Advanced Learning for Text and Graph Data

Lab session 1: Unsupervised Keyword Extraction

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1 Introduction

In this lab session, you will get hands-on experience with the **graph-of-words** representation of text and see how methods from social network analysis can applied to this representation to **extract keywords**. Keyword extraction is a fundamental NLP task used in many areas like information retrieval (search engines), summarization, natural language generation, visualization... Today, we will focus on **unsupervised single-document keyword extraction**.

2 Text preprocessing

Before constructing a graph-of-words, the document needs to be cleaned. The standard steps include (1) conversion to lower case, (2) punctuation removal, (3) tokenization, and (4) stopword removal. Additionally, for keyword extraction, research has shown that (5) part-of-speech-based filtering (retaining only nouns and adjectives) and (6) stemming ("winner", "winning", and "win" → "win") can be useful. These steps are implemented in the `clean_text_simple` function, found within the `library.py` file.

3 Graph-of-words

There are many ways to represent text as a graph. Today, we will use the classical statistical approach of [6], based on the distributional hypothesis ("We shall know a word by the company it keeps") [3]. This method applies a fixed-size sliding window of size W over the text from start to finish[1]. Each unique term in the document is represented by a node of the graph, and two nodes are linked by an edge if the terms they represent co-occur within the window. Edge weights encode co-occurrence counts. Unlike the vector space model that assumes term independence, graphs-of-words capture term dependency, and even term order, if directed edges are used (see Figure 1).

3.1 Your turn

Fill the gaps in the `clean_text_simple` and `terms_to_graph` functions (in `library.py`). Then, use the `gow_toy.py` script to build a graph for the text shown in Figure 1, with a window of size 4. Validate your results by comparing some edges (source, target, and weight) with that of Figure 1. Also, evaluate

[1]interactive demo: `https://safetyapp.shinyapps.io/GoWvis/` [10]

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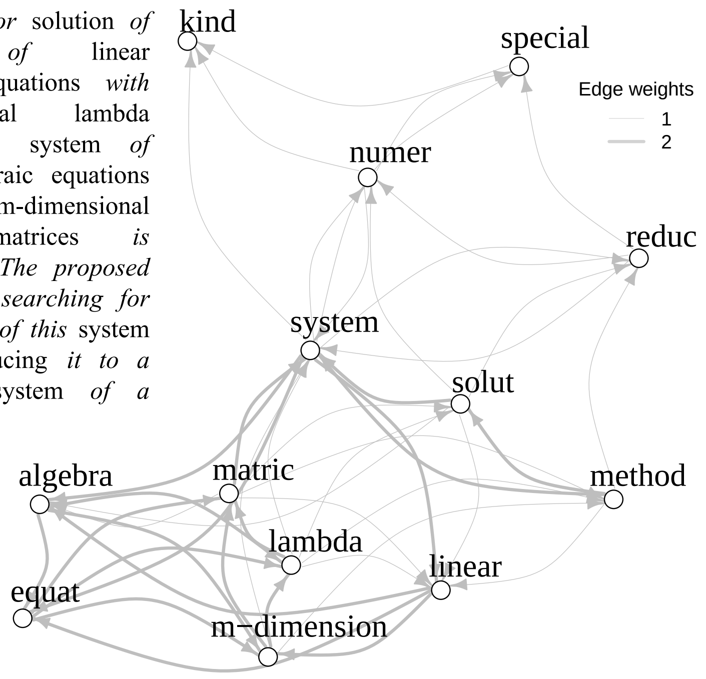

Figure 1: Graph-of-Words representation with POS-based screening, and directed, weighted edges. Non-(nouns and adjectives) in *italic*. Words have been stemmed. $W = 4$

the impact of window size on the density of the graph, defined as $|E|/|V|(|V|-1)$ and accessible via the `.density()` `igraph` method. What do you observe?

4 Keyword Extraction

4.1 Influential words

In social networks, it was shown that **influential spreaders**, that is, those individuals that can reach the largest part of the network in a given number of steps, are better identified via their **core numbers** rather than through their PageRank scores, betweenness centralities, or degrees [5]. For instance, a less connected person who is strategically placed in the core of a network will be able to disseminate more than a hub located at the periphery of the network, as shown in Figure 2.

Interestingly, taking into account the cohesiveness information captured by graph degeneracy was shown to vastly improve keyword extraction performance [7, 9], meaning that natural language features an important ”social” aspect. Keywords can thus be seen as “influential” words of graphs-of-words.

4.2 Graph degeneracy

The concept of graph degeneracy was introduced by [8] with the k-core decomposition technique and was first applied to the study of cohesion in social networks.

4.2.1 k-core

A core of order k (or **k-core**) of G is a maximal connected subgraph of G in which every vertex v has at least degree k. If the edges are unweighted, the degree of v is simply equal to the count of its incident edges (number of neighbors), while in the weighted case, the degree of v is the sum of the weights

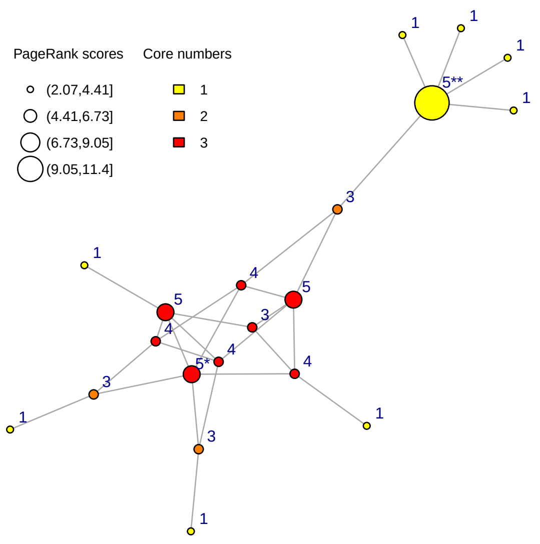

Figure 2: Degree vs PageRank score vs unweighted core number. Node labels indicate degrees. Nodes $*$ and $**$ both have same degree (5) and high PageRank numbers (resp. in $(6.73, 9.05]$ and $(9.05, 11.4]$). However, node $*$ lies in a much more central location and is therefore a much better spreader, which is captured by its higher core number (3 vs 1) but not by degree or PageRank (the PageRank score of node $**$ is even greater than that of node $*$).

of its incident edges. Edge direction can be taken into account in both cases, by considering only the incoming or the outgoing edges rather than all of them. Also, in both cases, node degrees (and thus, k) are integers since edge weights are integers.

4.2.2 k-core decomposition

As shown in Figure 3, the **k-core decomposition** of G is the set of all its cores from 0 (G itself) to k_{max} (its main core). It forms a hierarchy of nested subgraphs whose cohesiveness and size respectively increase and decrease with k. The **core number** of a node is the highest order of a k-core subgraph that contains this node. The main core of G is a coarse approximation of its densest subgraph.

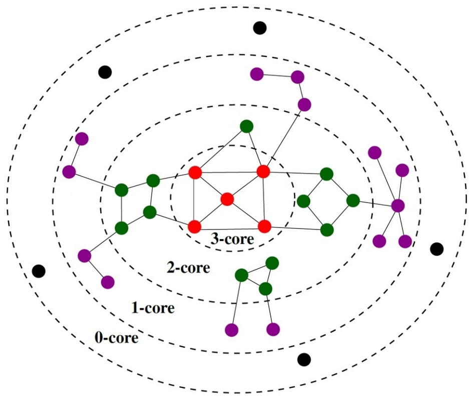

Figure 3: Illustration of the k-core decomposition.

Algorithms 1 and 2 respectively show the *unweighted* [8] and *generalized* [1] k-core decomposition algorithms. Both algorithms involve a pruning process that removes the lowest degree node at each step. By using $p(v) = \text{weighted\_degree}(v)$ as the vertex property function in Algorithm 2, we obtain the *weighted* k-core decomposition algorithm.

Algorithm 1 unweighted k-core decomposition

```
Input: graph $G = (V, E)$
Output: core numbers $c(v), \forall v \in V$
1: $i \leftarrow 0$
2: while $|V| > 0$ do
3:     while $\exists v : degree(v) \leq i$ do
4:         $c(v) \leftarrow i$
5:         $V \leftarrow V \setminus \{v\}$
6:         $E \leftarrow E \setminus \{(u, v) | u \in V\}$
7:     end while
8:     $i \leftarrow i + 1$
9: end while
```

Algorithm 2 generalized k-core decomposition

```
INPUT: graph $G = (V, E)$
OUTPUT: core numbers $c(v), \forall v \in V$
1.        $C := V$;
2.        for $v \in V$ do $p[v] := p(v, N(v, C))$;
3.        $build\_min\_heap(v, p)$;
4.        while $sizeof(heap) > 0$ do
4.1.          $C := C \setminus \{top\}$;
4.2.          $core[top] := p[top]$;
4.3.          for $v \in N(top, C)$ do
4.3.1.            $p[v] := \max\{p[top], p(v, N(v, C))\}$;
4.3.2.            $update\_heap(v, p)$;
              end;
          end;
```

Algorithm 1 can be implemented with complexity linear in the number of edges [2] while Algorithm 2 requires $\mathcal{O}(|E| \log |V|)$, which is also very affordable. This efficiency is achieved through the use of a min-oriented binary heap[2], which enables retrieving the vertex of lowest degree in logarithmic time $\mathcal{O}(\log |V|)$ at each step.

4.3 Your turn

Fill the gaps in the `unweighted_k_core` and `weighted_core_dec` functions in `library.py` to implement Algorithms 1 and 2. Use the `.strength()`[3] and `.delete_vertices() igraph` methods. Notes: `.delete_vertices()` automatically removes the edges incident on the node(s) deleted. To get weighted degrees, you need to use the `weights` argument of `.strength()`. Then, go back to the `gow_toy.py` script to decompose the graph shown in Figure 1. For `unweighted_k_core`, compare your results with that obtained via the `.coreness() igraph` method and Figure 4 below.

[2] `https://docs.python.org/2/library/heapq.html`,`https://en.wikipedia.org/wiki/Binary_heap`
[3] `http://igraph.org/python/doc/igraph.GraphBase-class.html#strength`

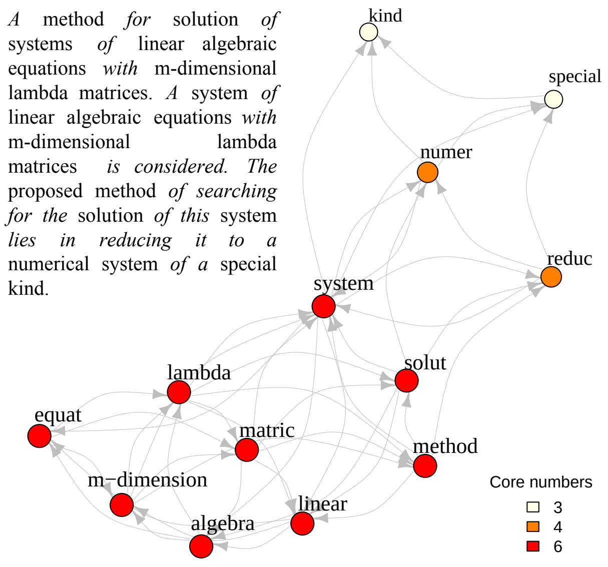

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Figure 4: The main core of the graph can be used as the keywords for the document.

5 Keyword extraction

5.1 Data set

We will use the test set of the Hulth 2003 dataset [4], that you can find inside the `data\Hulth2003testing\` folder. This dataset contains 500 scientific paper abstracts. For each abstract in the (`abstracts\` folder), human annotators have provided a set of keywords (`uncontr\` folder), that we will consider our gold standard. The keywords were freely chosen by the annotators and some of them may not appear in the original text. Thus, getting a perfect score is impossible on this dataset.

5.2 Baselines

We will evaluate the performance of the k-core-based approach against that of PageRank (applied on the same graph-of-words) and TF-IDF. For each baseline, the top $p = 33\%$ percent nodes will be retained as keywords.

5.3 Performance evaluation

We will evaluate the performance of the different techniques in terms of macro-averaged precision, recall and F1 score. Precision can be seen as the *purity* of retrieval while recall measures the *completeness* of retrieval. Finally, the F-1 score is the harmonic mean of precision and recall. More precisely, these metrics are defined as follows:

$$\text{precision} = \frac{tp}{tp + fp}$$

$$\text{recall} = \frac{tp}{tp + fn}$$

$$\text{F1-score} = 2\frac{\text{precision.recall}}{\text{precision} + \text{recall}}$$

Where tp, fp and fn respectively denote the number of true positives (the keywords returned by the system which are also part of the gold standard), false positives (the keywords returned by the system which are *not* part of the gold standard), and false negatives (the keywords from the gold standard that are *not* returned by the system).

Finally, macro-averaging consists in computing the metrics for each document and then taking the means at the collection level.

5.4 Your turn

Put everything together by filling the gaps in the `keyword_extraction.py` file and in the `accuracy_metrics` function (in `library.py`). For the baselines, you can use the `.pagerank()`[4] igraph method, and for tfidf, the `TfidfVectorizer`[5] function from the `scikit-learn` library. What can you say about the performance of the different approaches? What are the respective advantages/drawbacks of the (un)weighted k-core keyword extraction methods? How could they be improved?

References

[1] Batagelj, V., & Zavernik, M. (2002). Generalized cores. arXiv preprint cs/0202039.

[2] Batagelj, Vladimir, and Matjaz Zaversnik. "An O (m) algorithm for cores decomposition of networks." arXiv preprint cs/0310049 (2003).

[3] Harris, Z. S. (1954). Distributional structure. Word, 10(2-3), 146-162.

[4] Hulth, A. (2003, July). Improved automatic keyword extraction given more linguistic knowledge. In Proceedings of the 2003 conference on Empirical methods in natural language processing (pp. 216-223). Association for Computational Linguistics.

[5] Kitsak, M., et al. "Identification of influential spreaders in complex networks." Nature physics 6.11 (2010): 888-893.

[6] Mihalcea, R., & Tarau, P. (2004, July). TextRank: Bringing order into texts. Association for Computational Linguistics.

[7] Rousseau, F., Vazirgiannis, M. "Main core retention on graph-of-words for single-document keyword extraction." European Conference on Information Retrieval. Springer, Cham, 2015.

[8] Seidman, S. B. (1983). Network structure and minimum degree. Social networks, 5(3), 269-287.

[9] Tixier, A., Malliaros, F., and Vazirgiannis, M. "A graph degeneracy-based approach to keyword extraction." Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing. 2016.

[10] Tixier, Antoine, Konstantinos Skianis, and Michalis Vazirgiannis. "Gowvis: a web application for graph-of-words-based text visualization and summarization." Proceedings of ACL-2016 System Demonstrations (2016): 151-156.

[4]`http://igraph.org/python/doc/igraph.Graph-class.html#pagerank`

[5]`http://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.text.TfidfVectorizer.html`