An Effective Information Retrieval for Ambiguous Query

R.K. Roul* and S.K. Sahay†

BITS, Pilani - K.K. Birla, Goa Campus, Zuarinagar, Goa - 403726, India.

Abstract

Search engine returns thousands of web pages for a single user query, in which most of them are not relevant. In this context, effective information retrieval from the expanding web is a challenging task, in particular, if the query is ambiguous. The major question arises here is that how to get the relevant pages for an ambiguous query. We propose an approach for the effective result of an ambiguous query by forming community vector based on association concept of data mining using vector space model and the freedictionary. We develop clusters by computing the similarity between community vectors and document vectors formed from the extracted web pages by the search engine. We use Gensim package to implement the algorithm because of its simplicity and robust nature. Analysis shows that our approach is an effective way to form clusters for an ambiguous query.

Keywords: Information Retrieval, Clustering, Vector space model, Gensim.

1 Introduction

On the web, search engines are key for the information retrieval (IR) for any user query. However, resolving ambiguous query is a challenging task, hence a vibrant area of research. Due to short and ambiguity in the user query, retrieving the information as per the intention of user in large volume of web is not straightforward. The ambiguities in queries is due to the short query length, which is on an average is 2.33 times on a popular search engine [1]. In this context, Sanderson [2] reports that 7%-23% of the queries frequently occur in two search engines are ambiguous with the average length one. For e.g. the familiar word Java which is ambiguous as it has multiple senses viz. Java coffee, Java Island and Java programming language etc. In the user query, ambiguities can also exists which do not appear in surface. Because of such ambiguities, search engine generally does not understand in what context user is looking for the information. Hence, it returns huge amount of information, in which most of the retrieved pages are irrelevant to the user. These huge
amount of heterogeneous information retrieve not only increases the burden for search engine but also decreases its performance.

In this paper we propose an approach to improve the effectiveness of search engine by making clusters of word sense based on association concept of data mining, using vector space model of Gensim [6] and the freedictionary [13]. The association concept on which the clusters has formed can be describe as follows. Suppose, if user queried for the word Apple, which is associated in multiple context viz. computer, fruit, company etc. Each of this context associated with Apple is again associate with different word senses viz. computer is associated with the keyboard, mouse, monitor etc. Hence computer can be taken as community vector or cluster whose components/elements are the associated words keyboard, mouse, monitor, etc. Here, each element in the cluster represent the sense of computer vector for apple. So, if a user looking for apple as a computer, s/he may look for ‘apple keyboard’ or ‘apple mouse’ or ‘apple monitor’ etc. We use Minipar [16] to transform a complete sentence into a dependency tree and for the classification of words and phrases into lexical categories.

The paper is organized as follows. In section 2 we examine the related work on the information retrieval based on clustering technique. In section 3 we briefly discuss the Gensim package for the implementation of our approach. In section 4 we present our approach for the effective information retrieval in the context of user query. Section 5 contains analysis of the algorithm. Finally Section 6 is the conclusion of the paper.

2 Related Work

Ranking and Clustering are the two most popular methods for information retrieval on the web. In ranking, a model is designed using training data, such that model can sort new objects according to their relevance’s. There are many ranking models [14] which can be roughly categorized as query-dependent and query-independent models. In the other method i.e. clustering, an unstructured set of objects form a group, based on the similarity among each other. One of the most popular algorithms on clustering is k-means algorithm. However, the problem of this algorithm is that an inappropriate choice of clusters (k) may yield poor results. In case of an ambiguous query, word sense discovery is one of the useful method for IR in which documents are clustered in corpus. Discovering word senses by clustering the words according to their distributional similarity is done by Patrick et al, 2002. The main drawback of this approach is that they require large training data to make proper cluster and its performance is based on cluster centroid, which changes whenever a new web page is added to it. Hence identifying relevant cluster will be a tedious work.

Herrera et al., 2010 gave an approach, which uses several features extracted from the document collection and query logs for automatically identifying the users goal behind their queries. This approach success to classifies the queries into different categories like navigational, informational and transactional (B. J. Jansen et al., 2008) but fails to classify the ambiguous query. As query logs has been used, it may raise privacy concerns as long sessions are recorded and may led to ethical issues surrounding the users data collections. Lilyaa et.al [15] uses statistical relational learning (SRL) for the short ambiguous query based only on a short glimpse of user search activity, captured
in a brief search session. Many research has been done to map user queries to a set of categories (Powell et al., 2003; Dolin et al., 1998; Yu et al., 2001). But all of the above techniques fails to identify the user intention behind the user query.

The Word Sense Induction (Roberto Navigli et.al, 2010) method is a graph based clustering algorithm, in which snippets are clustered based on dynamic and finer grained notion of sense. The approach (Ahmed Sameh et al, 2010) with the help of modified Lingo algorithm, identifying frequent phrases as a candidate cluster label, the snippets are assigned to those labels. In this approach semantic recognition is identified by WordNet which enables recognition of synonyms in snippets. Clusters formation by the above two approaches not contain all the relevant pages of user choice. Our work uses free dictionary and association concept of data mining has been added to our approach to form clusters. Secondly it can handle the dynamic nature of the web as Gensim has been used. Hence the user intention behind the ambiguous query can be identified in simple and efficient manner.

In 2008, Jiyang Chen et. al. purposed an unsupervised approach to cluster results by word sense communities. Clusters are made based on dependency based keywords which are extracted for large corpus and manual label are assigned to each cluster. In this paper we form the community vector and eliminate the problem of manual assignment of the cluster lable. We use Gensim package to avoid the dependency of the large training corpus size [5], and its ease of implementing vector space model (e.g. LSI, LDA).

3 Gensim

Gensim package is a python library for vector space modeling, aims to process raw, unstructured digital texts (“plain text”). It can automatically extract semantic topics from documents, used basically for the Natural Language Processing (NLP) community. Its memory (RAM) independent feature with respect to the corpus size allows to process large web based corpora. In Gensism one can easily plugin his own input corpus and data stream and other vector space algorithms can be trivially incorporated in it.

In Gensim, many unsupervised algorithms are based on word co-occurrence patterns within a corpus of training documents. Once these statistical patterns are found, any plain text documents can be succinctly expressed in the new semantic representation and can be queried for the topical similarity against other documents and so on. In addition it has following salient features

- Straightforward interfaces, scalable software framework, low API learning curve and prototyping.
- Efficient implementations of several popular vector space algorithms, calculation of TF-IDF (term frequency-inverse document frequency), distributed incremental Latent Semantic Analysis, distributed incremental incremental Latent Dirichlet Allocation(LDA).
- I/O wrappers and converters around several popular data formats.
**Vector Space Model:**
In vector space model, each document is defined as a multidimensional vector of keywords in euclidean space whose axis correspond to the keyword i.e., each dimension corresponds to a separate keyword [4]. The keywords are extracted from the document and weight associated with each keyword determines the importance of the keyword in the document. Thus, a document is represented as,

\[ D_j = (w_{1j}, w_{2j}, w_{3j}, w_{4j}, \ldots, w_{nj}) \]

where \( w_{ij} \) is the weight of term \( i \) in document \( j \) indicating the relevance and importance of the keyword.

**TF-IDF Concept:** TF is the measure of how often a word appears in a document and IDF is the measure of the rarity of a word within the search index. Combining TF-IDF is used to measure the statistical strength of the given word in reference to the query. Mathematically,

\[ TF_i = \frac{n_i}{\sum_k n_k} \]

where, \( n_i \) is the number of occurrences of the considered terms and \( n_k \) is the number of occurrences of all terms in the given document

\[ IDF_i = \log \frac{N}{df_i} \]

where, \( N \) is the number of occurrences of the considered terms and \( df_i \) is the number of documents that contain term \( i \).

\[ TF-IDF = TF_i \times \log \frac{N}{df_i} \]

**Cosine Similarity Measure:** It is a technique to measure the similarity between the document and the query. The angle (\( \theta \)) between the document vector and the query vector determines the similarity between the document and the query and it is written as

\[ \cos \theta = \frac{\sum w_{q,j} w_{ij}}{\sqrt{\sum w_{q,j}^2} \sqrt{\sum w_{i,j}^2}} \] \hspace{1cm} (1)

\[ \sqrt{\sum w_{q,j}^2} \] and \[ \sqrt{\sum w_{i,j}^2} \] is the length of the query and document vector respectively.

If \( \theta = 0^o \) then the document and query is similar. As \( \theta \) changes from \( 0^o \) to \( 90^o \), the similarity between the document and query decreases i.e. \( D_2 \) will be more similar to query than \( D_1 \), if the angle between \( D_2 \) and query is smaller than the angle between \( D_1 \) and query.
4 Our Approach

Our approach for an ambiguous query is described below in five steps and depicted in the flow chart (Fig. 1).

1. **Web page extraction and preprocessing:** Submit the ambiguous query to a search engine and extract top \( n \) pages. Preprocess the retrieve corpus as follows:
   - Remove the stop and unwanted words.
   - Select noun as the keywords from the corpus using Minipar [16] and ignore other categories, such as verbs, adjectives, adverbs and pronounce.
   - Do stemming using porter algorithm [12].
   - Save each processed \( n \) pages as documents \( D_k \), where \( k = 1, 2, 3, \ldots, n \).

2. **Document vectors:** Compute TF and IDF score for all the keywords of each \( D_k \) using Gensim and make document vectors of all the retrieved pages.

3. **Cluster formation:** We use the freedictionary with the option **start with** to form the community vector of the queried word as follows
   - Submit the ambiguous query (say apple) to the freedictionary, preprocess the retrieved data i.e. remove the queried, stop & unwanted words. After stemming, save all the noun as keywords \( (W_j) \) in a file \( F_c \), where \( j = 1, 2, 3, \ldots, m \)
   - Now submit each \( W_j \) again to the freedictionary, preprocess the retrieved data and save the noun as keywords along with the queried word in a community file \( F_{W_j} \).
   - Search all the words of \( F_{W_j} \) in \( D_k \) using regular expression search technique.
   - Delete those words in \( F_{W_j} \) which are not present in \( D_k \).
   - \( W_j \) is the formed community vectors (clusters) whose elements are the words saved in the file \( F_{W_j} \)
   - Compute TF-IDF for each word in \( F_{W_j} \) in compare with \( D_k \) to form community vectors.

4. **Similarity check:** Compute the cosine similarities between the formed documents and community vectors using eq. 1.

5. **Assignment of Documents to the Clusters:** Assign the documents to that cluster which has maximum similarity.
5 Test Results

To illustrate our approach we took four sample documents as shown in Table 1. We preprocess the documents and extracted ten keywords (apple, computer, tree, keyboard, mouse, juice, country, vegetables, fruit, monitor) from the sample (Table 2). After assigning a token ID to each selected keyword (Table 3) TF & IDF are computed which is shown in Table 4. In Table 5 computed weight (TF-IDF) of all the four sample documents are given. With the calculated weight and respective token IDs, document vectors are generated (Table 6).

The community vectors are formed as described in the section 4 (Table 7) and the corresponding TF-IDF and weights are calculated (Table 8). Cosine similarity are calculated defined by the eq. 1. Now the similarity between each community vector (C1, C2) and the set of document vectors (D1, D2, D3 and D4) are computed and maximum values of the similarity between community
and document vectors form the cluster. From our experimental result, we found that (D1, D3) and (D2, D4) associated with C1 and C2 respectively i.e. two clusters are generated (Table 9 and 10).

As an example, from the Table 10 we say that if the user search the ambiguous word apple, s/he will get two clusters C1 and C2, containing most relevant documents.

6 Conclusion

For an ambiguous query, we propose an effective approach for the IR by forming the clusters of relevant web pages. For cluster formation we use standard vector space model and the freedictionary. From our approach we find that user intention behind ambiguous query can be identify significantly. This unsupervised approach not only handles the corpus by extracting and analyzing significant terms, but also form desire clusters for real time query. Further we would extend our work for the multi word query and improving these clusters using ranking techniques.

Acknowledgment

We are thankful to Bharat Deshpande and our colleague Aruna Govada and K.V. Santhilata for their useful discussions and valuable suggestions.

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Appendix

| D1 | apple computer released new wireless keyboard and apple trees are more in our country. |
|----|------------------------------------------------------------------------------------|
| D2 | all vegetables trees are different from apple trees.                               |
| D3 | the apple mouse is a multi-button USB mouse manufactured and sold by apple Inc.   |
| D4 | apple as juice or fruit is very tasty and apple launch new LED monitor.            |

Table 1: Sample documents taken for experiment.

| D1 | apple computer keyboard apple tree country                                       |
|----|----------------------------------------------------------------------------------|
| D2 | vegetable tree apple tree                                                         |
| D3 | apple mouse mouse apple                                                           |
| D4 | apple juice fruit apple monitor                                                   |

Table 2: Documents after preprocessing.
| Keyword | Token ID |
|---------|----------|
| apple   | 0        |
| computer| 1        |
| tree    | 2        |
| keyboard| 3        |
| mouse   | 4        |
| juice   | 5        |
| country | 6        |
| vegetable| 7    |
| fruit   | 8        |
| monitor | 9        |

Table 3: Keywords & respective token IDs.

| Keyword | D1 | TF1 | D2 | TF2 | D3 | TF3 | D4 | TF4 | IDF  |
|---------|----|-----|----|-----|----|-----|----|-----|------|
| apple   | 2  | 0.33| 1  | 0.25| 2  | 0.5 | 2  | 0.4 | 0    |
| computer| 1  | 0.16| 0  | 0   | 0  | 0   | 0  | 0   | 0.602|
| tree    | 1  | 0.16| 2  | 0.5 | 0  | 0   | 0  | 0   | 0.301|
| keyboard| 1  | 0.16| 0  | 0   | 0  | 0   | 0  | 0   | 0.602|
| mouse   | 0  | 0   | 0  | 0   | 2  | 0.5 | 0  | 0   | 0.602|
| juice   | 0  | 0   | 0  | 0   | 0  | 0   | 1  | 0.2 | 0.602|
| country | 1  | 0.16| 0  | 0   | 0  | 0   | 0  | 0   | 0.602|
| vegetable| 0  | 0   | 1  | 0.25| 0  | 0   | 0  | 0   | 0.602|
| fruit   | 0  | 0   | 0  | 0   | 0  | 0   | 1  | 0.2 | 0.602|
| monitor | 0  | 0   | 0  | 0   | 0  | 0   | 1  | 0.2 | 0.602|

Table 4: Calculation of TF-IDF for each documents.
| Keyword  | D1          | D2          | D3          | D4          |
|----------|-------------|-------------|-------------|-------------|
| apple    | 0           | 0           | 0           | 0           |
| computer | 0.09632     | 0           | 0           | 0           |
| tree     | 0.04816     | 0.1505      | 0           | 0           |
| keyboard | 0.09632     | 0           | 0           | 0           |
| mouse    | 0           | 0           | 0.301       | 0           |
| juice    | 0           | 0           | 0           | 0.1204      |
| country  | 0.09632     | 0           | 0           | 0           |
| vegetable| 0           | 0.1505      | 0           | 0           |
| fruit    | 0           | 0           | 0           | 0.1204      |
| monitor  | 0           | 0           | 0           | 0.1204      |

Table 5: Weight: TF x IDF.

| Documents | Corresponding Document Vectors                                                                 |
|-----------|-----------------------------------------------------------------------------------------------|
| D1        | [(0, 0), (1, 0.09632), (2, 0.04816), (3, 0.09632), (4, 0), (5, 0), (6, 0.09632), (7, 0), (8, 0), (9, 0)] |
| D2        | [(0, 0), (1, 0), (2, 0.1505), (3, 0), (4, 0), (5, 0), (6, 0), (7, 0.1505), (8, 0), (9, 0)]         |
| D3        | [(0, 0), (1, 0), (2, 0), (3, 0), (4, 0.301), (5, 0), (6, 0), (7, 0), (8, 0), (9, 0)]             |
| D4        | [(0, 0), (1, 0), (2, 0), (3, 0), (4, 0), (5, 0.1204), (6, 0), (7, 0), (8, 0.1204), (9, 0.1204)]   |

Table 6: Representation of document as vectors.
Table 7: Community vectors formed from communities as [ID, Frequency].

| Community Vector | Associated Keywords | [(ID, Frequency)] |
|------------------|---------------------|-------------------|
| Computer (C1)    | computer, keyboard, mouse, monitor | [(1,1), (3,1), (4,2), (9,1)] |
| Fruit (C2)       | fruit, tree, vegetable, juice | [(8,1), (2,3), (7,1), (5,1)] |

| Keyword | C1 | TF C1 | C2 | TF C2 | IDF | Weight = TF × IDF |
|---------|----|-------|----|-------|-----|-------------------|
| apple   | 0  | 0     | 0  | 0     | 0   | 0                 |
| computer | 1 | 0.25  | 0  | 0     | 0.602 | 0.1505          |
| tree    | 0  | 0     | 3  | 0.75  | 0.301 | 0.22575        |
| keyboard | 1 | 0.25  | 0  | 0     | 0.602 | 0.1505          |
| mouse   | 2  | 0.5   | 0  | 0     | 0.602 | 0.301           |
| juice   | 0  | 0     | 1  | 0.25  | 0.602 | 0.1505          |
| country | 0  | 0     | 0  | 0     | 0.602 | 0.1505          |
| vegetable | 0 | 0     | 1  | 0.25  | 0.602 | 0.1505          |
| fruit   | 0  | 0     | 1  | 0.25  | 0.602 | 0.1505          |
| monitor | 1  | 0.25  | 0  | 0     | 0.602 | 0.1505          |

Table 8: TF-IDF calculation for community vector.

| Document/Community | C1     | C2     | Resultant Cluster (Max(C1,C2)) |
|--------------------|--------|--------|--------------------------------|
| D1                 | 0.41939| 0.18165| C1 (Computer)                  |
| D2                 | 0.0    | 0.77149| C2 (Fruit)                     |
| D3                 | 0.75593| 0.0    | C1 (Computer)                  |
| D4                 | 0.21828| 0.5041 | C2 (Fruit)                     |

Table 9: Similarity between each community and document is tabulated.

| Query (apple) | Community (sense) | Cluster |
|---------------|-------------------|---------|
| Cluster 1     | Computer          | D1, D3  |
| Cluster 2     | Fruit             | D2, D4  |

Table 10: Final clustering of relevant documents.