

# Intelligent Query Expansion for the Queries Including Numerical Terms

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## Abstract

Generally the query input by a user contains terms that do not match those terms which are used to index the majority of the relevant documents. Sometimes the unretrieved relevant documents are indexed by a different set of terms than those in the query. In order to solve this problem it is necessary to modify the user's query. To do so the researchers have proposed query expansion to help the user to formulate what information is actually needed. For nonnumeric terms researchers purposed many good solutions but as numerical values do not have any synonyms or stemming words, previous approaches were restricted to match the document exactly to the numerical terms that were present in the query. The method presented in this paper searches for the approximate matching of numerical terms also. The method uses fuzzy weighing of query terms with the help of fuzzy triangular membership function.

**Keywords:** Fuzzy Membership Function, Information Retrieval, Numerical Terms, Query Expansion, Term-Weighting

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## 1. Introduction

For the information retrieval problem, many fuzzy query expansion methods have been studied for a long time. These methods include fuzzy term weighing, fuzzy inference rules, conceptual graphs, generation of fuzzy sets, fuzzy clustering techniques etc. These methods identify terms which are approximately related to query terms for query expansion. Such terms might be synonyms, related concepts, stemming variations or terms which are close to query terms in the text. Unfortunately these methods fail to identify terms which are close to numerical terms present in the query as numerical terms do not have any synonyms or stemming variations. Many times a user query may include numerical terms so in this context the query may be upgraded so that the results are generated over a range of numerical data. This can be done if search documents contain the results from approximate matching of numerical terms. Here, we propose a method through which results will be retrieved ranked on the basis of decreasing level of approximation to the numerical terms mentioned in the query. Our method looks for documents on the basis of a numerical range that is close to the numerical term present in the query. If the numerical value goes far away from the numerical term, its weight decreases and if the numerical value comes close to the numerical term, its

weight increases. We make use of fuzzy triangular membership function in our method.

The rest of this paper is organized as follows. In section 2, the related work is mentioned. In section 3, we discuss the basics of Fuzzy triangular Membership function. The next section discusses the basics of Fuzzy Query Term Weighing technique for information retrieval. In section 5, the proposed query expansion for numerical data range is explained. At last we conclude the paper.

## 2. Related Work

Popular query expansion techniques includes global analysis, association rule based, local analysis, global clustering, user query logs based etc.

In5, Roberto Navigli, Giuseppe Crisafulli proposed a word sense induction method that first acquires the meanings of query by means of graph based clustering and then clusters the results based on their semantic similarity. M. J. Martin Bantista, D. Sanchez, et al used fuzzy association rules for query refinement. From an initial set of documents text transactions and association rules were constructed which were used to determine the presence of a term in documents with a value between 0 and 16.

In7 K. Lee, W. Bruce Croft and James Allan presented a cluster-based re-sampling method to select better pseudo-relevant documents based on the relevance model. The method used document clusters to find dominant documents for the initial retrieval set, and then repeatedly feed the documents to emphasize the core topics of a query. S. Riezler, Y. Liu in<sup>8</sup> discussed approaches to process long queries. These methods deployed user query logs to rewrite the query terms into terms from document space using the statistical properties of terms.

Latent Semantic Indexing (LSI)<sup>9</sup> is similar to vector retrieval method in which the dependencies between terms are taken into consideration by modeling all the interrelationships among terms and documents during retrieval. Technology of semantic thesauri proposed by Yufeng Jing and W. Bruce Croft<sup>10</sup> construct a set of words along with a set of relations between these words. However, these techniques lead to large calculations and lowers query efficiency because of word ‘co-occurrence calculation.’

The conceptual graph is used as one of knowledge representation tools. H. Chen, K. J. Lynch proposed a way of regarding concept (keywords or terms) as a node to represent the relationship among concepts<sup>11</sup>. C. Y. Ng proposed an improved algorithm for constructing concept space in 2001<sup>12</sup>. The algorithm included only strong associations and employed various pruning techniques to avoid computation of weak associations. Query reformulation first expands the initial query with new terms and then reweighs the terms in the expanded query. Thus, the automatic query reformulation methods improve the initial queries through query expansion and term weighing. However, they do not rely on users to make relevance judgments<sup>13</sup>. They are often based on concept based retrieval<sup>14</sup>, language analysis<sup>15</sup>, term co-occurrences, PRF<sup>1</sup>. Kim et al. in<sup>18</sup> proposed a query term expansion and reweighting method which considers the term co-occurrence within the feed backed documents.

Jung et al. proposed a terms weighting scheme<sup>16</sup> which considers “absence terms” along with “occurrence terms”, in finding the degrees of similarity among document descriptor vectors, in which the “absence terms” means terms which are not present in a specific document and they are provided negative weights rather than assigning zero weights. Klink proposed an automatic reformulation method for improving the original query<sup>17</sup>. As user enters the query in natural language and natural language always contains impreciseness, here we used fuzzy logic. To formulate this concept we use fuzzy triangular membership function as this is the simplest and widely used. Generally user’s queries uses natural language and natural language contains lots of impreciseness, so in this paper fuzzy logic is used. We use fuzzy triangular membership function as this is the simplest and widely used.

### 3. Fuzzy Triangular Membership Function

In fuzzy sets, each element is mapped to [0, 1] by a membership function. It represents the degree of truth as an extension of valuation. Membership function is given by:

$$\mu_A : X [0,1] \quad (1)$$

where, [0, 1] means real numbers between 0 and 1 (including 0 and 1)<sup>4</sup>.

The triangular membership function is one of the most popular membership functions used. It is given by the following representation of membership values<sup>4</sup>.

0, x a<sub>1</sub>

$$\mu_{(A)}(X) = \frac{a_3 - x}{a_3 - a_2}, \quad a_2 < x < a_3 \quad (2)$$

0, X a<sub>3</sub>

Where, x is a value between a<sub>1</sub> and a<sub>3</sub>, whose membership needs to be calculated between 0 and 1. Figure 1 shows the graphical representation of triangular fuzzy function.

Thus, every numerical value between a<sub>1</sub> and a<sub>3</sub> can be mapped to a membership value between 0 and 1 using equation 1. From Figure 1 it is clear that the maximum membership lies at a<sub>2</sub> with value 1.

### 4. Fuzzy Weighted Query Method

In the weighted query method, the weight w<sub>ik</sub> of a term t<sub>i</sub> in document d<sub>k</sub> and the weight w<sub>iq</sub> of a term t<sub>i</sub> in the user query Q are calculated as follows<sup>3</sup>.

$$W_{ik} = \frac{tf_{ik}}{\max tf_{ik}} \times IDF_i \quad (3)$$

$$W_{iq} = (0.5 + 0.5 \times \frac{tf_{iq}}{\max tf_{iq}}) \times IDF_i$$

Where,  $tf_{ik}$  denotes the occurrence frequency of term t<sub>i</sub> in document d<sub>k</sub> and  $tf_{iq}$  denotes the occurrence frequency of term t<sub>i</sub> in the user’s query Q. IDF is the inverse document frequency of a term t<sub>i</sub><sup>1</sup>.

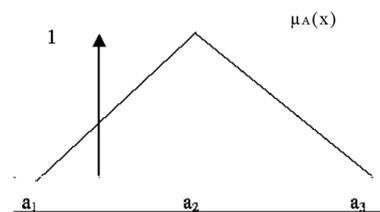


Figure 1. Triangular fuzzy function.

The calculation of the degree of similarity  $S(Q, dk)$  between the user's query vector  $Q$  and the document vector  $dk$  is as follows:

$$S(Q, d_k) = \frac{1}{s} \sum_{i=1}^s |w_{iq} - w_{ik}| \quad (4)$$

$Q = \langle w_1q, w_2q, \dots, w_sq \rangle$ ,  $w_{iq}$  denotes the weight of a term  $t_i$  in user query,

$dk = \langle w_1k, w_2k, \dots, w_sk \rangle$ ,  $w_{ik}$  denotes the weight of a term  $t_i$  in document  $d_k$ ,  $s$  denotes total number of terms in user query.

The system translates the original query terms into term weights based on calculated  $IDF^1$  and formula (3) and uses fuzzy rules to infer the weights of additional terms, and then these weights form a query vector  $Q$ . The system ranks documents according to their degrees of similarity with respect to the user's query using formula (4) and let the user browse the top  $n$  documents.

## 5. Proposed Query Expansion Method

In this section, we propose a new query expansion method that retrieves documents ranked on the basis of decreasing level of approximation to the numerical terms mentioned in the query. We make use of fuzzy triangular membership function to assign weights to the documents having approximate numerical range.

We will use the following notations in our query expansion method:

- 'q' represent all the terms present in the query,
- 'ti' represent non-numerical terms present in query,
- 'tj' represent numerical terms present in query, Thus,  $q = t_i + t_j$
- $v_j$  = Threshold used to determine numerical range around the numerical term present in the query  $t_j$  ( $v_j$  may be calculated as 10-15% of the numerical term present in query depending on the application).

Figure 2 represents the documents that contains the numerical terms close to  $t_j$  will have higher rank over the documents that contains numerical terms far from  $t_j$ . Now the query will run for a range of numerical values associated with weights between 0 and 1. The numerical value present in the query ( $t_j$ ) is assigned highest weight i.e. 1.

The proposed method uses the following algorithm for document retrieval.

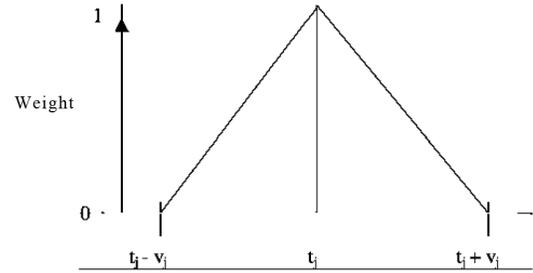


Figure 2. Fuzzy membership function for term  $t_j$ .

### 5.1 Algorithm

**Step 1: Separating the numerical and non-numerical terms:** We can make use of a data processing tool to extract the numerical terms ( $t_j$ ) and non-numerical terms ( $t_i$ ) from the submitted query.

**Step 2: For each numerical term in the given query, derive the appropriate numerical range for which the query needs to be run:** Once we have the numerical terms we find a range of numerical values using a threshold ' $v_j$ '. Our method will search for all those documents having numerical values that fall in numerical range starting from values  $t_j - v_j$  and extending up to values  $t_j + v_j$  that are associated with assigned weight.

We would only be considering integer numerical values in this range. Thus we will have  $(2v_j + 1)$  numerical values for each numerical term present in the query.

**Step 3: Assigning weights  $(w_{njkg})$  to the numerical range generated in step2:** Using fuzzy triangular membership function as explained, the numerical terms generated for each numerical term ( $t_j$ ) in step 1 are assigned weights between 0 and 1. The pseudo-code for step 2 is given below.

*Pseudo Code for assigning weights to generated numerical terms,*

- Let ' $t_j$ ' be a numerical value mentioned in the query.
  - Taking Threshold ' $v_j$ ', the numerical range is from  $(t_j - v_j)$  to  $(t_j + v_j)$  which consist of  $(2v_j + 1)$  values.
  - For each numerical value ' $x$ ' less than equal to  $(t_j - v_j)$  Assign weight  $[x] = 0$
  - For each numerical value ' $x$ ' greater than  $(t_j - v_j)$  and less than equal to  $t_j$  Assign weight  $[x] = \frac{(t_j - x)}{v_j}$
  - For each numerical value ' $x$ ' greater than  $t_j$  and less than  $(t_j + v_j)$  Assign weight  $[x] = \frac{(t_j + v_j) - x}{v_j}$
  - For each numerical value ' $x$ ' greater than equal to  $(t_j + v_j)$  Assign weight  $[x] = 0$
- ion model is shown in Figure 1.

Now we assigned weights to each numerical value present in the generated numerical range. Considering that each numerical term ( $t_j$ ) in the query will be associated with a range of 'k' numerical values, we represent the weight of  $k$ th element of  $j$ th numerical term in the query by  $w_{nj,k,q}$ .

**Step 4: Finding relevant documents based on non-numerical component of query and numerical range generated in step 2 using fuzzy weighing of query terms:** Step 3 gives a range of weighted numerical data values ( $w_{nj,k,q}$ ). The weights assigned to each numerical term falls between 0 and 1. Now for query expansion we follow the given steps:

- (i) Assign weights to non- numerical terms ( $t_i$ ) in the user query using weighted query method as explained in section 4. We represent these non-numerical term weights by  $w_{nniq}$ . The weight  $w_{nniq}$  of a non- numeric term  $t_i$  in the user query  $Q$  is calculated as<sup>3</sup>:

$$W_{miq} = \left( 0.6 + 0.6 \times \frac{tf_{iq}}{\max tf_{iq}} \right) \times IDF \tag{5}$$

Where,  $tf_{iq}$  denotes the occurrence frequency of term  $t_i$  in the user's query  $Q$ .

IDF is the inverse document frequency of a term  $t_i$ <sup>1</sup>.

- (ii) Assign weights to both numerical terms ( $t_i$ ) and non-numerical terms ( $t_j$ ) in the documents. The weight  $w_{ik}$  of term  $t$  (numeric as well as non- numeric) in document  $d_k$  is calculated as:

$$W = \frac{x}{\max} \times IDF_i \tag{6}$$

Where,  $tf_{ik}$  denotes the occurrence frequency of term  $t$  in document  $d_k$ .

IDF is the inverse document frequency of a term  $t$ <sup>1</sup>.

- (iii) Calculate the degree of similarity  $S(Q, d_k)$  between the user's query vector  $Q$  and the document vector  $d_k$  is as follows:

$$\overline{S(Q, d_k)} = \frac{\sum_{i=1}^s 1 - |w_{iq} - w_{ik}|}{s} \tag{7}$$

Where,  $S(Q, d_k) \in [0, 1]$ ,

$Q = \langle w_{1q}, w_{2q}, \dots, w_{sq} \rangle$ ,  $w_{iq}$  denotes the weight of a term  $t$  in user query,

$w_{iq}$   $w_{nniq}$  for a non- numeric term using equation 5,

$w_{iq}$   $w_{nj,k,q}$  for a numeric term as generated in step 2

$d_k = \langle w_{1k}, w_{2k}, \dots, w_{sk} \rangle$ ,  $w_{ik}$  denotes the weight of a term  $t$  (numeric as well as non- numeric) in document  $d_k$  using equation 6,  $s$  denotes total number of terms (numeric as well as non-numeric) in user query.

Figure 4 gives the step by step illustration of complete query expansion process.

Now we will explain the proposed method with the help of an example.

## 5.2 Intelligent Query Expansion Example

We illustrate our algorithm taking an example of a potential buyer looking for mobile phones over internet. Let us consider the search query to be "Mobile Phones around price 10000". The query terms are "Mobile", "Phones", "around", "price", "10000". Applying only term weighing technique would look for these terms, their synonyms and stemming words. However, from the method purposed it is clear that, the user intends to extend his search over a price range around Rs. 10000/-.

Finding range based on threshold  $v_j$ . We will get  $(2v_j + 1)$  numerical values for each numerical term present in the query. Let  $v_j$  be (10% of 10000) in this example which is 1000. Thus our numerical search ranges from 9000 (10000-1000) to 11000 (10000+1000) i.e. 2001 numerical values.

Assigning weights to the numerical query range using fuzzy triangular function. The triangular membership graph for this range is shown below

Thus,

- The documents holding numerical values less than or equal to 9000 will be assigned the smallest weight value as 0.
- The weights assigned to these 2001 numerical values can be calculated as (using equation 1):

$$\text{weight}(9001) = \frac{9001 - 9000}{10000 - 9000} = 0.001,$$

$$\text{weight}(9002) = \frac{9001 - 9000}{10000 - 9000} = 0.002,$$

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$$\text{weight}(9500) = \frac{9500 - 9000}{10000 - 9000} = 0.5,$$

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.....

$$\text{weight}(10000) = \dots\dots\dots = 1.0$$

$$\text{weight}(10001) = \frac{11000 - 10001}{11000 - 10000} = 0.999,$$

$$\text{weight}(10002) = \frac{11000 - 10002}{11000 - 10000} = 0.998,$$

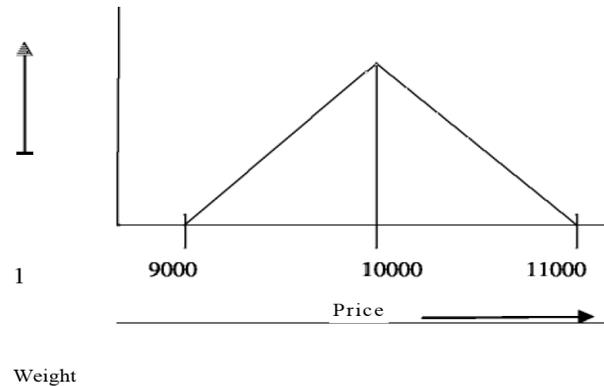
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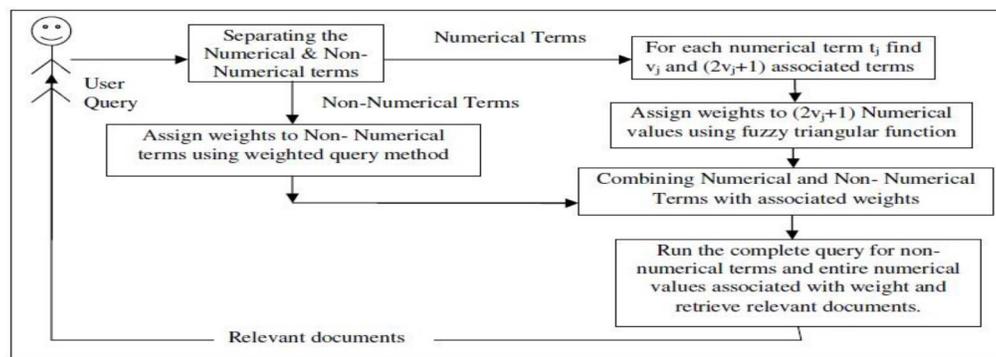
$$\text{weight}(10800) = \frac{11000 - 10800}{11000 - 10000} = 0.2,$$

.....

$$\text{weight}(11000) = \dots\dots\dots = 0.0$$



**Figure 3.** Fuzzy membership function for the example.



**Figure 4.** Proposed Query Expansion Process.

Now we combine the numerical and non- numerical terms and expand the query using fuzzy weighted technique. The weights for non- numerical terms are calculated using equation 5. The weights for numerical terms are calculated in step 2. Now using equation 7, the similarity of terms in query and document are calculated and relevant ranked documents are retrieved.

## 6. Conclusion

In this paper, an intelligent method for query expansion is presented that expands the query based on non-numerical as well as numerical terms present in the query. The proposed method is an improvement over traditional query expansion techniques that were restricted to match the document exactly to the numerical terms that were present in the query. This method searches for the approximate matching of numerical terms. So, it is more efficient for queries involving numerical terms. The approximated numerical range associated with weights between 0 and 1 is generated using fuzzy triangular membership function and then the query is expanded using fuzzy query weighing technique. Thus, the proposed method improves the retrieval accuracy and user satisfaction for the queries having numerical terms.

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Author of a paper had no conflict neither financially nor academically.