
REVIEW

A Review of Keyphrase Extraction

Eirini Papagiannopoulou¹ | Grigorios Tsoumakas¹

¹School of Informatics, Aristotle University of Thessaloniki, Thessaloniki, 54124, Greece

Correspondence

Eirini Papagiannopoulou, School of Informatics, Aristotle University of Thessaloniki, Thessaloniki, 54124, Greece
Email: epapagia@csd.auth.gr

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Keyphrase extraction is a textual information processing task concerned with the automatic extraction of representative and characteristic phrases from a document that express all the key aspects of its content. Keyphrases constitute a succinct conceptual summary of a document, which is very useful in digital information management systems for semantic indexing, faceted search, document clustering and classification. This article introduces keyphrase extraction, provides a well-structured review of the existing work, offers interesting insights on the different evaluation approaches, highlights open issues and presents a comparative experimental study of popular unsupervised techniques on five datasets.

KEYWORDS

Keyphrase extraction, review, survey, unsupervised keyphrase extraction, supervised keyphrase extraction, evaluation, empirical comparison

1 | INTRODUCTION

Keyphrase extraction is concerned with automatically extracting a set of representative phrases from a document that concisely summarize its content (Hasan and Ng, 2014). There exist both supervised and unsupervised keyphrase extraction methods. Unsupervised methods are popular because they are *domain independent* and do not need *labeled training data*, i.e. manual extraction of the keyphrases, which comes with subjectivity issues as well as significant investment in time and money. Supervised methods on the other hand, have more powerful modeling capabilities and

Abbreviations: -

typically achieve higher accuracy than the unsupervised ones according to previous studies (Kim et al., 2013; Caragea et al., 2014; Meng et al., 2017).

The versatility of keyphrases renders keyphrase extraction a very important document processing task. Keyphrases can be used for semantically indexing a collection of documents either in place of their full-text or in addition to it, enabling semantic and faceted search (Gutwin et al., 1999). In addition, they can be used for query expansion in the context of pseudo-relevance feedback (Song et al., 2006). They can also serve as features for document clustering and classification (Hulth and Megyesi, 2006). Furthermore, the set of extracted keyphrases can be viewed as an extreme summary of the corresponding document for human inspection, while the individual keyphrases can guide the extraction of sentences in automatic document summarization systems (Zhang et al., 2004). Keyphrase extraction is particularly important in the (academic) publishing industry for carrying out a number of important tasks, such as the recommendation of new articles or books to customers, highlighting missing citations to authors, identifying potential reviewers for submissions and the analysis of content trends (Augenstein et al., 2017).

There exists a number of noteworthy keyphrase extraction surveys. Hasan and Ng (2014) focus on the errors that are made by state-of-the-art keyphrase extractors: (a) *evaluation errors* (when a returned keyphrase is semantically equivalent to a gold one but it is evaluated as erroneous), (b) *redundancy errors* (when a method returns correct but semantically equivalent keyphrases), (c) *infrequency errors* (when a keyphrase appears one or two times in a text and the method fails to detect it), and (d) *overgeneration errors* (when a system correctly returns a phrase as a keyphrase because it contains a word that appears frequently in the document, but erroneously outputs additional phrases as keyphrases that contain this frequent word). Despite that their analysis is not based on a large number of documents, it is quite interesting and well-presented. An earlier survey by the same authors presents the results of an experimental study of state-of-the-art unsupervised keyphrase extraction methods, conducted with the aim of gaining deeper insights into these methods (Hasan and Ng, 2010). The main conclusions are the following: (a) methods should be evaluated on multiple datasets, (b) post-processing steps (e.g., phrase formation) have a large impact on the performance of methods, and, (c) Tfidf is a strong baseline. Boudin et al. (2016) study the effect of document pre-processing pipelines to the keyphrase extraction process, while Florescu and Caragea (2017a) examine how keyphrase extraction is affected by phrase ranking schemes.

Our article constitutes a contemporary review of the keyphrase extraction task, containing the following main contributions:

- A systematic presentation of both unsupervised (Section 2) and supervised (Section 3) keyphrase extraction methods via comprehensive categorization schemes based on the main properties of these methods. Our article reviews 37 additional methods compared to Hasan and Ng (2014). In addition, we contribute a time line of unsupervised and supervised methods to shed light on their evolution, as well as a presentation of the main types of features employed in supervised methods, along with a discussion of the issue of class imbalance.
- We present the different approaches that can be followed for evaluating keyphrase extraction methods, as well as the different evaluation measures that exist, along with their popularity in the literature (Section 4).
- We provide a list of popular keyphrase extraction datasets, including their sources and properties, as well as a comprehensive catalogue of commercial APIs and free software (Section 5) related to keyphrase extraction.
- We present a thorough empirical study, both quantitative and qualitative, among commercial APIs and state-of-the-art unsupervised methods, which allows to gain a deeper understanding of how the results are affected by different evaluation approaches, evaluation measures and ground truth standards (Section 6).

The article search strategy that we followed, involved searching for “keyphrase extraction” in the following databases

of scientific literature: Google Scholar, Springer Link, IEEE Xplore, ACM Digital Library and DBLP. We focused mainly on articles appearing at the high quality journals and conference proceedings that are given in Appendix C.

2 | UNSUPERVISED METHODS

The basic steps of an unsupervised keyphrase extraction system are the following (Hasan and Ng, 2010, 2014):

1. Selection of the candidate lexical units based on some heuristics. Examples of such heuristics are the exclusion of stopwords and the selection of words that belong to a specific part-of-speech (POS).
2. Ranking of the candidate lexical units.
3. Formation of the keyphrases by selecting words from the top-ranked ones or by selecting a phrase with a high rank score or whose parts have a high score.

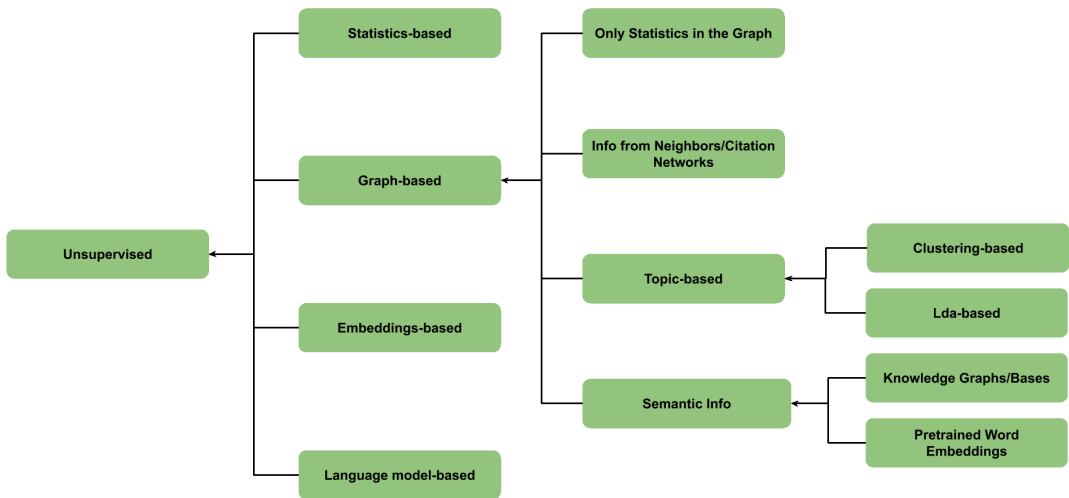


FIGURE 1 Presentation structure of the unsupervised keyphrase extraction methods.

Table 1 presents the time line of the main research approaches related to unsupervised keyphrase extraction that are cited in this survey. We present the methods discussed below, along with their key-characteristics that support our adopted presentation structure in the following sections. Each method can be characterized as (i) statistics-based (Stat.), (ii) graph-based that incorporates statistics (Stats into Graph), (iii) topic-based (labels in gray color) that uses clustering (Clust.), LDA or knowledge graphs (KG) to find the document's topics, (iv) methods that use citation networks or neighbors' information (C/N Info) as well as (v) semantics (Sem.), and (vi) language model-based methods (Lang. Mod.). According to Table 1, graph-based methods are the most popular ones. However, the statistics-based methods still hold the attention of the research community. Additionally, the incorporation of semantics seems to be helpful for the task as more and more methods use them. Figure 1 shows the presentation structure of the section. First, we present the statistics-based (Section 2.1) and the graph-based ranking methods (Section 2.2). Then, we discuss the methods that are based on embeddings (Section 2.3) as well as the category of language model-based methods

(Section 2.4).

Year	Methods	Stat.	Stats into Graph	Clust.	LDA	KG	C/N Info	Sem.	Lang. Mod.
2003	Tomokiyo and Hurst (2003)								✓
2004	Mihalcea and Tarau (2004)		✓						
2008	Wan and Xiao (2008) - SingleRank		✓						
	Wan and Xiao (2008) - ExpandRank		✓				✓		
2009	Liu et al. (2009)	✓		✓					
	El-Beltagy and Rafea (2009)	✓							
2010	Liu et al. (2010)		✓		✓				
	Rose et al. (2010)		✓						
2013	Bougouin et al. (2013)		✓	✓					
2014	Gollapalli and Caragea (2014)		✓				✓		
	Wang et al. (2014)		✓					✓	
2015	Sterckx et al. (2015a)		✓		✓				
	Sterckx et al. (2015b)		✓		✓				
	Danesh et al. (2015)		✓						
	Wang et al. (2015)		✓					✓	
2017	Teneva and Cheng (2017)		✓		✓				
	Florescu and Caragea (2017b)		✓						
	Shi et al. (2017)		✓	✓				✓	
2018	Campos et al. (2018b)	✓							
	Boudin (2018)		✓	✓					
	Bennani-Smires et al. (2018)							✓	
	Papagiannopoulou and Tsoumakas (2018)	✓						✓	
	Mahata et al. (2018)		✓					✓	
	Yu and Ng (2018)		✓			✓		✓	
2019	Won et al. (2019)	✓							

TABLE 1 A time line of all the unsupervised keyphrase extraction methods discussed in this review, along with their key-characteristics.

2.1 | Statistics-based Methods

TfIdf is the common baseline on the task. This method scores and ranks the phrases according to the formula:

$$TfIdf = Tf \times Idf$$

where *Tf* is the raw phrase frequency and $Idf = \log_2 \frac{N}{1 + |d \in D: phrase \in d|}$, with *N* the number of documents in the document set *D* and $|d \in D: phrase \in d|$ the number of documents in which the phrase appears. Effective variations of *TfIdf* are also implemented, such as taking the logarithm of the phrase frequency instead of the raw frequency to saturate the increase for high frequency words. Phrase frequency also contributes to alternative scoring schemes such as the one recently proposed by Florescu and Caragea (2017a). Specifically, the score of the phrase is calculated as:

$$mean \times Tf$$

where *mean* corresponds to the mean of the words' scores which constitute the phrase and *Tf* is the phrase frequency in the text document. This is not a free-standing scoring scheme, but it can be considered as an intermediate stage of an unsupervised method.

KP-Miner (El-Beltagy and Rafea, 2009) is a keyphrase extraction system that exploits various types of statistical information beyond the *Tf* and *Idf* scores. It follows a quite effective filtering process of candidate phrases and uses a scoring function similar to *TfIdf*. Particularly, the system keeps as candidates those that are not separated by punctuation marks/stopwords, considering at the same time the *least allowable seen frequency (lasf)* factor and a cutoff constant (*CutOff*) that is defined in terms of a number of words after which a phrase appears for the first time. Then, the system ranks the candidate phrases taking into account the *Tf* and *Idf* scores as well as the term position and a boosting factor for compound terms over the single terms.

Around the same time, co-occurrence statistics and statistical metrics based on external resources started to be used for *semantic* similarity calculation among the document's candidate terms. *KeyCluster* (Liu et al., 2009) tries to extract keyphrases that cover all the major topics of a document. First, it removes stopwords and selects the candidate terms. Then, it utilizes a variety of measures (co-occurrence-based or Wikipedia-based) to calculate the semantic relatedness of the candidate terms and groups them into clusters (using spectral clustering). Finally, it finds the exemplar terms of each cluster in order to extract keyphrases from the document.

The great importance of using both statistics and contexts info is confirmed by recent methods such as *YAKE* (Campos et al., 2018b) and the method proposed by Won et al. (2019). *YAKE*, besides the term's position/frequency, also uses new statistical metrics that capture context information and the spread of the terms into the document. First, *YAKE* preprocesses the text by splitting it into individual terms. Second, a set of 5 features is calculated for each individual term: *Casing* (W_{case} that reflects the casing aspect of a word), *Word Positional* ($W_{Position}$ that values more those words occurring at the beginning of a document), *Word Frequency* (W_{Freq}), *Word Relatedness to Context* (W_{Rel} that computes the number of different terms that occur to the left/right side of the candidate word), and *Word DifSentence* ($W_{DifSentence}$ quantifies how often a candidate word appears within different sentences). Then, all these features are used for the computation of the $S(w)$ score for each term (the smaller the value, the more important the word *w* would be).

$$S(w) = \frac{W_{Rel} * W_{Position}}{W_{case} + \frac{W_{Freq}}{W_{Rel}} + \frac{W_{DifSentence}}{W_{Rel}}}$$

Finally, a contiguous sequence of 1, 2 and 3-gram candidate keywords is generated using a sliding window of 3-grams. For each candidate keyword kw the following score is assigned:

$$S(kw) = \frac{\prod_{w \in kw} S(w)}{Tf(kw) * (1 + \sum_{w \in kw} S(w))}$$

The smaller the score the more meaningful the keyword will be. In addition, the method of Won et al. (2019) shows that using a combination of simple textual statistical features is possible to achieve results that compete with state-of-the-art methods. The first step of this method is the selection of the candidate phrases using morphosyntactic patterns. Then, for each candidate the following features are calculated: *Term Frequency*, i.e., the sum of each word frequency of the candidate phrase, *Inverse Document Frequency (Idf)*, *Relative First Occurrence*, i.e., the cumulative probability of the type $(1 - a)^k$ where $a \in [0, 1]$ measures the position of the first occurrence and k the candidate frequency, and, *Length*, i.e., a simple rule that scores 1 for unigrams and 2 for the remaining sizes. The final score of each candidate is the result of the product of these 4 features. Moreover, with respect to the observation that the larger document datasets are associated with a higher number of keyphrases per document, the top- N candidates are extracted for each document with $n = 2.5 \times \log_{10}(\text{doc size})$ (the 2.5 parameter was found experimentally).

2.2 | Graph-based Ranking Methods

The basic idea in graph-based ranking is to create a graph from a document that has as nodes the candidate phrases from the document and each edge of this graph connects related candidate keyphrases. The final goal is the ranking of the nodes using a graph-based ranking method, such as Google's PageRank (Brin and Page, 1998), Positional Function (Herings et al., 2005) and HITS (Kleinberg, 1999) or generally solving a proposed optimization problem on the graph. Based on the methods described below, PageRank has been successfully used for graph-based keyphrase extraction. PageRank is based on eigenvector centrality and recursively defines the weight of a vertex as a measure of its influence inside the graph-of-words, regardless of how cohesive its neighborhood is. However, Rousseau and Vazirgiannis (2015) consider the vertices of the main core as the set of keywords to extract from the document, as it corresponds to the most cohesive connected component of the graph. For this reason, the vertices are intuitively appropriate candidates.

TextRank was the first graph-based keyphrase extraction method proposed by Mihalcea and Tarau (2004) which inspired researchers to build upon it, leading to well-known state-of-the-art methods. First of all, the text is tokenized, and annotated with POS tags. Then, syntactic filters are applied to the text units, i.e., only nouns and adjectives are kept. Next, the lexical units that pass the filters mentioned above, i.e., the candidates, are added to the graph as nodes and an edge is added between the nodes that co-occur within a window of M words. The graph is undirected and un-weighted. The initial score assigned to each node is equal to 1 and then the PageRank algorithm runs until it converges. Specifically, for a node V_i the corresponding score function that is repeatedly computed is:

$$S(V_i) = (1 - \lambda) + \lambda * \sum_{j \in N(V_i)} \frac{1}{N(V_j)} S(V_j)$$

where $N(V_i)$ is the set of neighbors of V_i , $N(V_j)$ is the set of neighbors of V_j and λ is the probability of jumping from one node to another. Once the algorithm converges, the nodes are sorted by decreasing score.

SingleRank (Wan and Xiao, 2008) is an extension of TextRank which incorporates weights to edges. Similarly, to the statistical-based methods, the co-occurrence statistics are crucial information regarding the contexts. Hence, each

edge weight is equal to the number of co-occurrences of the two corresponding words. Then, the score function for a node V_i is computed in a similar way:

$$WS(V_i) = (1 - \lambda) + \lambda * \sum_{j \in N(V_i)} \frac{\#_{cij}}{\sum_{V_k \in N(V_j)} \#_{cjk}} WS(V_j)$$

where $\#_{cij}$ is the the number of co-occurrences of word i and word j . In a post-processing stage, for each continuous sequence of nouns and adjectives in the text document, the scores of the constituent words are summed up and the T top-ranked candidates are returned as keyphrases. Co-occurrences are also used by various graph-based methods such as the one of Rose et al. (2010), called *RAKE (Rapid Automatic Keyword Extraction)*, that utilizes both word frequency and word degree to assign scores to phrases. *RAKE* take as input parameters a list of stopwords, a set of phrase delimiters and a set of word delimiters to partition the text into candidate phrases. Then, a graph of word-word co-occurrences is created and a score (word frequency or the word degree or the ratio of degree to frequency) is assigned for each candidate phrase which is the sum of the scores of the words that comprise the phrase. In addition, *RAKE* is able to identify keyphrases that contain interior stopwords, by detecting pairs of words that adjoin one another at least twice in the same document, in the same order. Finally, the top T ranked candidate phrases are selected as keyphrases for the document.

In this vein, the more recent methods *SGRank* (Danesh et al., 2015) and *PositionRank (PR)* (Florescu and Caragea, 2017b) utilize statistical, positional, and, word co-occurrence information, thus improving the overall performance. In particular, *SGRank* (Danesh et al., 2015), first, extracts all possible n-grams from the input text, eliminating those that contain punctuation marks or whose words are anything different than noun, adjective or verb. Furthermore, it takes into account term frequency conditions. In the second stage, the candidate n-grams are ranked based on a modified version of Tfidf (similar to KP-Miner). In the third stage, the top ranking candidates are re-ranked based on additional statistical heuristics, such as position of first occurrence and term length. Finally, the ranking produced in stage three is incorporated into a graph-based algorithm which produces the final ranking of keyphrase candidates. *PositionRank (PR)* (Florescu and Caragea, 2017b) is a graph-based unsupervised method that tries to capture frequent phrases considering the word-word co-occurrences and their corresponding position in the text. Specifically, it incorporates all positions of a word into a biased weighted PageRank. Finally, the keyphrases are scored and ranked.

The rest of the graph-based methods are grouped into three main categories, i.e., the methods that incorporate information from similar documents or citation networks (Section 2.2.1), the topic-based methods (Section 2.2.2), and the graph-based methods that utilize semantics (Section 2.2.3), which are discussed in the following sections.

2.2.1 | Incorporating Information from Similar Documents/Citation Networks

The graph-based methods discussed earlier assume that the documents are independent of each other. Hence, only the information included in the target document, i.e., the phrase's Tfidf, position etc., is used during the keyphrase extraction process. However, related documents have mutual influences that help to extract keyphrases. *ExpandRank* (Wan and Xiao, 2008) is an extension of *SingleRank* that takes into consideration information from neighboring documents to the target document. It constructs an appropriate *knowledge context* for the target document that is used in the keyphrase extraction process and helps to extract important keyphrases from it. According to this method each document is represented by a vector with Tfidf scores. For a target document d_0 , its k nearest neighbors are identified, and a larger document set D of $k+1$ documents is created. Based on this document set, a graph is constructed, where each node corresponds to a candidate word in D , and edges are added between two nodes, (v_i, v_j) , that co-occur within

a window of M words in the document set. The weight of an edge, $e(v_i, v_j)$ is computed as follows:

$$e(v_i, v_j) = \sum_{d_k \in D} \text{sim}(d_0, d_k) \times \text{freq}_{d_k}(v_i, v_j)$$

where $\text{sim}(d_0, d_k)$ is the cosine similarity between d_0 and d_k , and $\text{freq}_{d_k}(v_i, v_j)$ is the co-occurrence frequency of v_i, v_j in document d_k . Once the graph is constructed, the rest of the procedure is identical to SingleRank.

A more related knowledge context to the target document can be also found via citation networks. In a citation network, information flows from one paper to another via the citation relation. In other words, the influence of one paper on another is captured through *citation contexts* (i.e., short text segments surrounding a paper's mention). In this vein, *CiteTextRank* (Gollapalli and Caragea, 2014) incorporates information from citation networks for the keyphrase extraction process capturing the information from such citation contexts. In particular, given a target document d and a citation network C ($d \in C$), a *cited context* for d is a context in which d is cited by a paper d_i , and a *citing context* for d is a context in which d is citing another paper d_j . The content of d is dubbed as *global context*. As a first step, they construct an undirected graph $G = (V, E)$ for d , with nodes the words from all types of contexts of d and edges between the nodes (v_i, v_j) , in case of co-occurrence within a window of M continuous tokens in any of the contexts. The weight of an edge is set equal to:

$$e_{ij} = \sum_{t \in TC} \sum_{c \in C_t} \lambda_t \cdot \text{sim}(c, d) \cdot \#_c(v_i, v_j)$$

where the TC are the available types of contexts in d (global, citing, cited), $\text{sim}(c, d)$ is the cosine similarity between the $TfIdf$ vectors of any context c of d and d , $\#_c(v_i, v_j)$ is the number of co-occurrences of v_i, v_j in context c , C_t is the set of contexts of type $t \in TC$ and λ_t is the weight for contexts of type t . Finally, they score the vertices using the PageRank algorithm.

2.2.2 | Topic-based Methods

Except the previous methods that use classic statistical heuristics (Tf , Idf , position) as well as context-aware statistics such as word-word co-occurrence information, there are also methods that try to return keyphrases related to the *topics* discussed in the document. Specifically, the topic-based methods try to extract keyphrases that are representative for a text document in terms of the topics it covers. Such methods usually apply clustering techniques or Latent Dirichlet Allocation (LDA) (Blei et al., 2003) to detect the main topics discussed.

Clustering-based Methods

TopicRank (TR) (Bougouin et al., 2013), first, preprocesses the text to extract the candidate phrases. Then, the candidate phrases are grouped into separate topics using hierarchical agglomerative clustering. In the next stage, a graph of topics is constructed whose edges are weighted based on a measure that considers phrases' offset positions in the text. Then, TextRank is used to rank the topics and one keyphrase candidate is selected from each of the N most important topics (first occurring keyphrase candidate). A more recent very similar method to TopicRank but more advanced is *MultipartiteRank (MR)* (Boudin, 2018) which introduces an in-between step where edge weights are adjusted to capture position information giving bias towards keyphrase candidates occurring earlier in the document. Note that the heuristic to promote a specific group of candidates, e.g., those that appear earlier in the text, can be adapted to satisfy other conditions/needs.

LDA-based Methods

Topical PageRank (TPR) (Liu et al., 2010) is a topic-based method upon which various topic-based methods have been built. TPR uses LDA to obtain the topic distribution $pr(z|w)$ of each word w , for topic $z \in K$, where K is the number of topics and the topic distribution $pr(z|d)$ of a new document d , for each topic $z \in K$. Then, for a document d , it constructs a word graph based on word-word co-occurrences by adding only the adjectives and nouns. The idea of TPR is to run a *Biased PageRank* for each topic separately. So, for every topic z , the topic-specific PageRank word scores are calculated as follows:

$$S_z(w_i) = \lambda \sum_{j:w_j \rightarrow w_i} \frac{e(w_j, w_i)}{O(w_j)} S_z(w_j) + (1 - \lambda) p_z(w_i)$$

where $p_z(w_i)$ is equal to $pr(z|w)$ which is the probability of topic z given word w , λ is a damping factor range from 0 to 1, $e(w_j, w_i)$ is the weight of link $e(w_j, w_i)$, and $O(w_j)$ is the out-degree of vertex w_j . The final PageRank word scores are obtained by the equation given above, iteratively, until convergence. Using the topic-specific importance scores of words, the ranking of candidate phrases with respect to each topic z separately is:

$$S_z(p) = \sum_{w_i \in p} S_z(w_i)$$

where p is a candidate phrase. Finally, the topic distribution of the document $p(z|d)$ is considered by integrating the topic-based rankings of candidates:

$$S(p) = \sum_1^K S_z(p) \times pr(z|d)$$

Single Topical PageRank (Single TPR) (Sterckx et al., 2015a) is an alternative method to avoid the large cost of TPR by running only one PageRank for each document. According to this method, the sum of the K topic-specific values of each word w_j is replaced by the concept of topical importance $W(w_j)$. Particularly, first, the cosine similarity ($W(w_j)$) is calculated between the vector of word-topic probabilities and the document-topic probabilities. Finally, the Single PageRank $S(w_j)$ becomes

$$S(w_i) = \lambda \sum_{j:w_j \rightarrow w_i} \frac{e(w_j, w_i)}{O(w_j)} S(w_j) + (1 - \lambda) \frac{W(w_i)}{\sum_{w \in V} W(w)}$$

where $V = \{w_1, \dots, w_N\}$ is the set of graph nodes. Moreover, in a related study, Sterckx et al. (2015b) propose the utilization of *multiple topic models* for the keyphrase extraction task to show the benefit from a combination of models. Particularly, the models disagree when they are trained on different corpora, as there is a difference in contexts between the corpora. This leads to different topic models and disagreement about the word importance. So, this disagreement is leveraged by computing a combined topical word importance value which is used as a weight in a Topical PageRank, improving the performance, in cases where the topic models differ substantially.

In this spirit, *Saliency Rank* (Teneva and Cheng, 2017) is quite close to Single TPR as it runs only once PageRank, incorporating in it a word metric called *word saliency* $S_\alpha(w)$, which is a linear combination of the *topic specificity* (Chuang et al., 2012a) and *corpus specificity* of a word (the last can be calculated counting word frequencies in a specific corpus). Intuitively, topic specificity measures how much a word is shared across topics (the less the word is shared across topics, the higher its topic specificity). Users can balance topic specificity and corpus specificity of the extracted

keyphrases and can tune the results according to particular cases. So, the Single PageRank becomes:

$$S(w_i) = \lambda \sum_{j:w_j \rightarrow w_i} \frac{e(w_j, w_i)}{O(w_j)} S(w_j) + (1 - \lambda) \times S_\alpha(w_i)$$

An interesting and probably effective direction in LDA-based methods would be the utilization of a topic model similar to the one proposed by El-Kishky et al. (2014). Indeed, most topic modeling algorithms model text corpora with unigrams, whereas human interpretation often relies on inherent grouping of terms into phrases. Particularly, El-Kishky et al. (2014) first propose an efficient phrase mining technique to extract frequent significant phrases and segment the text at the same time, which uses frequent phrase mining and a statistical significance measure. Then, they introduce a simple but effective topic model that restricts all constituent terms within a phrase to share the same latent topic, and assigns the phrase to the topic of its constituent words. Besides, the first part of the method (phrase mining) could be exploited to filter out false candidate keyphrases in the context of a keyphrase extraction pipeline.

2.2.3 | Graph-based Methods with Semantics

Semantics from Knowledge Graphs/Bases

The main problems of the topic-based methods are that the topics are too general and vague. In addition, the co-occurrence-based methods suffer from *information loss*, i.e., if two words never co-occur within a window size in a document, there will be no edges to connect them in the corresponding graph-of-words even though they are semantically related, whereas the statistics-based methods suffer from *information overload*, i.e., the real meanings of words in the document may be overwhelmed by the large amount of external texts used for the computation of statistical information. To deal with such problems and incorporate semantics for keyphrase extraction, Shi et al. (2017) propose a keyphrase extraction system that uses knowledge graphs. First, nouns and named entities (*keyterms*) are selected and grouped based on semantic similarity by applying clustering. Then, the keyterms of each cluster are connected to entities of DBpedia. For each cluster, the relations between the keyterms are detected by extracting the *h-hop keyterm graph* from the knowledge graph, i.e., the subgraph of DBpedia that includes all paths of length no longer than *h* between two different nodes of the cluster. Then, all the extracted keyterm graphs of the clusters are integrated into one and a Personalized PageRank (PPR) (Haveliwala, 2002) is applied on it to get the ranking score of each keyterm. The final ranking scheme of the candidate phrases uses the PPR score which is the sum of the PPR scores of the keyterms in it, as well as, the frequency and first occurrence position of the phrase. Moreover, this method could be categorized to the topic-based methods using clustering (see Table 1).

Similarly, Yu and Ng (2018) propose WikiRank, an unsupervised automatic keyphrase extraction method that tries to link semantic meaning to text. First, they use TAGME (Ferragina and Scaiella, 2010), which is a tool for topic/concept annotation that detects meaningful text phrases and matches them to a relevant Wikipedia page. Additionally, they extract noun groups whose pattern is zero or more adjectives followed by one or more nouns as candidate keyphrases. Then, a semantic graph is built whose vertices are the union of the concept set and the candidate keyphrase set. In case the candidate keyphrase contains a concept according to the annotation of TAGME an edge is added between the corresponding nodes. The weight of a concept is equal to the frequency of the concept in the full-text document. Moreover, they propose the score of a concept *c* in a subgraph of *G* to be:

$$S(c) = \sum_{i=0}^{\text{deg}(c)} \frac{w_c}{2^i}$$

where w_c is the weight of the concept c , and $deg(c)$ is the degree of c in the corresponding subgraph. The goal is to find the candidate keyphrase set Ω with the best coverage, i.e., the maximum sum of scores of the concepts annotated from the phrases in Ω .

Semantics from Pretrained Word Embeddings

Although the methods that utilize semantics from knowledge graphs/bases have shown their improvements, the keyphrase extraction process requires more background knowledge than just semantic relation information. Thus, Wang et al. (2014) propose a graph-based ranking model that considers semantic information coming from distributed word representations as background knowledge. Again, a graph of words is created with edges that represent the co-existence between the words within a window of M consecutive words. Then, a weight, called *word attraction score* is assigned to every edge, which is the product of two individual scores; a) the *attraction force* between two words that uses the frequencies of the words and the euclidean distance between the corresponding word embeddings and b) the *dice coefficient* (Dice, 1945; Stubbs, 2003) to measure the probability of two words co-occurring in a pattern, or by chance. Particularly, given a document d as a sequence of words w , i.e., $d = w_1, w_2, \dots, w_n$ the dice coefficient is computed as:

$$dice(w_i, w_j) = \frac{2 \times freq(w_i, w_j)}{freq(w_i) + freq(w_j)}$$

where $freq(w_i, w_j)$ is the co-occurrence frequency of words w_i and w_j , and $freq(w_i)$ and $freq(w_j)$ are the occurrence frequencies of w_i and w_j in d . Once more, a weighted PageRank algorithm is utilized to rank the words. Wang et al. (2015) propose an improved method that uses a *Personalized* weighted PageRank model with pretrained word embeddings and also more effective edge weights. Particularly, the strength of relation of a pair of words is calculated as the product of the *semantic relatedness* and *local co-occurrence co-efficient*, as:

$$sr(w_i, w_j) = semantic(w_i, w_j) \times cooccur(w_i, w_j)$$

where $semantic(w_i, w_j) = \frac{1}{1 - cosine(w_i, w_j)}$ with $cosine(w_i, w_j)$ to be the cosine similarity between the corresponding vectors. Furthermore, as co-occurrence co-efficient is used the Point-wise Mutual Information. Finally, the score of w_i is calculated as follows:

$$S(w_i) = (1 - \lambda)pr(w_i) + \lambda \times \sum_{w_j \in N(w_i)} \frac{sr(w_i, w_j)}{|out(w_j)|} S(w_j)$$

where $sr(w_i, w_j)$ is the strength of relatedness score between the two words calculated previously, $pr(w_i)$ is the probability distribution of word w_i , calculated as $\frac{freq(w_i)}{N}$ ($freq(w_i)$ is the occurrence frequency and N the number of total words), and $N(w_i)$ is the set of vertices incident to w_i

However, Wang et al. (2015) do not use domain-specific word embeddings and notice that training them might lead to improvements. This motivated Mahata et al. (2018) to present *Key2Vec*, an unsupervised keyphrase extraction technique from scientific articles that represents candidate keyphrases of a document by domain specific phrase embeddings and ranks them using a *theme-weighted* PageRank algorithm (Langville and Meyer, 2003). After exhaustive text preprocessing on a corpus of scientific abstracts, which is well-described in their work, *Fasttext* (Bojanowski et al., 2017) is utilized for training multiword phrase embeddings. First, the same text preprocessing is applied to the target document in order to get a set of unique *candidate keyphrases*. Then, a *theme excerpt*, i.e., the first sentence(s), is extracted from the document. Afterwards, a unique set of thematic phrases, i.e., named entities, noun phrases and

unigram words, are also extracted from the theme excerpt. Next, they get the vector representation of each thematic phrase using the trained phrase embedding model and perform vector addition to get the final *theme vector*. Moreover, the phrase embedding model is also used to get the vector representation for each candidate keyphrase. Then, they calculate the cosine distance between the theme vector and the vector for each candidate keyphrase, assigning a score to each candidate (*thematic weight*). Then, a directed graph is constructed with the candidate keyphrases as the vertices. Two candidate keyphrases are connected if they co-occur within a window size of 5 (bidirectional edges are used). In addition, weights are calculated for the edges using the semantic similarity between the candidate keyphrases obtained from the phrase embedding model and their frequency of co-occurrence, as in Wang et al. (2015). For the final ranking of the candidate keyphrases, a weighted personalized PageRank algorithm is used.

2.3 | Keyphrase Extraction based on Embeddings

Many methods for representation of words have been proposed. Representative techniques, which are based on a co-occurrence matrix, are Latent Dirichlet Allocation (LDA) (Blei et al., 2003) and Latent Semantic Analysis (LSA) (Deerwester et al., 1990). However, word embeddings came to the foreground by Mikolov et al. (2013), who presented the popular Continuous Bag-of-Words model (CBOW) and the Continuous Skip-gram model. Additionally, sentence embeddings (Doc2Vec (Lau and Baldwin, 2016) or Sent2vec (Pagliardini et al., 2018)) as well as the popular GloVe (Global Vectors) (Pennington et al., 2014) method are utilized by keyphrase extraction methods.

EmbedRank (Bennani-Smires et al., 2018) extracts candidate phrases based on POS sequences (phrases that consist of zero or more adjectives followed by one or multiple nouns). *EmbedRank* uses sentence embeddings (Doc2Vec or Sent2vec) to represent both the candidate phrases and the document in the same high-dimensional vector space. Finally, the system ranks the candidate phrases using the cosine similarity between the embedding of the candidate phrase and the document embedding.

Moreover, Papagiannopoulou and Tsoumakas (2018) present the *Reference Vector Algorithm (RVA)*, a method for keyphrase extraction, whose main innovation is the use of local word embeddings/semantics (in particular GloVe vectors), i.e., embeddings trained from the single document under consideration. The employed local training of GloVe on a single document and the graph-based family of methods can be considered as two alternative views of the same information source, as both methods utilize the statistics of word-word co-occurrence in a text. Then, the mean (*reference*) vector of the words in the document's title and abstract is computed. This mean vector is a vector representation of the semantics of the whole publication. Finally, candidate keyphrases are extracted from the title and abstract, and are ranked in terms of their cosine similarity with the reference vector, assuming that the closer to the reference vector is a word vector, the more representative is the corresponding word for the publication.

2.4 | Language Model-based Methods

Language modeling plays an important role in natural language processing tasks (Chen and Goodman, 1999). Generally, an N -gram language model assigns a probability value to every sequence of words $w = w_1 w_2 \dots w_n$, i.e., the probability $P(w)$ can be decomposed as

$$P(w) = \prod_{i=1}^n P(w_i | w_1, w_2, \dots, w_{i-1})$$

For example a trigram language model is the following:

$$P(w) = \prod_{i=1}^n P(w_i | w_{i-1}, w_{i-2})$$

Besides the N -gram language models there are also various types of models, such as the popular neural language models that use neural networks to learn the context of the words Merity et al. (2018).

Keyphrase extraction with N-gram language models Tomokiyo and Hurst (2003) create both unigram and n-gram language models on a foreground corpus (target document) and a background corpus (document set). Their main idea is based on the fact that the loss between two language models can be measured using the Kullback-Leibler divergence. Particularly, at phrase level, for each phrase, the *phraseness* is computed as the divergence between the unigram and n-gram language models on the foreground corpus and the *informativeness* is calculated as the divergence between the n-gram language models on the foreground and the background corpus. Then, the phraseness and informativeness are summed as a final score for each phrase. Finally, phrases are sorted based on this score.

3 | SUPERVISED METHODS

In this section, we present traditional supervised methods (Section 3.1) as well as deep learning methods (Section 3.2) along with the main categories of features that are used (Section 3.3). Section 3.4 discusses the performance of some earlier, state-of-the-art and more recent supervised methods on 3 popular keyphrase extraction datasets. Finally, we discuss the main problems of the supervised learning methods along with the proposed solutions (Section 3.5). Figure 2 shows the presentation structure of the supervised keyphrase extraction methods that is also consistent with their corresponding taxonomy.

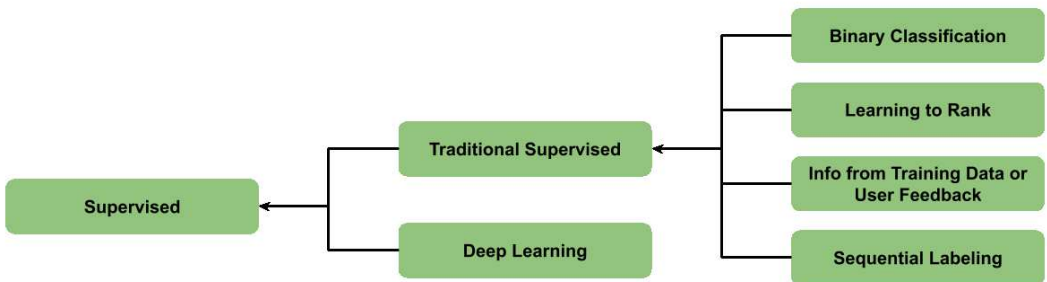


FIGURE 2 Presentation structure of supervised keyphrase extraction methods.

3.1 | Traditional Supervised Methods

Keyphrase Extraction as Binary Classification Task

In general, in supervised learning, a classifier is trained on annotated with keyphrases documents in order to determine whether a candidate phrase is a keyphrase or not. These keyphrases and non-keyphrases are used to generate positive and negative examples. In this section, we discuss the most representative methods of this category in terms

of the learning process they employ.

One of the first keyphrase extraction systems is KEA (Witten et al., 1999) which calculates for each candidate phrase its Tfidf score and its first occurrence, i.e., the position (offset in words from the start of the document) of the phrase's first appearance, and uses as learning algorithm Naive Bayes. Hulth (2003) proposes a system that utilizes linguistic knowledge. Particularly, for each candidate phrase of the training set four features are calculated: the within-document frequency, the collection frequency, the relative position of the first occurrence and part-of-speech (POS) tag sequence. In this case the machine learning approach is a rule induction system with bagging. An extension of KEA is proposed by Nguyen and Kan (2007). The existing feature set (Tfidf and first occurrence) is enhanced with additional features to incorporate position information (a section occurrence vector, i.e., a vector of frequency features for 14 generic section headers) and additional morphological/linguistic characteristics (POS tag sequence, suffix sequence and acronym status) of the keyphrases. Once more, as learning method they use Naive Bayes. Later, Medelyan et al. (2009) propose *Maui*, which extends KEA by introducing an alternative set of new features. Maui uses as features in the classification model the Tfidf score, the first occurrence, the *keyphraseness* which quantifies how often a candidate phrase appears as a tag in the training corpus, the phrase length (measured in words), the *Wikipedia-based keyphraseness* which is the probability of a phrase being a link in the Wikipedia, the *spread* of a phrase, i.e., the distance between its first and last occurrence of the phrase as well as additional features that utilize Wikipedia as a source of language usage statistics such as the *node degree*, the *semantic relatedness* and the *inverse Wikipedia linkage*. Maui uses bagged decision trees as classifier to capture interactions between features. Afterwards, Nguyen and Luong (2010) propose a method (*WINGNUS*) that extracts candidates using the regular expression rules used in Kim and Kan (2009). In their work, they also study the keyphrase distribution on the training data over the sections of documents, concluding that the best choice is either the full-text or a text segment comprising of title, headers, abstract, introduction, related work, conclusion and the first sentence of each paragraph. They experimented with various combinations of features from a large feature set using the Naive Bayes algorithm. Finally, they propose as the best features the Tfidf, the term frequency of the phrase substrings, the first occurrence and the length of the phrase.

Caragea et al. (2014) propose *CeKE*, a binary classification model (Naive Bayes classifier with decision threshold 0.9) that utilizes novel features from information of citation contexts (boolean features that are true if the candidate phrase occurs in cited/citing contexts and the Tfidf score of each phrase computed from the citation contexts), existing features from previous works (phrase Tfidf, first position, relative position and POS tags), and extended existing features (a boolean feature which is true if the Tfidf score is greater than a threshold and a boolean feature which is true if the distance of the first occurrence of a phrase from the beginning of a target paper is below some value). Shi et al. (2008) use Wikipedia as an additional feature source for their supervised keyphrase extraction method. The first step is the detection of the candidate keyphrases via mapping to the Wikipedia concepts that appear in the titles of Wikipedia articles, redirect/disambiguation pages and anchor text of Wikipedia articles. As each Wikipedia concept is related to at least one category, candidate topics can be defined for a document by collecting the corresponding concepts' categories. Then, a semantic bipartite graph is constructed where candidate keyphrases are connected with the document topics based on various semantic relation types, e.g., the synonym and hypernym relation. After the graph construction, a feature weight ($w_e = \lambda^l \cdot f_p$, where λ is a parameter that lies in (0,1) for the level of category l , and f_p is the frequency of the phrase in the document) is assigned to the candidate keyphrases and a proposed variant of the HITS algorithm that considers the link weights is used to compute the final *semantic feature weights* for each phrase. Finally, additional statistical, positional and linguistics features are computed, such as the appearance in the title, the phrase frequency, the phrase position and the phrase length, and a logistic regression model is used to predict the document's keyphrases.

Afterwards, Wang and Li (2017) propose a system (PCU-ICL) that incorporates features, such as stemmed un-

igrams, Tf, ldf, Tfldf, POS tags for every word in the phrase, phrase length, previous/next token of the phrase, POS of previous/next token of the phrase, distance between the phrase and the citation, a boolean feature that encodes whether the phrase is in IEEE taxonomy list, Wikipedia-based ldf, GloVe embedding of the phrase, and unsupervised model based features. An ensemble of unsupervised models, random forest (RF) and linear models are used for candidate keyphrase ranking. Recently, McIlraith and Weinberger (2018) have proposed *SurfKE*, a supervised method that learns feature representations based on the document's graph of words. The Gaussian Naive Bayes classifier is used to train their model.

Keyphrase Extraction as Learning to Rank Task

Learning to rank approaches learn a ranking function that sorts the candidate phrases based on their score of being a keyphrase, whereas classification methods have to make hard decisions. A representative method in this category is *Ranking SVM* (Jiang et al., 2009) which first constructs an appropriate training set by following a particular process. Suppose there is a training set of L documents $D = d_1, d_2, \dots, d_L$ and for each document k there are N_k candidate keyphrases, each of them is represented by a feature vector x_{ki} (the i th candidate keyphrase of the k th document) and the corresponding rank y_{ki} . In order to train a ranking function f^* , the training data is transformed into a set of ordered phrase pairs $(x_{ki} - x_{kj}, z_{k,ij})$ where $z_{k,ij}$ shows their preference relationships, $z_{k,ij} = +1$ if $y_{k,i} > y_{k,j}$ and $z_{k,ij} = -1$, otherwise. Then, an SVM model is trained on this training set that ends up to an optimization problem whose optimal solution are the ω weights, denoted as ω^* and the corresponding ranking function becomes:

$$f^*(x) = \langle \omega^*, x \rangle$$

MIKE (Zhang et al., 2017) is a more advanced learning to rank method. First, it selects the candidate words by applying stopword and POS filters. Then, a graph of words is constructed based on the co-occurrence relations between the candidate words within the target document. Afterwards, features of candidate words and their co-occurrences (i.e., *node features*, such as Tfldf, ldf over a certain threshold, first occurrence, relative position, POS tags, and citation Tfldf as well as *edge features* which are based on the co-occurrence frequency between candidate word pairs in the word graph), *topic distributions* of candidates and *relative importance relation* between candidates (i.e., prior knowledge based on some documents that defines a partial ordering between keyphrases - non keyphrases pairs) are collected and integrated into a random-walk parametric model. Then, the model defines a loss function, which is optimized using gradient descent, in order to learn the parameters, and computes the ranking score of each candidate word. Finally, consecutive words, phrases or n-grams are scored by using the sum of scores of individual words that comprise the phrase.

Keyphrase Extraction Using Supervision

Bougouin et al. (2016) (TopicCoRank) extend the unsupervised method TopicRank, making it capable of assigning domain-specific keyphrases that do not necessarily occur within the document, by unifying a second graph with the domain to the basic topic graph. Particularly, the keyphrases manually assigned to the training documents are considered as controlled keyphrases. In addition, these controlled keyphrases are not further clustered as they are supposed to be non-redundant. The unified graph is denoted as $G = (V = T \cup K, E = E_{in} \cup E_{out})$, where V are the graph vertices that comprise the set of topics $T = t_1, t_2, \dots, t_n$ and the set of controlled keyphrases $K = k_1, k_2, \dots, k_m$. Furthermore, the set E_{in} contains edges of type $\langle t_i, t_j \rangle$ or $\langle k_i, k_j \rangle$, whereas the set E_{out} contains edges of type $\langle k_i, t_j \rangle$. An edge connects a controlled keyphrase k_i with a topic t_j if the controlled keyphrase is a member of the topic. Moreover, two topics t_i and t_j or two controlled keyphrases k_i and k_j are connected in case they co-occur within a sentence of the document or as keyphrases of a training document, respectively. The weight of the edge $\langle t_i, t_j \rangle$ is the number of times ($w_{i,j}$) topics t_i and t_j co-occur in the same sentence within the document. Similarly, a weight is assigned to the

edge $\langle k_i, k_j \rangle$ equal to the number of times $(w_{i,j})$ keyphrases k_i and k_j are associated to the same document among the training documents. TopicCoRank assigns a score to every topic $(S(t_i))$ or controlled keyphrase $(S(k_i))$ using graph co-ranking, simulating the voting concept based on inner (R_{in}) and outer recommendations (R_{out}) :

$$S(t_i) = (1 - \lambda_t)R_{out}(t_i) + \lambda_t R_{in}(t_i)$$

$$S(k_i) = (1 - \lambda_k)R_{out}(k_i) + \lambda_k R_{in}(k_i)$$

where

$$R_{in}(v_i) = \sum_{v_j \in E_{in}(v_i)} \frac{w_{ij} S(v_j)}{\sum_{v_k \in E_{in}(v_j)} w_{jk}}$$

$$R_{out}(v_i) = \sum_{v_j \in E_{out}(v_i)} \frac{S(v_j)}{|E_{out}(v_j)|}$$

where v_i is a node of a keyphrase or a topic, λ_t and λ_k are parameters that control the influence of the inner recommendation over the outer recommendation.

Yang et al. (2018) propose a model to extract a set of keyphrases that correspond to particular events. In the first phase, they segment each document into phrases. In the second phase, they use a Task-oriented Latent Dirichlet Allocation model (ToLDA) to extract candidate phrases for specific events. More precisely, they treat each event as a topic in their topic model. The ToLDA model utilizes a small set of *seed* keyphrases (defined by the user) to guide the topics' generation process. In this way, the extracted phrases are more related/oriented to the seed keyphrases. In the last phase, they apply the PMI-IR algorithm Turney (2001) to get the synonyms of the candidate phrases. Finally, the candidate phrases are evaluated by inspectors, and the selected phrases are the final phrases which can be treated as seed keyphrases. The last two phases can be run iteratively.

Sequential Labeling

We should not omit the recent work on keyphrase extraction where the task has been treated as a sequence tagging task using Conditional Random Fields (CRFs) by Gollapalli et al. (2017). The features that are used represent linguistic, orthographic, and structure information from the document. Furthermore, they investigate feature-labeling and posterior regularization in order to integrate expert/domain-knowledge throughout the keyphrase extraction process. In addition, Sogaard and Bingel (2017) exploit the idea of multi-task learning approaches (Caruana, 1993) and joint modeling of tasks (Miwa and Bansal, 2016; Hashimoto et al., 2017; Bekoulis et al., 2018a,b) to study the performance effectiveness of the keyphrase detection task (on the SemEval 2017 Task 10 dataset) when training along with other sequence labeling tasks (e.g., POS tagging, chunking) in a multi-task learning fashion.

3.2 | Deep Learning Methods

Zhang et al. (2016) investigate the task of keyphrase extraction from tweets. They propose a deep recurrent neural network (RNN) model with two hidden layers. In the first hidden layer, they capture the keyword information, while in the second one, they extract the keyphrase based on the keyword information using a sequence labeling approach.

Later, Meng et al. (2017) (seq2seq) proposed a generative model for keyphrase prediction using an encoder-decoder framework that captures the semantic meaning of the content via a deep learning method (CopyRNN). First, the data is transformed into text-keyphrase pairs and then an RNN Encoder-Decoder model is applied to learn the mapping from the source sequence to target sequence. The key idea here is the compression of the source text into a hidden-layer representation with an encoder and the keyphrase generation with a decoder, based on the previous hidden-layer representation. However, the main drawbacks of this approach is that the generated keyphrases suffer from *duplication* (at least two phrases expressing the same meaning) and *coverage* (important topics in the document are not covered) issues, as it ignores the correlation among the target keyphrases. Hence, Chen et al. (2018) propose CorrRNN, an alternative sequence-to-sequence architecture, capable of capturing such type of correlation constraints, i.e., (1) keyphrases should cover all document's topics and (2) differ from each other. Particularly, a coverage mechanism (Tu et al., 2016) is utilized to memorize which text parts of the document have been covered by previous phrases. Additionally, a review mechanism is proposed to satisfy the second constraint. More specifically, the review mechanism models the correlation between the already returned keyphrases and the keyphrase that is going to be returned.

From another point of view, both the latter methods (Meng et al., 2017; Chen et al., 2018) are mainly based on massive amounts of labeled documents for the training process. Ye and Wang (2018) try to deal with this problem by proposing two approaches for leveraging unlabeled data. The most effective way that is adopted in the context of the first approach (based on the experimental results) is the construction of synthetic labeled data by assigning keyphrases obtained by 2 unsupervised keyphrase extraction methods, the TfIdf and the TextRank (Mihalcea and Tarau, 2004), to unlabeled documents. Particularly, they run the 2 methods separately, and then they get the union of the two returned keyphrases' sets. After the construction of the synthetic data, the labeled data is mixed with the synthetic ones to train the sequence-to-sequence model. For the second approach to leverage unlabeled documents, a multi-task learning framework combines the basic task of keyphrase generation with an auxiliary task. The auxiliary task that has been chosen is the title generation which has been studied as a summarization problem (Rush et al., 2015). Specifically, the 2 tasks share an encoder network but have different decoders. In the multi-task learning approach, the following training strategy is adopted: first, the parameters are estimated on the auxiliary task, with the dataset which is assigned with titles for unlabeled data for one epoch, then, the model is trained on the main task with the labeled dataset for 3 epochs. This training strategy is followed up to the convergence of the model of the main task.

However, Wang et al. (2018) improve the performance of keyphrase extraction in the unlabeled/insufficiently labeled target domain by transferring knowledge from resource-rich source domain (cross-domain perspective). More specifically, a Topic-based Adversarial Neural Network (TANN) is proposed that makes use of both labeled data in the related resource-rich domain and unlabeled data in source/target domain. The TANN model consists of 4 components:

- i) **Topic-based encoder:** first, the input sentence is read by a Bidirectional Long Short-Term Memory (Bi-LSTM) Network encoder, which is used to capture the sequential information and then more attention is paid to the words related to the documents' topics by considering the correlation score between the topic vector and the text words (topic correlation mechanism).
- ii) **Domain discriminator:** as there are some common words like "we introduce/we propose" across domains, which are good indicators for the following keyphrases, adversarial learning is used to ensure that the extracted features by the encoder are invariant to the change of domains.
- iii) **Target bidirectional decoder:** to balance the effort of the adversarial process to eliminate all the domain-private information in the target domain, a bidirectional decoder with bidirectional reconstruction loss is used in the target domain.
- iv) **Keyphrase tagger:** the output representation of the topic-based encoder is given as input to the keyphrase tagger

to predict the label of each word in the source text.

Finally, Basaldella et al. (2018) propose a Bi-LSTM RNN which is able to exploit previous and future context of a given word. First, the document is split into sentences that are tokenized in words. Then, each word is associated to a word embedding. Finally, word embeddings are fed into a Bi-LSTM RNN. In this vein, Alzaidy et al. (2019) combine a Bi-LSTM layer to model the sequential text data with a Conditional Random Field (CRF) layer to model dependencies in the output. Particularly, the first layer of the model is a Bi-LSTM network that captures the semantics of the input text sequence. The output of the Bi-LSTM layer is passed to a CRF layer that gives a probability distribution over the tag sequence using the dependencies among labels (i.e., KP: keyphrase word, Non-KP: not keyphrase word) of the entire sequence.

3.3 | Types of Features

Supervised keyphrase extraction methods employ different types of features to discover the importance of documents' terms. Table 2 gives an overview of the most popular features used by supervised methods. We also provide a categorization of the features that belong in the same family. Each category of features is discussed in a separate section. Table 3 gives an overview of the most representative supervised keyphrase extraction methods in terms of the learning algorithm they employ and the type of their input features/the knowledge they incorporate: statistical (Stat.), positional (Posit.), linguistic (Ling.), context (Cont.), stacking (Stack.) and external knowledge (Ext.). Once again, the categorization scheme and the table can be extended as new methods are developed with new features, feature categories and additional methods.

3.3.1 | Statistical Features

Features, such as the *term frequency (Tf)*, the *inverse document frequency (Idf)*, the *TfIdf* score as well as statistical scores, such as the *phrase entropy* are very popular and utilized by many methods, e.g., Witten et al. (1999) (KEA), Medelyan et al. (2009) (MAUI), Caragea et al. (2014) (CeKE), Hulth (2003), McIlraith and Weinberger (2018) (SurfKE), Wang and Li (2017) (PCU-ICL), Jiang et al. (2009) (Ranking SVM), Nguyen and Kan (2007), Zhang et al. (2017) (MIKE), Shi et al. (2008), Bougouin et al. (2016), and Nguyen and Luong (2010) (WINGNUS). In some cases, thresholds are used for the scores mentioned above for the creation of boolean features, ending up to values such as *high*, *low* etc. Moreover, Gollapalli et al. (2017) detect the features that co-occur with the keyphrases very often and incorporate this information via extra features, whereas Yang et al. (2018) adopt a user-guided Task-oriented Latent Dirichlet Allocation model (ToLDA) to generate topic distributions.

3.3.2 | Positional Features

This category includes features that indicate the *appearance of phrases in specific positions (e.g. the 1st occurrence of the phrase in the text)*, *sections*, *titles*, *abstracts*, *citation contexts*. The part(s) of the document, i.e., section, title, abstract where the phrases occur, imply the importance of the corresponding phrases. For instance, phrases that appear in title or in early parts of the document indicate that these phrases play an important role. Examples of such methods that use this type of information are Jiang et al. (2009) (Ranking SVM), Zhang et al. (2017) (MIKE), Shi et al. (2008) and Gollapalli et al. (2017). Nguyen and Kan (2007) utilize a vector of frequency features for 14 generic section headers (e.g., Abstract, Categories and Subject Descriptors, General Terms, Introduction, Conclusions etc.). A maximum

entropy-based classifier is used to infer the above generic section header.

The *exact position of the 1st/last occurrence of a phrase* or even though an average score of its positions in the text gives useful information for the role of a phrase as keyphrase. Popular supervised models are trained incorporating the above features, e.g., Witten et al. (1999) (KEA), Medelyan et al. (2009) (MAUI), Caragea et al. (2014) (CeKE), Jiang et al. (2009) (Ranking SVM), Zhang et al. (2017) (MIKE), Shi et al. (2008) and Nguyen and Luong (2010) (WINGNUS). The *spread* is another feature related to positional information which is calculated as the number of words between the first and last occurrences of a phrase in the document (Medelyan et al., 2009) (MAUI). In the same spirit, features, such as the *distance between phrase and citation* (Wang and Li, 2017) (PCU-ICL) seem to help the learning process, whereas sequential labeling approaches benefit from information for the internal structure of a text, e.g., the annotation of *sentence boundaries* (Gollapalli et al., 2017).

3.3.3 | Linguistic Features

Hulth (2003) has shown for the first time, through an extended empirical study, that the use of POS tag(s) as a feature improves the performance of a supervised keyphrase extraction system regardless the selection approach of the candidate phrases. *Phrase POS features* or *Noun Phrase (NP)-chunking* to discover phrases that match a predefined POS pattern have been also utilized by Caragea et al. (2014) (CeKE), Wang and Li (2017) (PCU-ICL), Zhang et al. (2017) (MIKE) and Gollapalli et al. (2017). Besides the POS tag sequence feature, Nguyen and Kan (2007) consider morphological features, i.e., the *suffix sequence* and the *acronym status*.

Other types of linguistic features, such as the *stemmed* form of the words (Wang and Li, 2017; Gollapalli et al., 2017) or boolean features that indicate whether the term *is a stopword/consists of punctuation/has capitalized letter(s)* are also met in the bibliography (Wang and Li, 2017) (PCU-ICL). Finally, a quite popular feature is the *phrase length* which is adopted by various methods, such as Wang and Li (2017) (PCU-ICL), Medelyan et al. (2009) (Maui), Jiang et al. (2009) (Ranking SVM), Shi et al. (2008) and Nguyen and Luong (2010) (WINGNUS).

3.3.4 | Context Features

The context of a word shows its meaning. In particular, even though we do not know a term, we can guess its meaning based on the context where it is used. Context-based features are quite useful for the keyphrase extraction task which is a process that is inseparable from extracting the central meaning of a text document and the expression of the topics discussed in it. The context of a phrase can also be simply expressed by providing the *previous/next token of the phrase* of interest (Wang and Li, 2017) (PCU-ICL). This type of features often appears along with *POS/syntactic features of the previous/next token of the target phrase* (Wang and Li, 2017) (PCU-ICL). The same paradigm is followed by the sequential labeling approach in Gollapalli et al. (2017) where similar *bigram/skipgram/compound features* related to stems and POS tag(s) are exploited.

Alternative types of context meaning can be captured by positional information incorporating the *relative position of the phrase in a given text*, i.e., the position of the first occurrence of a phrase normalized by the length of the target publication (Caragea et al., 2014) (CeKE), (Hulth, 2003), (Zhang et al., 2017) (MIKE), and (Wang and Li, 2017) (PCU-ICL). Recently, McIlraith and Weinberger (2018) (SurfKE) as well as Meng et al. (2017), Chen et al. (2018), Wang et al. (2018), Alzaidy et al. (2019) and Ye and Wang (2018) go one step beyond the context-based features by *learning features/embeddings* using graph structures and neural networks, respectively.

Feature Category	Description
Statistical	<ul style="list-style-type: none"> › - Tf/Idf/TfIdf - Number of sentences containing the phrase - Words or phrase entropy - Correlations between features and the phrase - Topic distributions (LDA)
Positional	<ul style="list-style-type: none"> › - Appearance in specific parts of the fulltext, e.g., sections, titles etc. - Position of the (1st or last) occurrence - Distance between phrase and citation - Section occurrence vector - Sentence boundaries - Spread
Linguistics	<ul style="list-style-type: none"> › - Stemmed unigram - Boolean features: IsCapilazed, IsStopword, AllPunctuation - POS tags, NP-chunking - Phrase length - Suffix sequence - Acronym status
Context	<ul style="list-style-type: none"> › - Previous/next token of the phrase - POS/syntactic features of previous/next token of phrase - Relative position of the phrase in given text - Learning embeddings/features (using NN/graph) - Bigram, skipgram, compound features (stem, pos, chunk etc.)
Stacking	<ul style="list-style-type: none"> › - Unsupervised methods output - Supervised methods output
External Knowledge	<ul style="list-style-type: none"> › - Existence of the phrase in ontologies (IEEE) or as a Wikipedia link - Wikipedia based Idf/phraseness - (Pretrained) Word embedding of the phrase - Supervised keyphraseness - Bias based on previous research - TitleOverlap - Semantic feature weight (returned by HITS with Wikipedia Info)

TABLE 2 A categorization of the most popular features that are used by supervised keyphrase extraction methods.

3.3.5 | Stacking

Stacking is a way to ensemble models. The idea is that we build various learners and then use them to build another model (i.e., their predictions are used as features for a second level model), and so on. We usually end up with a model that has better performance than any individual intermediate model. Wang and Li (2017) (PCU-ICL) stack trees upon output from unsupervised keyphrase extraction methods, i.e., TextRank and SGRank, whereas Gollapalli et al. (2017)

also incorporate information from the output of TfIdf, TextRank, SingleRank, and ExpandRank.

Moreover, models are stacked upon supervised approaches. Specifically, at a second layer Wang and Li (2017) (PCU-ICL) stack a linear model (linear SVM) upon random forest. Finally, Gollapalli et al. (2017) imply a high probability of a word to be a keyphrase when the phrase is identified by CeKE and Maui through special labeled features.

3.3.6 | External Knowledge

There is a great deal of features that are calculated based on external knowledge sources/corpora. In this category, there are boolean features that indicate the *existence of the phrase in an ontology/knowledge base*, e.g., IEEE, (Wang and Li, 2017) (PCU-ICL) as well as numeric features based on statistics, such as the *Wikipedia based Idf* calculation (Wang and Li, 2017) (PCU-ICL) and the *Wikipedia based keyphraseness* which is the likelihood of a phrase being a link in the Wikipedia corpus (Medelyan et al., 2009) (Maui). Similar to these features is the *supervised keyphraseness* which counts the number of times a phrase appears as a keyphrase in the training data (Medelyan et al., 2009) (Maui), the *semantic feature weight* for each candidate phrase that is returned by a graph-based ranking approach incorporating semantic information from Wikipedia (Shi et al., 2008), and the *TitleOverlap* which is the number of times a phrase appears in the title of other documents in DBLP database (Nguyen and Luong, 2010) (WINGNUS). Another source of external knowledge is previous research results or expert knowledge that can affect the output of the keyphrase extraction system with the introduction of *bias* (Gollapalli et al., 2017) via labeled features whose values are restricted using a posterior regularization framework. In the same spirit, the interaction with the user in Yang et al. (2018) as well as the utilization of reference keyphrases from the training data in Bougouin et al. (2016) can be considered as introducing external knowledge into the system.

Recently, features based on pretrained word embeddings are widely used. Particularly, deep learning methods (Basaldella et al., 2018; Zhang et al., 2016; Wang et al., 2018; Alzaidy et al., 2019) use such embeddings as input. Additionally, GloVe pretrained word embeddings are used along with an Idf-weighted scheme for each phrase representation by Wang and Li (2017) (PCU-ICL).

3.4 | Comparative Experimental Results

As we don't conduct experiments ourselves for supervised methods, we here present results for supervised methods, taking experimental results from the scientific publications that are included in our study. Table 4 shows the performance of some earlier, state-of-the-art and more recent supervised methods according to the F_1 -measure on 3 popular keyphrase extraction datasets (see Section 5.1 for further details about the datasets) at the top 5 ($F_1@5$) and top 10 ($F_1@10$). The performance evaluation is based on the *exact match evaluation* where the number of correctly matched phrases with the golden ones are determined based on string matching. We see that the performances of the two state-of-the-art supervised models, i.e., Maui and KEA, are unstable on some datasets, but Maui achieves better performance than the KEA baseline model. Undoubtedly, the deep learning methods CopyRNN and CorrRNN achieve better F_1 scores compared to the 2 baselines (Maui and KEA), indicating that their models learn the mapping patterns from source text to target keyphrases to a satisfying degree. In addition, the limited results of WINGNUS method on Semeval dataset seem to be quite promising, as the method achieves quite high F_1 scores compared to the baselines. However, the deep learning methods, except for RNN, outperform all the other methods. Finally, the coverage and the review mechanisms that are used by CorrRNN make the difference regarding its high performance in all datasets.

Year	Method	ML Algorithm	Stat.	Posit.	Ling.	Cont.	Stack.	Ext.
1999	Witten et al. (1999)	Naive Bayes	✓	✓				
2003	Hulth (2003)	Rule Induction/Bagging	✓		✓	✓		
2007	Nguyen and Kan (2007)	Naive Bayes	✓	✓	✓			
2008	Shi et al. (2008)	Logistic Regression	✓	✓	✓			✓
2009	Medelyan et al. (2009)	Bagged Decision Trees	✓	✓	✓			✓
2010	Jiang et al. (2009)	SVM	✓	✓	✓			
	Nguyen and Luong (2010)	Naive Bayes	✓	✓	✓			✓
2014	Caragea et al. (2014)	Naive Bayes	✓	✓	✓	✓		
2016	Zhang et al. (2016)	RNN						✓
	Bougouin et al. (2016)	Graph-based Method	✓					✓
2017	Wang and Li (2017)	Ensemble (RF/SVM)	✓	✓	✓	✓	✓	✓
	Meng et al. (2017)	seq2seq Learning				✓		
	Gollapalli et al. (2017)	CRFs	✓	✓	✓	✓	✓	✓
	Zhang et al. (2017)	Random-walk Parametric Model	✓	✓	✓	✓		
2018	McIlraith and Weinberger (2018)	Naive Bayes	✓			✓		
	Chen et al. (2018)	seq2seq Learning				✓		
	Ye and Wang (2018)	Multi-task Learning (seq2seq Model)				✓		
	Basaldella et al. (2018)	Bi-LSTM RNN Task-oriented LDA	✓					✓
	Yang et al. (2018)	Model Topic-based				✓		✓
	Wang et al. (2018)	Adversarial Neural Network						
	Alzaidy et al. (2019)	Bi-LSTM-CRF Sequence Labeling				✓		✓

TABLE 3 A time line of all the supervised keyphrase extraction methods discussed in this review, along with their key-characteristics.

Methods	Semeval		Krapivin		NUS	
	F ₁ @5	F ₁ @10	F ₁ @5	F ₁ @10	F ₁ @5	F ₁ @10
KEA	0.025	0.026	0.110	0.152	0.069	0.084
MAUI	0.044	0.039	0.249	0.216	0.249	0.268
CopyRNN	0.291	0.296	0.302	0.252	0.342	0.317
CorrRNN	0.320	0.320	0.318	0.278	0.358	0.330
RNN	0.157	0.124	0.135	0.088	0.169	0.127
WINGNUS	0.205	0.247	-	-	-	-

TABLE 4 Performance of supervised keyphrase extraction methods. There are no available results for WINGNUS regarding the Krapivin and NUS datasets in the scientific literature.

3.5 | Subjectivity and Class Imbalance

Unbalanced training data is a very common problem in supervised keyphrase extraction because candidate phrases that are not annotated by humans as keyphrases are considered as negative training examples. This problem occurs for many reasons (e.g., authors select as keyphrases those that promote their work in a particular way or those that are popular regarding concept drift etc.) which can be summarized into one, subjectivity. Stercx et al. (2016) conduct an interesting study where they conclude that unlabeled keyphrase candidates are not reliable as negative examples.

To deal with this problem, Stercx et al. (2016) propose to treat supervised keyphrase extraction as Positive Unlabeled Learning based on Elkan and Noto (2008) by assigning weights to training examples depending on the document and the candidate. Particularly, they try to model the annotations by multiple annotators and the uncertainty of negative examples. Firstly, they train a classifier on a single annotator's data and use the predictions on the negative/unlabeled phrases as weights. Then, a second classifier is trained on the re-weighted data to predict a final ranking/labels of the candidates. It is worth to see in depth the process discussed above step by step. A weight equal to 1 is assigned to every positive example and the unlabeled examples are duplicated such that one copy is considered as positive (weight $w(x) = P(\text{keyphrase}|x, s = 0)$, s indicates whether x is labeled or not) and the other copy as negative (weight $1 - w(x)$). According to Stercx et al. (2016), this weight is not just a factor of the prediction of the initial classifier as proposed in Elkan and Noto (2008). Actually, they normalize the predictions and they include a measure for pairwise co-reference between unlabeled candidates and known keyphrases in a function $\text{Coref}(\text{candidate}, \text{keyphrase}) \in \{0, 1\}$ returning 1 if one of the binary indicator features, presented in Bengtson and Roth (2008) is present.

To sum up, the problem of subjectivity could be partially addressed using multiple annotators or treating supervised keyphrase extraction as Positive Unlabeled Learning (Chuang et al., 2012b; Stercx et al., 2016). In this direction, Stercx et al. (2018) propose as solution the creation of new collections for the evaluation of keyphrase extraction methods, derived from various sources with multiple annotations. The golden set of keyphrases, which is utilized for evaluation reasons, also incorporates subjectivity issues. Therefore, the need for reliable semantic evaluation approaches is also evident. Although there is a variety of evaluation approaches in the keyphrase extraction task, the most preferred one is the more classic and strict exact (string) matching.

4 | EVALUATION APPROACHES

Undoubtedly, it is a legitimate objective to have evaluation measures or approaches that offer a fair comparison of the keyphrase extraction methods, i.e., a ranking of the performance of the methods in order to determine which one is the most effective. However, we are also interested in knowing the method's accuracy, i.e., which percentage of the golden keyphrases the method returns or an indicative score related to the success rate. In this section, we briefly describe the most well-known evaluation measures that are used to evaluate the performance of the methods included in the literature review:

1. Precision/Recall/ F_1 -measure:

Precision is defined as:

$$precision = \frac{\text{number of correctly matched}}{\text{total number of extracted}} = \frac{TP}{TP+FP}$$

where TP is the number of true positives and FP the number of false positives, respectively.

Recall is defined as:

$$recall = \frac{\text{number of correctly matched}}{\text{total number of assigned}} = \frac{TP}{TP + FN}$$

where TP is the number of true positives and FN the number of false negatives, respectively.

F_1 -measure is defined as:

$$F_1\text{-measure} = 2 \times \frac{precision \times recall}{precision + recall}$$

2. *Ranking Quality Measures* are used to measure the ranked extracted phrases. Such measures take into account the relative order of the phrases extracted by the keyphrase extraction systems. Popular ranking evaluation measures in the keyphrases extraction task are the following:

- *Mean Reciprocal Rank (MRR)* (Voorhees, 1999) that is defined as follows:

$$MRR = \frac{1}{|D|} \sum_{d \in D} \frac{1}{rank_d}$$

where $rank_d$ is denoted as the rank of the first correct keyphrase with all extracted keyphrases, D is the document set for keyphrase extraction and d is a specific document.

- *Mean Average Precision (MAP)* (Liu and Özsu, 2009) that also takes the ordering of a particular returned list of keyphrases into account. The average precision (AP) of the list is defined as follows:

$$AP = \frac{\sum_{r=1}^{|L|} P(r) \cdot rel(r)}{|L_R|}$$

where $|L|$ is the number of items in the list, $|L_R|$ is the number of relevant items, $P(r)$ is the precision when the returned list is treated as containing only its first r items, and $rel(r)$ equals 1 if the r^{th} item of the list is in the golden set and 0 otherwise.

By averaging AP over a set of n document cases, we obtain the Mean Average Precision (MAP), defined as fol-

lows:

$$MAP = \frac{1}{n} \cdot \sum_{i=1}^n AP_i$$

where AP_i is the average precision of the extracted keyphrases list returned for a document.

3. *Binary preference measure (Bpref)* (Buckley and Voorhees, 2004) is a summation-based measure of how many relevant phrases are ranked before irrelevant ones and it is defined as follows:

$$Bpref = \frac{1}{R} \sum_{r \in R} 1 - \frac{|n \text{ ranked higher than } r|}{M}$$

where R are the correct keyphrases within M extracted keyphrases in which r is a correct keyphrase and n is an incorrect keyphrase for a document.

4. *Average of Correctly Extracted Keyphrases - (ACEK)* is the average number of the extracted keyphrases that also belong to the document's golden set of keyphrases. This was the first type of performance evaluation that is used in the keyphrase extraction task but it is not widely used anymore, as precision and recall offer a more complete view for a system's performance in terms of the set of the extracted keyphrases.

The above measures are usually calculated following one of the following directions (approaches):

- *Exact match evaluation* where the number of correctly matched phrases with the golden ones are determined based on string matching. In most cases, stemming is a preprocessing step to determine the match of two keyphrases.
- *Manual evaluation* where experts decide whether the returned keyphrases by a system are wrong or right. However, this type of evaluation requires the investment of time and money and is characterized by great subjectivity (Zesch and Gurevych, 2009)
- *Partial match evaluation*, a looser evaluation process that is proposed by Rousseau and Vazirgiannis (2015), which calculates the Precision, Recall and F_1 -measure between the set of words found in all golden keyphrases and the set of words found in all extracted keyphrases. Again, stemming is a required preprocessing step. However, such type of evaluation cannot evaluate the syntactic correctness of the phrases or deal with more complex issues such as over-generation problems and overlapping keyphrase candidates.

Furthermore, Kim et al. (2010a) study the issue of n-gram-based evaluation measures for automatic keyphrase extraction. In this study various evaluation measures developed for machine translation and summarization are included as well as the R-precision evaluation measure. However, such kind of evaluation, is not widely adopted by the keyphrase extraction community, as it is not found in any of the scientific publications included in the current survey.

In Fig. 3, we show the popularity of the most well-known evaluation measures that have been used in the keyphrase extraction task, which is based on our bibliographic study. Some works have used more than one types of evaluation measures/approaches. Infrequent as well as insignificant evaluation approaches are categorized to the "Other" group of methods. Precision/Recall/ F_1 -measure has indeed been used in the majority of the related work. However, their calculation based on the exact phrase matching, which is very popular as well, is too strict and equally penalizes a predicted keyphrase that is completely different from a golden keyphrase and a predicted keyphrase whose words are a subset or superset of the words of a golden keyphrase. Furthermore, this type of evaluation cannot identify the semantic similarity of two different phrases. Additionally, another issue of this approach is that even small variants in

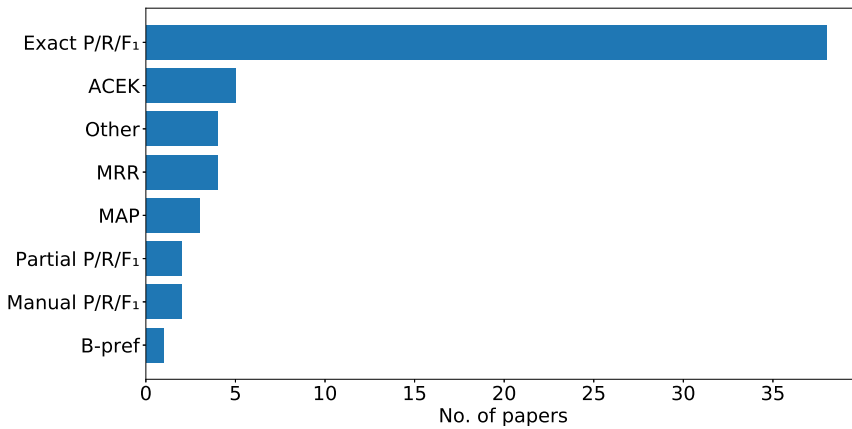


FIGURE 3 Popularity of evaluation approaches. ACEK, MRR, MAP and B-pref are used along with the exact match evaluation approach.

the keyphrases have considerable impact on the evaluation results (Kim et al., 2010a). Suppose we would like to find the keyphrases of the 628247.txt file from the Krapivin dataset whose golden set of keyphrases includes the phrases “approximate search” and “similarity search” and the keyphrase extraction method returns as output the keyphrase “approximate similarity search”, i.e., a correct keyphrase that appears in the text. However, the exact match evaluation approach will consider this keyphrase as wrong. For this reason, this type of evaluation could be considered as suboptimal. Moreover, Precision/Recall/ F_1 -measure at the top N phrases, where $N = 5, 10, 15, 20$, prevail over the ranking quality measures, as the success rate at top of the ranking seems to more important compared to the actual ordering of the keyphrases in most applications.

We believe that this discussion will eventually be more fruitful for the research community and stir more research. A solution to the above problems is the development of semantic evaluation approaches for the keyphrase extraction task. In this direction, Papagiannopoulou and Tsoumakas (2018) proposed an alternative evaluation, focused on the “gold” keyphrases’ comparison with the returned keyphrases of a system, that exploits the representation of the words as vectors. Particularly, the cosine similarity is computed between the mean word vector derived from the ground truth’s keyphrases and the mean word vector of the system’s phrases.

5 | DATASETS AND SOFTWARE

In this section, we refer to popular datasets that are used for the development and evaluation of the keyphrase extraction methods (Section 5.1). Moreover, in Section 5.2, we present available free and commercial keyphrase extraction software providing a short description with their corresponding features.

5.1 | Datasets

Keyphrase extraction systems have been evaluated on datasets from various text sources, i.e., full-text scientific publications, paper abstracts and news documents. Some of the most well-known datasets are given in Table 5 grouped by their type of source. For each dataset, we give its (i) name (Dataset), (ii) creator(s) (Created By), (iii) number of

text documents (Docs), (iv) text language (Language), (v) annotators (Annotation Type), which can be author-assigned keyphrases, reader-assigned keyphrases or controlled/uncontrolled keyphrases assigned by professional indexers, and (vi) the number of times that the dataset is used in the evaluation process with respect to the scientific articles that are included in the current survey. There are also 16 papers that use other, not so well-known datasets, that are not publicly available or are created for the evaluation of their methods.

A number of datasets for evaluating keyphrase extraction algorithms are available on Github^{1,2}, as well as on the website of Sujatha Das Gollapalli³.

Type	Dataset	Created By	Docs	Language	Annotation Type	Freq.
Full-text Papers	NUS	Nguyen and Kan (2007)	211	English	Authors/Readers	9
	Krapivin	Krapivin et al. (2008)	2304	English	Authors	6
	Semeval2010	Kim et al. (2010b)	244	English	Authors/Readers	12
	Citeulike-180	Medelyan et al. (2009)	180	English	Readers	1
Paper Abstracts	Inspec	Hulth (2003)	2000	English	Indexers	21
	KDD	Gollapalli and Caragea (2014)	755	English	Authors	6
	KP20k	Meng et al. (2017)	567830	English	Authors	3
	WWW	Gollapalli and Caragea (2014)	1330	English	Authors	6
News	DUC-2001	Wan and Xiao (2008)	308	English	Readers	10
	500N-KPCrowd	Marujo et al. (2012)	500	English	Readers	4
	110-PT-BN-KP	Marujo et al. (2011)	110	Portuguese	Readers	1
	Wikinews	Bougouin et al. (2013)	100	French	Readers	1

TABLE 5 Popular evaluation datasets grouped by their type of source (Type).

Furthermore, several approaches to the creation of such datasets have been proposed, in the past (Medelyan et al., 2009; Sterckx et al., 2018). Recently, Sterckx et al. (2018) have created new keyphrase extraction collections consisting of on-line news/sports, lifestyle magazines as well as newspaper articles, annotated by multiple annotators. These collections are available for research purposes upon request to the article's authors.

5.2 | Keyphrase Extraction Software

Both commercial and free software is developed for keyphrase extraction. In this section, we briefly present available free keyphrase extraction software (Section 5.2.1) as well as some well-known commercial keyphrase extraction APIs (Section 5.2.2).

¹<https://github.com/zelandiya/keyword-extraction-datasets>

²<https://github.com/snkim/AutomaticKeyphraseExtraction>

³<https://sites.google.com/site/sujathadas/home/datasets>

5.2.1 | Free Software

Table 6 presents free keyphrase extraction software along with some useful features, such as the implemented methods, supported languages and implementation language. There are software packages that include only one keyphrase extraction method (Maui, KEA, seq2seq, TextRank, YAKE, RAKE, TopicCoRank) and others that have more than one methods implemented (PKE - Python Keyphrase Extraction (Boudin, 2016), the KE package, Sequential Labeling, Cite-TextRank). As far as the supported languages by each software concerned, RAKE supports English, French and Spanish, TopicCorank supports English and French, KEA and Maui support English, French, German and Spanish, whereas TextRank supports additional languages, e.g., Swedish, Danish, Dutch, Italian etc. Although the default language in PKE and YAKE is English, keyphrases can also be extracted in other languages by setting the language parameter to the desired language.

5.2.2 | Commercial Software

As far as the commercial keyphrase extraction software concerned, to the best of our knowledge, Google Cloud Natural Language API⁴ has not included a service devoted to keyphrase extraction. However, an interesting feature of this API is the one of *entity recognition* which identifies entities and labels by types, such as person, organization, location, event, product, and media. Furthermore, our empirical analysis presented in Table 7 shows that the entity recognition feature provided by Google's API is an alternative option, as it returns satisfactory results compared to the state-of-the-art methods of the keyphrase extraction task. In the same direction, the TextRazor API⁵ offers *entity recognition* service that besides the classic confidence score (confidence related to the validity of the returned entity), it also gives the relevance score, which shows the relevance of the returned entity to the source text. Microsoft offers its commercial software for keyphrase extraction via Microsoft's Text Analytics APIs⁶. Moreover, Aylien Text Analysis API⁷ performs a variety of complex NLP tasks on documents including keyphrase extraction, whereas, IBM and Amazon offer their commercial solutions for advanced text analysis as well as keyphrase extraction via Watson Natural Language Understanding API⁸. and the Comprehend API⁹.

Google¹⁰, TextRazor¹¹, IBM¹², and Microsoft Text Analytics¹³ APIs have a wide range of supported languages, however, Amazon Comprehend API performs direct text analysis only on English and Spanish texts. Particularly, Amazon Comprehend proposes the conversion of the text of an unsupported language to English or Spanish via the Amazon Translate, and then uses Amazon Comprehend to perform text analysis. Finally, the Aylien Text Analysis¹⁴ API supports the following 6 languages regarding the keyphrase extraction feature: English, German, French, Italian, Spanish and Portuguese.

In Section 6.2, Table 7 shows the performance of the commercial APIs discussed above on 5 popular datasets of the task. We should note that this empirical study is conducted in the context of the survey on the task using very

⁴<https://cloud.google.com/natural-language>

⁵<https://www.textrazor.com/>

⁶<https://azure.microsoft.com/en-us/services/cognitive-services/text-analytics>

⁷<https://docs.aylien.com/s>

⁸<https://www.ibm.com/watson/services/natural-language-understanding/>

⁹<https://aws.amazon.com/comprehend/>

¹⁰<https://cloud.google.com/natural-language/docs/languages>

¹¹<https://www.textrazor.com/languages>

¹²<https://console.bluemix.net/docs/services/natural-language-understanding/language-support.html>

¹³<https://docs.microsoft.com/en-us/azure/cognitive-services/text-analytics/text-analytics-supported-languages>

¹⁴<https://docs.aylien.com/textapi/#language-support>

domain-specific texts from keyphrase extraction data collections. Thus, *such type of evaluation of commercial general purpose APIs, whose internal working is not actually known, should not be considered as a positive or negative attitude in favor of the APIs with high performance on the datasets.*

Name	Impl. Lang.	Methods	Languages
Maui	Java	Medelyan et al. (2009)	multilingual
YAKE	Python	Campos et al. (2018a)	multilingual
TopicCoRank	Python	Bougouin et al. (2016)	English/French
RAKE	Python	Rose et al. (2010)	multilingual
KEA	Java Python wrapper	Witten et al. (1999)	multilingual
PKE	Python	TfIdf, Witten et al. (1999) Nguyen and Luong (2010) El-Beltagy and Rafea (2009) Wan and Xiao (2008) Bougouin et al. (2013) Boudin (2018) Florescu and Caragea (2017b) Sterckx et al. (2015a)	multilingual
seq2seq	Python	Meng et al. (2017)	English
KE package	C++	TfIdf, Wan and Xiao (2008) Mihalcea and Tarau (2004) Wan and Xiao (2008)	English*
TextRank	Python	Mihalcea and Tarau (2004)	multilingual
Sequential Labeling	Java	Witten et al. (1999) Gollapalli et al. (2017) Caragea et al. (2014) Medelyan et al. (2009)	English*
CiteTextRank	Java	TfIdf, Mihalcea and Tarau (2004) (Wan and Xiao, 2008) (Gollapalli and Caragea, 2014)	English*

The * symbol indicates that no other supported languages are explicitly mentioned.

TABLE 6 Free keyphrase extraction software along with some useful features, such as the implementation language, implemented methods and supported languages.

6 | EMPIRICAL EVALUATION STUDY

One of the biggest issues for keyphrase extraction remains the reliable evaluation measures/approaches and an analysis of the shortcomings by existing ones. In this section, we present an empirical study among commercial APIs (Section 6.2) and state-of-the-art as well as popular/recent unsupervised methods (Section 6.3) using different evaluation approaches (exact, partial, manual evaluation) and measures (F_1 -measure, MAP). We investigate their relation to see whether different evaluation approaches could lead to different conclusions concerning the performance comparison (Section 6.4). Furthermore, we investigate the way in which the different keyphrase extraction systems and measures

behave with respect to the different gold standards (Section 6.5). We also present a qualitative analysis that highlights the differences between various evaluation approaches (Section 6.6).

6.1 | Experimental Setup

Popular commercial APIs commonly used to extract keyphrases from texts (discussed in Section 5.2.2) as well as unsupervised methods from all basic categories are included in our empirical study, in Sections 6.2 and 6.3, respectively. However, the experimental results of the commercial general purpose APIs, should not be considered as a positive or negative attitude in favor of the APIs (see clarification in Section 5.2.2). The unsupervised methods that participate in the experimental comparison are (i) the statistical-based methods KP-Miner (KPM), YAKE and Tfidf, (ii) the graph-based methods SingleRank (SR), TopicRank (TR), MultipartiteRank (MR), PositionRank (PR), RAKE and (iii) the RVA method that utilizes word embeddings. Finally, a variant of Tfidf (Tfidf2) is developed for the evaluation purposes that combines popular statistical and positional heuristics of the task. Specifically, Tfidf2 has slight differences compared to Tfidf as it ranks the phrases in a particular document according to their Tfidf score by keeping only the candidates that consist of terms with term frequency greater than 3 and belong to the set of the first 100 nouns or adjectives that appear in the text.

Many keyphrase extraction methods have been evaluated using texts from scientific publications (see Table 5). We choose 3 popular datasets that contain full-text publications from the computer science domain, i.e. Krapivin, Semeval2010 (Semeval) and NUS. Additionally, we are interested in studying the performance of keyphrase extraction methods in short texts, hence, we experimented with the well-known Inspec dataset that contains abstracts from journal papers from the disciplines Computers and Control, and Information Technology. Finally, we use the 500N-KPCrowd news dataset, which contains broadcast news stories from 10 different categories, to see how the systems perform on texts of general domain. Since the SemEval and NUS datasets come with both author and reader assigned keyphrases, we use both sets of keyphrases as a gold standard in the experimental study of Sections 6.2 and 6.3. We should note that all methods extract keyphrases from the full-text articles except for RVA which uses the full-text to create the vector representation of the words and then returns keyphrases only from the abstract. Furthermore, we give as input to the APIs only the abstracts of the articles in order to avoid additional costs. However, concerning the 500N-KPCrowd articles, whose average length is approximately 2607 characters, we give as input to the APIs the first 1500 characters of each text document where at least 75% of the keyphrases appear. For all competing methods we use the default parameters proposed in the corresponding articles.

According to Fig. 3, Precision/Recall/ F_1 -measure have indeed been used in the majority of the related work. As most methods have been evaluated based on these measures, we choose the F_1 -measure as the main measure of our study. We adopt two different automatic evaluation approaches for the calculation of the F_1 -score: i) the strict exact match evaluation approach, which computes the F_1 -score between golden keyphrases and candidate keyphrases, after stemming and removal of punctuation marks, and ii) the simple and more loose partial match evaluation, which calculates the F_1 -measure between the set of words found in all golden keyphrases and the set of words found in all extracted keyphrases after stemming and removal of punctuation marks. We also provide the Mean Average Precision (MAP) score to evaluate the ranking of the returned keyphrases according to the exact match evaluation.

We compute $F_1@10$, $F_1@20$, $MAP@10$, $MAP@20$, as accuracy at the top of the ranking is more important in typical applications. We used the NLTK Python suite for preprocessing, and the PKE toolkit (Boudin, 2016) for the implementations of most unsupervised keyphrase extraction methods. For YAKE¹⁵ and RAKE¹⁶ methods we use their

¹⁵<https://github.com/LIAAD/yake>

¹⁶<https://github.com/zelandiya/RAKE-tutorial>

corresponding implementations that are available on Github.

6.2 | Commercial APIs

Comparing the commercial APIs' performance on the 4 datasets of scientific publications, i.e., Semeval, NUS, Krapivin, and Inspec, we find the IBM API in the first place followed by Google API in the second place except for Semeval at $F_1@10$ and NUS where Aylien API and Google API win, respectively. Aylien API and Textrazor API are quite competitive between each other with the second one to perform better on Krapivin dataset as well as at $F_1@20$ on NUS and Inspec datasets. Amazon API is the worst-performing among the commercial APIs in all datasets.

Moreover, we compare the keyphrase extraction commercial APIs (including entity extraction services) based on their performance on the 500N-KPCrowd dataset, which includes hundreds of text documents of news stories, i.e., a domain other than that of scientific publications. Aylien API and Google API achieve high F_1 -scores with values that lie quite close to each other. In the following ranking positions, we see IBM API, Textrazor API and Amazon API, respectively. For the sake of completeness, Appendix B (Tables 17 and 18) reports the APIs' performance based on the MAP measure using the exact match evaluation and the F_1 -score using the partial match evaluation.

APIs	Semeval		NUS		Krapivin		Inspec		500N-KPCrowd	
	@10	@20	@10	@20	@10	@20	@10	@20	@10	@20
IBM	0.100	0.118	0.115	0.117	0.114	0.106	0.256	0.270	0.081	0.133
GOOGLE	0.089	0.106	0.135	0.141	0.106	0.096	0.168	0.192	0.143	0.210
Amazon	0.037	0.062	0.035	0.063	0.034	0.054	0.063	0.109	0.058	0.093
Textrazor	0.073	0.084	0.099	0.113	0.096	0.097	0.116	0.140	0.062	0.098
Aylien	0.101	0.092	0.121	0.108	0.080	0.062	0.123	0.132	0.143	0.229

TABLE 7 $F_1@10$ and $F_1@20$ according to the exact match evaluation on 5 datasets.

6.3 | Unsupervised Keyphrase Extraction Methods

6.3.1 | Exact Match Evaluation Approach

F_1 -measure

According to the exact match (Table 8), KPM outperforms all the other methods in the first 3 datasets, i.e., Semeval, NUS, and Krapivin (full-text scientific publications), by a large margin, usually followed by TfIdf2 (2nd) and TfIdf (3rd) over all top @N rankings except for Semeval dataset at $F_1@10$ where YAKE is 3rd. We see that the modified version of TfIdf (TfIdf2) achieves considerably higher performance than the original TfIdf. MR is usually in the 4th position for all $F_1@N$ scores in all datasets. PR, TR and RAKE follow, alternating their ranking positions. Particularly, PR achieves higher $F_1@10$, RAKE performs better at $F_1@20$, whereas TR has lower scores on the NUS dataset. In the next ranking positions, RVA achieves similar $F_1@20$ to PR and TR. SR is the worst-performing among the methods in all datasets.

We benchmark the performance of all keyphrase extraction methods on the Inspec dataset, which contains short texts (abstracts of scientific articles). We exclude the RVA method from the comparison, as it needs the full-text of a document to create the vector representation of the words. We notice that the previous worst-performing SR method outperforms all the other methods. PR is the second one and MR, TR are in the third and fourth positions, respectively.

Next in the ranking is RAKE that beats YAKE and Tfldf, which have equivalent performances. However, in this dataset Tfldf2 achieves lower F_1 -scores than Tfldf.

F_1	Semeval		NUS		Krapivin		Inspec		500N-KPCrowd	
	@10	@20	@10	@20	@10	@20	@10	@20	@10	@20
YAKE	0.160	0.169	0.188	0.180	0.124	0.109	0.197	0.212	0.107	0.168
Tfldf	0.154	0.176	0.201	0.205	0.126	0.113	0.197	0.212	0.179	0.243
Tfldf2	0.172	0.191	0.229	0.217	0.156	0.138	0.184	0.193	0.180	0.233
KPM	0.208	0.219	0.259	0.243	0.190	0.161	0.107	0.106	0.143	0.178
RAKE	0.114	0.147	0.134	0.142	0.091	0.096	0.216	0.233	0.064	0.066
MR	0.146	0.161	0.147	0.149	0.112	0.100	0.245	0.269	0.156	0.224
TR	0.134	0.142	0.126	0.118	0.099	0.086	0.235	0.249	0.148	0.209
PR	0.131	0.127	0.146	0.128	0.102	0.085	0.253	0.273	0.145	0.206
SR	0.036	0.053	0.044	0.063	0.026	0.036	0.278	0.295	0.096	0.164
RVA	0.096	0.125	0.096	0.115	0.093	0.099	-	-	-	-

TABLE 8 $F_1@10$ and $F_1@20$ according to the exact match evaluation approach of all methods for all datasets.

Moreover, we compare the keyphrase extraction methods based on their performance on the 500N-KPCrowd dataset, which includes hundreds of text documents of news stories, i.e., a domain other than that of scientific publications. Again, we exclude the RVA method from the comparison, as it needs an abstract/summary of the text document to complete the keyphrase extraction process. Tfldf2 and Tfldf outperform all the other methods followed by MR. TR and PR are in the 3rd position achieving F_1 -scores with quite close values to each other. In the following ranking positions, there are KPM, YAKE and SR, respectively, whereas the worst-performing method is RAKE.

MAP

In terms of MAP that is computed in the context of the exact match approach (Table 9), the non-commercial methods' ranking on the Semeval, NUS, and Krapivin datasets (full-text scientific publications) is quite similar to the one inferred by the F_1 -scores described above. Once more, the Inspec dataset is used to benchmark the methods on short texts. Particularly, in the first 4 ranking positions we come across the same methods as before, i.e., based on the F_1 -score, but in another order. MR and SR share the first position, followed by TR, and PR, respectively. The same holds for the next ranking positions where we find YAKE/RAKE, Tfldf, Tfldf2, and KPM, respectively. Furthermore, the keyphrase extraction methods follow a different ranking order based on their MAP scores on the 500N-KPCrowd dataset. Once again, Tfldf2 and Tfldf outperform all the other methods, whereas, MR, TR, PR follow in the next places but without notable differences. The lower performances are achieved by YAKE, RAKE and SR, respectively.

Summary

To sum up, the results of F_1 and MAP scores on the datasets of the full-text scientific publications (Semeval, Krapivin, and NUS) according to the exact match evaluation approach confirm the superiority of the statistical methods (KPM, Tfldf2, Tfldf, and YAKE in that order) over the graph-based ones, as the full-texts contain sufficient statistical information to distinguish keyphrases from non-keyphrases. At the same time, the large amount of information makes harder the detection of keyphrases by the graph-based methods. Furthermore, graph-based methods (SR, MR,

PR, TR and RAKE) outperform the statistical methods in the task of keyphrase extraction from short scientific texts (results on Inspec dataset). Finally, the classical statistical methods of Tfldf and its variation Tfldf2 ranked first with respect to F_1 and MAP scores in the task of keyphrase extraction from news articles, usually followed by the quite decent results of MR and KPM. We see that the modified version of Tfldf (Tfldf2) achieves considerably higher performance than the original Tfldf in all datasets except for the Inspec dataset where both methods do not perform well as the abstracts do not contain enough text to enable the separation of keyphrases from non-keyphrases. However, for the graph-based methods, the opposite is observed. In particular, abstracts capture adequately the co-occurrence (proximity) of words that is necessary for graph creation, avoiding at the same time the noise of the full-texts. Additionally, the threshold of Tfldf2 regarding the term frequency of a candidate keyword (greater than 3) impinges the keyphrase extraction process from short texts where the term frequencies range in low values. Once more, the high performance of the MR method compared to the rest graph-based methods in most datasets implies that the graph-based methods can benefit by integrating different types of information, such as topical, positional and statistical information.

MAP	Semeval		NUS		Krapivin		Inspec		500N-KPCrowd	
	@10	@20	@10	@20	@10	@20	@10	@20	@10	@20
YAKE	0.106	0.065	0.104	0.063	0.044	0.025	0.109	0.070	0.151	0.118
Tfldf	0.097	0.062	0.119	0.074	0.045	0.026	0.100	0.066	0.355	0.257
Tfldf2	0.110	0.070	0.136	0.083	0.056	0.033	0.094	0.056	0.365	0.253
KPM	0.144	0.090	0.160	0.098	0.073	0.042	0.058	0.029	0.302	0.197
RAKE	0.058	0.041	0.062	0.040	0.023	0.015	0.106	0.073	0.141	0.074
MR	0.093	0.058	0.076	0.047	0.040	0.023	0.153	0.098	0.253	0.194
TR	0.081	0.049	0.069	0.040	0.034	0.020	0.144	0.088	0.243	0.179
PR	0.073	0.042	0.068	0.039	0.030	0.017	0.136	0.091	0.241	0.176
SR	0.013	0.009	0.012	0.009	0.005	0.003	0.153	0.103	0.096	0.091
RVA	0.050	0.035	0.036	0.026	0.026	0.017	-	-	-	-

TABLE 9 MAP@10 and MAP@20 according to the exact match evaluation approach of all methods for all datasets.

6.3.2 | Partial Match Evaluation Approach

According to the partial match evaluation approach proposed by Rousseau and Vazirgiannis (2015) (Table 10) KPM outperforms all the other methods in the first 3 datasets, i.e., Semeval, NUS, and Krapivin (full-text scientific publications), by a large margin, usually followed by Tfldf2 (2nd) in most cases. MR often follows in the next position in the ranking achieving quite high scores in Semeval and NUS at $F_1@10$, while YAKE performs better than MR in Krapivin and NUS at $F_1@20$. Tfldf, PR, TR, and RVA are quite competitive between each other and are usually in the next places alternating their ranking among the datasets. Finally, RAKE and SR are the worst-performing among the state-of-the-art methods in all datasets. The experimental results regarding the Inspec dataset show that the previous worst-performing SR method outperforms all the other methods. Next in the ranking order are MR (2nd) and TR (3rd), followed by PR, RAKE, Tfldf, YAKE that have similar F_1 -scores. The worst ranking scores are achieved by KPM and

TfIdf2 methods. Furthermore, on the news dataset (500N-KPCrowd) the SR outperforms all the other methods, followed by TR (2nd) and MR (3rd). Next in the ranking order are PR, YAKE and TfIdf, respectively, without considerable differences. In the last ranking positions, we see the rest statistical methods (YAKE, TfIdf2, RAKE).

pF ₁	Semeval		NUS		Krapivin		Inspec		500N-KPCrowd	
	@10	@20	@10	@20	@10	@20	@10	@20	@10	@20
YAKE	0.319	0.381	0.400	0.414	0.345	0.340	0.479	0.522	0.256	0.345
TfIdf	0.305	0.365	0.373	0.394	0.309	0.306	0.474	0.540	0.247	0.366
TfIdf2	0.345	0.413	0.436	0.457	0.392	0.390	0.443	0.478	0.217	0.288
KPM	0.389	0.451	0.468	0.482	0.422	0.402	0.305	0.311	0.169	0.210
RAKE	0.297	0.334	0.335	0.327	0.271	0.248	0.494	0.515	0.077	0.079
MR	0.362	0.401	0.407	0.383	0.342	0.303	0.515	0.553	0.315	0.421
TR	0.345	0.378	0.375	0.351	0.312	0.277	0.509	0.540	0.318	0.423
PR	0.294	0.317	0.371	0.350	0.342	0.302	0.494	0.538	0.264	0.377
SR	0.284	0.297	0.322	0.309	0.290	0.256	0.565	0.586	0.328	0.424
RVA	0.332	0.365	0.374	0.380	0.348	0.337	-	-	-	-

TABLE 10 F₁@10 and F₁@20 according to the partial match evaluation approach (pF₁) of all methods for all datasets.

Summary

To conclude, the results of F₁-scores with respect to the partial match evaluation on the datasets of the full-text scientific publications (Semeval, Krapivin, and NUS) confirm the superiority of the statistical methods (KPM, TfIdf2, and YAKE in that order) over the graph-based ones. The large amount of information in the full-texts benefits statistical methods, facilitating the separation between keyphrases and non-keyphrases, whereas the redundant information existing in full-texts does not facilitate the graph-based methods to model the correlations between the words. A text document contains hundreds/thousands of words whereas the number of keywords is very small. Hence, there is a number of words that are not keywords but play an important role in the description of the document's topics (expressed by the keywords), impeding the keyphrase extraction process. However, once more, the high performance of the MR method compared to the rest of the graph-based methods implies the potential of the graph-based methods to exploit various types of information. Furthermore, RVA's performance witnesses the effectiveness of keyphrase extraction from scientific publications using only their titles and abstracts. Papagiannopoulou and Tsoumakas (2018) conducted experiments using the same evaluation approach (Rousseau and Vazirgiannis, 2015) and two versions of each unsupervised keyphrase extraction method, one with the title/abstract and one with the full-text of each article. The abstract version of both RVA and the graph-based methods is better than the fulltext version according to the partial match evaluation approach, possibly due to the redundancy which is included in the fulltexts. The opposite holds for TfIdf, since abstracts do not contain enough text to enable the separation of keyphrases from non-keyphrases. In addition, the use of a local word vector representation that would be more oriented to the keyphrase detection than the GloVe (which is used by RVA) seems to be promising. Furthermore, similar to the exact match evaluation, graph-based methods (SR, MR, and TR) outperform the statistical methods in the task of keyphrase extraction from

short scientific texts (results of Inspect dataset), since the abstracts seem to capture adequately the required context of words for the graph creation, avoiding the noise of the full-texts. Finally, the graph-based methods (SR, TR, MR, and PR) are highly ranked in the task of keyphrase extraction from news articles. We see that the modified version of Tfidf (Tfidf2) achieves considerably higher performance than the original Tfidf in the full-text publication datasets, whereas on the Inspect and news datasets (500N-KPCrowd) both methods do not perform well.

6.3.3 | General Remarks

Both evaluation strategies confirm the superiority of the statistical methods (KPM, Tfidf2) over the graph-based ones in the task of keyphrase extraction from full-text scientific publications. Yet, the partial evaluation benefits the graph-based methods ranking them in higher positions compared to the exact match evaluation. This is also evident from the results in the 500N-KPCrowd dataset where the graph-based methods are highly ranked with respect to the partial F_1 -scores. At the same time, the partial evaluation strategy seems to give more reasonable results, as recent methods outperform the baseline of the task (Tfidf) in more cases. In addition, the high performance of the MR method compared to the rest graph-based methods is confirmed by both evaluation approaches. Finally, it would be interesting to see the development of a Tfidf variant, similar to Tfidf2, which would be universally adopted as the baseline of the task.

In addition, we provide some guidelines to practitioners. In case of keyphrase extraction from fulltexts of scientific articles, statistical methods are a decent option, as they offer a good balance between performance and computation time compared to the graph-based methods that achieve lower accuracy and have higher computation time (due to PageRank that runs in most of the graph-based methods). However, in case of keyphrase extraction from short texts, graph-based methods are suggested as more appropriate, since their computation cost is not considerable due to the short length of texts, and they perform better than the statistical methods. Particularly, SingleRank is the best option in comparison with the more recent methods of TR, PR and MR. It seems that in short texts the information coming from the graph-of-words and co-occurrence statistics is sufficient. There is no need for any additional positional or topical information, as the words do not appear in a long text (position does not play an important role in documents of a few lines) and the frequencies of similar keyphrase candidates (that are grouped in topics by TR, MR) are quite low due to the limited text. For text documents that are not from a specific domain both statistical and graph-based methods achieve good performance according to the exact and partial evaluation approaches. So, it is up to the practitioner's choice which category of methods will use, based on the computation cost that is related to the length of the text.

In Section 6.4, we go one step further from describing intuitively the properties of the two evaluation approaches. More specifically, we investigate their properties (measuring (i) the correlation between the F_1 -scores calculated with respect to the exact/partial evaluation approaches and the F_1 -scores based on the manual evaluation, (ii) how close their actual values are regarding human computed F_1 -scores, and (iii) testing the scores' distributions). In this way, we recommend which evaluation strategy should be preferred in certain situations, providing more meaningful insights.

6.4 | Exact vs Partial Matching

The majority of the keyphrase extraction articles that we reviewed present experimental results based on exact matching of predicted and golden keyphrases. An important limitation of this evaluation approach, however, is that it penalizes methods even if they predict keyphrases that are semantically similar to the golden ones (Rousseau and Vazirgiannis, 2015; Wang et al., 2015). On the other hand, partial matching rewards methods when they predict words that appear in golden keyphrases, even when their predicted keyphrases are not themselves appropriate for the cor-

responding article. In order to obtain a deeper understanding of the pros and cons of exact and partial matching, this section empirically investigates their relationship to manual evaluation.

We randomly selected 50 full-text articles from the Krapivin dataset and extracted keyphrases from them using one statistical method (KPM) and one graph-based method (MR). We calculated the $F_1@10$ of these methods for each article based on exact and partial matching, as well as based on manual evaluation according to the following process. Given an article, each of the top 10 predicted keyphrases was evaluated as true positive if both the authors of this review paper considered it relevant to the article, after reading the whole article, focusing on the abstract and introduction for articles outside our expertise.

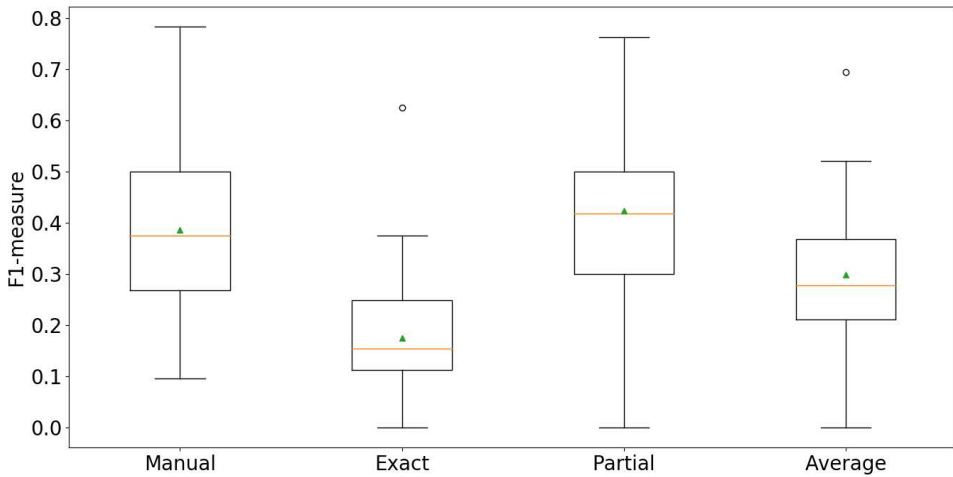
We use three different statistical tools to study how the $F_1@10$ scores obtained via exact and partial matching are related to the $F_1@10$ scores obtained via manual evaluation: (i) The Spearman coefficient in order to study their correlation, (ii) the Wilcoxon signed-rank non-parametric test at a significance level of 0.05 for assessing whether they come from the same distribution, and (iii) the Mean Squared Error (MSE), in order to measure their distance. Table 11 shows the results, including an additional evaluation approach that simply averages the $F_1@10$ scores of exact and partial matching.

	Spearman			Wilcoxon			MSE		
	Exact	Partial	Average	Exact	Partial	Average	Exact	Partial	Average
KPM	0.63692	0.34969	0.49194	≈ 0.00000	0.09023	0.00011	0.05981	0.03122	0.02635
MR	0.34413	0.20348	0.25634	≈ 0.00000	0.32243	0.00097	0.05465	0.03241	0.02814

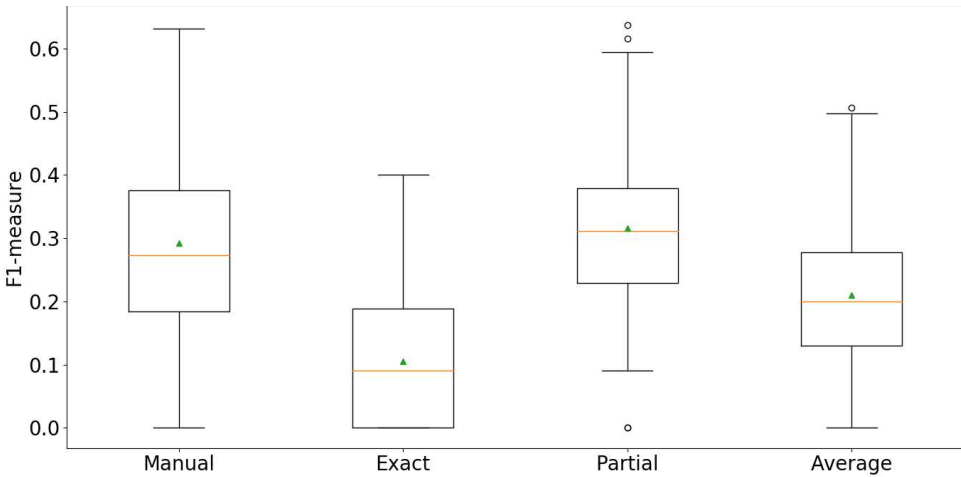
TABLE 11 Spearman correlation coefficient, Wilcoxon signed-rank test p value, and Mean Squared Error (MSE) between the $F_1@10$ scores obtained via manual evaluation and those obtained via exact/partial matching along with their average. The second best values are emphasized in italic typeface whereas the best values are in bold.

We first see that the $F_1@10$ scores obtained via manual evaluation are more correlated to the ones obtained via exact matching than those obtained via partial matching for both keyphrase extraction methods. This is expected to a certain extent, as exact matching is a lower bound of manual evaluation: a human would definitely evaluate as true positive an extracted keyphrase that matches a golden keyphrase and might also evaluate as true positive a predicted keyphrase that doesn't match a golden keyphrase but is semantically equivalent to it. Partial matching on the other hand may lead to both lower $F_1@10$ scores when predicted keyphrases are representative of the article, but don't contain words that appear in the golden keyphrases, and higher $F_1@10$ scores when predicted keyphrases are not related to the article, yet contain words that appear in golden keyphrases.

The above reasoning further explains the results of the Wilcoxon test, which show us that the $F_1@10$ scores of exact matching do not come from the same distribution as those of manual evaluation, in contrast to the $F_1@10$ scores of partial matching. Fig. 4 shows box plots of the $F_1@10$ scores obtained via manual evaluation, exact and partial matching, as well as their average. As expected, we notice that the scores of exact matching are coming from a distribution with a lower and more concentrated range of values, compared to those of manual evaluation. We also see that the scores of partial matching have similar statistics with that of the manual evaluation with a slightly higher median and interquartile range values.



(a) KPM

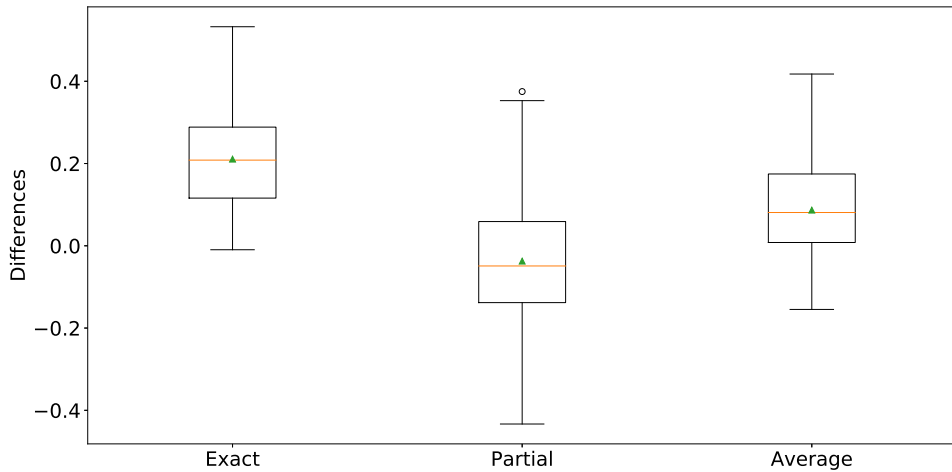


(b) MR

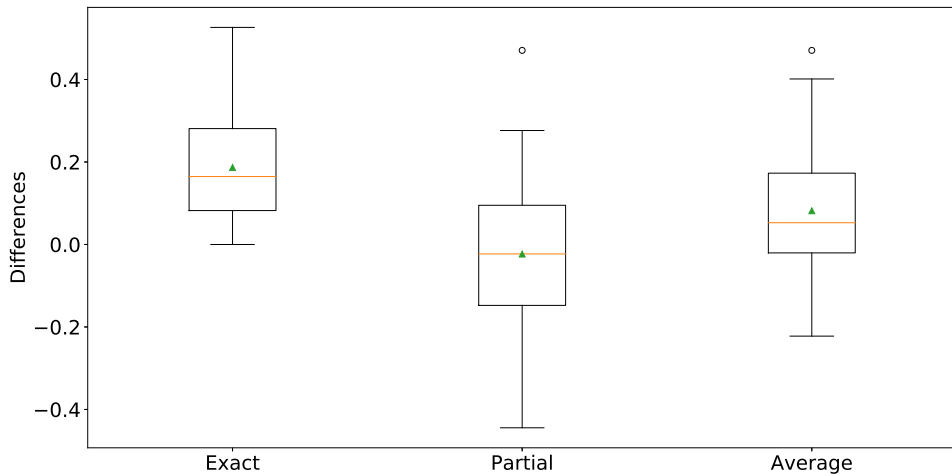
FIGURE 4 Box plots of the $F_1@10$ scores obtained via manual evaluation, exact matching, partial matching and taking the average of exact and partial matching.

We now come to the most important aspect of our analysis, which concerns the MSE between manual evaluation and exact/partial matching. We see that partial matching has lower mean squared error than exact matching, while the lowest MSE is achieved by taking the average $F_1@10$ scores of the two approaches. Figure 5 shows box plots of the distribution of differences between the F_1 -scores based on the manual evaluation and the F_1 -scores based on the exact (Exact), partial (Partial) and average (Average) evaluation approaches for the 50 manually evaluated documents. As expected, we notice that the differences between manual and exact matching F_1 -scores range to higher positive values as the exact matching is a lower bound of manual evaluation. We also see that the differences of between manual and partial matching F_1 -scores have lower median/mean almost equal to zero and wide interquartile range values.

Finally, the differences between manual and average matching F_1 -scores have a slightly higher median/mean but more concentrated range of values around zero, compared to the rest types of differences (Exact, Partial). Figure 6 (see Appendix D), shows an alternative view of the differences between the F_1 -score values based on the manual evaluation and the F_1 -score values calculated according to the exact (solid line), partial (dashed line) and average (dotted line) evaluation approaches for KPM and MR methods.



(a) KPM



(b) MR

FIGURE 5 Distribution of differences between the F_1 -scores based on the manual evaluation and the F_1 -scores based on the exact (Exact), partial (Partial) and average (Average) evaluation approaches for the 50 manually evaluated documents given on the x axis.

Our analysis suggests that researchers should consider the average of exact and partial matching for empirical

comparison of keyphrase extraction methods. In addition, we stress the need for automatic evaluation approaches that take into account the semantic similarity between predicted and golden keyphrases.

6.5 | The Role of the Evaluation Gold Standards

There are keyphrase extraction datasets such as the Semeval and the NUS that come with both author and reader assigned keyphrases. In this section, we investigate the extent to which different gold evaluation standards affect the performance estimation of various keyphrase extraction systems, coming to completely different conclusions with respect to i) the rank of the methods regarding their performance or ii) the actual accuracy of a method. Table 12 shows the $F_1@10$ scores using the exact match evaluation of the keyphrase extraction methods for the Semeval and NUS datasets based on 4 different evaluation gold standards: the union of the authors' and readers' keyphrases (Union), the authors' keyphrases (A), the readers' keyphrases (R) and the intersection of the authors' and readers' keyphrases (Inter.). In this part of the study, only the text documents that have both author and reader assigned keyphrases participate, i.e., 243 and 150 text documents from Semeval and NUS, respectively.

In all the keyphrase extraction methods, the highest $F_1@10$ scores appear when the union of the authors' and readers' keyphrases is regarded as the evaluation gold standard, as the higher the number of the golden keyphrases, the higher the probability of true positive cases in a system's output. On the contrary, the usage of the intersection between the authors' and readers' keyphrases as a gold standard leads to lower $F_1@10$ scores in almost all cases, as there are quite few keyphrases that are chosen by both authors and readers for a specific article. Authors' motivations differ from those of readers' ones, since authors usually aim not only to the summarization of their work via keyphrases but also to the promotion of their work considering phrases related to research trends etc. In addition, experimental results based on the $F_1@20$, $MAP@10$, and $MAP@20$ result in a similar conclusion to that one of the Table 12, i.e., the highest scores appear in the case of the evaluation gold standard that corresponds to the union of the authors' and readers' keyphrases.

First of all, we observe differences in the ranking order of the methods based on the average $F_1@10$ scores across the documents of each dataset. Particularly, in the case of $F_1@10$ scores there are more evident differences in the NUS dataset. For example, the 5th position of the ranking belongs to MR regarding the union of the keyphrases as a gold evaluation standard. However, the gold evaluation standard of the authors' keyphrases gives the 5th ranking position to PR. A deeper insight to the correlation as well as the scores' distributions of the 4 evaluation gold standards is presented below.

First, we utilize the Spearman's correlation to assess the monotonic relationship (linear or not) between the union of the authors'-readers' keyphrases and the authors' keyphrases (Union-A) as well as the readers' keyphrases (Union-R). Moreover, we investigate the correlation between the authors' and the readers' keyphrases (A-R) (see Tables 13 and 14). If there are no repeated data values, a perfect Spearman correlation of +1 or -1 occurs when each of the variables is a perfect monotone function of the other. The union of the keyphrases is moderately correlated to the authors' keyphrases evaluation gold standard for all keyphrase extraction methods in both datasets. Furthermore, the union of the keyphrases is strongly correlated to the readers' keyphrases evaluation gold standard for all keyphrase extraction methods in both datasets. Finally, the authors' keyphrases is weakly/moderately correlated to the readers' keyphrases evaluation gold standard in both datasets. We should not omit that all strong/moderate correlations are statistically significant with significance level 0.05.

Exact Match	Semeval				NUS			
F ₁ @10	Union	A	R	Inter.	Union	A	R	Inter.
YAKE	0.160	0.120	0.138	0.101	0.205	0.147	0.186	0.132
TfIdf	0.154	0.115	0.131	0.090	0.213	0.143	0.193	0.109
TfIdf2	0.172	0.144	0.144	0.119	0.240	0.171	0.222	0.151
KPM	0.208	0.168	0.173	0.124	0.274	0.194	0.246	0.157
RAKE	0.114	0.074	0.105	0.061	0.149	0.103	0.128	0.061
MR	0.146	0.099	0.126	0.091	0.164	0.118	0.150	0.122
TR	0.134	0.084	0.115	0.080	0.143	0.098	0.134	0.102
PR	0.131	0.108	0.110	0.081	0.155	0.123	0.131	0.103
SR	0.036	0.017	0.034	0.016	0.047	0.023	0.041	0.019
RVA	0.096	0.052	0.095	0.036	0.100	0.064	0.095	0.043

TABLE 12 F₁@10 of all methods for the Semeval and NUS datasets using various evaluation gold standards. The scores are calculated according to the exact match evaluation.

In this vein, we investigate the correlation (linear or not) between the intersection of the authors' and readers' keyphrases and the authors' keyphrases (Inter.-A) as well as the readers' keyphrases (Inter.-R). Moreover, we investigate the correlation between the intersection and the union of the authors' and the readers' keyphrases (Inter.-Union) (see Tables 15 and 16). The intersection of the keyphrases is moderately correlated to the authors' keyphrases evaluation gold standard for all keyphrase extraction methods in both datasets, except for the SR method at the NUS dataset that is weakly correlated. Furthermore, the intersection of the keyphrases is weakly/moderately correlated to the readers' keyphrases evaluation gold standard for all keyphrase extraction methods in both datasets. Finally, the intersection of the keyphrases gives weakly/moderately correlated scores to the union of keyphrases gold standard in both datasets.

In addition, we are interested in investigating whether the F₁-scores based on the various evaluation gold standards come from the same distribution. For this reason, we use the Wilcoxon signed-rank test. The scores based on the union of the keyphrases and the scores using the authors' keyphrases evaluation gold standard come from different distributions for all keyphrase extraction methods in both datasets. Furthermore, for almost all methods at the Semeval dataset the scores based on the union of the keyphrases and the scores using the readers' keyphrases evaluation gold standard come from different distributions, while at the NUS dataset the corresponding scores come from either different or same distributions. Additionally, in most methods the scores based on the authors' keyphrases and the scores using the readers' keyphrases evaluation gold standard come from different distributions (see Tables 13 and 14).

Tables 15 and 16 show that the scores based on the intersection of the keyphrases and the scores using the authors' keyphrases evaluation gold standard come from different distributions for the most methods in both datasets. Furthermore, the scores based on the intersection of the keyphrases and the scores using the readers' keyphrases evaluation gold standard come from different distributions in both datasets. The same holds for the scores based on the intersection's keyphrases and the scores using the union's keyphrases evaluation gold standard.

Semeval						
Exact Match	Spearman			Wilcoxon		
F ₁ @10	Union-A	Union-R	A-R	Union-A	Union-R	A-R
YAKE	0.588	0.834	0.299	≈0.000	≈0.000	0.031
TfIdf	0.641	0.844	0.357	≈0.000	≈0.000	0.010
TfIdf2	0.652	0.832	0.330	≈0.000	≈0.000	0.708
KPM	0.614	0.802	0.278	≈0.000	≈0.000	0.542
RAKE	0.570	0.898	0.380	≈0.000	0.034	≈0.000
MR	0.590	0.854	0.342	≈0.000	≈0.000	≈0.000
TR	0.573	0.836	0.309	≈0.000	0.001	≈0.000
PR	0.559	0.845	0.299	≈0.000	≈0.000	0.760
SR	0.491	0.862	0.356	≈0.000	0.278	≈0.000
RVA	0.478	0.876	0.280	≈0.000	0.015	≈0.000

TABLE 13 Results of Spearman correlation coefficient and Wilcoxon signed-rank test between the scores calculated based on the evaluation using the union of the keyphrases and the authors' keyphrases (Union-A), the union of the keyphrases and the readers' keyphrases (Union-R), as well as the authors' keyphrases and the readers' keyphrases (A-R) for the Semeval dataset.

NUS						
Exact Match	Spearman			Wilcoxon		
F ₁ @10	Union-A	Union-R	A-R	Union-A	Union-R	A-R
YAKE	0.671	0.846	0.379	≈0.000	0.021	0.001
TfIdf	0.560	0.879	0.269	≈0.000	0.016	≈0.000
TfIdf2	0.593	0.844	0.255	≈0.000	0.075	0.001
KPM	0.523	0.864	0.200	≈0.000	≈0.000	0.001
RAKE	0.622	0.813	0.238	≈0.000	0.015	0.031
MR	0.579	0.880	0.312	≈0.000	0.153	0.006
TR	0.591	0.865	0.308	≈0.000	0.842	0.001
PR	0.633	0.801	0.296	≈0.000	0.001	0.465
SR	0.560	0.831	0.115	≈0.000	0.862	0.045
RVA	0.620	0.869	0.401	≈0.000	0.301	≈0.000

TABLE 14 Results of Spearman correlation coefficient and Wilcoxon signed-rank test between the scores calculated based on the evaluation using the union of the keyphrases and the authors' keyphrases (Union-A), the union of the keyphrases and the readers' keyphrases (Union-R), as well as the authors' keyphrases and the readers' keyphrases (A-R) for the NUS dataset.

Semeval						
Exact Match	Spearman			Wilcoxon		
F ₁ @10	Inter.-A	Inter.-R	Inter.-Union	Inter.-A	Inter.-R	Inter.-Union
YAKE	0.701	0.457	0.386	≈0.000	≈0.000	≈0.000
Tfldf	0.619	0.513	0.439	≈0.000	≈0.000	≈0.000
Tfldf2	0.641	0.489	0.465	≈0.000	≈0.000	≈0.000
KPM	0.697	0.570	0.551	≈0.000	≈0.000	≈0.000
RAKE	0.781	0.553	0.472	≈0.000	≈0.000	≈0.000
MR	0.384	0.312	0.212	0.156	≈0.000	≈0.000
TR	0.341	0.221	0.127	0.364	≈0.000	≈0.000
PR	0.442	0.349	0.194	0.001	≈0.000	≈0.000
SR	0.553	0.312	0.231	0.949	0.002	0.001
RVA	0.357	0.310	0.269	0.003	≈0.000	≈0.000

TABLE 15 Results of Spearman correlation coefficient and Wilcoxon signed-rank test between the scores calculated based on the evaluation using the intersection of the keyphrases and the authors' keyphrases (Inter.-A), the intersection of the keyphrases and the readers' keyphrases (Inter.-R), as well as the intersection and the union of authors' and readers' keyphrases (Inter.-Union) for the Semeval dataset.

NUS						
Exact Match	Spearman			Wilcoxon		
F ₁ @10	Inter.-A	Inter.-R	Inter.-Union	Inter.-A	Inter.-R	Inter.-Union
YAKE	0.685	0.477	0.383	0.040	≈0.000	≈0.000
Tfldf	0.607	0.383	0.370	≈0.000	≈0.000	≈0.000
Tfldf2	0.612	0.440	0.424	0.002	≈0.000	≈0.000
KPM	0.610	0.327	0.331	≈0.000	≈0.000	≈0.000
RAKE	0.650	0.411	0.350	≈0.000	≈0.000	≈0.000
MR	0.508	0.243	0.248	0.908	0.001	≈0.000
TR	0.367	0.192	0.197	0.856	0.001	≈0.000
PR	0.498	0.361	0.267	0.191	≈0.000	≈0.000
SR	0.214	0.023	0.009	0.567	0.002	≈0.000
RVA	0.332	0.236	0.169	0.019	≈0.000	≈0.000

TABLE 16 Results of Spearman correlation coefficient and Wilcoxon signed-rank test between the scores calculated based on the evaluation using the intersection of the keyphrases and the authors' keyphrases (Inter.-A), the intersection of the keyphrases and the readers' keyphrases (Inter.-R), as well as the intersection and the union of authors' and readers' keyphrases (Inter.-Union) for the NUS dataset.

To sum up, it is strongly recommended to the research community to explicitly mention which set of keyphrases is regarded as a gold evaluation standard in the experiments, since different evaluation gold standards give different performance ranking and score estimations. Particularly, the union of the keyphrases evaluation gold standard is strongly correlated to the readers' evaluation gold standard for all keyphrase extraction methods in both datasets. Moreover, the average $F_1@10$ scores with respect to readers' evaluation gold standard seem to be closer to the scores with respect to the union's evaluation gold standard, even though in most cases at the Semeval dataset and in half cases of the NUS dataset the union's and the readers' evaluation gold standards give scores coming from different distributions. Using both types of annotations, i.e., authors' keyphrases and multiple annotators' (readers') keyphrases, we have at our disposal a quite expanded set of keyphrases. However, using only the multiple annotators' keyphrases, we end up to a decent number of gold unbiased keyphrases certainly depending on the methodology followed for the annotation process and the collective effort. On the other hand, authors' sets of keyphrases contain fewer but sufficient phrases to cover the topics of the target document. Such type of evaluation standard usually gives lower performance scores, moderately correlated with those resulting from the union keyphrases' gold evaluation standard. Finally, the intersection's evaluation gold standard is not recommended, as it is quite strict, contains a very small number of keyphrases, and does not guarantee that all topics discussed in the target documents are covered by the intersection of the keyphrases, since authors and readers may use different expressive means/vocabularies and do not share same annotation motivations.

6.6 | Qualitative Analysis

Via this qualitative study, we would like to highlight the limitations of the exact match evaluation, especially in cases where we are interested in the actual performance (success rate) of a method. Additionally, we show a case where the "looser" partial match strategy gives lower scores than the exact match one. Finally, we give an example that the partial match evaluation can be harmful, failing to assess properly the syntactic correctness of the return keyphrases. We use MR to extract the keyphrases from 3 publication full-texts of the Krapivin dataset collection.

First, we present an example where the F_1 -score with respect to the partial evaluation is greater than the corresponding exact match score and closer to the corresponding score with respect to the manual evaluation, which intuitively is the expected case. We quote the publication's title and abstract below in order to get a sense of its content:

Title: Exact algorithms for finding minimum transversals in rank-3 hypergraphs.

Abstract: We present two algorithms for the problem of finding a minimum transversal in a hypergraph of rank 3, also known as the 3-Hitting Set problem. This problem is a natural extension of the vertex cover problem for ordinary graphs. The first algorithm runs in time $O(1.6538n)$ for a hypergraph with n vertices, and needs polynomial space. The second algorithm uses exponential space and runs in time $O(1.6316n)$.

The corresponding set of the "gold" keyphrases are: $\{\textit{hypergraph}, \textit{3-hitting set}, \textit{exact algorithm}, \textit{minimum transversal}\}$. For evaluation purposes, we transform the set of "gold" keyphrases into the following one (after stemming and removal of punctuation marks, such as dashes and hyphens):

$\{\textit{(hypergraph)}, \textit{(3hit, set)}, \textit{(exact, algorithm)}, \textit{(minimum, transvers)}\}$

The MR's result set is given in the first box below, followed by its stemmed version in the second box. The words that are both in the golden set and in the set of our candidates are highlighted with bold typeface:

{problem, case, branching, 3hitting set problem, time, edges, minimum transversals, algorithms, number, rank3 hypergraphs}

{{(problem), (case), (branch), (3hit, set, problem), (time), (edg), (minimum, transvers), (algorithm), (number), (rank3, hypergraph)]}}

According to the exact match evaluation approach, the top-10 returned candidate keyphrases by MR include 1 True Positive (TP), the bigram phrase *minimum transversals*, 9 False Positives (FPs) and 3 False Negatives (FNs). Hence,

$$precision = \frac{TPs}{TPs+FPs} = 0.10 \quad recall = \frac{TPs}{TPs+FNs} = 0.25 \quad F_1 = 2 \times \frac{precision \times recall}{precision+recall} = 0.14$$

However, the stemmed set of words found in all golden keyphrases used by the partial match evaluation approach is the following:

{(hypergraph), (3hit), (set), (exact), (algorithm), (minimum), (transvers)}

and the set of words found in all extracted keyphrases by MR is given below:

{{(problem), (case), (branch), (3hit), (set), (time), (edg), (minimum), (transvers), (algorithm), (number), (rank3), (hypergraph)]}}

According to the partial match evaluation approach, the top-10 returned candidate keyphrases by MR include 6 TPs, 7 FPs and 1 FN. Consequently,

$$precision = 0.46 \quad recall = 0.86 \quad F_1 = 0.60$$

In this case it is confirmed that the exact match evaluation seems to be too strict whereas the looser partial match approach is closer to the actual performance of the MR method. However, partial match evaluation considers as TPs unigram phrases that have trivial meaning without their context words, e.g., the unigram *algorithm* instead of the bigram *exact algorithm*.

We give an example where the exact match evaluation corresponds to a higher F_1 -score than the partial match evaluation. The results are based on the output of the MR method. We quote the publication's title and abstract below in order to get a sense of its content:

Title: Finite state machines for strings over infinite alphabets.

Abstract: Motivated by formal models recently proposed in the context of XML, we study automata and logics on strings over infinite alphabets. These are conservative extensions of classical automata and logics defining the regular languages on finite alphabets. Specifically, we consider register and pebble automata, and extensions of first-order logic and monadic second-order logic. For each type of automaton we consider one-way and two-way variants, as well as deterministic, nondeterministic, and alternating control. We investigate the expressiveness and complexity of the automata and their connection to the logics, as well as standard decision problems. Some of our results answer open questions of Kaminski and Francez on register automata.

The corresponding set of the "gold" keyphrases are: {xml, automata, first-order logic, expressiveness, pebbles, monadic second-order logic, infinite alphabets, registers}. For evaluation purposes, we transform the set of "gold" keyphrases into the following one (after stemming and removal of punctuation marks, such as dashes and hyphens):

{(xml), (automata), (firstord, logic), (express), (pebbl)}
 (monad, secondord, logic), (infini, alphabet), (regist)}

The MR's result set is given in the first box below, followed by its stemmed version in the second box. The words that are both in the golden set and in the set of our candidates are highlighted with bold typeface:

{pebbles, mso, finite set, set, proof, strings, pebble automata, automata, positions, data values}
{{ pebbl }, (mso), (finit, set), (set), (proof), (string), (pebbl, automata), (automata), (posit), (data, valu)}

According to the exact match evaluation, the top-10 returned candidate keyphrases by MR include 2 True Positives (TPs), the unigram phrases *pebbles* and *automata*, 8 False Positives (FPs) and 6 False Negatives (FNs). Hence,

$$\textit{precision} = 0.20 \quad \textit{recall} = 0.25 \quad F_1 = 0.22$$

However, partial match evaluation approach uses the stemmed set of words found in all golden keyphrases, i.e.:

{(xml), (automata), (firstord), (logic), (express), (pebbl), (monad), (secondord), (infini), (alphabet), (regist)}
 and the set of words found in all extracted keyphrases by MR, i.e.:

{{ pebbl }, (mso), (finit), (set), (proof), (string), (automata), (posit), (data), (valu)}
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According to the partial match evaluation, the top-10 returned candidate keyphrases by MR include 2 TPs, *pebbles* and *automata*, 8 FPs and 9 FNs. Hence,

$$\textit{precision} = 0.20 \quad \textit{recall} = 0.18 \quad F_1 = 0.19$$

So, it is quite usual in cases where there are unigram keyphrases as TPs and multiword keyphrases as FPs/FNs, the exact match F_1 -score to be higher than the partial match F_1 -score. Note that both evaluation approaches fail to recognize as TP the unigram keyphrase *mso* which is an abbreviation of the multiword keyphrase *monadic second-order logic*. Finally, in Appendix we give A an example where the partial match evaluation can be considered as harmful compared to the strict exact match evaluation.

7 | CONCLUSIONS AND FUTURE DIRECTIONS

Keyphrases are multi-purpose knowledge gems. They constitute a concise summary of documents that is extremely useful both for human inspection and machine consumption, in support of tasks such as faceted search, document classification and clustering, query expansion and document recommendation. Our article reviews the existing body of work on keyphrase extraction and presents a comprehensive organization of the material that aims to help newcomers and veterans alike navigate the large amount of prior art and grasp its evolution.

We present a large number of both unsupervised and supervised keyphrase extraction methods, including recent deep learning methods, categorizing them according to their main features and properties, and highlighting their strengths and weaknesses. We discuss the challenges that supervised methods face, namely the subjectivity that characterizes the existing annotated datasets and the imbalance of keyphrases versus non-keyphrases. In addition, we

discuss how keyphrase extraction methods are currently evaluated, and present a long list of free and commercial keyphrase extraction software and APIs, as well as the main collections of documents with associated keyphrases that are used for obtaining experimental results.

Our review includes an extensive empirical evaluation study of keyphrase extraction. We compare commercial APIs, as well as unsupervised methods ourselves, while for supervised methods we include a table with results collected from the corresponding papers. The results show that simple unsupervised methods, such as TfIdf2, are strong baselines that should be considered in empirical studies and that deep learning methods achieve state-of-the-art results. Among unsupervised methods, we notice that graph-based methods work better for short, while statistical methods work better for long documents.

Our evaluation study presents a thorough analysis of the exact and partial matching approaches, concluding with the recommendation of considering their average, and highlighting the need for approaches that take the semantic similarity of predicted and golden keyphrases. In addition, our study investigates how the different golden keyphrase sources (authors and readers) affect the evaluation of keyphrase extraction methods, concluding that they play a significant role and should be explicitly considered and reported in empirical studies.

A lot of progress still remains to be done in this challenging task, as the accuracy of state-of-the-art systems has not reached satisfactory levels yet. At the moment, the most exciting developments in mastering language are coming from the frontier of deep learning and unsupervised language models (Devlin et al., 2019; Yang et al., 2019; Cer et al., 2018). The exploitation of such models for keyphrase extraction and/or generation appears as the most interesting future direction.

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A | QUALITATIVE RESULTS

We give an example where the partial match evaluation can be considered as harmful compared to the strict exact match evaluation. The results are based on the output of the MR method. Once again, we quote the publication’s title and abstract below in order to get a sense of its content:

Title: Programming and Verifying Real-Time Systems by Means of the Synchronous Data-Flow Language LUSTRE.
 Abstract: The benefits of using a synchronous data-flow language for programming critical real-time systems are investigated. These benefits concern ergonomony (since the dataflow approach meets traditional description tools used in this domain) and ability to support formal design and verification methods. It is shown, using a simple example, how the language LUSTRE and its associated verification tool LESAR, can be used to design a program, to specify its critical properties, and to verify these properties. As the language LUSTRE and its uses have already been discussed in several papers, emphasis is put on program verification.

The corresponding set of the “gold” keyphrases are: {*sampling, matrix algorithms, low-rank approximation*}. For evaluation purposes, we transform the set of “gold” keyphrases into the following one (after stemming and removal of punctuation marks, such as dashes and hyphens):

$\{(s\text{ampl}), (matrix, algorithm), (lowrank, approxim)\}$

The MR’s result set is given in the first box below, followed by its stemmed version in the second box. The words that are both in the golden set and in the set of our candidates are highlighted with bold typeface:

{low-rank approximations, algorithm, singular vectors, rows, lemma, assumption a1, entries, problem, modern applications, matrix}

{{**lowrank**, **approxim**}, (algorithm), (singular, vectort), (row), (lemma), (assumpt, a1), (entri), (problem), (modern, applic), (matrix)}

According to the exact match evaluation, the top-10 returned candidate keyphrases by MR include 1 True Positive (TP), the bigram phrase *low-rank approximations*, 9 False Positives (FPs) and 2 False Negatives (FNs). We should notice that this example belongs to the less usual case where the exact match evaluation is close to the manual evaluation, i.e., in a right direction, indicating the actual success rate of the method. Hence, *precision* = 0.10, *recall* = 0.33, $F_1 = 0.15$

However, partial match evaluation approach uses the stemmed set of words found in all golden keyphrases, i.e.:

$\{(s\text{ampl}), (matrix), (algorithm), (lowrank), (approxim)\}$

and the set of words found in all extracted keyphrases by MR, i.e.:

{{**lowrank**}, (**approxim**), (**algorithm**), (singular), (vector), (row), (lemma), (assumpt), (a1), (entri), (problem), (modern), (appli), (**matrix**)}

According to the partial match evaluation, the top-10 returned candidate keyphrases by MR include 4 TPs, *lowrank*, *approxim*, *algorithm* and *matrix*, 10 FPs and 1 FN. Hence, *precision* = 0.29, *recall* = 0.80, $F_1 = 0.42$

Despite the fact that the partial match evaluation gives F_1 -scores closer to the manual ones, we see here that the F_1 -score based on the partial match evaluation is quite far from the actual performance of the method on the specific document. Particularly, the partial match strategy fails to evaluate the syntactic correctness of the returned phrases *algorithm* and *matrix*, which have very general meaning when they returned as unigrams by MR compared to the bigram gold keyphrase *matrix algorithm*.

B | COMMERCIAL APIS EVALUATION

MAP	Semeval		NUS		Krapivin		Inspec		500N-KPCrowd	
	@10	@20	@10	@20	@10	@20	@10	@20	@10	@20
IBM	0.066	0.041	0.071	0.042	0.047	0.028	0.146	0.093	0.095	0.078
GOOGLE	0.060	0.038	0.088	0.056	0.042	0.025	0.090	0.060	0.258	0.209
Amazon	0.017	0.013	0.011	0.010	0.008	0.007	0.018	0.016	0.059	0.047
Textrazor	0.109	0.062	0.113	0.069	0.062	0.035	0.084	0.051	0.202	0.143
Aylien	0.061	0.034	0.063	0.036	0.027	0.015	0.054	0.034	0.170	0.165

TABLE 17 MAP@10 and MAP@20 according to the exact match evaluation approach of all APIs for all datasets.

pF ₁	Semeval		NUS		Krapivin		Inspec		500N-KPCrowd	
	@10	@20	@10	@20	@10	@20	@10	@20	@10	@20
IBM	0.282	0.307	0.375	0.344	0.348	0.305	0.569	0.583	0.348	0.445
GOOGLE	0.233	0.253	0.375	0.374	0.368	0.336	0.444	0.501	0.267	0.362
Amazon	0.190	0.268	0.188	0.267	0.180	0.227	0.261	0.388	0.239	0.356
Textrazor	0.212	0.258	0.278	0.316	0.289	0.302	0.348	0.411	0.167	0.240
Aylien	0.278	0.305	0.339	0.341	0.296	0.295	0.401	0.480	0.237	0.336

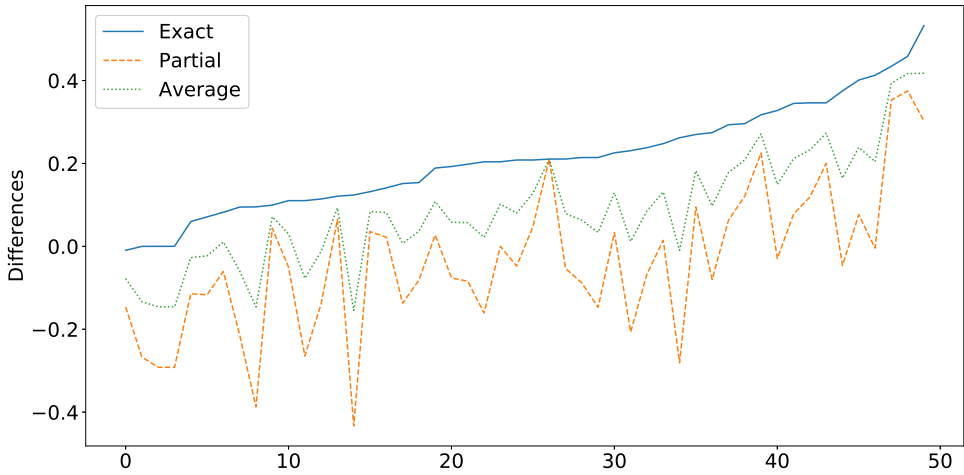
TABLE 18 F₁@10 and F₁@20 according to the partial match evaluation approach (pF₁) of all APIs for all datasets.

C | BIBLIOGRAPHIC SOURCES

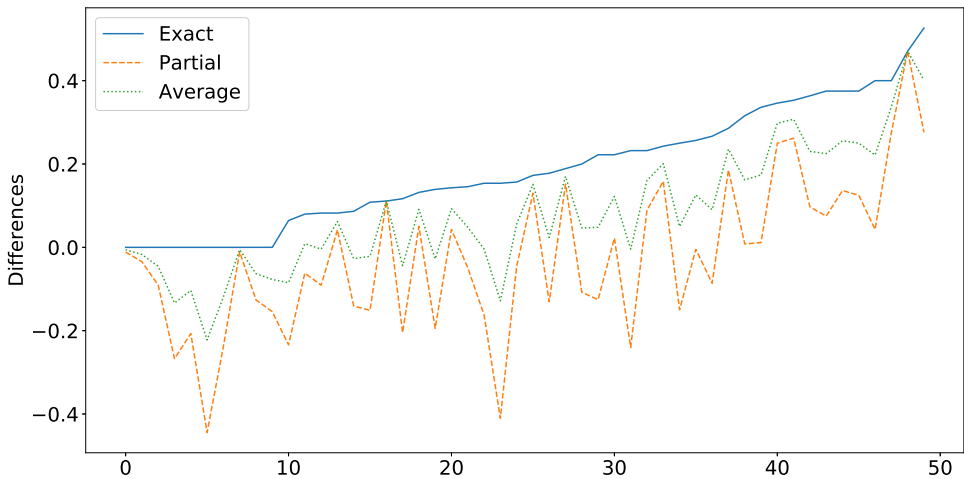
Journal	Publisher
ACM Transactions on Computer-Human Interaction	ACM
Information Systems	ELSEVIER
Decision Support Systems	ELSEVIER
Information Processing & Management	ELSEVIER
Language Resources and Evaluation	Springer
Data Science and Engineering	Springer
Text Mining: Applications and Theory	Wiley
Conference (Abbreviation)	Proceedings Publisher
Annual Meeting of the Association for Computational Linguistics (ACL)	ACL
Conference on Empirical Methods in Natural Language Processing (EMNLP)	ACL
International Conference on Computational Linguistics (COLING)	ACL
Conference of the North American Chapter of the Association for Computational Linguistics (NAACL)	ACL
International Joint Conference on Natural Language Processing (IJCNLP)	ACL
European Conference on Information Retrieval (ECIR)	Springer
ACM International Conference on Information and Knowledge Management (CIKM)	ACM
International World Wide Web Conference (WWW)	ACM
ACM International Conference on Research and Development in Information Retrieval (SIGIR)	ACM
International Conference on Language Resources and Evaluation (LREC)	ELRA
Annual Conference of the International Speech Communication Association (Interspeech)	ISCA
IEEE International Conference on Data Mining (ICDM)	IEEE
AAAI Conference on Artificial Intelligence (AAAI)	AAAI

TABLE 19 The main journals and conferences that were used as sources of related articles in this survey.

D | AUTOMATIC VS MANUAL SCORES



(a) KPM



(b) MR

FIGURE 6 Differences between the F_1 -scores based on the manual evaluation and the F_1 -scores based on the exact (solid line), partial (dashed line) and average (dotted line) evaluation approaches for the 50 manually evaluated documents given on the x axis.

In Fig. 6 we plot the differences between the F_1 -score values based on the manual evaluation and the F_1 -score values calculated according to the exact (solid line), partial (dashed line) and average (dotted line) evaluation approaches for KPM and MR methods. The differences between manual and average scores range closer to 0 in comparison with the

differences between manual-exact and manual-partial scores, respectively. Particularly, most differences between manual-exact scores are positive (manual scores are greater than the exact match scores), whereas there are many differences between manual-partial scores that are negative (manual scores are lower than the partial match scores).