Candidate Extraction Impact on Automatic Keyphrase Extraction

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Abstract

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1 Introduction

Keyphrases are single or multi-word expressions that represent the main topics of a document. Keyphrases are useful in many tasks such as information retrieval (Medelyan and Witten, 2008), document summarization (Litvak and Last, 2008) or document clustering (Han et al., 2007). Although scientific articles usually provide them, most of the documents have no associated keyphrases. Therefore, the problem of automatically assigning keyphrases to documents is an active field of research.

Automatic keyphrase extraction methods are divided into two categories: supervised and unsupervised methods. Supervised methods typically recast keyphrase extraction as a binary classification task (Witten et al., 1999; Sujian et al., 2003; Eichler and Neumann, 2010). For unsupervised methods, keyphrase extraction is often considered as a ranking task and many approaches are used (Barker and Cornacchia, 2000; Mihalcea and Tarau, 2004). As distinct as they are, both supervised and unsupervised methods rely on a preliminary candidate extraction step which identifies single and multi-word expressions that have the same syntactic properties than a keyphrase. These expressions are the only textual units that can be extracted as keyphrases. Therefore, we believe that the extraction of candidate keyphrases plays a direct role in automatic keyphrase extraction.

In this paper, we focus on the candidate extraction step and show its impact on the performance of automatic keyphrase extraction. Various methods are commonly employed to extract keyphrase candidates[1]. Usually, a set of either single words, n-grams filtered by stop words, NP-chunks or sequences of words matching given patterns is extracted (Hulth, 2003). According to the chosen method, the extracted set contains more or less candidates, and the amount of these that are actual keyphrases may vary. Hence, a few questions arise. How the different sets influence the keyphrase extraction? Do large candidate sets introduce noise that affects the performance of some keyphrase extraction methods?

We seek to better understand the impact of candidate extraction methods on keyphrase extraction by studying the aforementioned questions. We first quantify the differences between the candidate sets obtained by the commonly used methods and we propose to use other methods developed for automatic term detection (Castellví et al., 2001; Evans and Zhai, 1996) to show that such methods provide solid keyphrase candidates. Then, we evaluate the impact of the candidate extraction methods over three dissimilar keyphrase extraction methods. We select KEA (Witten et al., 1999) to represent supervised methods, TF-IDF (Spärck Jones, 1972) to represent unsupervised methods that require a collection of documents and TopicRank (Bougouin et al., 2013) to represent unsupervised methods that only make use of the analyzed document.

Results show that...

2 Definition of Candidate Keyphrases

Candidate keyphrases are textual units which can be selected as keyphrases of a document. Hence, they must have the same syntactic and linguistic properties than ground truth keyphrases. This section aims to determine those properties by analysing three standard evaluation datasets, for keyphrase extraction, and by providing statistics about their reference keyphrases (ground truth keyphrases).

[1] In this work, we do not consider methods which use a manually defined controlled vocabulary.

2.1 Keyphrase Extraction Datasets

Keyphrase extraction datasets are used to train or evaluate keyphrase extraction methods. Hence, they are collections of documents paired with reference keyphrases given by authors, readers or both. Unlike the methods to automatically extract keyphrases, human annotators do not only provide keyphrases contained into the documents. This problem of missing keyphrases leads to a bias of the training or evaluation of keyphrase extraction methods. In this work, we use three standard datasets which differ in terms of document size, type and language. The problem of missing keyphrases is partially bypassed using stemmed forms when comparison between reference and candidate keyphrases is needed.

The **DUC** dataset (Over, 2001) is a collection of 308 English news articles covering about 30 topics (e.g. tornadoes, gun control, etc.). This collection is the test dataset of the DUC-2001 summarization evaluation campaign. This part of DUC-2001 is the only one that contains keyphrases, annotated by Wan and Xiao (2008). We split the collection into two sets: a training set containing 208 documents and a test set containing 100 documents.

The **SemEval** dataset (Kim et al., 2010) contains 284 English papers collected from the ACM Digital Libraries (conference and workshop papers). The papers are divided into three sets: a trial set containing 40 documents (unused in this work), a training set containing 144 documents and a test set containing 100 documents. As for the associated keyphrases, these are provided by both authors and readers.

The **DEFT** dataset (Paroubek et al., 2012) is a collection of 244 French scientific papers belonging to the Humanities and Social Sciences domain. DEFT is divided into three sets: a trial set containing 50 documents (not used in this work), a training set containing 141 documents and a test set containing 93 documents. The only available reference keyphrases are the ones given by authors.

Table 1 shows the statistics about the three datasets. As these statistics are used to guide our work, we restrain them to the training sets. As said before, the datasets differ in terms of size, type and language. Moreover, it is worth noticing that the number of keyphrases, as well as the ratio of missing ones and their average number of tokens differ too. This observation is due to the fact that there is not a unique methodology (guideline) to associate keyphrases to a document. To better fit the requirements, such guidelines should not only be used by human annotators, but also by automatic keyphrase extraction methods.

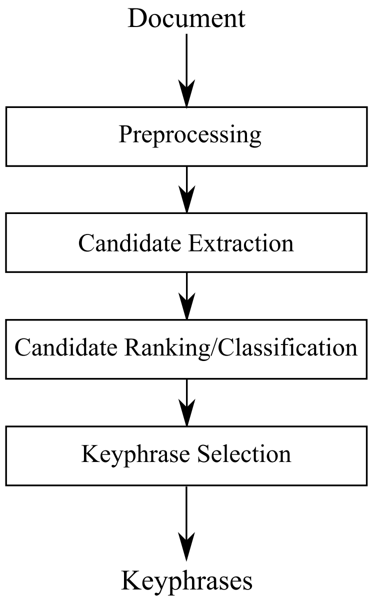

Figure 1: Processing steps of automatic keyphrase extraction methods.

2.2 Reference Keyphrases Analysis

Despite the fact that the data are not homogeneous, this section aims to determine the syntactic properties of most keyphrases, for English (intersecting information from DUC and SemEval training sets) and for French (using DEFT training set).

DONNER DES EXEMPLES

Donner les séquences de POS les plus fréquentes dans le gold standard.

3 Candidate Extraction

Objectif + pré-requis.

3.1 N-Gram Extraction

3.2 NP-Chunk Extraction

3.3 Pattern Matching

3.4 Term Extraction

4 Keyphrase Extraction

Fonctionnement général.

	Statistics	Corpora		
		DUC	SemEval	DEFT
Documents	Language	English	English	French
	Type	News	Papers	Papers
	Documents	208	144	141
	Tokens/document	912.0	5134.6	7276.7
	Keyphrases/document	8.1	15.4	5.4
	Missings keyphrases	3.9%	13.5%	18.2%
Keyphrases	Unigrams	26.2%	20.2%	66.4%
	Bigrams	54.1%	53.4%	20.7%
	Trigrams and more	19.7%	26.4%	12.9%
	Containing nouns	90.8%	95.9%	79.3%
	Containing proper nouns	18.7%	5.8%	16.8%
	Containing adjectives	41.6%	40.5%	28.8%
	Containing verbs	0.9%	3.4%	0.5%
	Containing adverbs	1.3%	0.6%	0.5%
	Containing prepositions	0.2%	1.2%	12.7%
	Containing determiners	0.0%	0.0%	8.1%
	Containing others	1.3%	2.1%	5.8%

Table 1: Training dataset statistics. As a matter of consistency regarding the training and the evaluation of keyphrase extraction methods, the percentage of missing keyphrases is determined based on the stemmed form of the reference keyphrases.

4.1 TF-IDF

4.2 TopicRank

4.3 KEA

5 Evaluation

Expliquer les deux évaluations: intrinsèque et extrinsèque.

5.1 Experimental Setting

5.2 Candidate Extraction

Donner le rappel max et comparer avec la taille des différents ensemble.

Quels sont les termes candidats communs aux ensembles, les propriétés ?

5.3 Keyphrase Extraction

Quelles sont les performances de chaque méthode avec chaque ensemble de termes candidats ?

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Statistics	Corpora		
	DUC	SemEval	DEFT
Language	English	English	French
Type	News	Papers	Papers
Documents	100	100	93
Tokens/document	877.3	5177.7	6839.4
Keyphrases/document	7.94	14.7	5.2
Tokens/keyphrase	2.1	2.1	1.6
Missings keyphrases	2.8%	22.1%	21.1%

Table 2: Test dataset statistics. As a matter of consistency regarding the training and the evaluation of keyphrase extraction methods, the percentage of missing keyphrases is determined based on the stemmed form of the reference keyphrases.

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Methods	DUC		SemEval		DEFT	
	Candidates	Rmax	Candidates	Rmax	Candidates	Rmax
{1..2}-grams	310539	78.8	949225	61.4	1374905	67.3
{1..3}-grams	515903	94.0	1816327	73.1	2593221	74.1
{1..4}-grams	714917	95.8	2705335	75.3	3847599	78.2
{1..5}-grams	905094	96.3	3574701	75.9	5085447	78.5
NP chunks						
Longest NPs	49845	88.7	155189	62.4	224083	61.1
Best patterns						
Subcompounds						
TermSuite-spec		23.8		16.3		13.9
TermSuite-full	77357	46.1	196477	32.4	310150	53.4

Table 3: Candidate extraction statistics. Rmax stands for maximum recall, i.e. it is the percentage of candidates that match with reference keyphrases.

Methods	DUC			SemEval			DEFT		
	P	R	F	P	R	F	P	R	F
{1..2}-grams	9.6	13.2	11.0	16.2	11.4	13.3	11.6	21.8	15.0
{1..3}-grams	9.0	12.4	10.3	16.4	11.5	13.4	11.6	22.0	15.0
{1..4}-grams	9.0	12.4	10.3	16.4	11.5	13.4	11.6	21.9	15.0
{1..5}-grams	8.6	11.9	9.8	16.4	11.5	13.4	11.6	22.0	15.0
NP chunks									
Longest NPs	13.3	18.2	15.2	18.3	12.9	15.0	12.8	23.6	16.4
Best patterns									
Subcompounds									
TermSuite-spec	9.5	13.2	10.9	9.4	6.8	7.8	5.4	10.7	7.1
TermSuite-full	11.5	16.0	13.2	12.9	9.3	10.7	12.5	23.5	16.1

Table 4: Comparison of candidate extraction methods, when extracting 10 keyphrases with the **TF-IDF** method. Results are expressed as a percentage of precision (P), recall (R) and f-score (F).

Methods	DUC			SemEval			DEFT		
	P	R	F	P	R	F	P	R	F
{1..2}-grams									
{1..3}-grams									
{1..4}-grams									
{1..5}-grams									
NP chunks									
Longest NPs									
Best patterns									
Subcompounds									
TermSuite									

Table 5: Comparison of candidate extraction methods, when extracting 10 keyphrases with **TopicRank**. Results are expressed as a percentage of precision (P), recall (R) and f-score (F).

Methods	DUC			SemEval			DEFT		
	P	R	F	P	R	F	P	R	F
{1..2}-grams									
{1..3}-grams									
{1..4}-grams									
{1..5}-grams									
NP chunks									
Longest NPs									
Best patterns									
Subcompounds									
TermSuite									

Table 6: Comparison of candidate extraction methods, when extracting 10 keyphrases with **KEA**. Results are expressed as a percentage of precision (P), recall (R) and f-score (F).