Automatic Keyphrase Extraction via Topic Decomposition

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- What is keyphrase extraction?
- Method
  - Supervised
    - Learning algorithms for keyphrase extraction (Turney, 2000)
  - Unsupervised
    - TFIDF
    - TextRank: Bringing order into texts (Rada Mihalcea and Paul Tarau. 2004)

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Motivation

What about topic ?

Relevance: Good keyphrases should be relevant to the major topics of the given document.

Coverage: An appropriate set of keyphrases should also have a good coverage of a document's major topics.

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Coverage An appropriate set of keyphrases should also have a good coverage of a document's major topics.

Building Topic Interpreters

Method Latent Dirichlet Allocation (LDA)

Datasets Wikipedia snapshot at March 2008

word	prob.
DRUGS	.069
DRUG	.060
MEDICINE	.027
EFFECTS	.026
BODY	.023
MEDICINES	.019
PAIN	.016
PERSON	.016
MARIJUANA	.014
LABEL	.012
ALCOHOL	.012
DANGEROUS	.011
ABUSE	.009
EFFECT	.009
KNOWN	.008
PILLS	.008

word	prob.
MIND	.081
THOUGHT	.066
REMEMBER	.064
MEMORY	.037
THINKING	.030
PROFESSOR	.028
FELT	.025
REMEMBERED	.022
THOUGHTS	.020
FORGOTTEN	.020
MOMENT	.020
THINK	.019
THING	.016
WONDER	.014
FORGET	.012
RECALL	.012

word	prob.
DOCTOR	.074
DR.	.063
PATIENT	.061
HOSPITAL	.049
CARE	.046
MEDICAL	.042
NURSE	.031
PATIENTS	.029
DOCTORS	.028
HEALTH	.025
MEDICINE	.017
NURSING	.017
DENTAL	.015
NURSES	.013
PHYSICIAN	.012
HOSPITALS	.011

Figure: An example of probabilistic topic model

Topic-Decomposed PageRank

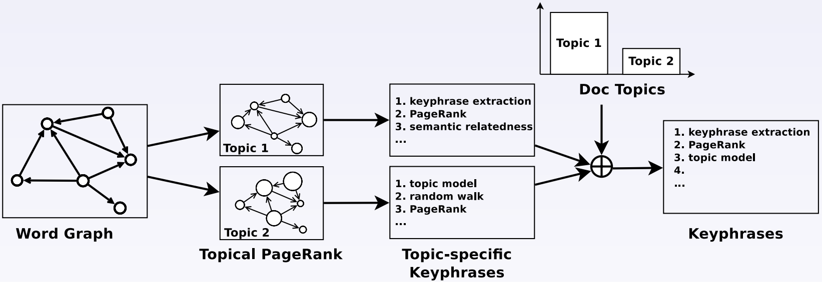
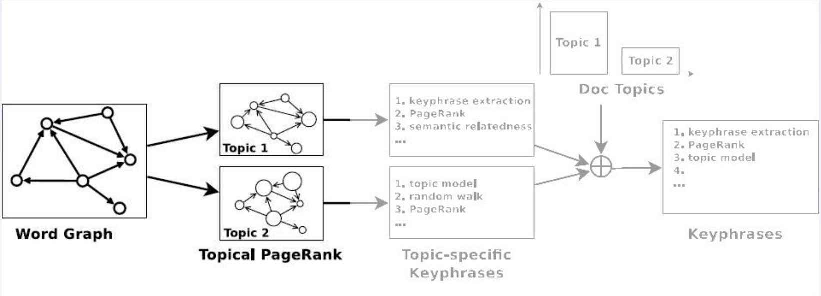


Figure: Topical PageRank for Keyphrase Extraction. (TPR)

Calculate Ranking Scores by TPR



$$R_z(w_i) = \lambda \sum_{j: w_j \to w_i} \frac{e(w_j, w_i)}{O(w_j)} R_z(w_j) + (1 - \lambda) p_z(w_i). \quad (1)$$

- $p_z(w) = pr(w|z)$, probability of word w given topic z.
- $p_z(w) = pr(z|w)$, probability of topic z given word w.
- $p_z(w) = pr(w|z) \times pr(z|w)$, product of hub and authority.

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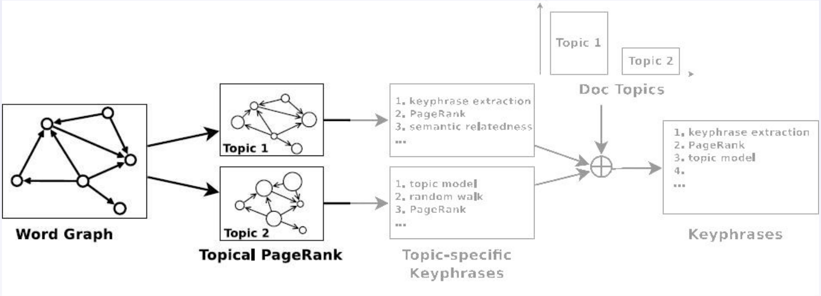

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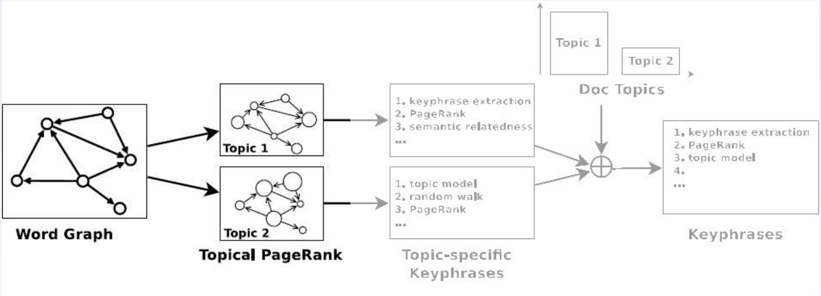

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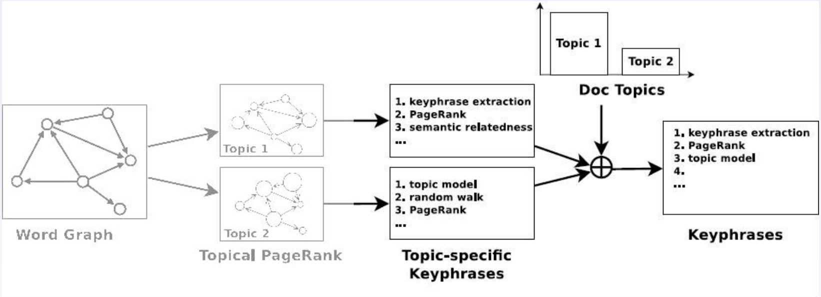
Extract Keyphrases Using Ranking Scores



Candidate Phrases noun phrases (Hulth, 2003)

`(adjective)*(noun)+`

Doc topic distribution $pr(z|d)$ for each topic z.

Phrase Score

$$R(p) = \sum_{z=1}^{K} R_z(p) \times pr(z|d). \quad (2)$$

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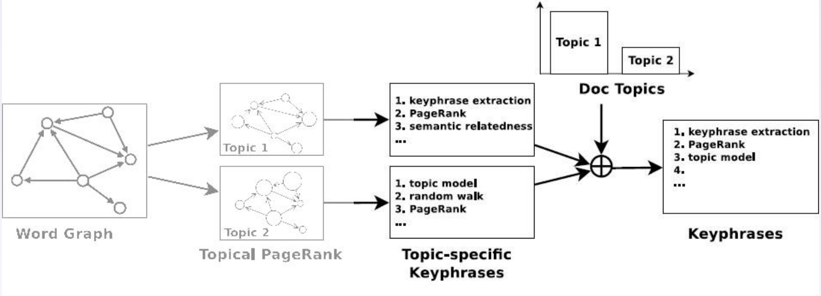

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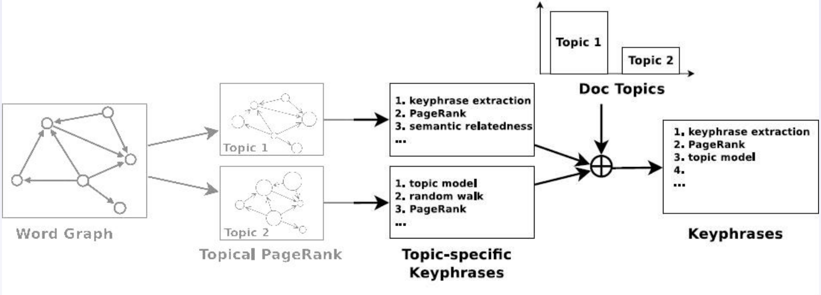

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Examples

Arafat Says U.S. Threatening to Kill PLO Officials

(a) Topic on “Terrorism”

(b) Topic on “Israel”

(c) Topic on “U.S.”

(d) TPR Result

Experiments

1. Datasets
   - NEWS: 308 news articles in DUC2001
   - RESEARCH: 2,000 abstracts of research articles (Hulth, 2003)
2. Evaluation Metrics
   - precision, recall, F-measure

$$p = \frac{c_{correct}}{c_{extract}}, \quad r = \frac{c_{correct}}{c_{standard}}, \quad f = \frac{2pr}{p+r}, \tag{3}$$

   - binary preference measure (Bpref)

$$\text{Bpref} = \frac{1}{R} \sum_{r \in R} 1 - \frac{|n \text{ ranked higher than } r|}{M}. \tag{4}$$

   - mean reciprocal rank (MRR)

$$\text{MRR} = \frac{1}{|D|} \sum_{d \in D} \frac{1}{rank_d}, \tag{5}$$

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Influences of Parameters - The Number of Topics K

K	Pre.	Rec.	F.	Bpref	MRR
50	0.268	0.330	0.296	0.204	0.632
100	0.276	0.340	0.304	0.208	0.632
500	0.284	0.350	0.313	0.215	0.648
1000	0.282	0.348	0.312	0.214	0.638
1500	0.282	0.348	0.311	0.214	0.631

Table: Influence of the number of topics K when the number of keyphrases $M=10$ on NEWS.

Influences of Parameters - Damping Factor λ

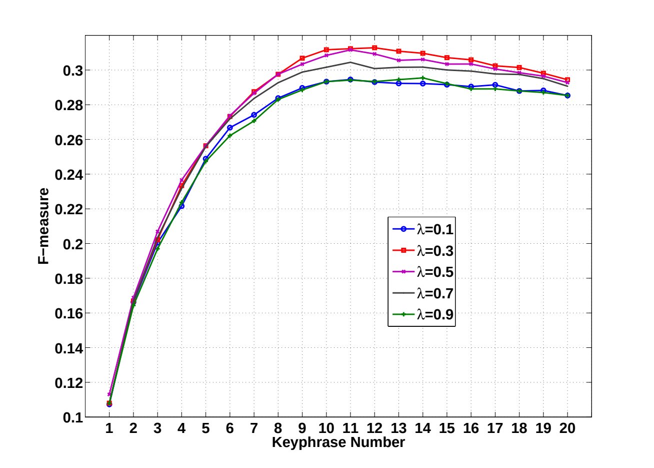

Figure: F-measure of TPR with $\lambda = 0.1, 0.3, 0.5, 0.7$ and 0.9 when M ranges from 1 to 20 on NEWS.

Different Preference Values

Pref	Pre.	Rec.	F.	Bpref	MRR
$pr(w\|z)$	0.256	0.316	0.283	0.192	0.584
$pr(z\|w)$	0.282	0.348	0.312	0.214	0.638
prod	0.259	0.320	0.286	0.193	0.587

Table: Influence of three preference value settings when the number of keyphrases $M = 10$ on NEWS.

Comparing with Baseline Methods

Method	Pre.	Rec.	F.	Bpref	MRR
TFIDF	0.239	0.295	0.264	0.179	0.576
PageRank	0.242	0.299	0.267	0.184	0.564
LDA	0.259	0.320	0.286	0.194	0.518
TPR	**0.282**	**0.348**	**0.312**	**0.214**	**0.638**

Table: Comparing results on `NEWS` when the number of keyphrases $M = 10$.

Method	Pre.	Rec.	F.	Bpref	MRR
TFIDF	0.333	0.173	0.227	0.255	0.565
PageRank	0.330	0.171	0.225	0.263	0.575
LDA	0.332	0.172	0.227	0.254	0.548
TPR	**0.354**	**0.183**	**0.242**	**0.274**	**0.583**

Table: Comparing results on `RESEARCH` when the number of keyphrases $M = 5$.

Comparing with Baseline Methods

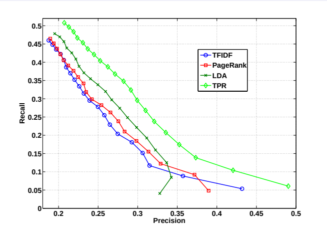

Figure: Precision-recall results on NEWS, M ranges from 1 to 20.

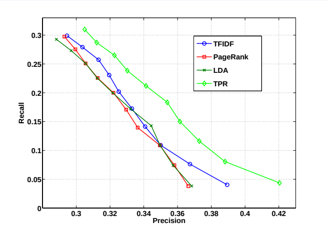

Figure: Precision-recall results on RESEARCH, M ranges from 1 to 10.

Conclusion

- TPR outperform all baselines on both datasets
- TPR enjoys advantages of both LDA and TFIDF/PageRank methods
- Bpref and MRR serve as supplemental metrics for evaluation

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Thank You !
QUESTIONS ?

My Homepage

http://nlp.csai.tsinghua.edu.cn/~hwy/