunn test [58], assessed whether clusters generated by those methods are statistically different from one another. Four metrics—precision, recall, overall F-measure, mutual information of FLSC for different $k$ are listed in Table IV.

According to nineteen clustering schemes involved to compare our clustering method and for each clustering number $k$ there are 50 test runs conducted, the Kruskal–Wallis $H$-test [57] has been used to evaluate the performance of these clustering methods. The Kruskal–Wallis $H$-test is a nonparametric method used for comparing two or more samples whether originating from the same distribution [57], [59]. The Kruskal–Wallis $H$-test extends the Mann–Whitney U test to compare more than two groups. Instead of assuming samples to be normal by using one-way ANOVA test, we used Kruskal–Wallis $H$-test to evaluate the clustering performance. When rejecting the null hypothesis of the Kruskal–Wallis $H$-test, it means at least one sample stochastically dominates the others. However, the Kruskal–Wallis $H$-test does not identify where the differences occur and how many differences occur. Twenty samples generated by different clustering schemes with the same sample size 50 for each $k$ were evaluated by using the Kruskal–Wallis $H$-test and then performing Bonferroni–Dunn multiple comparison test accordingly, while the null hypothesis of the Kruskal–Wallis $H$-test was rejecting [59], [60]. The Bonferroni–Dunn test [58] is a nonparametric mean rank or median test that computes a more conservative significant level for each multiple comparisons test based only on the overall significant level for the multiple samples obtained from those clustering methods. The Bonferroni–Dunn test with the goal of improving statistical power is able.
to identify which clustering schemes are significantly different from the others. All statistical analyses were performed using R (http://cran.r-project.org) computer software package (Version 3.1.2). The p-value \( p < 0.05 \) was considered statistically significant.

In general, fuzzy clustering algorithms can achieve better performance than traditional clustering algorithms as shown in Table III. For each \( k \), the Kruskal–Wallis \( H \)-test shows whether the performance of these methods are significantly different. If the normalized mutual information of some clustering schemes is fixed and not able to automatically adjust. Ant-based fuzzy clustering is able to adapt the conditional possibility of a term belonging to a topic; however, the common terms and the label bias problem [61] induce the documents not able to be clustered into proper semantic topics.

The experimental results show that the FLSC performs better than comparative algorithms in term of quality of the cluster performance. An increase in cluster purity clearly established the fact that the fuzzy linguistic topological space inherently captures the semantics of the documents. The experimental setup of some well-known traditional algorithms and three fuzzy clustering algorithms are tested on the “Reuters-21578, Distribution 1” dataset defined for the evaluation. The mutual information and F-measure results for the algorithms are reported in Tables II–IV. The proposed approach clearly had shown an improvement in most of test cases. The mutual information and F-measure for dataset “Reuters-21578, Distribution 1” produce a significant improvement when the number of selected clusters become higher. This analysis reveals when the document contains multiple topics and more heterogeneous, our suggested approach is exceptionally good.

### VII. Conclusion

Polysemies, phrases, and term dependencies are the limitations of search technology [3]. A single term is not able to identify a latent concept in a document, for instance, the term...
“Network” associated with the term “Computer,” “Traffic,” or “Neural” denotes different concepts. A group of solid cooccurring named entities can clearly define a CONCEPT. The semantic hierarchy generated from frequently cooccurring named entities of a given collection of web documents, form a simplicial complex. The complex can be decomposed into connected components at various levels (in various level of skeletons). We believe each such connected component properly identify a concept in a collection of web documents.

To identify and discriminate the correct topics in a collection of documents, the combinations of features and their cooccurring relationships are the clue, and the possibilities display how significant they will be. All features in documents compose a topologically probabilistic space, more specifically a simplicial complex associated with probabilistic measures to denote the underlying structure. The complex can be geographically decomposed into inseparable components at various levels (in various levels of skeletons) that each component properly corresponds to topics in a collection of documents. Of course, the topics that a component induced are either topologically distinguishable, or perfectly included in other induced topics.

We can effectively discover such a maximal fuzzy simplexes and use them to cluster the collection of web documents. Based on our website and our experiments, we find that FLSC is a very good way to organize the unstructured and semistructured data on our website and our experiments, we find that FLSC is a very good way to organize the unstructured and semistructured data into several semantic topics. It also illustrates that geometric complexes are an effective model for automatic web documents clustering.

**APPENDIX A**

(3,1)-SKELETON $S^1_3$ OF EXAMPLE 1

In Fig. 4, the (3,1)-skeleton $S^1_3$ is the leftover after the removal of all 0-simplexes from $S^3$:

1) $\text{Simplex}(a, b, c, d)$ and its ten faces:
   - $\text{Simplex}(a, b, c)$
   - $\text{Simplex}(a, b, d)$
   - $\text{Simplex}(a, c, d)$
   - $\text{Simplex}(b, c, d)$
   - $\text{Simplex}(a, b)$
   - $\text{Simplex}(a, c)$
   - $\text{Simplex}(b, c)$
   - $\text{Simplex}(a, d)$
   - $\text{Simplex}(b, d)$
   - $\text{Simplex}(c, d)$

2) $\text{Simplex}(a, c, h)$ and its three faces:
   - $\text{Simplex}(a, c)$
   - $\text{Simplex}(a, h)$
   - $\text{Simplex}(c, h)$

3) $\text{Simplex}(c, h, e)$ and its three faces:
   - $\text{Simplex}(c, h)$
   - $\text{Simplex}(h, e)$
   - $\text{Simplex}(c, e)$

4) $\text{Simplex}(e, h, f)$ and its three faces:
   - $\text{Simplex}(e, h)$
   - $\text{Simplex}(h, f)$
   - $\text{Simplex}(e, f)$

5) $\text{Simplex}(e, f, x)$ and its three faces:
   - $\text{Simplex}(e, f)$
   - $\text{Simplex}(e, x)$
   - $\text{Simplex}(f, x)$

6) $\text{Simplex}(f, g, x)$ and its three faces:
   - $\text{Simplex}(f, g)$
   - $\text{Simplex}(g, x)$
   - $\text{Simplex}(f, x)$

7) $\text{Simplex}(g, x, y)$ and its three faces:
   - $\text{Simplex}(g, x)$
   - $\text{Simplex}(g, y)$
   - $\text{Simplex}(x, y)$

8) $\text{Simplex}(w, x, y, z)$ and its ten faces:
   - $\text{Simplex}(w, x, y)$
   - $\text{Simplex}(w, x, z)$
   - $\text{Simplex}(w, y, z)$
   - $\text{Simplex}(w, x, z)$
   - $\text{Simplex}(x, y, z)$
   - $\text{Simplex}(x, y, z)$
   - $\text{Simplex}(x, y, z)$
   - $\text{Simplex}(x, y, z)$

Note that $\text{Simplex}(a, c)$, $\text{Simplex}(c, h)$, $\text{Simplex}(h, e)$, $\text{Simplex}(e, f)$, $\text{Simplex}(f, x)$, $\text{Simplex}(g, x)$, and $\text{Simplex}(x, y)$, all are common faces of 2-simplexes $\text{Simplex}(a, c, d)$, $\text{Simplex}(a, c, h)$, $\text{Simplex}(c, e, h)$, $\text{Simplex}(e, f, x)$, $\text{Simplex}(g, x, y)$, and $\text{Simplex}(w, x, y)$. Therefore, they generate a connected path from $\text{Simplex}(a, b, c, d)$ to $\text{Simplex}(w, x, y, z)$, and subpaths. Therefore, the $S^1_3$ complex is connected. This assertion also implies that $S^3_1$ is connected.

Hence, the IDEA consists of a single CONCEPT (please note the technical meaning of the IDEA and CONCEPT given in Section IV).

**REFERENCES**


I-Jen Chiang received the Ph.D. degree in both computer science and information engineering and biomedical engineering from the National Taiwan University, Taipei, Taiwan, in 1997. He was a Visiting Scholar at the University of California at Berkeley, Berkeley, USA, in the academic year 1997/1998, and a Visiting Scholar at Academia Sinica, Taipei, Taiwan, in 2006/2007. He served as the General Secretary of Asia Pacific Association for Medical Informatics from 2009 to 2011. He was also one of the co-founders of Taiwan Evidence-based Medicine Association. He is currently an Associate Professor of the Graduate Institute of Biomedical Informatics, Taipei Medical University, and Adjunct Assistant Professor of the Institute of Biomedical Engineering, National Taiwan University. He is a faculty member of the International Partnership in Health Informatics that is an education partnership program established in 1998 and consists of University of Amsterdam, University of Heidelberg, University of Minnesota, University of Utah, University for Health Informatics and Technology, Taipei Medical University, and University of Washington. He is also a faculty member of the International Summer and Winter Term (ISWT) of Indian Institute of Technology Kharagpur, Kharagpur, India. His research interests include data mining, text/web mining, eCommerce, big data analytics, statistical pattern recognitions, and cloud computing. During his career, he worked at GaGaMedia in 2000.

Charles Chih-Ho Liu received the M.S. degree from Graduate Institute of Medical Informatics, Taipei Medical University, Taipei, Taiwan, and is working toward the Ph.D. degree in medical engineering in National Taiwan University, Taipei. He received the Medical Doctor degree in National Taiwan University in 1990, and completed the surgical residency program in National Taiwan University Hospital. From 1997, he worked as a Visiting Staff in Plastic Surgical Department, Cathay General Hospital, Taipei, and was the General Secretary of Taiwan Society of Aesthetic Plastic Surgery from 2010 to 2012 and from 2014 to 2016. He was also one of the Co-founders of Taiwan Evidence-based Medicine Association. His research interests include data mining on healthcare database, and natural language processing and bibliometrics of medical texts.

Yi-Hsin Tsai received the Medical Doctor degree in National Taiwan University, Taipei, Taiwan, in 1998, and completed the neurosurgical residency program in National Taiwan University Hospital in 2005. He is currently working toward the Ph.D. degree in medical engineering with National Taiwan University, Taipei, Taiwan. He worked as an attending Neurosurgeon in Surgical Department, Yuan General Hospital, Kaohsiung City, Taiwan, from July 2005 to June 2006; as an attending Neurosurgeon at Yunlin Branch of National Taiwan University Hospital from July 2006 to June 2008; as an attending Surgeon at Trauma Department and neurosurgeon at Neurosurgical Division of Surgical Department from July 2008 to July 2012; and as an attending neurosurgeon at Neurosurgical Division of Surgical Department at Far-Eastern Memorial Hospital, New Taipei City, Taiwan. His research interests include data mining on healthcare database, and big data analysis on intensive care units.

Ajit Kumar received the Ph.D. degree in medical informatics from Taipei Medical University, Taipei, Taiwan; the Master’s degree in computer application from Bundelkhand University, Jhansi, India; and the Bachelor’s degree in computer science from Allahabad University, Allahabad, India. He has been exposed to a variety of fields, such as computer science, healthcare, cognitive science, linguistics, statistics by assuming different roles (eight years teaching, research, and industry experiences) in various settings (India, Taiwan, Libya, Nigeria). His work has been widely published in the form of peer-reviewed journal papers, book chapter contributions, refereed proceedings, and conference papers. His research interests include human–computer Interaction, software engineering, and computer applications in Healthcare.
Discovering Latent Semantics in Web Documents Using Fuzzy Clustering

I.-J. Chiang, Member, IEEE, Charles Chih-Ho Liu, Yi-Hsin Tsai, and Ajit Kumar

Abstract—Web documents are heterogeneous and complex. There exists complicated associations within one web document and linking to the others. The high interactions between terms in documents demonstrate vague and ambiguous meanings. Efficient and effective clustering methods to discover latent and coherent meanings in context are necessary. This paper presents a fuzzy linguistic topological space along with a fuzzy clustering algorithm to discover the contextual meaning in the web documents. The proposed algorithm extracts features from the web documents using conditional random field methods and builds a fuzzy linguistic topological space based on the associations of features. The associations of cooccurring features organize a hierarchy of connected semantic complexes called “CONCEPTS,” wherein a fuzzy linguistic measure is applied on each complex to evaluate 1) the relevance of a document belonging to a topic, and 2) the difference between the other topics. Web contents are able to be clustered into topics in the hierarchy depending on their fuzzy linguistic measures; web users can further explore the CONCEPTS of web contents accordingly. Besides the algorithm applicability in web text domains, it can be extended to other applications, such as data mining, bioinformatics, content-based, or collaborative information filtering, etc.

Index Terms—Fuzzy aggregation algorithm, fuzzy linguistic topological space, fuzzy semantic topology, fuzzy web hierarchical clustering, named entity recognition (NER).

I. INTRODUCTION

SEARCH engines are indispensable tools to find, filter, and extract the desired information, which attempt to aid users in gathering relevant contents from web. Lawrence et al. [1] and Henzinger [2] surveyed and compared search engines, such as AltaVista, Excite, HotBot, Infosseek, Lycos, Northern Light, and Google. Both studies have shown the weaknesses of these search engines and proposed some solutions to overcome some of the weaknesses. A sophisticated mechanisms to recognize the latent semantics in the returned search results is crucial to enhance comprehensiveness of a search engine. The complex and high interactions between terms in documents demonstrate vague and ambiguous meanings. Polysynemes, synonyms, homonyms, phrases, dependence, and spams limit the capabilities of search technologies and strongly diminish the comprehensiveness of the results returned from the search engines [3].

Web document clustering is one of the indispensable techniques [4], [5] to discover contextual meaning (hereinafter called semantics) from the returned heterogeneous web pages [6], [7]. Consider users’ queries are also vague and unconscious [8]. Numerous document clustering methods have been proposed; some are based on probabilistic models equipped with distance and similarity measures [9], and others use matrix factorization [10], and data mining techniques, such as SOM [11]. A document is usually represented as a feature vector, which can be viewed as a point in the multidimensional space, to match users’ queries. Many methods, including k-means [12], hierarchical clustering [13], and nearest-neighbor clustering [14], select a set of key terms or phrases to organize the feature vectors depending on the differences between documents to capture semantics in order to fit users’ intents. Suffix-tree clustering [15] is a phrase-based approach, which carries out document clustering depending on the similarities between documents.

When the documents provide imprecise information, the use of fuzzy set theory is advisable. Fuzzy c-means and fuzzy hierarchical clustering algorithms were deployed for document clustering [16]–[18]. Fuzzy c-means and fuzzy hierarchical clustering need prior knowledge about “number of clusters” and “initial cluster centroids,” which are considered to be serious drawbacks of these approaches. To address these drawbacks, ant-based fuzzy clustering algorithms [19]–[21] and fuzzy k-means clustering algorithms [22] were proposed that can deal with unknown number of clusters. Moreover, the similarity measures and bag of words [23] were the main limitation of those methods to capture the semantics in the collection of documents. Based on Vector Space Model [24], the similarity between two documents is measured with vector distance, such as Euclidean distance, Manhattan distance, etc. These methods do not take contextual meaning into consideration. Ontology-based fuzzy document clustering schemes [25], [26] were used to cluster documents with a limited subsets of selected terms based on the defined ontology. Those methods restrict the application domains, which makes them difficult to be generalized if the domain does not have a proper ontology.

Some approaches consider the cooccurrence of terms, but neglect whether terms cooccur in the same context. For example, two terms “Wall” and “Street” do not represent a meaningful theme, say “Wall Street” if these are located at different places in a document. Moreover, polysemy and other important issues are also ignored. Lin and Chiang [27] pictured the geometric aspect of latent semantics from the given set of documents. Basically, features (keywords or noun phrases) are taken as vertices and the associations (frequent co-occurring features) as edges in a graph. If the graph is a network, the complex interactions are represented as a graph. A complex interaction graph is called a cooccurrence graph. The cooccurrence graph is a network of vertices and edges where the vertices represent words and the edges represent cooccurring relationships between words. The network of vertices and edges forms a complex interaction graph. A complex interaction graph is a network of vertices and edges where the vertices represent words and the edges represent cooccurring relationships between words. The network of vertices and edges forms a complex interaction graph.
among those features are taken as links to represent semantic clusters, which are "simplicial complexes" in geometry. Chen et al. [28] proposed a fuzzy hierarchical clustering approach to discover a set of highly related fuzzy frequent itemsets to represent the candidate clusters. Zaidi and Melancon [29] presented a decomposition technique by breaking the network organized by cooccurrence keywords with the centroids, that is, the nodes with the maximum degree, and a cutoff threshold into several clusters. Song et al. [30] advocated using part-of-speech and WordNet lexicon to keep the terms in accordance to document subjects or titles, and then perform document clustering using WordNet hierarchical structures.

Most of the subsequent methods have tried to resolve the semantic clustering problem without much consideration to the semantic hierarchy in documents. A fuzzy linguistic measure is given to evaluate a set of features in a document on both "the relevance of the document belonging to a topic" and "the differentials between the other topics" in order to facilitate and enhance relevant information access for the web users. Furthermore, the fuzzy clustering algorithm clusters those documents into homogeneous semantic topics to discover latent semantics in returned documents. Each semantic cluster represents an individual "topic" that indicates the essence or summary from the subset of returned documents. Users can identify topics that are relevant to their intents. For instance, a query term "jaguar" can be classified into the "animal" topic or "automobile" topic according to the semantics of the returned documents, and users can explore their favorite topics from the classified semantic clusters. As another example, let us consider a simple query, "network," which can yield different topics depending on if it appears close to a term, such as "computer," "traffic," "artificial neural," or "biological neural" in significant fragments of the returned documents. A fuzzy estimate is applied to reveal the uncertainty and vagueness between a term and its adjacent terms in context. Besides, the fuzzy estimates can capture linguistic aspects, such as synonyms and polysemies. Therefore, the aim of this study is to develop a novel fuzzy hierarchical clustering algorithm based on the concepts of fuzzy linguistic topological spaces [31], which can discover the latent semantics in text corpora.

In Section II, we introduce NERs and fuzzy linguistic measures of entities to represent term level semantics. Section III defines and illustrates the fuzzy semantics in a collection of documents from geometric points of view. Building the hierarchical semantic architectures from the collection of named entities is described in Section IV. Section V presents the clustering algorithm for aggregating semantics into several semantic units, each of which represents a concept in the document collection. Documents can then be clustered based on the concepts identified by the algorithm. Experimental results obtained from three different data sets are described in Section VI, which is followed by the conclusion section.

II. FUZZY LINGUISTIC ASPECT

This paper addresses a novel clustering algorithm to discover the latent semantics in a text corpus from a fuzzy linguistic perspective. Besides the applicability in text domains, it can be extended to the applications, such as data mining, bioinformatics, content-based or collaborative information filtering, etc.

As shown in Fig. 1, web documents can constitute several latent semantic topics equipped with numerical coefficients (fuzzy linguistic coefficients) that indicate the significance levels of these inherent situations. A collection of documents X and its corresponding fuzzy linguistic topological space L are two finite and discrete topological spaces, where \( L = \{C_1, C_2, \ldots, C_n\} \) and \( C_i \) denotes a semantic topological category. A discrete topological category is composed of all discrete features, that is, attribute-value pairs. The features in a document are extracted by using semisupervised learning schemes [32] called named entities.

"Named entity recognition" (NER) can identify one item from a set of features that have similar attributes, i.e., named categories. Examples of named categories are person, affiliations, location, etc. Consider the polysemy like the term "jaguar" can be classified as "animal," "vehicle," etc. If the term "jaguar" is associated with the items, such as "cat," "tiger," and "feline," the term "jaguar" is more possible to be classified into the named category "animal." Fuzzy linguistic coefficient is given to measure the possibilities of a term belonging to every category, where the term is associated with other cooccurring terms.

The general framework of our clustering method consists of two phases. The first phase, feature extraction, is to extract key named entities from a collection of "indexed" documents; the second phase, fuzzy clustering, is to determine relations between features and identify their linguistic categories.

The kernel of the first phrase is to identify the key features and their named categories. In order to identify features in documents, we deployed the NER method. From a given sentence, NER method first finds out the segmented entities composed of a sequence of words, and then classify the entities by a type or named category, such as person, organization, location, etc.

This paper considers only noun entities, especially some representative entities. Therefore, discriminative linear chain
**Definition 1:** Let $W = \{x_1, x_2, \ldots, \}$ denote features extracted from documents, and $\Theta = \{z_1, z_2, \ldots, z_m\}$ be the named category set. A membership function for $z_j$ is represented as $\rho_j$, that the value $\rho_j(x_i) = P(z_j|x_i)$ evaluates the membership degree of $x_i$ belonging to named category $z_j$.

Based on the membership function $\rho_j(x)$, we then need to evaluate the possibility of a feature $x$ in a document that could be classified into the named category $z$. In our case, the value of $\rho_j(x)$ is normalized to the real unit interval $[0, 1]$ for the sake of simplification and uniform. Generally, few words other than functional words are more frequent in a document; moreover, some keywords may occur frequently across documents. Therefore, simple frequency of the occurrence of words is not adequate.

Techniques, such as TFIDF [38], have been proposed to deal with some of these problems. The TFIDF value is the weight of features in each document. While considering relevant documents to a search query, if the TFIDF value of a feature is large, it will pull more weight than features with lesser TFIDF values.

The TFIDF value is obtained from two functions $tf$ and $idf$ [38], where $tf$ denotes term frequency that appears in a document, and $idf$ denotes inverse document frequency, where document frequency is the number of documents that contain the feature $x$ in category $z$, and $\times$ is a fuzzy operator as shown in Fig. 2, where $\alpha$ and $\beta$ are two thresholds respectively for term frequency and inverse document frequency:

$$\mu_z(x) = \begin{cases} 
1 & \text{if } tf_z(x) \leq \alpha \text{ or } idf_z(x) \geq \beta \\
(tf_z(x) - \alpha) \times (idf_z(x) - \beta) & \text{otherwise.}
\end{cases}$$

where $tf_z(x)$ denotes the number of feature $x$ in a document being classified into $z$, $idf_z(x)$ denotes inverse document frequency where document frequency is the number of documents that contain the feature $x$ in category $z$, and $\times$ is a fuzzy operator.

The membership was defined under the assumption that a feature occurring frequently in a document is more likely to be an interesting feature, a set of features that only occur in a large number of documents are more likely to be associated with a uncommon category among those documents, and such the thresholds $\alpha$ and $\beta$ should be given a higher score. Consider the phrase “the ferocious jaguar” because the term “the” is so common, term frequency trend to incorrectly emphasize the returned documents used the word “the” more frequently, without giving enough weight to the meaningful terms “ferocious” and “jaguar” by using high score $\alpha$. Hence, the threshold $\beta$ incorporated with the idf is set to high score that diminishes the weights of the memberships of the features that occur very frequently and increases the weights of the memberships of features that occur rarely in the returned documents.

Semantics is shown in the relationship between features and their named categories. At the second phase, discovering the underlying connections and interactions between named entities is crucial to understand semantics. Except the word level information, the associations existed between two (or more) named entities show the semantic level relationships, such as synonym, antonym, homonym, polysemy, and metonym. We can use a fuzzy linguistic measure defined for each document to evaluate both: 1) the relevance of the document belonging to a topic, and 2) the difference between the other topics.
Those cooccurring named entities in context along with fuzzy linguistic estimates can capture not only semantic level relationships, but can reveal uncertainty and vagueness among them as well. A more complicated situation arises when users search an unfamiliar field with rapidly evolving themes and nonuniform terminology. In such situations, the problem of semantic level relationships becomes more significant. For example, someone performs research on applications of stem cells. The “Endothelial Progenitor Cell (EPC)” plays a key role in the pathogenesis of two major diseases, tumor vasculogenesis and myocardial repair; and new paradigm of therapeutic modalities are rapidly developing. EPCs are highly related to mesenchymal stromal cells and very small embryonic-like cells, and all belong to a higher class of bone marrow-derived stem and progenitor cells by which different authors can refer by various terminologies.

Supposedly, a researcher who is unfamiliar to this domain may start the query with “stem cell” and add a new term, such as “pluripotent,” perhaps a little later. The relevance between these terms can help to clarify such new topics that are uncovered in the current ontology. The underlying cooccurring associations may also discriminate the difference between different trends, “embryonic” and “mesenchymal” stem cells, and even between the pathogenesis of “vasculogenesis” and “angiogenesis” that provides new insight to the literature survey.

Based on membership functions, the other fuzzy linguistic measure, which is the so-called fuzzy latent relational measure, is used to perform context-based segmentation on a set of cooccurring terms. This measure is used to generate the longest semantic phrases instead of single terms.

Definition 4: Let \( S = \{x_1, x_2, \ldots, x_n\} \) be a set of terms, in which each \( x_i \) can be a single word or multiword, for instance, “school,” “age” or “school age.” The fuzzy latent relational measure \( \mu_z \) denotes to be the significance of the associations of \( S \) in a document belonging to a named category \( z \), that is,

\[
\mu_z(S) = \mu_z(x_1) \land \mu_z(x_2) \land \cdots \land \mu_z(x_n) = \min_{x \in S} \mu_z(x)
\]

where \( \land \) is a fuzzy intersection operator.

A minimal threshold \( \theta \) is imposed to filter out the associations and terms that their significance values are small; that is, if \( \mu_z(S) \leq \theta \), \( \mu_z(S) \) will be set to be 0. The elements in the set \( S \) will be ignored to be considered in the category \( z \).

III. HIERARCHICAL FUZZY LINGUISTIC TOPOLOGICAL SPACES

This section introduces a novel hierarchical fuzzy linguistic topological space model, which is based on the concept of fuzzy linguistic topological spaces [31] and combinatorial topology [41]. This model can discover the hierarchy of semantics from a collection of documents.

Before explaining the algorithm, let us define some basic notions of the hierarchical model. The central notion is \( n \)-simplex.

Definition 5: A fuzzy semantic \( n \)-simplex, or simple \( n \)-simplex, is a set of independent abstract vertices \( \{v_0, \ldots, v_{n+1}\} \), in which each vertex is a categorized named entity. An \( r \)-face of an \( n \)-simplex \( \{v_0, \ldots, v_{n+1}\} \) is an \( r \)-simplex \( \{v_{i_0}, \ldots, v_{i_r}\} \) whose vertices are a subset of \( \{v_0, \ldots, v_{n+1}\} \) with cardinality \( r + 1 \).

An \( n \)-simplex basically implies a semantic topic, or called a semantics. A fuzzy linguistic function or membership evaluates the consensus state on an \( n \)-simplex. It is based on a fuzzy characterization of the coincidence concept and obtained by means of several conjunction functions for handling linguistic weighted information from every tuple of elements in the \( n \)-simplex. Consensus consists of combining simplexes organized by different documents with a view to obtain more elaborate semantics [42].

Definition 6: Let \( A \) be a semantic topic induced by an \( n \)-simplex generated from a document, and \( B \) be another semantic topic. Let \( x \) be a vertex or a set of vertices in the simplex to demonstrate an existed relationship in \( A \). A fuzzy linguistic function, \( \text{separation} \ \sigma \), between semantic topic \( A \) and semantic topic \( B \) is given by

\[
\sigma(A, B) = 1 - \bigvee_{x \in A, z \in \Theta} \min_{x \in A} (\mu_z(x|A) \wedge \mu_z(x|B))
\]

where \( \bigvee \) denotes the maximum operation, and \( \wedge \) denotes the minimum operation. The fuzzy latent relational measure \( \mu_z(x|A) \) denotes the membership of a named entity \( x \) in \( A \) belonging to a category \( z \), so does \( \mu_z(x|B) \).

The separation function denotes the maximal possible difference between the semantics generated from a document and a semantics. It indicates the possibility that \( A \) cannot be classified into \( B \). We need to define the dominance \( \delta \) of \( A \) over \( B \).

Definition 7: The dominance function is given by

\[
\delta(A, B) = \bigvee_{x \in A, z \in \Theta} \max_{z \in \Theta} (\mu_z(x|A) \wedge \mu_z(x|B)).
\]

The dominance function is illustrated in Fig. 3. When the peak in \( \mu_z(x|A) \) coincides with the peak in \( \mu_z(x|B) \), we have \( \delta(A, B) = 1 - \sigma(A, B) \). Notice that while \( \delta(A, A) = 1 \); \( \delta(A, B) \neq \delta(B, A) \), in general. The dominance function is a fuzzy linguistic function that demonstrates the consensus state between two groups, that is, two simplexes. Two simplexes can be merged into one if their dominance value is bigger than a threshold, and their separation value is less than a threshold. We will set the fuzzy latent relational measure of every element in the simplex to be 1, that means they are coincident with their
corresponding named categories after two simplexes have been merged.

These fuzzy linguistic functions satisfy the Apriori condition [43]. If a set cannot be classified into a semantic category, that means the dominance function of the set belonging to the category should be not bigger than a threshold and the separation function of the set not belonging to the category should be not less than a threshold. Both the domination function and the separation function are commonly derived from the minimum operation of all the fuzzy latent relational measure of each feature in the set. According to the minimum operation of all super sets is not bigger than the minimum operation of the original set, it induces that the domination function of its superset is not bigger than a threshold and the separate function of its superset is not less than a threshold. Therefore, if a set cannot be merged into a semantic category, neither can its superset. Vice versa, if a set can be merged into a semantic category, so can its subsets.

Based on the fuzzy linguistic functions, a hierarchical aggregation algorithm is addressed to cluster documents from 0-simplexes to the semantic hierarchy. Geometrically, 0-simplex is a vertex; 1-simplex is an open segment \((v_0, v_1)\) that does not include its end points; 2-simplex is an open triangle \((v_0, v_1, v_2)\) that does not include its edges and vertices; 3-simplex is an open tetrahedron \((v_0, v_1, v_2, v_3)\) that does not include all the boundaries. For each simplex, all its proper faces (boundaries) are not included. An n-simplex is the high-dimensional analogy of those low-dimensional simplexes (segment, triangle, and tetrahedron) in n-space. Geometrically, an n-simplex uniquely determines a set of \(n + 1\) linearly independent vertices, and vice versa. An n-simplex is the smallest convex set in a euclidean space \(R^n\) that contains \(n + 1\) points \(v_0, \ldots, v_n\) that do not lie in a hyperplane of dimension less than \(n\). For example, there is the standard n-simplex

\[
\delta^n = \left\{ (t_0, t_1, \ldots, t_{n+1}) \in R^{n+1} \mid \sum_i t_i = 1, t_i \geq 0 \right\}.
\]

The convex hull of any \(m\) vertices of the n-simplex is called an m-face. The 0-faces are the vertices, the 1-faces are the edges, the 2-faces are the triangles, and the single n-face is the whole n-simplex itself. Formally,

**Definition 8:** A fuzzy semantic simplicial complex, or simple complex is a finite set of simplexes that satisfies the following two conditions:

1) Any set consisting of one vertex is a simplex.
2) Any face of a simplex from a complex is also in this complex.

The vertices of the complex \(v_0, v_1, \ldots, v_n\) is the union of all vertices of those simplexes (44, pp. 108).

If the maximal dimension of the constituting simplexes is \(n\), then the complex is called n-simplex. An n-simplex is a closed set of all m-simplexes, where \(m \leq n\). All simplexes from returned documents becomes simplexes in the complex.

To discover all simplexes in the complex is able to discover all semantics in the returned documents. The corresponding notion of combinatorial n-simplex can be defined by (combinatorial) r-simplexes.

We need much more precise notions. A \((n, r)\)-skeleton (denoted by \(S^r_n\)) of n-simplex is an n-complex, in which all k-simplexes \((k \leq r)\) have been removed. Two simplexes in a complex are said to be directly connected if the intersection of them is a nonempty face. Two simplexes in a complex are said to be connected if there is a finite sequence of directly connected simplexes connecting them. For any nonempty two simplexes A, B are said to be r-connected if there exists a sequence of k-simplexes \(A = S_0, S_1, \ldots, S_m = B\) such that \(S_j\) and \(S_{j+1}\) has an h-common face for \(j = 0, 1, \ldots, m - 1\), where \(r \leq h \leq k\).

The maximal r-connected subcomplex is called a r-connected component. Note that an r-connected component implies that there does not exist any r-connected component that is a super set of it. A maximal r-connected subcomplexes of n-simplex is called r-connected component. A maximal r-connected component of n-simplex is called connected component, if \(r = 0\).

IV. SEMANTIC STRUCTURE

From a collection of documents, a complex of co-occurring named entity associations can be generated. Obviously, a simple complex is a certain concept. The 0-simplex (Network) represents a vague CONCEPT. It can be combined into many different concepts. For example, in the following 1-simplexes (computer, network), (traffic, network), (neural, network), (communication, network), etc., express further and richer semantic than their individual 0-simplexes. Of course, the 1-simplex (neural, network) is not conspicuous than the 2-simplexes (artificial neural network) and (biology, neural, network).

A collection of documents may carry a set of distinct CONCEPTS. Each concept, we believe, is carried by a connected component of the complex of semantic simplexes.

1) An IDEA (in the forms of complex of cooccurring named entity associations) may consist of many CONCEPTS (in the form of connected components) that consists of PRIMITIVE CONCEPTS (in the form of simplexes). The maximal simplexes of highest dimension is called MAXIMAL PRIMITIVE CONCEPT. A simplex is said to be a maximal if no other simplex in the complex is a superset of it. Intuitively, the geometric dimension represents the degree of preciseness or depth of the latent semantics that are represented by simplexes.

**Example 1:** In Fig. 4, an IDEA comprises twelve terms that are organized in the forms of 3-complex, denoted by \(S^3_3\). Simplex(a, b, c, d) and Simplex(w, x, y, z) are two maximal simplexes of 3, the highest dimension. That is, the \((3, 3)\)-skeleton \(S^3_3\) consists of two non-connected 3-simplexes or two MAXIMAL PRIMITIVE CONCEPTS.

Next, let us consider the \((3, 2)\)-skeleton \(S^2_3\), by removing all 0-simplexes and 1-simplexes from \(S^3_3\):

1) Simplex(a, b, c, d) and its four faces:
   a) Simplex(a, b, c),
   b) Simplex(a, b, d),
   c) Simplex(a, c, d),
   d) Simplex(b, c, d).

2) Simplex(a, c, h).
3) Simplex(c, h, e).
4) Simplex(e, h, f).
5) Simplex(e, f, x).
6) Simplex(f, g, x).
7) Simplex(g, x, y).
8) Simplex(w, x, y, z) and its four faces:
   a) Simplex(w, x, y),
   b) Simplex(w, x, z),
   c) Simplex(w, y, z),
   d) Simplex(x, y, z).

There are no common faces between any two simplexes; therefore, $S^2_2$ has eight connected components, or eight CONCEPTS.

Consider the (3, 1)-skeleton $S^1_1$. After removing all 0-simplexes from $S^3_1$, the simplexes Simplex(a, c), Simplex(c, h), Simplex(h, e), Simplex(e, f), Simplex(f, x), Simplex(g, x), and Simplex(x, y), all are common faces among the CONCEPTS generated from $S^3_1$. These simplexes also make $S^1_1$ to be connected. See Appendix for more details.

A complex connected component or simplex of a skeleton represent a more technically refined IDEA, CONCEPT or PRIMITIVE CONCEPT. If a maximal connected component of a skeleton contains only one simplex, this component is said to organize a primitive concept.

Based on the hierarchies of primitive CONCEPTS, we can define the notion of layered clustering. As can be seen in Example 1, connected components in $S^n_k$ are contained in that of $S^n_{k'}$, where $k \geq r$.

Example 2: Fig. 5 is 2-complex composed of the term set $V = \{t_A, t_B, t_C\}$ in a collection of documents. It is a closed 2-simplex; we recall here that a closed simplex is a complex that consists of one simplex and all its faces. In the skeleton $S^2_1$, all 0-simplexes are ignored, that is, the terms depicted in dashed lines. The simplex set $S = \{\text{Simplex}_1^2, \text{Simplex}_2^2, \text{Simplex}_3^2, \text{Simplex}_1^3, \text{Simplex}_2^3, \text{Simplex}_3^3\}$ is the closed 2-simplex that consists of one 2-simplex and three 1-faces, Simplex$_1^2$, Simplex$_2^2$, and Simplex$_3^2$ (0-faces are ignored). These $r$-simplexes ($0 \leq r \leq 2$) represents frequent itemsets (term-associations) from $V$, where $W = \{w_{A,B}, w_{B,C}, w_{C,A}, w_{A,B,C,}, w_{A,B,C}\}$ denote their corresponding supports. The lines connecting Simplex$_1^3$ and three vertices represent the incidences of 2-simplex and 0-simplex; the incidences with 1-simplexes are not shown to avoid overcrowding in the figure.

According to Example 1, it is obvious that simplexes within the higher level skeleton $S^n_1$ is contained in the lower level skeleton $S^n_{k'}$ within the same $n$-complex, $r \geq k$. Fig. 6 shows the hierarchy, wherein each skeleton is represented as a layer. For the purpose of simplicity, we skip the middle layer, namely, $S^n_2$, $0 \leq r < 3$, and is not shown.

By considering different skeletons, we can draw distinct layer of CONCEPTS:
1) In full complex $S = S^n_0$, in this example, only has one CONCEPT (one connected component).
2) In $S^n_1$, this complex still has only one CONCEPT.
3) In $S^n_2$, this complex has eight CONCEPTS.
4) In $S^n_3$, this complex has two CONCEPTS; they are two MAXIMAL PRIMITIVE CONCEPTS.
For each choice, say $S^0_k$, we have, in this case, eight CONCEPTS to label the documents (or cluster the documents). A document is labeled CONCEPT$^k$, if the document has high TFIDF values on the term-associations that defines CONCEPT$^k$. By considering different cases, we have layered clusters. In fact, we could consider a very coarse clustering, that is, we consider only the MAXIMAL PRIMITIVE CONCEPTS, which is the case of $S^0_0$. For the purpose of illustration, we used an oversimplified example.

In general, the simplexes at the lower layers could have common faces between them. Therefore, using all layers of CONCEPTS at the same time will produce vague discrimination as shown in Fig. 7, in which an overlapped CONCEPTS induced by (lower dimensional) common faces could exist. As seen in the skeleton $S^3$, the maximal connected components generated from simplexes $\text{Simplex}(a, b, c, d)$ and $\text{Simplex}(a, c, h)$ have a common face $\text{Simplex}(a, c)$ that makes some documents unable to get properly discriminated in accordance with the generated association rules from term $a$ and term $c$, so are the other maximal connected components in the skeleton. Because of the intersection produced by such faces, a proper way is to ignore the lower dimensional skeleton, as much as application can tolerate.

V. FUZZY HIERARCHICAL AGGREGATION ALGORITHM

Web documents can be clustered based on maximal simplexes of any dimension (CONCEPTS). Note that web documents clustered by CONCEPTS contains common lower dimensional faces (low dimension simplex, in particular a 0-simplex), which is a consequence of Apriori property. In this sense, the methodology provides a soft approach; wherein we allow lower dimension to overlap with CONCEPTS existing across different clusters. The fuzzy hierarchical aggregation algorithm is divided into three phases.

**Phase 1:** Perform feature extractions using CRF methods to generate named entities.

**Phase 2:** Calculate the fuzzy linguistic value of every named entity to every named category.

**Phase 3:** Perform hierarchical aggregation clustering in order to generate the semantic hierarchy from the set of coincident named entities.

The algorithm that generates hierarchical aggregation clustering based on fuzzy linguistic memberships is mentioned as below.

**Require:** $V = \{x_1, x_2, \ldots, x_n\}$ be the vertex set of all reserved named entities generated from $W$ associated with their categories $\Theta$ in a collection of documents.

**Ensure:** $\mathcal{H}$ is the hierarchy of connected components.

Let $S = \{\{x_1\}, \{x_2\}, \ldots, \{x_n\}\}$ be the set of all 0-simplexes initially.

Given two thresholds $\alpha$ and $\beta$.

Let $k \leftarrow 0$.

while $k \leq \alpha$ do

Let $S_i$ and $S_j$ be two $n$-simplexes in $S$.

while $\delta(S_i, S_j) \geq \alpha$ and $\sigma(S_i, S_j) \leq \beta$ do

$S' \leftarrow S_i \cup S_j$.

Add $S'$ to $S$.

end while

$k \leftarrow (k + 1)$

end while

The algorithm starts from the set of all 0-simplexes, that is, all single named entities. The algorithm hence aggregates web documents into different categories to be the PRIMITIVE CONCEPTS. If a web document contains a PRIMITIVE CONCEPT, it means that web document highly equates to such concept. According to the Apriori property, all the subclusters in the concept are also contained in this web document. The algorithm can classify web document into the category identified with such concept. Generally, a web document consisting of more than one PRIMITIVE CONCEPTS, in that case, it can be classified into multicategories.

VI. EXPERIMENTAL RESULTS

Fuzzy latent semantic clustering (FLSC) organizes the returned web documents hierarchically.

A. System

As we know, Google provides a flat list of search result snippets, and PubMed returns a summarized list of the abstracts of medical literatures associated with MeSH terms. Starting from a user query on-the-fly over two remote search engines (PubMed and Google), our system hierarchically generates all the CONCEPTS. A semantic tree represents the CONCEPT hierarchy in which the root is the user query. Except the root, all terms on the other nodes can be considered to be advanced search queries. A query of a node is then aggregated with other cooccurring entities to become more primitive on its branches of the
Since the simplexes of the higher dimension are aggregated with several IDEA and the lower dimensions are uncertain, the lower dimensions the CONCEPTS are put near to the root of hierarchy, and vice versa in the system.

The system depicted in Fig. 8 demonstrates the search results from PubMed, for a search query "nod2." A hierarchy of clusters is built on the return results. The abstract (unstructured) and MeSH terms (semi-structured) are in use to cluster them. The same term "pain" has been taken to retrieve information from Google. The returned result snippets are grouped into several clusters as shown in Fig. 9.

### B. Results

The experimental evaluation of document clustering approaches usually measures their effectiveness than their efficiency [45]. In other words, to measure the ability of an approach is to make a right categorization. Entropy estimates the clustering performance [46] based on the human expert’s decisions. An expert submit hundreds of medical queries form our system to evaluate the clustering results returned from PubMed and Google, respectively. More than 200 000 web pages or snippets have been returned. In general, the average entropy is around 0.14 ± 0.06 for PubMed, and 0.27 ± 0.08 for Google. PubMed has defined metadata of various medical literature with the help of human experts. Without using these metadata, the average entropy was estimated to be 0.21 ± 0.09. Accordingly, we can courageously suggest that the CONCEPTS organized by FLSC can generate semantic concept clustering of web pages.

Consider the contingency table for a topic of a category (see Table I); recall, precision, and $F_\beta$ [47] are three direct measures of the effectiveness of a NER method. Precision and recall with respect to a topic are respectively defined as follows:

\[
\text{Precision}_i = \frac{TP_i}{TP_i + FP_i},
\]

\[
\text{Recall}_i = \frac{TP_i}{TP_i + FN_i}.
\]

The $F_\beta$ introduced by van Rijsbergen [48] combines precision and recall by the following formula:

\[
F_\beta = \frac{(\beta^2 + 1) \times \text{Precision}_i \times \text{Recall}_i}{\beta^2 \times \text{Precision}_i + \text{Recall}_i}.
\]

$F_1$ measure used in this paper was obtained when $\beta$ is set to be 1, which means precision and recall are equally weighted for evaluating the performance of clustering. Because many categories would be generated and need to be compared, the overall precision and recall were calculated as the average of all precisions and recalls belonging to categories, respectively. $F_1$ is calculated as the mean of individual results. It is a macroaverage of the categories.

In a nonoverlapping scenario, each document belongs to exactly one cluster. Three validation metrics: precision, recall, and $F$-measure, are proper to evaluate the performance of crisp clustering algorithms. The overlapping clustering schemes has been involved in a widely variety of application domains because many real problems are naturally overlapped, for example, in social network analysis, computational biology, recommendation systems, etc. Information theoretic measures [49], [50], such as entropy and mutual information, hence have been used to estimate how much information is shared from the labeled instances in a cluster, especially, for a hierarchical clustering schemes [51]. Mutual information is defined extendedly from entropy. In order to compare effectiveness with other methods, two different evaluation metrics, normalized mutual information [49], [52], [53] and overall $F$-measure [54], [55], were also used.

<table>
<thead>
<tr>
<th>Topic $z_i$</th>
<th>Clustering Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Expert YES</td>
<td>TP, FN,</td>
</tr>
</tbody>
</table>

**Table I: Contingency Table for Topic $z_i$**
Given the two sets of topics $C$ and $C'$, let $C$ denote the topic set defined by experts, $C'$ denote the topic set generated by a clustering method, and both derived from the same corpora $X$.

Let $N(X)$ denote the total number of documents, $N(z, X)$ denotes the number of documents in a topic $z$, and $N(z, z', X)$ denotes the number of documents both in topic $z$ and topic $z'$, for any topics in $C$. The normalized mutual information (NMI) metric $\text{MI}(C, C')$ is defined as follows:

$$\text{MI}(C, C') = \frac{\sum_{z \in C, z' \in C'} P(z, z') \log_2 \left( \frac{P(z, z')}{P(z)P(z')} \right)}{\max(H(C), H(C'))}$$

where $P(z) = N(z, X)/N(X)$, $P(z') = N(z', X)/N(X)$, and $P(z, z') = N(z, z', X)/N(X)$. The normalized mutual information metric $\text{MI}(C, C')$ will return a value between zero and $\max(H(C), H(C'))$ where $H(C)$ and $H(C')$ define the entropies of $C$ and $C'$, respectively. The higher $\text{MI}(C, C')$ value means that two topics are almost identical, otherwise more independent. The normalized mutual information metric $\tilde{\text{MI}}(C, C')$ is therefore transferred to be

$$\tilde{\text{MI}}(C, C') = \frac{\text{MI}(C, C')}{\max(H(C), H(C'))}.$$ 

Let $F_i$ be an F-measure for each cluster $z_i$ defined above. The overall F-measure can be defined as follows:

$$F = \sum_{z' \in C} P(z') \times \max_{z \in C} F(z, z')$$

where $F(z, z')$ calculates the F-measure between $z$ and $z'$.

“Reuters-21578, Distribution 1” collection consisted of newswire articles. The articles are assigned into 135 so-called topics that are in use to affirm the clustering results. In our test, the documents with multiple topics (category labels) and with single topic were separated, and the topics with less than five documents were removed. Table II shows the summary of the “Reuters-21578, Distribution 1” collection. Two to ten topics had been randomly selected to evaluate FLSC and other methods. For each clustering method, each test run was conducted on a selected topic and calculated the normalized mutual information of the topic and its corresponding cluster accordingly. After conducting 50 test runs on a fixed number of $k$ topics where $2 \leq k \leq 10$, the final performance scores were obtained by averaging mutual information measures from these 50 test runs.

The mutual information are used to compare the fuzzy latent semantic clustering method with the other methods as listed in [53], ant-fuzzy clustering algorithm [21], hierarchical-hyperspherical divisive fuzzy c-means [22], ontology-based fuzzy document clustering algorithm [26], and $k$-clique-community finding algorithm [56] is shown in Table III: FLSC = Fuzzy Latent Semantic Clustering; AFC = ant-fuzzy clustering algorithm; H2D-FCM = hierarchical-hyperspherical divisive fuzzy c-means; OBFDc = ontology based fuzzy document clustering; GMM = Gaussian mixture model; NB = naive Bayes clustering; KM = traditional k-means; GMM + DFM = Gaussian mixture model followed by the iterative cluster refinement method; NC = spectral clustering algorithm based on normalized cut criterion; RC = spectral clustering based on ratio cut criterion; BP = spectral clustering-based bipartite normalized cut; NMF = nonnegative matrix factorization; CF = concept factorization; NCW = normalized-cut weighted form; CCF = $k$- clique-community finding algorithm. Two statistical testing methods, Kruskal–Wallis H-test [57] and the Bonferroni–Dunn test [58], assessed whether clusters generated by those methods are statistically different from one another. Four metrics—precision, recall, overall F-measure, mutual information of FLSC for different $k$ are listed in Table IV.

According to nineteen clustering schemes involved to compare our clustering method and for each clustering number $k$, there are 50 test runs conducted, the Kruskal–Wallis H-test [57] has been used to evaluate the performance of these clustering methods. The Kruskal–Wallis H-test is a nonparametric method used for comparing two or more samples whether originating from the same distribution [57], [59]. The Kruskal–Wallis H-test extends the Mann–Whitney U test to compare more than two groups. Instead of assuming samples to be normal by using one-way ANOVA test, we used Kruskal–Wallis H-test to evaluate the clustering performance. When rejecting the null hypothesis of the Kruskal–Wallis H-test, it means at least one sample stochastically dominates the others. However, the Kruskal–Wallis H-test does not identify where the differences occur and how many differences occur. Twenty samples generated by different clustering schemes with the same sample size 50 for each $k$ were evaluated by using the Kruskal–Wallis H-test and then performing Bonferroni–Dunn multiple comparison test accordingly, while the null hypothesis of the Kruskal–Wallis H-test was rejecting [59], [60]. The Bonferroni-Dunn test [58] is a nonparametric mean rank or median test that computes a more conservative significant level for each multiple comparisons test based only on the overall significant level for the multiple samples obtained from those clustering methods. The Bonferroni–Dunn test with the goal of improving statistical power is able to...
to identify which clustering schemes are significantly different from the others. All statistical analyses were performed using R (http://cran.r-project.org) computer software package (Version 3.1.2). The p-value \( p < 0.05 \) was considered statistically significant.

In general, fuzzy clustering algorithms can achieve better performance than traditional clustering algorithms as shown in Table III. For each \( k \), the Kruskal–Wallis \( H \) test shows whether the performance of these methods is significantly different. If the normalized mutual information of some clustering schemes is stochastically dominating the others, the Bonferroni–Dunn test is assigned to identify which clustering methods perform better or worse than most of the other clustering methods. In our experiments, while \( k \geq 6 \), FLSC does significantly surpass other clustering schemes \( (p < 0.05) \). The experiments show that FLSC is more suitable to handle the heterogenous phenomenon of web documents than the others. The binary divisive fuzzy clustering scheme, H2D-FCM, was not able to properly partition the documents hierarchically according to the common terms, as well as the complicated relationship among the documents that indicate semantic topics cannot be separated into binary sets at each level. The polysemy is getting worse, while the number of clusters we considered is increasing. Although the ontology-based fuzzy clustering algorithm selected the meaningful terms based on an ontology, the ratios of the terms belonging to different topics is fixed and not able to automatically adjust. Ant-based fuzzy clustering is able to adapt the conditional possibility of a term belonging to a topic; however, the common terms and the label bias problem \[61\] induce the documents not able to be clustered into proper semantic topics.

The experimental results show that the FLSC performs better than comparative algorithms in term of quality of the cluster produced. An increase in cluster purity clearly established the fact that the fuzzy linguistic topological space inherently captures the semantics of the documents. The experimental setup of some well-known traditional algorithms and three fuzzy clustering algorithms are tested on the “Reuters-21578, Distribution 1” dataset defined for the evaluation. The mutual information and F-measure results for the algorithms are reported in Tables II–IV. The proposed approach clearly had shown an improvement in most of test cases. The mutual information and F-measure for dataset “Reuters-21578, Distribution 1” produce a significant improvement when the number of selected clusters become higher. This analysis reveals when the document contains multiplicities and more heterogeneous, our suggested approach is exceptionally good.

### VII. Conclusion

Polysemes, phrases, and term dependencies are the limitations of search technology \[3\]. A single term is not able to identify a latent concept in a document, for instance, the term

| TABLE III
| Normalized Mutual Information Comparison of FLSC Method With Other Sixteen Methods on “Reuters-21578, Distribution 1” Dataset |
|---|---|---|---|---|---|---|---|---|---|
| \( k \) | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| FLSC | 0.421 | 0.489 | 0.572 | 0.636 | 0.696 | 0.742 | 0.796 | 0.801 | 0.822 | 0.634 |
| AFC | 0.546 | 0.521 | 0.567 | 0.562 | 0.613 | 0.659 | 0.663 | 0.687 | 0.679 | 0.596 |
| H2D-FCM | 0.480 | 0.468 | 0.463 | 0.455 | 0.522 | 0.548 | 0.525 | 0.562 | 0.547 | 0.507 |
| OBFDC | 0.535 | 0.543 | 0.562 | 0.557 | 0.623 | 0.655 | 0.672 | 0.679 | 0.676 | 0.622 |
| CCF | 0.569 | 0.563 | 0.607 | 0.62 | 0.605 | 0.624 | 0.633 | 0.647 | 0.676 | 0.616 |
| GMM | 0.475 | 0.468 | 0.462 | 0.516 | 0.551 | 0.522 | 0.551 | 0.557 | 0.548 | 0.517 |
| NB | 0.466 | 0.348 | 0.401 | 0.405 | 0.409 | 0.404 | 0.435 | 0.411 | 0.418 | 0.411 |
| GMM+DFM | 0.47 | 0.466 | 0.45 | 0.513 | 0.531 | 0.506 | 0.535 | 0.535 | 0.536 | 0.505 |
| KM | 0.404 | 0.402 | 0.461 | 0.525 | 0.561 | 0.548 | 0.583 | 0.597 | 0.618 | 0.522 |
| KM-NC | 0.438 | 0.462 | 0.525 | 0.554 | 0.592 | 0.577 | 0.594 | 0.607 | 0.618 | 0.552 |
| SKM | 0.458 | 0.407 | 0.499 | 0.561 | 0.567 | 0.558 | 0.591 | 0.598 | 0.619 | 0.54 |
| SKM-NCW | 0.434 | 0.423 | 0.515 | 0.556 | 0.577 | 0.563 | 0.593 | 0.602 | 0.612 | 0.542 |
| BP-NCW | 0.391 | 0.377 | 0.431 | 0.478 | 0.493 | 0.5 | 0.519 | 0.529 | 0.532 | 0.472 |
| AA | 0.443 | 0.415 | 0.488 | 0.531 | 0.571 | 0.542 | 0.587 | 0.594 | 0.611 | 0.531 |
| NC | 0.484 | 0.461 | 0.555 | 0.592 | 0.617 | 0.594 | 0.64 | 0.634 | 0.643 | 0.58 |
| RC | 0.417 | 0.381 | 0.505 | 0.46 | 0.485 | 0.456 | 0.548 | 0.484 | 0.495 | 0.47 |
| NMF | 0.48 | 0.426 | 0.498 | 0.559 | 0.591 | 0.552 | 0.603 | 0.603 | 0.623 | 0.548 |
| NMF-NCW | 0.494 | 0.5 | 0.586 | 0.615 | 0.637 | 0.613 | 0.654 | 0.659 | 0.658 | 0.602 |
| CF | 0.48 | 0.429 | 0.503 | 0.563 | 0.592 | 0.556 | 0.613 | 0.609 | 0.629 | 0.553 |
| CF-NCW | 0.496 | 0.505 | 0.595 | 0.616 | 0.644 | 0.615 | 0.66 | 0.66 | 0.656 | 0.606 |

| TABLE IV
| Precision, Recall, Overall F-Measure, and Normalized Mutual Information of FLSC on “Reuters-21578, Distribution 1” Dataset |
|---|---|---|---|---|---|---|---|---|---|
| \( k \) | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| Precision | 0.9845 | 0.9579 | 0.9385 | 0.9352 | 0.8909 | 0.9013 | 0.9148 | 0.8913 | 0.8859 |
| Recall | 0.7085 | 0.6384 | 0.6453 | 0.6056 | 0.5916 | 0.6534 | 0.6822 | 0.6688 | 0.6805 |
| Overall F-measure | 0.7988 | 0.7287 | 0.7399 | 0.7348 | 0.7096 | 0.6878 | 0.7343 | 0.7343 | 0.7472 |
| NMI | 0.4617 | 0.5051 | 0.6221 | 0.6866 | 0.7148 | 0.7925 | 0.8936 | 0.8848 | 0.9006 |
“Network” associated with the term “Computer,” “Traffic,” or “Neural” denotes different concepts. A group of solid cooccurring named entities can clearly define a CONCEPT. The semantic hierarchy generated from frequently cooccurring named entities of a given collection of web documents, form a simplicial complex. The complex can be decomposed into connected components at various levels (in various level of skeletons). We believe each such connected component properly identify a concept in a collection of web documents.

To identify and discriminate the correct topics in a collection of documents, the combinations of features and their cooccurring relationships are the clue, and the possibility displays how significant they will be. All features in documents compose a topologically probabilistic space, more specifically a simplicial complex associated with probabilistic measures to denote the underlying structure. The complex can be geographically decomposed into inseparable components at various levels (in various levels of skeletons) that each component properly corresponds to topics in a collection of documents. Of course, the topics that a component induced are either topologically distinguishable, or perfectly included in other induced topics.

We can effectively discover such a maximal fuzzy simplexes and use them to cluster the collection of web documents. Based on our website and our experiments, we find that FLSC is a very good way to organize the unstructured and semistructured data into several semantic topics. It also illustrates that geometric complexes are an effective model for automatic web documents clustering.

APPENDIX A

(3, 1)-SKELETON $S_3^1$ OF EXAMPLE 1

In Fig. 4, the (3, 1)-skeleton $S_3^1$ is the leftover after the removal of all 0-simplexes from $S_3^1$:

1) $\text{Simplex}(a, b, c, d)$ and its ten faces:
   a) $\text{Simplex}(a, b, c)$,
   b) $\text{Simplex}(a, b, d)$,
   c) $\text{Simplex}(a, c, d)$,
   d) $\text{Simplex}(b, c, d)$,
   e) $\text{Simplex}(a, b)$,
   f) $\text{Simplex}(a, c)$,
   g) $\text{Simplex}(b, c)$,
   h) $\text{Simplex}(a, d)$,
   i) $\text{Simplex}(b, d)$,
   j) $\text{Simplex}(c, d)$.

2) $\text{Simplex}(a, c, h)$ and its three faces:
   a) $\text{Simplex}(a, c)$,
   b) $\text{Simplex}(a, h)$,
   c) $\text{Simplex}(c, h)$.

3) $\text{Simplex}(c, h, e)$ and its three faces:
   a) $\text{Simplex}(c, h)$,
   b) $\text{Simplex}(h, e)$,
   c) $\text{Simplex}(c, e)$.

4) $\text{Simplex}(e, h, f)$ and its three faces:
   a) $\text{Simplex}(e, h)$,
   b) $\text{Simplex}(h, f)$,
   c) $\text{Simplex}(e, f)$.

5) $\text{Simplex}(e, f, x)$ and its three faces:
   a) $\text{Simplex}(e, f)$,
   b) $\text{Simplex}(e, x)$,
   c) $\text{Simplex}(f, x)$.

6) $\text{Simplex}(f, g, x)$ and its three faces:
   a) $\text{Simplex}(f, g)$,
   b) $\text{Simplex}(g, x)$,
   c) $\text{Simplex}(f, x)$.

7) $\text{Simplex}(g, x, y)$ and its three faces:
   a) $\text{Simplex}(g, x)$,
   b) $\text{Simplex}(g, y)$,
   c) $\text{Simplex}(x, y)$.

8) $\text{Simplex}(w, x, y, z)$ and its ten faces:
   a) $\text{Simplex}(w, x, y)$,
   b) $\text{Simplex}(w, x, z)$,
   c) $\text{Simplex}(w, y, z)$,
   d) $\text{Simplex}(x, y, z)$,
   e) $\text{Simplex}(w, x)$,
   f) $\text{Simplex}(w, y)$,
   g) $\text{Simplex}(w, z)$,
   h) $\text{Simplex}(x, y)$,
   i) $\text{Simplex}(x, z)$,
   j) $\text{Simplex}(y, z)$.

Note that $\text{Simplex}(a, c), \text{Simplex}(c, h), \text{Simplex}(h, e), \text{Simplex}(e, f), \text{Simplex}(f, x), \text{Simplex}(g, x),$ and $\text{Simplex}(x, y)$, all are common faces of 2-simplexes $\text{Simplex}(a, c, d)$, $\text{Simplex}(a, c, h), \text{Simplex}(c, e, h), \text{Simplex}(e, f, x), \text{Simplex}(g, x, y),$ and $\text{Simplex}(w, x, y)$. Therefore, they generate a connected path from $\text{Simplex}(a, b, c, d)$ to $\text{Simplex}(w, x, y, z)$, and subpaths. Therefore, the $S_3^1$ complex is connected. This assertion also implies that $S_3^1$ is connected. Hence, the IDEA consists of a single CONCEPT (please note the technical meaning of the IDEA and CONCEPT given in Section IV).

REFERENCES


I-Jen Chiang received the Ph.D. degree in both computer science and information engineering and biomedical engineering from the National Taiwan University, Taipei, Taiwan, in 1997. He was a Visiting Scholar at the University of California at Berkeley, Berkeley, USA, in the academic year 1997/1998, and a Visiting Scholar at Academia Sinica, Taipei, Taiwan, in 2006/2007. He served as the General Secretary of Asia Pacific Association for Medical Informatics from 2009 to 2011. He was also one of the co-founders of Taiwan Evidence-based Medicine Association. He is currently an Associate Professor of the Graduate Institute of Biomedical Informatics, Taipei Medical University and Adjunct Associate Professor of the Institute of Biomedical Engineering, National Taiwan University. He is a faculty member of the International Partnership in Health Informatics that is an education partnership program established in 1998 and consists of University of Amsterdam, University of Heidelberg, University of Minnesota, University of Utah, University for Health Informatics and Technology, Taipei Medical University, and University of Washington. He is also a faculty member of the International Summer and Winter Term (ISWT) of Indian Institute of Technology Kharagpur, Kharagpur, India. His research interests include data mining, text/web mining, eCommerce, big data analytics, statistical pattern recognitions, and cloud computing. During his career, he worked at Newegg, Inc., as the Director of Lab from 2006 to 2013. He was the Founder and Chief Executive Officer of a major online stock quote company acquired by GiGaMedia in 2000.

Charles Chih-Ho Liu received the M.S. degree from Graduate Institute of Medical Informatics, Taipei Medical University, Taipei, Taiwan, and is working toward the Ph.D. degree in medical engineering in National Taiwan University, Taipei. He received the Medical Doctor degree in National Taiwan University in 1990, and completed the surgical residency program in National Taiwan University Hospital. From 1997, he worked as a Visiting Staff in Plastic Surgical Department, Cathay General Hospital, Taipei and was the General Secretary of Taiwan Society of Aesthetic Plastic Surgery from 2010 to 2012 and from 2014 to 2016. He was also one of the Co-founders of Taiwan Evidence-based Medicine Association. His research interests include data mining on healthcare database, and natural language processing and bibliometrics of medical texts.

Yi-Hsin Tsai received the Medical Doctor degree in National Taiwan University, Taipei, Taiwan, in 1998, and completed the neurosurgical residency program in National Taiwan University Hospital in 2005. He is currently working toward the Ph.D. degree in medical engineering with National Taiwan University, Taipei, Taiwan.

He worked as an attending Neurosurgeon in Surgical Department, Yuan General Hospital, Kaohsiung City, Taiwan, from July 2005 to June 2006; as an attending Neurosurgeon at Yunlin Branch of National Taiwan University Hospital from July 2006 to June 2008; as an attending Neurosurgeon at Neurosurgical Division of Surgical Department from July 2008 to July 2012; and as an attending neurosurgeon at Neurosurgical Division of Surgical Department at Far-Eastern Memorial Hospital, New Taipei City, Taiwan. His research interests include data mining on healthcare database, and big data analysis on intensive care units.

Ajit Kumar received the Ph.D. degree in medical informatics from Taipei Medical University, Taipei, Taiwan; the Master's degree in computer application from Bundelkhand University, Jhansi, India; and the Bachelor's degree in computer science from Allahabad University, Allahabad, India. He has been exposed to a variety of fields, such as computer science, healthcare, cognitive science, linguistics, statistics by assuming different roles (eight years teaching, research, and industry experiences) in various settings (India, Taiwan, Libya, Nigeria). His work has been widely published in the form of peer-reviewed journal papers, book chapter contributions, refereed proceedings, and conference papers. His research interests include human-computer Interaction, software engineering, and computer applications in Healthcare.