# FRAKE: Fusional Real-time Automatic Keyword Extraction

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### Abstract

Keyword extraction is the process of identifying the words or phrases that express the main concepts of text to the best of one's ability. Electronic infrastructure creates a considerable amount of text every day and at all times. This massive volume of documents makes it practically impossible for human resources to study and manage them. Nevertheless, the need for these documents to be accessed efficiently and effectively is evident in numerous purposes. A blog, news article, or technical note is considered a relatively long text since the reader aims to learn the subject based on keywords or topics. Our approach consists of a combination of two models: graph centrality features and textural features. The proposed method has been used to extract the best keyword among the candidate keywords with an optimal combination of graph centralities, such as degree, betweenness, eigenvector, closeness centrality and etc, and textural, such as Casing, Term position, Term frequency normalization, Term different sentence, Part Of Speech There have also been attempts to distinguish keywords from candidate phrases and consider them on separate keywords. For evaluating the proposed method, seven datasets were used: Semeval2010, SemEval2017, Inspec, fao30, Thesis100, pak2018, and Wikinews, with results reported as Precision, Recall, and F- measure. Our proposed method performed much better in terms of evaluation metrics in all reviewed datasets compared with available methods in literature. An approximate 16.9% increase was witnessed in F-score metric and this was much more for the Inspec in English datasets and WikiNews in forgone languages.

Keywords: Keyword extraction, Key-phrase extraction, Natural language processing

### 1. Introduction

These days, people have difficulty finding a particular document among the vast volume of documents they create daily. There are typically millions of text and web pages stored every day, making them impossible to analyze without indexing. Accordingly, if the documents index with expressions, analyzing them becomes highly convenient. Using an expression makes understanding a document much more accessible. An expression can be a single or a series of words or phrases called keywords or key phrases. Keyword or Key-phrase extraction is the process of identifying the primary concept of a document by examining the set of terms composing it[1].

There are three approaches to keyword or phrase extraction in natural language processing: text approach, graph approach, and hybrid. Text-based approaches based on textual features could be used in extracting text from documents, such as Part of Speech (POS), mean TF, etc. The graph modeling approach is to represent words and relations as nodes and edges in a graph by co-occurrences or N-grams. When graphs are created, statistical analysis is applied to scoring nodes to select the top words as keywords. Hybrid models rely on both text and graph methods in order to extract keyword (phrase) combinations.

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"fuzzy systems overlapping gaussian concepts approximation properties sobolev norms in paper approximating capabilities fuzzy systems overlapping gaussian concepts considered the target function assumed sampled either regular gird according uniform probability density by exploiting connection radial basis functions approximators new method computation system coefficients provided showing guarantees uniform approximation derivatives target function."

Figure 1: Sample document.

The rest of this study is organized as follows: the second section contains a literature review of mobile price prediction. Section 3 presents the proposed methods. The experimental results are given and discussed in section 4. Some conclusions are drawn in the final section, and the areas for further researches are identified, as well.

#### 2. Related Works

A two-pronged approach may apply to studies relating to keywords: Extraction & Generation. This paper employs a keyword extraction approach, meaning that the keywords should appear in the document to be selected as keywords. Based on the second stage of the division of keyword extraction methods, related words can be sorted into four groups: statistical, textual, graph-based, and hybrid. In statistical methods, top-scoring words were chosen as index words of the document, and the score was calculated arithmetically. TF-IDF[2] and co-occurrence[3] can be listed as the most well-known statistical keywords extractor methods.

Textual methods are based on the linguistic features of words in a document, such as lexical, syntactic, and semantic. Part of speech tags of words of a document was one of the text-based keyword extraction methods that ignored stop words[4]. Morphology is a linguistic analysis subset that is used in the keyword extraction process. Morphology-based approaches[5] need a thesaurus, and WordNet[6] is the most famous one. However, language dependency is the major drawback of this approach. Additionally, some linguistic characteristics in textual-based keyword extraction can be described as "Noun phrase chunking" [7], Ontology[8] or "Lexical chains"[9].

The idea behind graph-based methods is to construct a graph from document elements. Word cooccurrence networks are often used to show the relationships between words in a document. There is an edge between two nodes if the relevant words co-occur within a window in a co-occurrence graph with nodes representing words. Additionally, most centrality metrics such as degree, closeness, betweenness, and eigenvector are used to identify the nodes with the highest score, and their keywords are then identified as candidates. Graph-based methods have gained good results in this area, and several methods exist; one of them is Text Rank.[10], Single Rank [11], Topic page Rank[12], Position Rank[13], Multipartite Rank[14], Expended Rank[11].

These hybrid models combine two previously mentioned categories, textual-based and graph-based. In a hybrid model, the aim is to calculate each text and graph-based feature separately and then combine them in a method. Combining and scoring methods are the main contribution of works. Mike[15], Sgrank[16], Key2Vec[17], RaKUn[18] are examples of hybrid methods.

# 3. FRAKE

The proposed method, called FREAK, is a fusion of two parallel keyword extraction approaches, graph features and textural features, and each of the techniques has its advantages. Illustration of the proposed method is shown in fig. 2. The proposed method consists of 5 steps; pre-processing, feature extraction, scores computation, key-phrase generation, and ranking, respectively, with the aim of extracting keywords. In the following sub-sections, every step is expanded. To make each step sensible, the output of those steps are shown with an example. The example document is shown in fig 1.

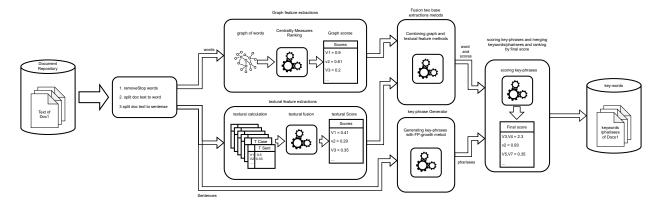


Figure 2: Diagram of the proposed FRAKE model.

### 3.1. Pre-processing

As discussed at the beginning of the section, our method consists of two parallel stages in the primary stage, one of which is for the first stage and the second part for the second stage. To proceed with extracting keywords from the graph, we need the word list and the relationship of all the text words with their neighbors. As opposed to the extraction of keywords from the local benchmark, we need to separate the sentences. During this step, the input data are separated into words, sentences, and stop words are dropped from the input data. The example output is shown in fig 3.

### Algorithm 1: pre-processing

Input: text,alpha,Lang
sentences = split text into sentences
for each sentence ∈ sentences do
 words = split sentence into words(text)

change word to lowercase (words),
Remove stop word(words, Lang)
All words = append(words)

end

Output: List of sentences, All words

# 3.2. Feature extracting

Feature extraction consists of three steps: graph features extraction, textural features extraction and scoring these features. graph features and textural features extraction steps are parallel and extract features simultaneously. Each of the features represents different sight of the document, and the novelty of this paper is to fusion them to get an overview.

### 3.2.1. Graph features

Graphs are deployed to represent relations and make them easy to understand. Also, provide more computational results. Graphs consist of nodes and vertices,  $G = \{V, E\}$ , and nodes of the created unweighted and undirected graph are words, and vertices are 3-gram (trigram) of words. Figure 4 shows an example of a document and its graph. Once the graph is created, centralities are deployed to score each node. Graph centralities are measures of how nodes of a graph look from a different point of view. The centralities used in this paper are degree centrality(DE), closeness centrality(CL), betweenness centrality(BE), eigenvector centrality(EV), structural holes(SH), page rank(PR), clustering coefficient(CC), and eccentricity(EC). These eight centralities are the most used in NLP and graph representation scoring.

- Sentence 1: "fuzzy systems overlapping gaussian concepts approximation properties sobolev norms".
- Sentence 2: "in paper approximating capabilities fuzzy systems overlapping gaussian concepts considered".
- Sentence 3: "the target function assumed sampled either regular gird according uniform probability density by exploiting connection radial basis functions approximators new method computation system coefficients provided showing guarantees uniform approximation derivatives target function".
- Words: 'fuzzy', 'systems', 'overlapping', 'gaussian', 'concepts', 'approximation', 'properties', 'sobolev', 'norms', 'paper', 'approximating', 'capabilities', 'fuzzy', 'systems', 'overlapping', 'gaussian', 'concepts', 'considered', 'target', 'function', 'assumed', 'sampled', 'regular', 'gird', 'according', 'uniform', 'probability', 'density', 'exploiting', 'connection', 'radial', 'basis', 'functions', 'approximators', 'new', 'method', 'computation', 'system', 'coefficients', 'provided', 'showing', 'guarantees', 'uniform', 'approximation', 'derivatives', 'target', 'function'.

Figure 3: The sentence segmentation and tokenization of example document fig 1.

Several scores are assigned to every node based on their centrality, so eight scores are assigned to every node of the graph. In addition, this step should return a single score for every word; to that end, PCA is deployed. A PCA technique reduces the dimensionality of a dataset while increasing interpretability and minimizing information loss[19]. Nowadays, different versions of PCA with different aims are developed. PC1 is the first principal component used in NLP, and keyword extraction task[20] and we employed it to achieve one score per node (word). This progress is shown in algorithm 2.

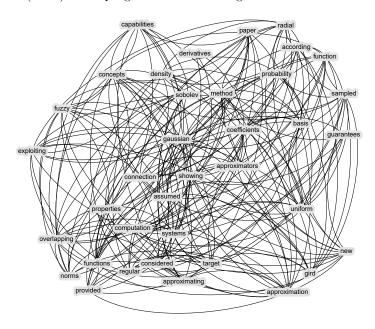


Figure 4: The generated graph of example document fig 1.

# 3.2.2. textural features

Word itself and its position in a document is essential and could make sense in understanding meaning. The features that have been utilized in this paper are capital letters, the position of the word, frequency of word in sentences of document, term frequency of word, and part of speech (POS) tag of word. Algorithm 3 details the features. Each of the features calculates a score. Finally, the textural feature score calculates

### Algorithm 2: build graph and compute centrality measures Score

```
Input: AllWords
for each word \in unique(AllWords) do
   G.node = unique(AllWords[word])
end
for each i \in AllWords do
   G.addEdge(AllWords list[i], AllWords list[i+2])
   G.addEdge(AllWords list[i], AllWords list[i+1])
   G.addEdge(AllWords list[i], AllWords list[i-1])
   G.addEdge(AllWords list[i], AllWords list[i-2])
for each Centrality \in \{DE, CL, BE, EV, SH, PR, CC, EC\} do
   for each word \in words of Graph do
    | word centrality scores[Centrality] = calculate Centrality score (word, Centrality)
   end
   word.graph-Score = Sum(word centrality score * PC1 coefficient for each centrality )
end
Output: graph scores
```

in algorithm 3.

# Algorithm 3: Feature extraction and Compute textural measures scores

# 3.3. Scores computation

In this part, calculated scores of words by graph features and textural features are merged to claim one score per word. Multiply is used to combine two scores, as can be seen in algorithm 4.

# 3.4. Key-phrase generation

Key-phrase is a word or a couple of words (phrases) that convey the document's meaning. In the last part, keywords and scores are extracted. In this part, keywords are extracted from extracted text to generate key-phrases. N-grams is a general technique combining words to generate phrases, and determining N (length of N-gram) is one of the most issues. In this paper, HUPM<sup>1</sup>[21], which core is FP-Growth, is applied to sentences to generate key-phrases. The phrase's score is calculated by summing the calculated scores for each keyword in the phrase.

<sup>&</sup>lt;sup>1</sup>High Utility Pattern Mining

# ${\bf Algorithm~4:}~{\bf compute~final~score~from~graph~scores~and~Sentence~scores$

Input: graph-Score , textural-Score

for each word  $\in$  words do

 $| \ \, word.final\text{-}score = word.graph\text{-}Score \times word.textural\text{-}Score$ 

 $\mathbf{end}$ 

Sorting(words)
Output: final score

Table 1: Candidate keywords in couple with graph-based score, textual-based score and Final score of the example document.

Words	Graph-based score	Texture score	Final score
uniform	1.77	3.92	6.95
concepts	1.46	4.71	6.87
target	1.61	3.93	6.34
systems	1.13	4.86	5.49
fuzzy	1.11	4.94	5.48
overlapping	1.15	4.21	4.85
function	1.19	3.93	4.66
gaussian	1.14	3.91	4.45
properties	1.18	3.58	4.22
approximation	1.12	3.68	4.1
density	1.26	3.14	3.94
sobolev	1.12	3.51	3.92
norms	1.1	3.46	3.81
paper	1.1	3.41	3.75
capabilities	1.11	3.38	3.74
gird	1.18	3.17	3.73
probability	1.18	3.14	3.7
guarantees	1.2	3.08	3.68
connection	1.15	3.12	3.6
sampledeither	1.12	3.19	3.57
coefficients	1.15	3.09	3.56
derivatives	1.16	3.07	3.55
radial	1.11	3.12	3.48
computation	1.12	3.09	3.46
functionsapproximators	1.11	3.11	3.44
basis	1.09	3.11	3.4
method	1.09	3.1	3.39
showing	1.25	2.7	3.38
considered	1.17	2.78	3.26
assumed	1.15	2.76	3.18
according	1.15	2.74	3.16
exploiting	1.16	2.72	3.16
provided	1.17	2.7	3.15
regular	1.12	2.53	2.84
new	1.11	2.51	2.78

Table 2: Dataset summary statistics

Dataset	Lang.	Input	Topic	# documents	Avg # words in documents	# key- words (percent)
SemEval2010 [22]	en	Article	Computer science	243	8332.34	4002 (16.47)
SemEval2017 [23]	en	Paragraph	Scientific	493	178.22	8969 (18.19)
Inspec [24]	en	Abstract	Computer science	2000	128.20	29230 (14.64)
Fao30 [25]	en	Article	Agricultural	30	4777.40	997 (33.23)
Thesis100 [26]	en	Thesis	Scientific	100	4728.86	767 (7.67)
pak2018 [27]	pl	Abstract	Misc	50	97.36	232(4.64)
WikiNews [28]	$\operatorname{fr}$	News	Misc	100	293.52	1177 (11.77)

### 3.5. Keywords ranking

The last step is to select key-phrases between candidates, which are generated from the previous parts. To this aim, the words and phrases are then sorted descendingly by their scores, and the top K is picked as keyphrases for the entire document.



Figure 5: The word cloud illustration of keywords and key-phrases example fig 1.

## 4. Experiments and Results

In this section, the evaluation of the proposed methods and comparison are detailed. First, benchmark data sets are introduced, followed by performance metrics.

## 4.1. Datasets

Evaluation of the proposed methods has been done on 7 benchmark datasets. Summary of datasets is shown on table 2. As shown in table 2, various inputs and topics are selected for evaluation. To proving language-independency of the proposed method, two datasets are non-English.

#### semeval 2010

Semival2010 consists of 244 articles indexed by ACM in four computer science area, namely; distributed systems, information retrieval, distributed artificial intelligence, and social science, introduced by Kim et al. [22]. The input type is articles in the length of 6 till 8 pages and keywords are labelled by authors and expert. It is worthwhile to say that keywords may not be in the text. Summery of the dataset is shown in table 2.

#### SemEval2017

Semival2017 contains 500 articles abstract indexed by ScienceDirect equally divided in area of computer science, material engineering, and physics. Experts label the keywords. The dataset introduced fir the first time by Augenstein et al. [23]. Summery of the dataset is shown in table 2.

### Inspec

Inspec[24] includes 2000 articles abstracts in computer science collected between the years 1998 and 2002. Each document has two sets of keywords: the controlled keywords, which are manually controlled assigned keywords that appear in the Inspec thesaurus but may not appear in the document, and the uncontrolled keywords, which are freely assigned by the editors (that is, they are not restricted to the thesaurus or the document). In our experiments, we consider a union of both sets as the keywords. In table 2 summary of Inspec has been shown.

## fao30

fao30 is a collection of 30 agricultural documents from the Food and Agriculture Organization (FAO) of the United Nations. The fao30 is introduced in [25], and a summary is shown in table 2. Six experts annotated foo30. fao30 is deployed to evaluate methods in long and non-scientific documents.

### The sis 100

Thesis100[26] has included 100 master and PhD thesis of the University of Waikato, New Zeland in English. The domain of the thesis100 made available is quite different ranging from chemistry, computer science, philosophy, history, and others. Such as fao30, the Thesis100 is used to evaluating methods in long documents (more than 10 pages).

# pak2018

pak2018 is a dataset in Polish set of 50 abstracts of journals on technical topics collected from Measurement Automation and Monitoring<sup>2</sup> and introduced by Campos et al. [27]. The keywords are author-assigned, and a summary of the dataset is displayed in table 2.

### WikiNews

WikiNews[28] is a French corpus created from the French version of WikiNews $^3$  that contains 100 news articles published between May 2012 and December 2012 and manually annotated by at least three students. More details are given in table 2.

Table 3:	Comparison	of features of	of the state-of-the-art	methods and the	proposed method.

Method	1	Unsupervi	$\operatorname{sed}$	Language dependence			
	Statistical	Textual	Graph-based	Stop words	POS tag	Stream data	
Proposed method		✓	✓	✓	✓		
TF-IDF [2]	✓			✓			
KP-Miner [29]	✓			✓			
YAKE [27]		$\checkmark$		✓			
RaKUn [18]		$\checkmark$					
Text Rank [10]			$\checkmark$		$\checkmark$		
Single Rank [11]			$\checkmark$	✓	$\checkmark$		
Topic Rank [28]			$\checkmark$	✓	$\checkmark$		
Topical Page Rank [12]			$\checkmark$	✓	$\checkmark$	$\checkmark$	
Posotion Rank [13]			$\checkmark$	✓	$\checkmark$		
Multiparted Rank [14]			$\checkmark$	✓	$\checkmark$	$\checkmark$	
Expended Rank [11]			$\checkmark$		$\checkmark$		

#### 4.2. Results

Calculating results starts with defining metrics. Afterward, metrics are defined, and the results of the proposed method compared to those of state-of-the-art methods are discussed.

Three primary metrics are used in evaluating keyword extraction methods are precision, recall, and F1-score. To calculating these metrics, 4 concepts, TP, TN, FP, FN, should be defined. TP denotes to the phrase correctly defined as a keyword. TN denotes to the phrase correctly define as a not keyword. FP denotes the phrase incorrectly define as a keyword, and FN denotes the phrase does not define as a keyword incorrectly. Respectively, precision and recall calculate by equation 1 and equation 2. F1-score means the harmonic mean of the precision and recall, as equation 3.Traditionally, keyword extraction is a ranking problem. Based on this, we opted to calculate Precision at k (Precision@k), Recall at k (Recall@k) and F1-score at k (F1-score@k) to determine the effectiveness of the proposed method.

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

$$F1 - score = 2. \frac{Precision \times Recall}{Precision + Recall}$$
(3)

The features of the state-of-the-art methods used as baselines compared with the proposed method have been shown in table 3. As you see, two models of unsupervised, statistical and graph-based, methods with approaches on pre-processings detailed. To evaluation the state-of-the-art methods, implementation obtained from pke<sup>4</sup> {https://github.com/boudinfl/pke} developed by Boudin. Table 4, 5, 6 are the results of the methods in each of metrics.

Comparing the proposed method with other state-of-the-art methods, The proposed method performs the best in all metrics and datasets except the Thesis100. Thissis100 is consists of very long texts, MSc thesis, with a low ratio of keywords to documents (7.67% based on table 2). Nevertheless, the proposed method obtains third place compared to other methods in all of the metrics. As seen, the graph-based methods outperformed this dataset. It is worthwhile to say that the comparisons have been made in Polish and France documents and the proposed method reaches the best results.

<sup>2</sup>http://pak.info.pl/

<sup>3</sup>https://www.wikinews.org/

<sup>&</sup>lt;sup>4</sup>python keyphrase extraction

Table 4: Comparison of methods on Precision @ 10.

Methods	Dataset							
Methods	SemEval10	SemEval17	Inspec	Fao30	Thesis100	pak18	WikiNews	
Proposed Method (FRAKE)	0.415	0.536	0.572	0.294	0.24	0.126	0.537	
TF-IDF [2]	0.316	$-\bar{0}.\bar{4}8\bar{8}$	0.475	$\bar{0}.\bar{2}5\bar{1}$	$-\bar{0}.\bar{2}8^{}$	0.104	0.441	
KP-Miner [29]	0.347	0.398	0.349	0.222	0.291	0.1	0.452	
YAKE [27]	0.345	0.334	0.329	0.1	0.062	0.054	0.151	
Text Rank [10]	0.019	0.335	0.345	0	0.003	0.008	0.098	
Single Rank [11]	0.028	0.151	0.293	0.007	0.008	0.027	0.269	
Topic Rank [28]	0.237	0.436	0.465	0.129	0.168	0.04	0.463	
Topical Page Rank [12]	0.027	0.401	0.42	0.007	0.11	0.012	0.331	
Position Rank [13]	0.076	0.438	0.473	0.025	0.031	0.035	0.443	
MultiPartite Rank [14]	0.268	0.458	0.497	0.159	0.194	0.037	0.442	
Expanded Rank [11]	0.027	0.396	0.413	0.007	0.008	0.013	0.273	

Table 5: Comparison of methods on Recall @ 10.

Methods	Dataset							
	SemEval10	SemEval17	Inspec	Fao30	Thesis100	pak18	WikiNews	
Proposed Method (FRAKE)	0.343	0.544	0.607	0.287	0.316	0.296	0.564	
TF-IDF [2]	0.285	0.5	-0.45	$-0.\overline{226}$	-0.347	0.247	0.468	
KP-Miner [29]	0.313	0.405	0.359	0.2	0.354	0.185	0.464	
YAKE [27]	0.311	0.342	0.345	0.1	0.079	0.123	0.155	
Text Rank [10]	0.017	0.31	0.326	0	0.003	0.17	0.098	
Single Rank [11]	0.025	0.141	0.551	0.006	0.009	0.013	0.256	
Topic Rank [28]	0.213	0.400	0.431	0.116	0.21	0.08	0.438	
Topical Page Rank [12]	0.024	0.37	0.395	0.006	0.012	0.022	0.315	
Position Rank [13]	0.068	0.405	0.444	0.023	0.045	0.073	0.419	
MultiPartite Rank [14]	0.242	0.421	0.463	0.143	0.242	0.074	0.462	
Expanded Rank [11]	0.024	0.366	0.399	0.006	0.009	0.027	0.26	

Table 6: Comparison of methods on F1-score @ 10.

Methods	Dataset							
	SemEval10	SemEval17	Inspec	Fao30	Thesis100	pak18	WikiNews	
Proposed Method (FRAKE)	0.375	0.54	0.589	0.29	0.272	0.177	0.55	
TF-IDF [2]	0.3	$-\bar{0}.\bar{4}9\bar{3}$	0.462	$-0.\overline{2}38$	-0.315	0.146	0.454	
KP-Miner [29]	0.329	0.402	0.354	0.21	0.319	0.129	0.457	
YAKE [27]	0.327	0.338	0.337	0.1	0.07	0.075	0.153	
Text Rank [10]	0.018	0.322	0.33	0	0.003	0.011	0.098	
Single Rank [11]	0.026	0.145	0.381	0.007	0.009	0.017	0.263	
Topic Rank [28]	0.224	0.417	0.448	0.122	0.187	0.053	0.45	
Topical Page Rank [12]	0.026	0.385	0.407	0.007	0.012	0.015	0.323	
Position Rank [13]	0.072	0.421	0.458	0.024	0.037	0.047	0.43	
MultiPartite Rank [14]	0.254	0.439	0.48	0.15	0.215	0.05	0.452	
Expanded Rank [11]	0.025	0.381	0.401	0.007	0.009	0.017	0.266	

#### 5. Conclusion

A novel keyword extraction method called FRAKE is presented in this paper. FRAKE fuses two approaches, graph, and textural features, in order to extract keywords and key phrases. During the proposed method, five steps are included: pre-processing, extraction of graph features and textural features, computation of the Score, generation of key-phrases, and ranking of Key-phrases. It is shown that the proposed method performs best in English, Polish, and French texts.

#### **Declarations**

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# Conflicts of interests

The authors have no conflicts of interest to declare that are relevant to the content of this article.

### Ethical approval

This article does not contain any studies with human participants or animals performed by any of the authors.

# Data availability

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

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