Candidate Extraction Impact on Automatic Keyphrase Extraction

Adrien Bougouin and **Florian Boudin** and **Béatrice Daille**
Université de Nantes, LINA, France
{adrien.bougouin,florian.boudin,beatrice.daille}@univ-nantes.fr

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; Tomokiyo and Hurst, 2003; 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.

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 match with the ground truth 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. Also, we propose to use another method developed to extract noun-phrases for document indexing (Evans and Zhai, 1996) and we argue that such term detection method (Castellví et al., 2001) provides solid keyphrase candidates. Then, we evaluate the impact of the candidate extraction methods on 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 document to analyse.

Results show that...

2 Definition of Candidate Keyphrases

Candidate keyphrases are textual units which can be selected as keyphrases of the document they are extracted from. 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

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

keyphrases (ground truth keyphrases).

2.1 Keyphrase Extraction Datasets

Keyphrase extraction datasets are used to train or evaluate keyphrase extraction methods. Hence, the datasets are collections of documents paired with reference keyphrases, given by authors, readers or both. Unlike the studied methods, human annotators do not only extract keyphrases which are contained into the document. 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 type and/or language. The problem of missing keyphrases is partially bypassed using their stemmed forms during comparisons, when training or evaluating methods.

The **DUC** dataset (Over, 2001) is a collection of 308 English news articles covering about 30 news topics. This is the part of the dataset made for the DUC 2001 summarization evaluation campaign that has been annotated by Wan and Xiao (2008) for keyphrase extraction evaluation purpose. We split this 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 284 scientific 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 that belongs to the Humanities and Social Sciences domain. As SemEval, DEFT is divided into threee 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. Unlike DUC and SemEval, the only available reference keyphrases are the ones given by authors.

Table 2 gives statistics about the datasets. As we aim to use these statistics to lead this work, we restrain the discussion to observations made with the training sets.

Continue

2.2 Keyphrase Analysis

This section focuses on the reference keyphrase statistics presented in Table 2. The aim is to determine the syntactic properties of most keyphrases, for English (combining information from DUC and SemEval) and for French (using DEFT information).

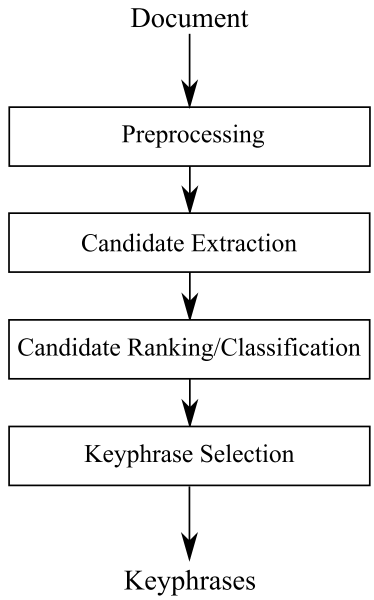

Figure 1: Processing steps of automatic keyphrase extraction methods.

- Les Keyphrases sont principalement des unigrammes et bi-grammes (mais une tendance inversée entre anglais et français). - Presque toutes les keyphrase contiennent un nom. - L'usage d'adjectifs est fréquent (40 et 30%). - Très peu de verbes. - Usage fréquent de prépositions et determinants pour le français (uniquement).

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		5134.6	7276.7
	Keyphrases/document	8.1	15.4	5.4
	Missings keyphrases		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 keyphrase 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		5179.6	6844.0
Keyphrases/document		14.7	5.2
Missings keyphrases			

Table 2: Test dataset statistics. As a matter of consistency regarding the training and the evaluation of keyphrase extraction methods, the percentage of missing keyphrase 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						
{1..3}-grams						
{1..4}-grams						
{1..5}-grams						
NP chunks						
Longest NPs						
Best patterns						
TermSuite						
CLARIT'96						

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	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0
{1..3}-grams	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0
{1..4}-grams	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0
{1..5}-grams	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0
NP chunks	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0
Longest NPs	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0
Best patterns	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0
TermSuite	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0
CLARIT'96	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0

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	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0
{1..3}-grams	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0
{1..4}-grams	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0
{1..5}-grams	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0
NP chunks	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0
Longest NPs	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0
Best patterns	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0
TermSuite	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0
CLARIT'96	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0

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	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0
{1..3}-grams	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0
{1..4}-grams	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0
{1..5}-grams	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0
NP chunks	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0
Longest NPs	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0
Best patterns	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0
TermSuite	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0
CLARIT'96	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0

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).