Keyphrase Extraction: An Unsupervised Approach

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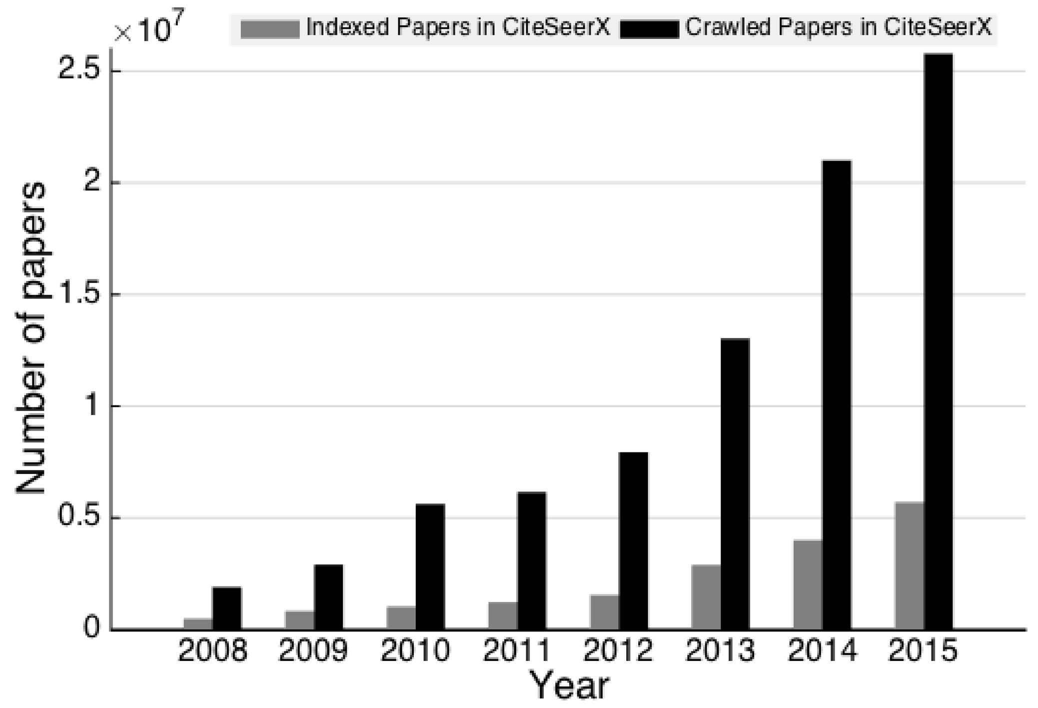
Why Keyphrase Extraction?

- Large and growing amounts of research articles indexed by digital libraries.



- Navigating in these digital libraries has become very challenging.
- Keyphrases of a document can allow for *efficient processing of more information in less time* and can improve many natural language processing and information retrieval tasks, e.g., summarization and contextual advertisement.
- Keyphrase extraction is defined as the problem of automatically extracting descriptive phrases or concepts from a document.

Previous Approaches to Keyphrase Extraction

- Many approaches to keyphrase extraction have been proposed in the literature along two lines of research: supervised and unsupervised.
- In the supervised line of research, different feature sets (e.g., *term frequency, relative position of the first occurrence, part-of-speech tag*) and classification algorithms (e.g., Naive Bayes) give rise to various supervised keyphrase extraction models [Hulth(2003), Caragea et al.(2014)Caragea, Bulgarov, Godea, & Gollapalli].
- Many features used to encode a candidate phrase in the supervised approaches have influenced the progress of unsupervised line of research.
  - Candidate words to be added in the graph are words with certain part of speech tags [Mihalcea & Tarau(2004), Gollapalli & Caragea(2014)] and *tf* or *tf-idf* are used to rank candidate phrases in a document [Barker & Cornacchia(2000)].
- We posit that other information can be leveraged that has the potential to improve the keyprase extraction task.

From Data to Knowledge

- Intuitively, keyphrases occur very early in a document and appear frequently.

> Factorizing Personalized **Markov Chains** for Next-**Basket Recommendation**
> by Steffen Rendle, Christoph Freudenthaler and Lars Schmidt-Thieme
>
> Recommender systems are an important component of many websites. Two of the most popular approaches are based on **matrix factorization** (MF) and **Markov chains** (MC). MF methods learn the general taste of a user by factorizing the matrix over observed user-item preferences. [...] In this paper, we present a method bringing both approaches together. Our method is based on personalized transition graphs over underlying **Markov chains**. [...] We show that our factorized personalized MC (FPMC) model subsumes both a common **Markov chain** and the normal **matrix factorization** model. For learning the model parameters, we introduce an adaption of the Bayesian Personalized Ranking (BPR) framework for sequential basket data. [...]

Author-input keyphrases: *Basket Recommendation, Markov Chain, Matrix Factorization*

Figure: The title, abstract and author-input keyphrases (marked in red in the text) for the 2010 best paper award winner in the World Wide Web conference.

- *Can position information improve the performance of unsupervised keyphrase extraction task? How can we design an efficient and effective unsupervised approach for keyphrase extraction by exploiting the position information of a phrase in a document?*

Proposed Approach

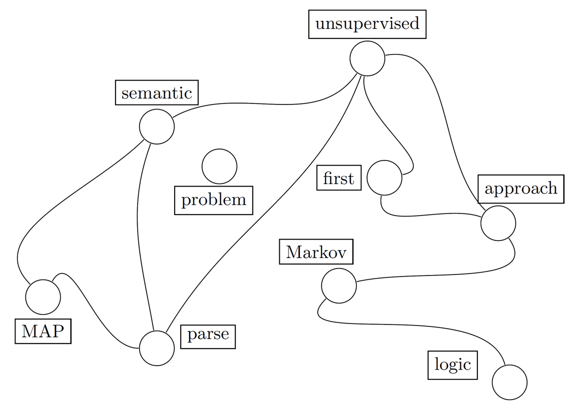
We propose a fully unsupervised graph-based algorithm that incorporates information from all positions of a word's occurrences into a biased-PageRank to score keywords that are later used to score keyphrases.

- Our approach involves there essential steps:
  1. The graph construction at the word level;
  2. The design of biased-PageRank algorithm;
  3. The scoring of multi-word phrases.

Graph Construction

> Unsupervised Semantic Parsing
>
> We present the **first unsupervised approach** to the **problem** of learning a **semantic parser**, using **Markov logic**. Our **USP system** transforms **dependency trees** into **quasi-logical forms**, recursively induces **lambda forms** from these, and **clusters** them to **abstract** away **syntactic variations** of the **same meaning**. The **MAP semantic parse** of a **sentence** is obtained by recursively assigning its **parts** to **lambda-form clusters** and composing them. We evaluate our **approach** by using it to extract a **knowledge base** from **biomedical abstracts** and **answer questions**. **USP** substantially outperforms **TextRunner**, **DIRT** and an **informed baseline** on both **precision** and **recall** on this **task**.

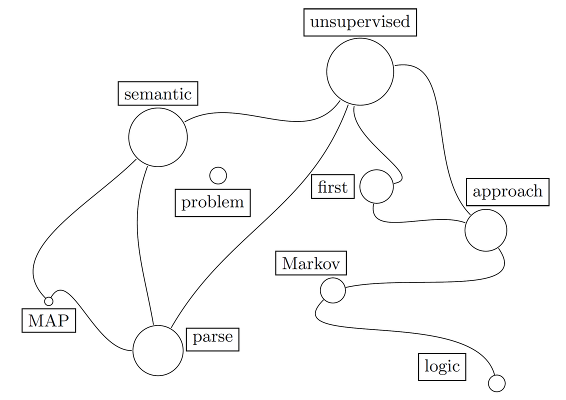
- window = 3



Position Biased PageRank

- The idea of our approach is to assign higher probabilities to those words that occur very early in the document.
- We weight each candidate word with its inverse position in the document. If the same word appears multiple times in target document, then we add all its position weights.
- Similar to Haveliwala [Haveliwala(2002)], we biased PageRank to prefer these words by incorporating the weight of a word in the equation of PageRank as follows:

$$s(v_i) = (1-\alpha)\cdot p(v_i) + \alpha \cdot \sum_{v_j \in Adj(v_i)} \frac{w_{ji}}{\sum_{v_k \in Adj(v_j)} w_{jk}} s(v_j)$$



- Multi-word phrases are scored by using the sum of scores of individual words that comprise the phrase [Wan & Xiao(2008)].

Datasets

Dataset	#Docs	Kp	AvgKp	unigrams	bigrams	trigrams	n-grams ($n \geqslant 4$)
KDD *	834	3093	3.70	810	1770	471	42
WWW *	1350	6405	4.74	2254	3139	931	81
Nguyen	211	882	4.18	260	457	132	33

Table: A summary of our datasets

* Datasets available at `http://www.cse.unt.edu/~ccaragea/keyphrases.html`.

Baselines

- *TF-IDF.* Keyphrases are ranked based on their term-frequency-inverse document frequency score [Barker & Cornacchia(2000)].
- *ExpandRank.* A word graph was built for each paper and its local textual neighbors [Wan & Xiao(2008)].
- *TopicalPageRank (TPR).* Latent Dirichlet Allocation is used to infer the topic distribution of words and documents and keyphrases are ranked by aggregating the topic-specific scores [Liu et al.(2010)Liu, Huang, Zheng, & Sun].

Results

How does our approach compare with other existing state-of-the-art methods?

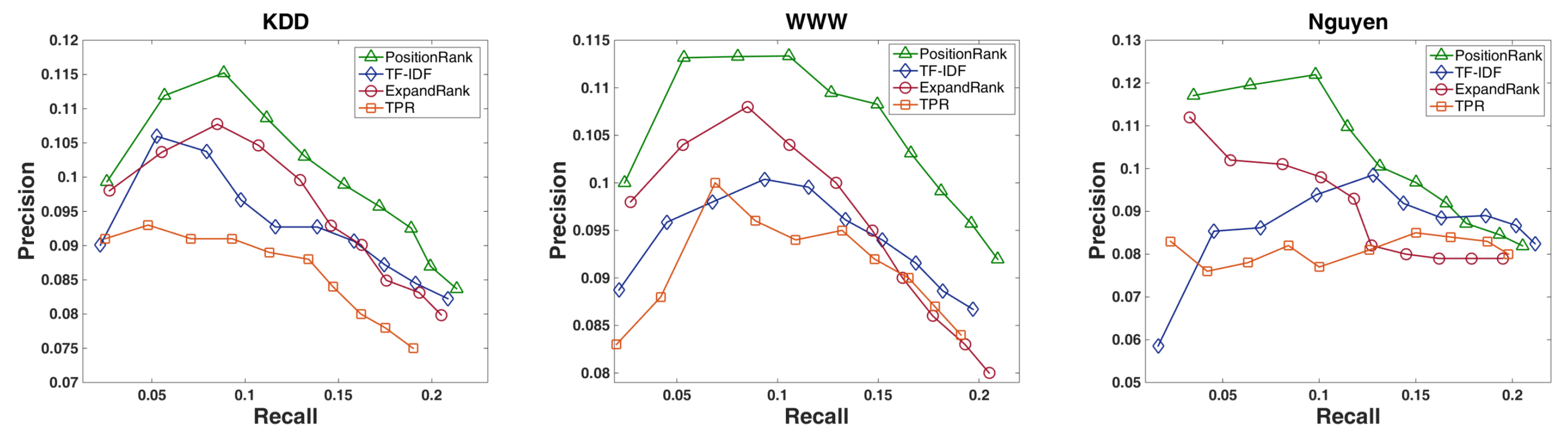


Figure: Precision-Recall curves for our proposed model and baselines on the three datasets.

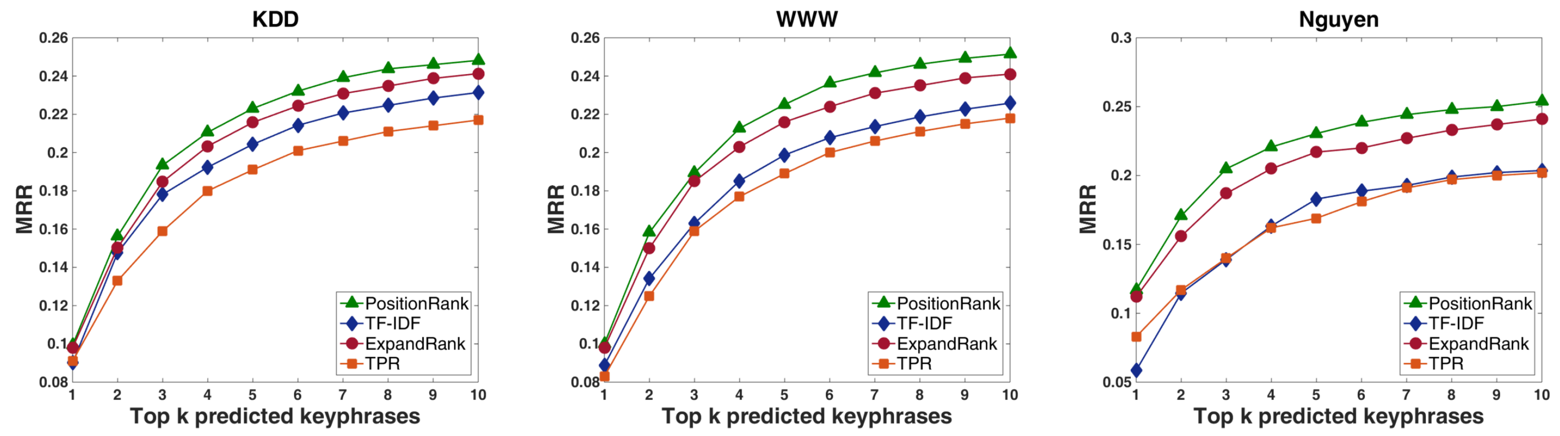


Figure: MRR curves for our proposed model and baselines on the three datasets.

Conclusion and Future Work

- Conclusions:
  - We proposed an unsupervised graph-based model which incorporates both the relative position and the frequency of a term into a biased PageRank.
  - Our experiments on three datasets show that our proposed model achieves better performance than strong baselines.
- Future directions:
  - Further evaluation of our approach on other types of documents, e.g. news articles, transcripts, etc.

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WWW: https://corinaflorescu.github.io/cs/