

AN ALGORITHM TO SELF-EXTRACT SECONDARY KEYWORDS AND THEIR COMBINATIONS BASED ON ABSTRACTS COLLECTED USING PRIMARY KEYWORDS FROM ONLINE DIGITAL LIBRARIES

Natarajan Meghanathan¹, Nataliya Kostyuk², Raphael Isokpehi² and Hari Cohly²

¹Department of Computer Science, ²Department of Biology, Jackson State University,
1400 John Lynch St, Jackson, MS 39217, USA
natarajan.meghanathan@jsums.edu

ABSTRACT

The high-level contribution of this paper is the development and implementation of an algorithm to self-extract secondary keywords and their combinations (combo words) based on abstracts collected using standard primary keywords for research areas from reputed online digital libraries like IEEE Explore, PubMed Central and etc. Given a collection of N abstracts, we arbitrarily select M abstracts ($M \ll N$; M/N as low as 0.15) and parse each of the M abstracts, word by word. Upon the first-time appearance of a word, we query the user for classifying the word into an Accept-List or non-Accept-List. The effectiveness of the training approach is evaluated by measuring the percentage of words for which the user is queried for classification when the algorithm parses through the words of each of the M abstracts. We observed that as M grows larger, the percentage of words for which the user is queried for classification reduces drastically. After the list of acceptable words is built by parsing the M abstracts, we now parse all the N abstracts, word by word, and count the frequency of appearance of each of the words in Accept-List in these N abstracts. We also construct a Combo-Accept-List comprising of all possible combinations of the single keywords in Accept-List and parse all the N abstracts, two successive words (combo word) at a time, and count the frequency of appearance of each of the combo words in the Combo-Accept-List in these N abstracts.

KEYWORDS

Self-Extraction, Abstracts, Secondary Keywords, Combo Keywords, Frequency, Training

1. INTRODUCTION

Each research area has its own set of keywords that need to be used to extract relevant documents of interest. This often requires the help of human subject matter experts who list the set of keywords that can be used for document search in a research area. However, with rapid evolution of different fields of research, it becomes inevitable to automate the process of identifying keywords based on the abstracts and publications available for specific research areas, rather than relying on availability of human experts. In this paper, we develop an algorithm to for self-extracting secondary keywords and their combinations, referred to as combo words, based on abstracts that have been collected from online digital libraries using standard primary keywords. Our proposed algorithm efficiently parses a randomly selected subset of the collection of abstracts and uses the list of acceptable single keywords, formed through the training, to count the frequency of these single secondary keywords and their combo words in all of the abstracts. The acceptable list of single secondary keywords is constructed by parsing the randomly selected abstracts, word by word, and querying the user whether to accept

or not accept a word when seen for the first time. As we parse through more abstracts, we observe that the number of times the user is queried for classification reduces drastically.

The identification of most commonly used unique secondary keywords and their combo words will aid in the efficient search and filtering of the vast amount of information (like abstracts and publications) available for specific research areas in well-known online digital libraries. Eventually, our proposed approach can be used in the construction of an ontology tree of keywords for specific research areas. The rest of the paper is organized as follows: In Section 2, we describe in detail the algorithm for self-extraction of secondary keywords and their combo words. Section 3 presents the evaluation of the proposed algorithm and the results obtained for the frequency distribution of secondary keywords and their combo words in the following three research areas: Sensor Networks, Autism and Language Development, Autism and Genetics. Section 4 lists related work. Section 5 concludes the paper and also lists our future research direction.

2. ALGORITHM TO SELF-EXTRACT KEYWORDS

The proposed algorithm first constructs an acceptable list of secondary keywords (*Accept-List*) by parsing M randomly selected abstracts out of the total of N abstracts collected for a specific research area from online digital libraries. The algorithm operates using two datasets: a set of acceptable keywords (referred to as *Accept-List*) and a set of non-acceptable words (referred to as *Non-Accept-List*). Initially both these datasets are empty. We parse each of the M abstracts, word by word. If a word parsed by the algorithm is neither in the *Accept-List* nor in the *Non-Accept-List*, we ask the user to classify the word into one of these two lists. The word is appropriately appended to either of the two lists selected by the user. If the algorithm encounters a word that is already in one of the two lists, then the user is not queried again. After the set of acceptable words is built by parsing the M abstracts, we now parse all the N abstracts, word by word, and count the frequency of appearance of each of the words in *Accept-List* in these N abstracts. If an acceptable word appears in an abstract, we increment its frequency counter by one, irrespective of the number of times the word appears in the abstract. The algorithm outputs the secondary keywords from the *Accept-List* in the decreasing order of the frequency of appearance of the words in the N abstracts. The pseudo code for returning the frequency of appearance of the secondary keywords is illustrated in Figure 1. We also construct a *Combo-Accept-List* comprising of all possible combinations of the single keywords in *Accept-List* and parse all the N abstracts, two successive words (combo word) at a time, and count the frequency of appearance of each of the combo words in *Combo-Accept-List* in these N abstracts. The pseudo code for returning the frequency of appearance of the secondary combo keywords is illustrated in Figure 2.

Input: Set A – set of abstracts in text format; total number of abstracts $N = |A|$

M – size of the training set of abstracts

Separator-List = { , . ; - ' < > () [] / " : }

Auxiliary Variables: Training-Set TS – set of M abstracts randomly selected from A ; $TS \subseteq A$

Accept-List – set of keywords acceptable as secondary keywords

Non-Accept-List – set of words not acceptable as secondary keywords

User-Choice = {0 or 1} for a word

Already-Accounted-Words – set of keywords in *Accept-List* already accounted for their presence in a particular abstract

Output: Set *Freq-Sec-KW* – set storing the frequency of appearance of each word in the *Accept-List* in the decreasing order of the frequency of their appearance in the N abstracts

Initialization: $Accept-List \leftarrow \Phi$
 $Non-Accept-List \leftarrow \Phi$
 $Training-Set TS \leftarrow \Phi$

Begin *Self-Extract-Key-Words*

// Form the training set of abstracts

```
1  while ( $|TS| < M$ ) do
2    Generate a random integer  $m \in [1 \dots N]$ 
3    if  $A[m] \notin TS$  then
4       $TS \leftarrow TS \cup A[m]$ 
5    end if
6  end while
```

// Build the *Accept-List* and *Non-Accept-List*

```
7  for every abstract  $P \in TS$  do
8    for every word  $W \in P$  do
9      if  $W \notin Separator-List$  then
10     if  $W \notin Accept-List$  AND  $W \notin Non-Accept-List$  then
11        $User-choice \leftarrow$  Ask user to enter 0 to put the word in Non-Accept-List or 1 for
           Accept-List
12       if  $User-choice = 1$  then
13          $Accept-List \leftarrow Accept-List \cup \{W\}$ 
14       else
15          $Non-Accept-List \leftarrow Non-Accept-List \cup \{W\}$ 
16       end if
17     end if
18   end if
19 end for
20 end for
```

// Count the frequency of appearance of the words in *Accept-List*

```
21 for every word  $W \in Accept-List$ 
22    $Freq-Sec-KW(W) \leftarrow 0$ 
23 end for
24 for every abstract  $Q \in A$  do
25    $Already-Accounted-Words \leftarrow \Phi$ 
26   for every word  $W \in Q$  do
27     if  $W \notin Separator-List$  AND  $W \notin Non-Accept-List$  then
28       if  $W \notin Already-Accounted-Words$  AND  $W \in Accept-List$  then
29          $Freq-Sec-KW(W) \leftarrow Freq-Sec-KW(W) + 1$ 
30          $Already-Accounted-Words \leftarrow Already-Accounted-Words \cup \{W\}$ 
31       end if
32     end if
33   end for
34 end for
```

35 **Sort** the words in *Freq-Sec-KW* in the decreasing order of the frequency of appearance of the secondary keywords

return *Freq-Sec-KW*

End Self-Extract-Key-Words

Figure 1: Algorithm to Self-Extract Single Secondary Keywords

Input: *Accept-List* // list of acceptable keywords
 Set *A* – set of abstracts in text format; total number of abstracts $N = |A|$
Separator-List = { , . ; - ' < > () [] / " ' : }

Auxiliary Variables: *Already-Accounted-Combo-Words* – set of keywords in *Accept-List* already accounted for their presence in a particular abstract
Combo-Accept-List // list of acceptable combinations of keywords

Output: Set *Freq-Comb-Sec-KW* // – set storing the frequency of appearance of combination of any two keywords in the *Accept-List* in the decreasing order of the frequency of their appearance in the N abstracts

Initialization: *Combo-Accept-List* $\leftarrow \Phi$

Begin Self-Extract-Combo-Key-Words

// Build the *Combo-Accept-List*

```

1  for every index  $i \in [0 \dots |Accept-List|-1]$  do
2    for every index  $j \in [i+1 \dots |Accept-List|]$  do
3       $W1 \leftarrow Accept-List[i]$ 
4       $W2 \leftarrow Accept-List[j]$ 
5       $W12 = W1 W2$ 
6       $W21 = W2 W1$ 
7       $Combo-Accept-List = Combo-Accept-List \cup \{W12\}$ 
8       $Combo-Accept-List = Combo-Accept-List \cup \{W21\}$ 
9    end for
10 end for

```

// Count the frequency of appearance of combination of keywords in *Combo-Accept-List*

```

11 for every combo word  $W_{ij} \in Combo-Accept-List$ 
12    $Freq-Combo-Sec-KW(W_{ij}) \leftarrow 0$ 
13 end for
14 for every abstract  $Q \in A$  do
15   Already-Accounted-Combo-Words  $\leftarrow \Phi$ 
16   for every combo word  $W \in Q$  do
17     if  $W \notin Separator-List$  AND  $W \in Combo-Accept-List$  then
18       if  $W \notin Already-Accounted-Combo-Words$  then
19          $Freq-Combo-Sec-KW(W) \leftarrow Freq-Combo-Sec-KW(W) + 1$ 
20         Already-Accounted-Combo-Words  $\leftarrow Already-Accounted-Combo-Words \cup \{W\}$ 
21       end if
22     end if
23   end for
24 end for

```

25 **Sort** the words in *Freq-Combo-Sec-KW* in the decreasing order of the frequency of appearance of the combination of secondary keywords

return *Freq-Combo-Sec-KW*

End *Self-Extract-Combo-Key-Words*

Figure 2: Algorithm to Self-Extract Combo Words (Combinations of Secondary Keywords)

3. ALGORITHM EVALUATION AND RESULTS

We implemented the proposed algorithm in Java. We selected the following three research areas for testing our algorithm: (i) Sensor Networks – SN, (ii) Autism and Language Development – ALD and (iii) Autism and Genetics – AG. We used the well-known digital libraries like IEEE Explore (for Sensor Networks) [1] and PubMed (for Autism and Language Development; Autism and Genetics) [2] for collecting the abstracts. For each of these research areas, we collected $N = 100$ abstracts and constructed the *Accept-List* by letting $M = 15, 30$ and 50 abstracts. After the construction of the *Accept-List* for a particular value of M , we parsed all the N abstracts and counted the frequency of appearance of each of the keywords in *Accept-List*, in each of the N abstracts. Also, for each value of M , we constructed a *Combo-Accept-List* comprising of all possible combinations of the single keywords in *Accept-List* and parsed all the N abstracts, two successive words (combo word) at a time, and counted the frequency of appearance of each of the combo words in the *Combo-Accept-List* in these N abstracts. While computing the frequency distribution, a keyword in the *Accept-List* is counted only once for an abstract, even though the keyword may appear more than once. The same rule is applied while computing the frequency of the combo words. In other words, the frequency of appearance of a keyword and a combo word can be at most N , the total number of abstracts parsed.

3.1 Effectiveness of the Training Approach

The effectiveness of our training approach is measured by measuring the percentage of words for which the user is queried for classification when the algorithm parses through the words of each of the M abstracts. For each of the three research areas, we observed that as M grows larger, the percentage of words for which the user is queried for classification reduces drastically. This is illustrated through Figures 3.1, 3.2 and 3.3. We notice in these three figures that the slope of the trend line for all the three sets of abstracts decreases drastically as M grows from small to moderate values. As M grows from moderate to larger values, the trend line becomes flat (i.e., slope equals 0), indicating that smaller to moderate values of M is sufficient to construct the *Accept-List*.

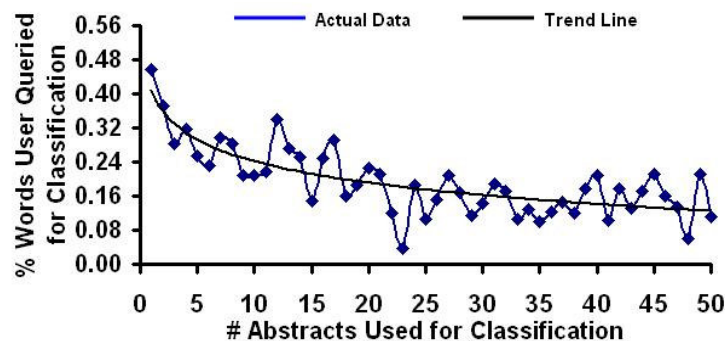


Fig 3.1: Results for Sensor Networks

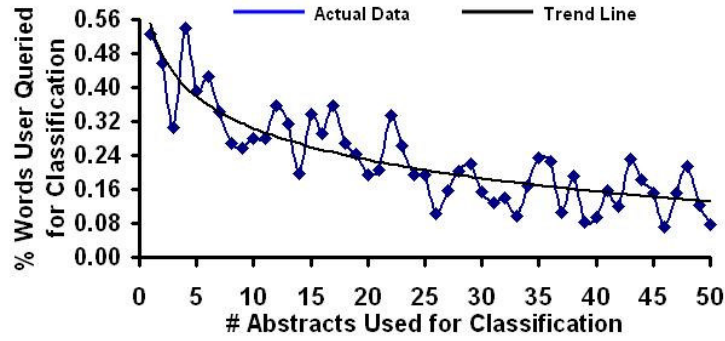


Fig 3.2: Results for Autism and Language Development

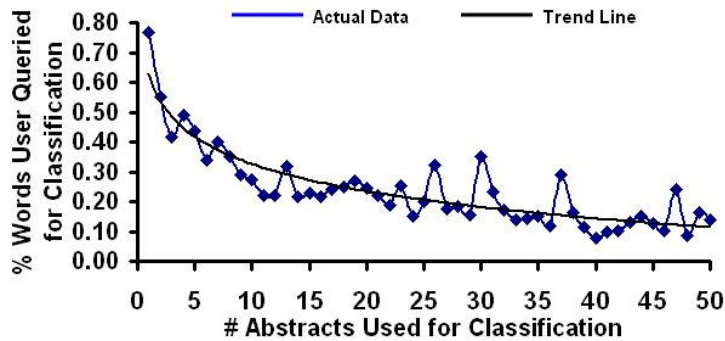


Fig 3.3: Results for Autism and Genetics

Figure 3: Percentage of Words the Self-Extraction Algorithm Queries the User for Classification Vs the Number of Abstracts Used for Classification

Table 1: Top 15 Single Keywords and Top 15 Combo Words of Single Keywords Extracted from IEEE Abstracts with the Search String: “Wireless Sensor Networks”

#	Top 15 Single Keywords	Freq	Top 15 Combo Words of Single Keywords	Freq
1	Node	65	Routing Protocol	16
2	Wireless	64	Ad hoc	15
3	Application	59	Wireless Communication	8
4	Base	48	Energy Consumption	7
5	Design	43	Environmental Monitoring	7
6	Protocol	41	Power Consumption	6
7	Data	40	Sensing Computation	5
8	Energy	38	Real time	5
9	Communication	38	Malicious Attack	5
10	Deploy	37	Battery Power	5
11	System	36	Sink Node	4
12	Performance	35	Layer Protocol	4
13	Simulation	35	MAC Layer	4
14	Computation	32	Data Fusion	4
15	Time	30	Topology Control	4

3.2 Frequency of Appearance of the Secondary Keywords and their Combo Words

We noticed that the frequency of appearance of the top 15 keywords and the top 15 combo words of these secondary keywords in the N=100 abstracts for a specific research area remains the same for different values of M with a confidence interval above 95%. Hence, the data presented in Tables 1, 2 and 3 illustrate the frequency of appearance of the secondary keywords and their combo words obtained for $M = 15$. The results are the same for $M = 30$ and $M = 50$ randomly selected abstracts.

Table 2: Top 15 Single Keywords and Top 15 Combo Words of Single Keywords Extracted from PubMed Abstracts with the Search String: “Autism and Language Development”

#	Top 15 Single Keywords	Freq	Top 15 Combo Words of Single Keywords	Freq
1	Disorder	69	Autism Spectrum Disorder	49
2	Children	69	Development Disorder	14
3	Spectrum	51	Social Interaction	14
4	Age	46	Young Child	13
5	Behaviour	43	Language Impairment	11
6	Social	43	Development Delay	11
7	ASD	39	Pervasive Development	9
8	Diagnosis	35	PDD nos	7
9	Assessment	32	Impairment SLI	7
10	Communication	31	Receptive Language	7
11	Function	31	ASD Group	7
12	Cognition	30	Language Ability	7
13	Association	29	Language Disorder	7
14	Clinical	29	Verbal IQ	6
15	Delay	27	Social Behaviour	6

Table 3: Top 15 Single Keywords and Top 15 Combo Words of Single Keywords Extracted from PubMed Abstracts with the Search String: “Autism and Genetics”

#	Top 15 Single Keywords	Freq	Top 15 Combo Words of Single Keywords	Freq
1	Disorder	75	Autism Spectrum Disorder	32
2	Association	53	Mental Retardation	20
3	Phenotype	37	Neurodevelopment Disorder	13
4	Spectrum	36	X Syndrome	9
5	Syndrome	33	Nucleotide Polymorphism	9
6	Patient	31	Bipolar Disorder	8
7	Family	31	Risk Factor	6
8	Behavior	30	Hyperactivity Disorder	6
9	Neuron	29	Gene Expression	6
10	Genome	28	Binding Protein	5
11	Clinical	28	Gene Factor	5
12	Cause	28	Molecular Gene	5
13	Control	26	Deficiency Hyperactivity	5
14	Mental	25	Psychiatric Disorder	5
15	Chromosome	24	Chromosome Abnormality	5

4. RELATED WORK

In [3], a model for extracting keywords from abstracts and titles was proposed and tested on a set of abstracts of academic papers containing keywords composed by their authors. However, this model does not adopt an effective training module to build a list of acceptable keywords and lacks the ability to prioritize the keywords based on their frequency of appearance in the abstracts. In [4], the authors presented a model for automatic annotation of protein functions based on biological information directly extracted from MEDLINE [5] abstracts. However, unlike our proposed algorithm in this paper, the model proposed in [4] is not generic and has been developed to specifically extract domain-specific information from the analysis of a set of protein families.

Usui et. al [6] developed a tool to customize the index tree of different Neuroinformatics platforms by allowing a user to recognize the most relevant terms and easily incorporate the preferred terms over the list of suggested terms. However, this model is too memory consuming as it requires the use of a large two-dimensional matrix whose row index represents the keywords, filtered after stop word removal and stemming, column index corresponds to the documents and the entries in the matrix correspond to the number of times each keyword appears in a document. Also, the list of keywords returned by their model is hypothetical and heavily depends on the weighting scheme used to prioritize the entries in the matrix. On the other hand, our proposed algorithm uses a simple single-dimension list, *Accept-List*, of keywords formed through linear parsing of the abstracts. Also, we exclusively rely on counting the frequency of appearance of the acceptable list of secondary keywords in the entire set of abstracts collected for a specific research area.

5. CONCLUSIONS AND FUTURE RESEARCH DIRECTION

The proposed algorithm can be used to efficiently extract secondary keywords based on abstracts collected using the names of the specific research areas as the primary keywords from online digital libraries. The algorithm works with abstracts as text files and parses the abstracts word by word using pre-defined separator lists. The effectiveness of our training approach to build the acceptable list of secondary keywords is vindicated by the exponential decreasing trend of the percentage number of words for which the user is queried for classification, as we increase the number of abstracts used for training. For each of the three research areas explored in this paper, we observed that a mere 15% of abstracts randomly selected from the set of all abstracts are sufficient to effectively identify and rank the secondary keywords and their combo words. The algorithm builds the acceptable list on a randomly generated subset of the collection of abstracts and hence the secondary keywords extracted are representative of the entire research area. The top 15 secondary keywords and their combo words listed in Tables 1, 2 and 3 are widely used terminologies and words in the specific research areas. The application of the algorithm has been tested for two widely different domains of research: Sensor Networks and Autism.

In the near future, we plan to use the algorithm to construct an ontology tree and directed acyclic graph of keywords for different research areas and this can be used for efficient literature search and effective retrieval of documents from online digital libraries that store vast amount of information. We will adapt the pseudo code in Figure 1 to form an acceptable list of combo words, directly extracted from a random subset of the abstracts, and then determine the frequency distribution of these combo words. We will compare such a frequency distribution of combo words with that obtained for combo words based on combinations of secondary keywords.

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