Keywords lie far from the mean of all words in local vector space

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Abstract
Keyword extraction is an important document process that aims at finding a small set of terms that concisely describe a document’s topics. The most popular state-of-the-art unsupervised approaches belong to the family of the graph-based methods that build a graph-of-words and use various centrality measures to score the nodes (candidate keywords). In this work, we follow a different path to detect the keywords from a text document by modeling the main distribution of the document’s words using local word vector representations. Then, we rank the candidates based on their position in the text and the distance between the corresponding local vectors and the main distribution’s center. We confirm the high performance of our approach compared to strong baselines and state-of-the-art unsupervised keyword extraction methods, through an extended experimental study, investigating the properties of the local representations.

1. Introduction
Automatic Keyword Extraction (AKE) aims at finding the most representative words that summarize the contents of a document, without the expensive and time-consuming involvement of human annotators (Hasan and Ng 2014; Vega-Oliveros et al. 2019). AKE is useful in several tasks, such as query expansion (Song et al. 2006), faceted search (Gutwin et al. 1999), text summarization (Zhang et al. 2004), document clustering and text classification (Hulth and Megyesi 2006). As the amount of online digital textual information, e.g., e-newspapers, digital libraries with scientific literature, encyclopedias, blogs, magazines, etc., increases, the task of AKE becomes more and more popular, attracting much attention from the research community (Papagiannopoulou and Tsoumakas 2020; Vega-Oliveros et al. 2019; Merrouni et al. 2019).

Several AKE methods have been proposed in the past. Traditional unsupervised graph-based approaches consider the central nodes of a graph-of-words as the most representative ones (Mihalcea and Tarau 2004). Moreover, there exist strong baselines that use common statistics (e.g., term frequency-inverse document frequency, known as Tf-Idf) and/or heuristics (e.g., position in the document) to detect the most significant terms. Furthermore, state-of-the-art approaches for the task span both classical supervised machine learning methods (Medelyan et al. 2009) and deep learning techniques (Meng et al. 2017) that perform better compared to unsupervised ones. However, supervised methods demand labelled data and are biased towards the domain of the training corpus. Another drawback of most AKE methods is the use of external tools, e.g., part-of-speech (POS) taggers, for grammatical/syntactic analysis and the use of (pre-trained) static or dynamic word embeddings that have a bias over the corpora domains used for training or need supervised fine-tuning.
In this paper, inspired by the idea of using local word vector representations (Papagiannopoulou and Tsoumakas 2018) and the outlying behaviour of the keywords (Papagiannopoulou and Tsoumakas 2019), we propose a new unsupervised method for keyword extraction. First, our approach builds a local vector representation for each word that encodes the words’ neighbourhood. Then, we estimate the distribution’s center (mean vector) of the words. Since the majority of a document’s terms have neutral meaning or hardly related to the documents’ topics, the main bulk of the words that determine the distribution’s center are the non-keywords. Finally, we score and rank the words utilizing their corresponding distance from the distribution’s center and the position of their first occurrence in the text (the index of the first sentence where the word occurs first), as keywords usually appear early in the document (Florescu and Caragea 2017) and are distant from the distribution’s center. Our empirical study confirms the high performance of our approach (in terms of the F₁-measure) on three datasets compared to state-of-the-art unsupervised keyword extraction methods.

As a small motivational example, Fig. 1 projects 50d local GloVe (Pennington et al. 2014) representations of the words learned by training GloVe on the full-text of a target academic publication from the NUS (Nguyen and Kan 2007) collection on the first two principal components. The figure’s caption provides information regarding the article’s title and keywords. We notice that keywords are far from the main bulk of the words that are centered around (0,0). The center of the distribution is the blue “x” annotated with M (mean). Similar plots, supportive of our key intuition, are also obtained from other documents (see Fig. 9 in the Appendix for an additional example).

![PCA 2d projection of the 50d local GloVe vectors for the article with title “Obfuscated databases and group privacy” and keywords {database, obfuscation, privacy}.

Figure 1: PCA 2d projection of the 50d local GloVe vectors for the article with title “Obfuscated databases and group privacy” and keywords {database, obfuscation, privacy}.

Our contributions are the following: (1) We propose a new unsupervised AKE approach that employs local word vector representations to model the main distribution of a document’s words. Counter to existing methods, e.g., Key2Vec (Mahata et al. 2018), EmbedRank (Bennani-Smires et al. 2018), RVA (Papagiannopoulou and Tsoumakas 2018), etc., we consider the distribution’s center closer to the non-keywords, since the main bulk of words are neutral or slightly relevant.
to the documents’ topics. The proposed method outperforms strong baselines and state-of-the-art approaches of the task. (2) We show via an empirical study that simpler local word vector representations, based on the words’ co-occurrences within a specific window, encode statistical information equivalent to the one encoded by the local GloVe word embeddings. (3) We investigate the properties of local word embeddings and the effect of robust statistics in the calculation of the distribution’s center. Unlike the main direction in text mining that uses the cosine similarity/distance, we suggest distance metrics that incorporate the vectors’ magnitude or covariance estimations to capture the similar behaviour of the non-keywords’ vectors over the keywords’ ones.

The rest of the paper is organized as follows. Section 2 presents related work on unsupervised AKE (Section 2.1) and pre-trained/local embeddings in the context of this task (Section 2.2). Section 3 describes our approach (Section 3.1) providing intuitions regarding its relationship with the graph-based approaches (Section 3.2). Section 4 investigates the properties of the local representations (Section 4.2), gives a comparison between our approach and the other state-of-the-art unsupervised keyword extraction methods (Section 4.3) and provides a qualitative study (Section 4.4). Finally, Section 5 concludes our work and presents future research directions.

2. Related Work

Keyword extraction is important for many tasks in text processing/mining (see Section 1). Moreover, it is the core process for various keyphrase extraction methods that form and rank the candidate phrases using the already scored candidate unigrams by a keyword extraction approach (Wan and Xiao 2008; Florescu and Caragea 2017). Furthermore, word embeddings came to the foreground by Mikolov et al. (2013), with the Continuous Bag-of-Words model (CBOW) and the Continuous Skip-gram model. Since then, many AKE methods utilise word embeddings, pre-trained or local ones, as either an external semantic information source or a more expressive representation than plain statistics, respectively. This section presents related work on the unsupervised AKE as well as the different types of word embeddings used in the context of this task.

2.1 Unsupervised Keyword Extraction

TextRank (Mihalcea and Tarau 2004) inspired researchers to build popular state-of-the-art methods. TextRank keeps only nouns and adjectives as candidates. Then, it constructs an undirected and unweighted graph-of-words with the candidates as nodes and edges between the nodes that co-occur within a window of W words. Finally, the PageRank (Brin and Page 1998) algorithm runs until it converges. SingleRank (Wan and Xiao 2008) is an extension of TextRank which incorporates weights to edges, i.e., each edge weight is equal to the number of co-occurrences of the two corresponding words within a specific window. In this vein, RAKE (Rose et al. 2010) creates a graph of word-word co-occurrences and assigns as a score to each candidate word its frequency or degree or the ratio of degree to frequency. Later, Florescu and Caragea (2017) proposed PositionRank, a graph-based unsupervised method that not only considers the word-word co-occurrences but also incorporates each word’s positions through a biased PageRank. Rousseau and Vazirgiannis (2015) propose k-Core decomposition (Seidman 1983; Batagelj and Zaversnik 2002, 2003) of unweighted or weighted graphs-of-words, whereas Tixier et al. (2016) apply the k-truss (Cohen 2008) algorithm to the task of keyword extraction, a triangle-based extension of k-Core. Recently, Biswas et al. (2018) proposed a graph-based keyword extraction method from tweets, using collective node weight that depends on many parameters, e.g., node’s centrality and strength of neighbours (Barrat et al. 2004) as well as word’s frequency and position.
Vega-Oliveros et al. (2019) present the performance of many centrality measures in terms of precision, recall and F1-score, suggesting the use of a combination of word rankings that the various centrality measures return, based on a multi-centrality index. Their experimental study includes nine different centrality measures and three collections. The centrality measures in graph-of-words considered for AKE are Eccentricity, Eigenvector, Clustering Coefficient, Betweenness, Degree, Closeness, PageRank, Structural Holes, k-Core. Although all measures show comparable results, PageRank performs better in most cases. Earlier, Lahiri et al. (2014) show that simple centrality measures, e.g., Degree and Strength (weighted Degree), or statistics, such as term frequency (TF) and term frequency-inverse document frequency (TF-Idf), perform as well as PageRank. Finally, recent statistical approaches, such as YAKE (Campos et al. 2018, 2020), use statistical metrics that capture context information and the spread of the terms into the document, besides the term’s position/frequency, etc.

2.2 Pre-trained and Local Word Embeddings

Various types of word embeddings are used in the context of keyphrase extraction. First, Wang et al. (2014, 2015) proposed graph-based approaches that incorporate semantic information coming from distributed word representations. Particularly, they have experimented with several pre-trained publicly available word vectors: SENNA (Collobert et al. 2011), Turian’s (Turian et al. 2010) and HLBL (Mnih and Hinton 2007) embeddings (the last one achieves the highest performance). This approach motivated Mahata et al. (2018) to present Key2Vec, a graph-based keyphrase extraction method that uses Fasttext (Bojanowski et al. 2017; Joulin et al. 2017) (multi-)word embeddings (trained on a corpus of scientific abstracts) to represent the candidate keyphrases of a document.

Later, EmbedRank (Bennani-Smires et al. 2018) employed publicly available pre-trained sentence embeddings, Doc2Vec (Lau and Baldwin 2016) or Sent2Vec (Pagliardini et al. 2018), to embed both candidate phrases and documents 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. In this vein, Papagiannopoulou and Tsoumakas (2018) present the Reference Vector Algorithm (RVA), a method for keyphrase extraction, whose main innovation is the use of local GloVe (Pennington et al. 2014) word vectors trained only on the target document (experiments with pre-trained embeddings lead to low performance).

3. Our Approach

We first describe our approach in Section 3.1. Then, we provide intuitions regarding the relationship between the proposed method and the graph-based approaches in Section 3.2.

3.1 Description

In the following four subsections, we present the four steps (stages) of our method: (a) the pre-processing of the document, (b) the formation of the local word vectors, (c) the calculation of the main distribution’s center, (d) the scoring and ranking process of the candidate keywords.

3.1.1 Pre-processing of the Document

Following the paradigm of graph-based approaches (Mihalcea and Tarau 2004, Wan and Xiao 2008, Florescu and Caragea 2017), where syntactic filters often restrict the candidate terms to nouns and adjectives, we remove from the target document: punctuation marks, stopwords, words with less than two characters and tokens consisting only of digits. Apart from the classic stopwords
list of the English language, we also remove common adjectives, reporting verbs, determiners and functional words. This way, we avoid considering trivial or unimportant terms that are unlikely to be keywords. Then, we apply stemming to reduce the inflected word forms into the root ones, ending up to the final set of $n$ candidates $W(w \in W)$.

### 3.1.2 Local Vector Representations

Papagiannopoulou and Tsoumakas (2018) show that local word embeddings perform better in the keyphrase extraction task than the global ones, i.e., pre-trained word vectors or vectors trained on large collection(s). Such local word vector representations came from the training of the GloVe model on the target document. This way, the ostensibly independent document’s statistics are encoded in a more expressive vector representation, as the GloVe model creates word vectors such that the dot product of each pair of vectors $(w_i, \tilde{w}_k)$ equals the logarithm of the probability of co-occurrence of the corresponding words in the text $(X_{ik})$, i.e.,

$$w_i^T \tilde{w}_k + b_i + \tilde{b}_k = \log(X_{ik})$$

where $i, k$ comprise the given pair of words, $w \in \mathbb{R}^d$ are the word vectors and $\tilde{w} \in \mathbb{R}^d$ are the separate context word vectors, respectively, whereas, $b_i$ and $b_j$ are the corresponding bias terms (for further details regarding the GloVe technique and the weighted least squares regression model that proposes see the work of Pennington et al. (2014)).

Such type of statistics, e.g. the word-word co-occurrences, are also the primary source of information for graph-based keyword extraction methods. In this vein, 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. In this work, we investigate the effectiveness of two different types of local word embeddings in the context of the AKE that use the document’s source statistics to construct the corresponding vectors. Specifically, we have studied the following vector representations:

1. local GloVe vector representations, i.e., the GloVe vectors’ matrix $G_{n \times q}$ where $n$ is the number of unique stemmed words in the text and $q$ is the number of vectors’ dimensions.
2. word-word co-occurrence statistics, i.e., the term-term matrix $C_{n \times n}$ where $n$ is the number of unique stemmed words in the text and the $C_{x,j}$ element of the matrix contains the number of co-occurrences between the words $(w_x, w_j)$ ($1 \leq x \leq n$ and $1 \leq j \leq n$) within a window of 10 words (we express each word in terms of their co-occurrences with the rest of the words).

### 3.1.3 Estimating the Center of the Main Distribution

The next step of our approach is the estimation of the distribution’s center (mean vector) of the document’s local word vectors (each word participates once in the computation). We investigate the efficacy of two distinct estimations. The first one considers the sample’s $(S)$ estimated mean $\vec{\mu}_S$ of the corresponding vector matrix, i.e., the $G_{n \times q}$ or $C_{n \times n}$, as the distribution’s center.

The second one employs the fast algorithm of Rousseeuw and van Driessen (1999) for the MCD estimator (Rousseeuw 1984) to model the dominant distribution of the words’ vectors. The MCD approach aims to find the subset $J$ of the word vector representations with size $h$ and mean $\vec{\mu}_J$ whose covariance matrix $\Sigma$ has the smallest determinant;

$$\vec{\mu}_J, \Sigma_J : \det \Sigma_J \leq \det \Sigma_K, \forall K \subset D, \ |K| = h$$

where $\vec{\mu}_J$ and $\Sigma_J$ the robust distribution’s center and covariance matrix of the corresponding word vectors’ matrix, i.e., the $G_{n \times q}$ or $C_{n \times n}$, respectively. This method, however, may break or not perform well in high-dimensional settings. For this reason, we apply the statistical procedure of

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\footnote{All the corresponding lists of words are available on our GitHub repository (URLs are provided in Section 4.1).}
Principal Component Analysis (PCA) \cite{Pearson1901,Hotelling1933}, which uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. This way, we keep only the first \( m \) principal components, where \( m \) is a small number, that finds the \( m \) dimensions through the high-dimensional dataset in which the data is most spread out.

Notice that our approach does not have to consider further term frequency thresholds or syntactic information, e.g., POS filters/patterns, for the candidate keyword identification. This means that there are no dependencies on external tools (e.g. POS taggers), which are also biased towards the domains of the corpora used for training.

3.1.4 Scoring Candidate Keywords
We score each word with a value \( S(w) \), \( w \in W \) considering positional and context information according to the following formula:

\[
S(w) = d(\vec{\mu}, \vec{v}) \times \frac{1}{z}
\]  

(3)

where \( d(\vec{\mu}, \vec{v}) \) is the distance between the distribution’s center \( \vec{\mu} \) (i.e., \( \vec{\mu}_S \) or \( \vec{\mu}_J \)) and the vector \( \vec{v} \) of the word \( w \) using the vector representation of our choice, i.e., GloVe vectors \((G_{n\times q})\) or term-term co-occurrences \((C_{n\times n})\), respectively. The \( z \) is the index of the first sentence where \( w \) occurs in the document, i.e., \( z = 1, 2, \ldots, r \) with \( r \) the total number of sentences. We choose not to use the word’s index but only the sentence index, as it offers a more general/useful information regarding the word’s importance. The higher the score \( S(w) \), the more important the word \( w \) for the document, i.e., we are interested in words that appear early in the document and have high distance values, as the main bulk of the words that determine the distribution’s center are the non-keywords.

For the computation of the distance \( d(\vec{\mu}, \vec{v}) \), we use the Euclidean distance \( d_E \), i.e.,

\[
d_E(\vec{v}, \vec{\mu}) = \sqrt{\sum_{i=1}^{l} (v_i - \mu_i)^2}
\]  

(4)

where \( l \) is the number of dimensions, i.e., equal to \( q, n \) or \( m \), depending on the type of the local vector representation and the need to apply dimensionality reduction with PCA or not. We have also experimented with the cosine and Mahalonobis distance measures (see Section 4.2 for an extensive discussion on the various types of distance metrics and local vectors as well as the role of robust statistics in the corresponding calculations).

3.2 Intuitions for the Relationship with the Graph-based Approaches
The majority of unsupervised AKE graph-based approaches utilise statistics of the target document, e.g., word-word co-occurrences, words’ position, etc. Such methods, first, construct a graph-of-words and, then, identify the most central vertices, considering them as keywords, by using various centrality measures, e.g., PageRank, Closeness, Betweenness, Eigenvector, \( k \)-Core, etc. In this section, we use the \( k \)-Core\footnote{We use the \( k \)-Core of undirected weighted graph-of-words constructed with a fixed-size sliding window equal to 10 following the pre-processing steps described in Section 3.1.1} to provide intuitions concerning the relationship between the graph-based approaches and the proposed one, as it enables us to concentrate on the main goal of the study. Particularly, \( k \)-Core returns only the most cohesive connected component-s of the graph-of-words without scoring the corresponding graph nodes. Hence, there is no need to set a threshold for the number of the top \( N \) high-scored words that the measure will return (e.g. the case of PageRank). Other centrality measures offer similar visualizations.
The $k$-Core of a graph $G = (V, E)$ is the maximal subgraph that contains vertices of degree $k$ or more, where $V$ is the set of vertices and $E$ the set of edges. Thus, the $k$-Core of a graph-of-words comprises usually a minority of “qualified” representatives for the whole graph (i.e., candidate keywords). Table 1 presents the average number of vertices that belong to the $k$-Core ($|k$-Core$|$), the average total number of vertices $|V|$ and the average ratio $\frac{|k$-Core$|}{|V|}$ for the corresponding documents in the training sets of 3 different datasets, Semeval (Kim et al. 2010), Krapivin (Krapivin et al. 2008), and NUS. We see that the $k$-Core subgraph in most cases contains a small percentage of nodes compared to $V$. This fact inspired us to think the document’s important terms as a minority that differs from the main bulk of insignificant words, which are close to the distribution’s center of the document’s local word vectors.

Table 1: $|k$-Core$|$ is the average number of vertices in the $k$-Core, $|V|$ the average total number of vertices and $\frac{|k$-Core$|}{|V|}$ is the average ratio for the documents of three datasets (Semeval, Krapivin, NUS).

| Dataset | $|k$-Core$|$ | $|V|$ | $\frac{|k$-Core$|}{|V|}$ |
|-------------|---------|---------|------------------|
| Semeval     | 70      | 645     | 0.110            |
| Krapivin    | 74      | 736     | 0.103            |
| NUS         | 72      | 778     | 0.095            |

Furthermore, to get a feel of the similarities between the proposed method and the graph-based approaches, Figures 2a and 2b visualize the $k$-Core subgraph of two documents from the NUS training set. The coloured vertices represent the intersection of the top $N = |k$-Core$|$ candidate keywords returned by our method and the $k$-Core subgraph of the corresponding document, whereas the darker ones belong to both the intersection and the set of authors’ keywords. Both approaches use the stemmed unigrams. Moreover, the caption of each figure provides information regarding the article’s title and authors’ keywords.

4. Experimental Study
Section 4.1 presents the experimental setup of the study. In Section 4.2, we investigate the properties (behaviour) of the local vector representations in the context of the AKE task. Section 4.3 shows a comparison of the proposed approach with other baselines and state-of-the-art methods, whereas Section 4.4 provides qualitative results.

4.1 Experimental Setup
We choose three well-known datasets that contain full-text articles from the computer science domain, NUS (Nguyen and Kan 2007), Semeval (Kim et al. 2010) and Krapivin (Krapivin et al. 2008) datasets with 211, 244 and 2304 documents, respectively. Semeval is already divided into training (144) and test (100) sets. However, there are no explicit guidelines for the division of the Krapivin and NUS. Thus, we select the first 400 papers from the Krapivin (following the paradigm of Meng et al. (2017)) and the last 100 papers from NUS in alphabetical order as the testing data. We should clarify that the empirical study presented in Section 4.2 uses only the training sets of the corresponding datasets, whereas the experimental comparison of Section 4.3 employs the test sets.
(a) Title: “A frequency-based and a Poisson-based definition of the probability of being informative”. Keywords: inverse document frequency (idf), independence assumption, probabilistic information retrieval, poisson distribution, information theory

(b) Title: “Improving the static analysis of embedded languages via partial evaluation”. Keywords: partial, evaluation, macros, value flow analysis, embedded languages

Figure 2: k-Core sets for two articles.
We compute $F_1@5$, $F_1@10$, $F_1@15$, as accuracy at the top of the ranking is more important in typical applications. We use exact string matching to determine the number of correctly matched words with the golden ones for a document. We also apply stemming to the output of the methods and the article’s golden words, as a pre-processing step before the evaluation process. We employ the authors’ keywords as a gold evaluation standard for all dataset collections. Regarding the GloVe setup, we used the default parameters ($x_{max} = 100, \alpha = \frac{3}{4}$, window size = 10) (Pennington et al. 2014), whereas the window for counting the co-occurrences between two words for the term-term word vector representation is equal to 10. The document frequency used by Tf-Idf approach (Section 4.3) is calculated separately for each dataset collection. The code of our method is available on our GitHub repository\(^c\), whereas, for the implementation of the competitive approaches, we employ the PKE\(^d\) toolkit and the NetworkX\(^e\) python library.

### 4.2 Empirical Study on Local Vector Representations

In this section, we use the training sets of the two smaller datasets (NUS and Semeval) to investigate the effectiveness of (a) the two local vector representations, i.e., GloVe and term-term co-occurrences vectors (t-t), (b) different distance metrics employed by the proposed approach via its scoring function (Equation 3), (c) the robust statistics in the calculation of the distribution’s center. Table 2 presents the $F_1$-scores of the proposed approach on the two datasets using the two different types of word vectors. For the distance calculation, which is necessary to score the candidates, we use either the sample’s mean (SM) or the robust mean (RM) given by the MCD estimator. We have experimented with various distance metrics including the Euclidean Distance (ED) (see Equation 4), i.e.:

1. **Cosine Distance (CD):**

   $$d_C(\vec{v}, \vec{\mu}) = 1 - \frac{\vec{v} \cdot \vec{\mu}}{||\vec{v}||_2 \cdot ||\vec{\mu}||_2}$$ (5)

2. **Mahalanobis Distance (MD):**

   $$d_M(\vec{v}, \vec{\mu}) = \sqrt{(\vec{v} - \vec{\mu})\Sigma^{-1}(\vec{v} - \vec{\mu})^T}$$ (6)

where $d_C$ (or $d_M$) is the cosine (or Mahalanobis) distance between the distribution’s center $\vec{\mu}$ (i.e., the sample’s mean $\vec{\mu}_S$ or the robust mean $\vec{\mu}_J$ from the MCD estimator) and the vector $\vec{v}$ of the word $w$ using the vector representation of our choice, i.e., GloVe vectors ($G_{n \times q}$) or term-term co-occurrences ($C_{n \times n}$), respectively. In the case of the MD, $\Sigma$ represents the covariance matrix that can be (a) the sample’s covariance (SC) matrix $\Sigma_S$, (b) the covariance matrix $\Sigma_{ML}$ based on the maximum likelihood covariance estimator (Rossi 2018) (MLC) or (c) the robust covariance (RC) matrix $\Sigma_J$ from the MCD estimator. However, the MCD estimator may break or not perform well in high-dimensional settings. For this reason, we apply PCA to the GloVe and t-t vectors’ matrices to keep only the first $m$ principal components, where $m$ is equal to 10.

\(^c\)https://github.com/epapagia/LocalVectors_AKE
\(^d\)https://github.com/boudinfl/pke
\(^e\)https://networkx.github.io/
Table 2 shows that t-t vectors in both datasets achieve the highest $F_1$-scores combined with Euclidean and Mahalanobis distance metrics, i.e., measures that consider the magnitude of the vectors and the correlations of the data, respectively. Only in the case of the cosine distance metric that is a judgment of orientation and not magnitude, GloVe vectors outperform the t-t vectors. In general, for all types of vectors, the scoring functions that incorporate Euclidean and/or Mahalanobis distance metrics achieve more or less equivalent results with high values compared to those that use the cosine distance.

Moreover, for the t-t vectors, the robust estimation of the sample’s mean does not lead to improved performance (at least on the averages of the $F_1$-scores) except for the case of the cosine distance (once again the improvements are not enough to exceed the high $F_1$-score values achieved by the Euclidean and the Mahalanobis metrics). In this vein, the maximum likelihood and the robust covariance estimation that the Mahalanobis distance incorporates causes no improvement on the scores. Regarding the GloVe vectors, the robust estimation of the distribution’s center, in most cases, slightly improves the method’s performance. Once more, the maximum likelihood and the robust covariance estimations within the Mahalanobis distance increase the corresponding $F_1$-scores.

Figures 3 and 4 offer insights regarding the effectiveness of the Euclidean and Mahalanobis distances compared to the cosine distance. Both figures present the PCA 2d projection on the first two principal components of the (a) 50d local GloVe and (b) term-term local embeddings for an article from the NUS collection with title “Index structures and algorithms for querying distributed RDF repositories” and keywords \{\textit{rdf, structure, optimization, querying, index}\}. The red circle points are the article’s keywords, whereas the rest of the words are the grey ones. The original sample’s center of the distribution is the blue “x” annotated with M (means), whereas the corresponding robust estimation is the black square annotated with RM. In particular, Fig. 4 shows the normalized (to unit variance) form of the vectors that the cosine distance considers, as the vectors’ magnitude is out of the scope of this metric. Such normalization makes difficult the detection of keywords, as it brings closer vectors that have a similar orientation and perhaps a different magnitude (see Fig. 3), i.e., loss of valuable statistical information. Similar plots, supportive of our interpretation, are also obtained from other documents (see Figs 7, 8, 10 and 11 in the Appendices).

The experimental results of Table 2 confirm the equivalence between the two local vector representations. The local GloVe vectors is an alternative view of the t-t vectors, suitable to capture in a few vectors’ dimensions the words’ context, useful especially in tasks where we are interested in global vectors by training the GloVe model in a large corpus. Hence, we suggest the usage of the

\[\text{The local vectors are normalized on the } m = 10 \text{ principal components that PCA generates.}\]
t-t vector representation instead of the local GloVe one, because of its high performance in both datasets and the simplicity concerning the construction of the vectors (the GloVe model requires both term-term co-occurrences calculations and multiple runs to achieve convergence).

Figure 3: PCA 2d projection of the (a) 50d local GloVe and (b) term-term local embeddings for the article.
4.3 Comparison with Other Approaches

Three baselines and four state-of-the-art unsupervised AKE methods participate in this empirical study. The Tf-Idf and First-N-Words (FNW) are the main baselines of the task that utilise
term frequencies in document/corpus level and the important heuristic of words’ position, respectively. In particular, FNW scores the candidate unigrams according to their first occurrence in the scientific article, i.e., we consider as more significant terms those that appear earlier in the publication. At the preprocessing stage of the above baselines, we remove English stopwords, symbols, punctuation, numerals, pronouns, spaces and adverbs. We keep only unigram alphanumerics with length greater than 1. Moreover, as a third baseline, we use our approach that considers only the Euclidean distance between the distribution’s center and each word vector (LV) to score the words.

Moreover, we have experimented with the PageRank (PR) and Betweenness (BT) centrality measures that are state-of-the-art for the AKE. We also compare our method with two additional state-of-the-art methods borrowed from the keyphrase extraction task, SingleRank (SR) and PositionRank (PosR), adapted to return unigrams instead of phrases. SR, PosR and BT use only nouns and adjectives for the graph-of-words construction. However, PR builds the graph-of-words following the pre-processing steps described in Section 3.1.1. All the competitive methods run on undirected graphs with word-word co-occurrences as weights on the edges.

Table 3. : F1-scores of various keyword extraction methods on the test sets of 3 different datasets at the top 5, 10, 15 returned keywords.

|        | NUS   | Semeval | Krapivin |
|--------|-------|---------|----------|
|        | @5    | @10     | @15      | @5    | @10     | @15      | @5    | @10     | @15      |
| Tf-Idf | 0.273 | 0.274   | 0.255    | 0.241 | 0.268   | 0.250    | 0.196 | 0.240   | 0.244    |
| FNW    | 0.356 | 0.393   | 0.328    | 0.312 | 0.325   | 0.285    | 0.341 | 0.367   | 0.337    |
| SR     | 0.375 | 0.384   | 0.353    | 0.319 | 0.320   | 0.295    | 0.312 | 0.353   | 0.349    |
| BT     | 0.361 | 0.373   | 0.346    | 0.317 | 0.309   | 0.289    | 0.314 | 0.344   | 0.335    |
| PR     | 0.373 | 0.388   | 0.354    | 0.326 | 0.318   | 0.290    | 0.306 | 0.351   | 0.346    |
| PosR   | 0.395 | 0.387   | 0.339    | 0.343 | 0.343   | 0.299    | 0.297 | 0.335   | 0.320    |
| LVb    | 0.354 | 0.361   | 0.315    | 0.297 | 0.299   | 0.280    | 0.277 | 0.325   | 0.323    |
| LV     | **0.431** | **0.438** | **0.385** | **0.387** | **0.387** | **0.344** | **0.385** | **0.426** | **0.400** |

Table 3 shows that our approach that uses local vectors (LV) outperforms all the other baselines and state-of-the-art unsupervised methods across all datasets. PosR and FNW achieve in many cases the second-best (underlined scores) or the third-best performance (italicized scores), whereas SR and PR follow with quite high F1-scores. Tf-Idf performs worse compared to the other approaches as it uses only term frequencies without considering context information, while FNW seems to be a quite strong baseline of the task. The decent and comparable F1-scores of LV to the rest techniques’ scores confirm the dynamics of simple local word representations to play a significant role in the AKE task.

All the state-of-the-art methods described above as well as the LV, LVb, focus on the detection of a set of words whose occurrences in a scientific publication highlight their role as keywords. The combination of term-term co-occurrence local vectors with general positional information, i.e., the id of the first sentence that a term appears (without the strict position of the first occurrence of the word), leads to the effective solution of LV. The value of the positional information is also evident from PosR and FNW that incorporate such knowledge and follow LV in the final ranking. Section 4.4 provides interesting insights regarding the influence of the two components, i.e., Euclidean distance and the positional information, on the final scoring scheme through qualitative results along with informative tables and figures.
4.4 Qualitative Results

In this section, we show the positive/negative impact of the positional information on our approach. We present the extracted keywords along with their scores using the LV and \( \text{LV}_b \) approaches. We also provide the information regarding each word’s position via the FNW baseline. We select two scientific publications from the Semeval dataset for this study. The first article (from now on referred to as Article I) entitled as “Live data center migration across WANs: a robust cooperative context aware approach” has the following set of authors’ keywords \{data, center, migration, virtual, server, storage\}. For the second one (i.e., Article II) with the title “Service interface: a new abstraction for implementing and composing protocols”, authors assign as keywords the terms \{protocol, frameworks, modularity, dynamic, replacement\}.

![Figure 5](image_url)

Figure 5: PCA 2d projection of the term-term local embeddings for the Article I.

Figure 5 shows the PCA 2d projection of the term-term local embeddings for the Article I. Once again, the red circle points are the authors’ keywords, whereas the rest of the words are the grey ones. The original sample’s center of the distribution is the blue “x” annotated with M, whereas the corresponding robust estimation is the black square annotated with RM. We see that this publication follows the basic assumption of the LV and \( \text{LV}_b \) approaches, i.e., keywords tend to be distant from the main distribution’s center. Table 4 presents the returned keywords, in their stemmed form (following the evaluation approach), ranked by decreasing importance scores. The golden keywords in the output of each method are emphasised as bold. Lines also organize the results into three ordered subsets of 5 words each, to facilitate their qualitative evaluation process, i.e., easy inspection at the top 5, 10 and 15 of the ranking, respectively. The results confirm that the pure version of our approach \( \text{LV}_b \) achieves to find 6/6 of the authors’ keywords at the top 15 returned results. However, LV, negatively affected by the positional information, ranks lower the keywords \{server, virtual\}, and, finally, misses the keyword storage (word in red bold typographical emphasis) that does not appear at the very beginning of the document.
Table 4: The top 15 returned (stemmed) keywords by LV, LV_b and FWN methods, ranked by decreasing importance scores for the Article I.

|        | LV  | LV_b | FWN |
|--------|-----|------|-----|
| data   | 70.7 | data | 70.7 | live | 0  |
| migrat | 48.9 | migrat | 48.9 | data | 1  |
| live   | 32.1 | server | 48.6 | center | 2 |
| center | 24.9 | live | 32.1 | migrat | 3 |
| across | 18.1 | virtual | 31.7 | wan | 5 |
| wan    | 14.8 | network | 30.2 | robust | 8 |
| servic | 10.3 | replic | 28.1 | cooper | 9 |
| server | 9.7  | storag | 26.9 | context | 10 |
| approach | 6.5  | center | 24.9 | awar | 11 |
| virtual | 6.3  | applic | 21.6 | approach | 12 |
| context | 6.2  | servic | 20.6 | abstract | 13 |
| cooper | 6.2  | across | 18.1 | signific | 15 |
| avail | 5.9  | use | 16.4 | concern | 16 |
| replic | 5.6  | system | 15.8 | internet | 18 |
| outag | 5.5  | remot | 15.7 | base | 20 |

Figure 6: PCA 2d projection of the term-term local embeddings for the Article II.

On the contrary, Fig. 6 shows that the keywords of Article II are not all quite distant from the main distribution’s center. Again, Table 5 presents the returned keywords ranked by decreasing importance. In this case, LV_b performs poorly, failing to detect the 50% (2/4) of the authors’ keywords at the top 15 returned results. However, LV, positively affected by the positional information, although it wrongly ranks lower the keywords {protocol, framework}, finally, manages to
detect the keyword *dynamic* (word in green bold typographical emphasis) that appears earlier in the document compared to the words (stemmed here) *request, stack, bound, etc.*

Table 5: The top 15 returned (stemmed) keywords by LV, LV\(_b\) and FWN methods, ranked by decreasing importance scores for the Article II.

| LV      | LV\(_b\) | FWN |
|---------|----------|-----|
| servic  | 73.617   | servic | 0 |
| protocol | 52.444 | protocol | 10 |
| modul   | 24.997   | base  | 5 |
| interfac| 12.685   | event | 7 |
| implement| 10.614 | modul | 9 |
| event   | 9.772    | framework | 10 |
| base    | 9.603    | implement | 15 |
| framework | 7.597 | interfac | 17 |
| compos  | 3.898    | request | 19 |
| approach | 2.996 | execut | 22 |
| network | 2.713    | bound  | 25 |
| abstract| 2.559    | issu   | 27 |
| interact| 2.332    | stack  | 30 |
| *dynam* | 2.191    | handl  | 31 |
| compar  | 1.488    | notif  | 36 |

5. Conclusions and Future Work

This work presents a new unsupervised keyword extraction approach, whose main innovation is that we consider the distribution’s center closer to the non-keywords, since the main bulk of words are neutral or slightly relevant to the documents’ topics, in contrast to existing methods. Our empirical study offers evidence that local word vector representations, such as GloVe or equivalent/simpler local vectors based on the words’ co-occurrences, can lead to better keyword extraction results compared to popular state-of-the-art unsupervised approaches. Unlike the main direction in text mining that uses the cosine similarity/distance, we recommend distance metrics that incorporate the vectors’ magnitude (Euclidean distance) or covariance estimations (Mahalanobis distance) to capture the similar behaviour of the non-keywords’ vectors over the keywords’ ones.

We hope this work paves the way to the researchers for further investigation on local representations. In particular, we envisage implications of our work towards (a) improved keyword extraction methods based on local word embeddings, (b) applying local word embeddings to other information processing tasks, and (c) developing novel methods for learning local word embeddings that will incorporate positional information or even semantics. Soon, we intend to build on top of this work, a solution that estimates the effectiveness of robust estimations regarding the distribution’s center, covariance matrix, etc. based on the properties of the document’s local vector representations.
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Appendix A. Local GloVe Word Vectors

Figure 7: (a) unnormalized and (b) normalized PCA 2d projection of the GloVe vectors for the article with title “Learning Spatially Variant Dissimilarity (SVaD) measures” and keywords \{learning, dissimilarity, measures, clustering\}.

Figure 8: (a) unnormalized and (b) normalized PCA 2d projection of the GloVe vectors for the article with title “Obfuscated databases and group privacy” and keywords \{obfuscation, database, privacy\}.
Figure 9: PCA 2d projection of the 50d local GloVe vectors for the article from the NUS collection with title “Index structures and algorithms for querying distributed RDF repositories” and keywords \{rdf, structure, optimization, querying, index\}.

Appendix B. Local Vectors based on Term-Term Co-occurrences

Figure 10: (a) unnormalized and (b) normalized PCA 2d projection of the term-term vectors for the article with title “Learning Spatially Variant Dissimilarity (SVaD) measures” and keywords \{learning, dissimilarity, measures, clustering\}.
Figure 11: (a) unnormalized and (b) normalized PCA 2d projection of the term-term vectors for the article with title “Obfuscated databases and group privacy” and keywords \{obfuscation, database, privacy\}.