Supervised Keyphrase Extraction Leveraging Candidate Clustering

Adrien Bougouin Akiko Aizawa

NII, Tokyo (JAPAN)

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Introduction

Problem statement

Keyphrases

- Word or multi-word expressions
- **Overview** of the content of a document

Applications

- Document indexing
- Document clustering
- Text summarization
- Query expansion
- Targeted advertising
- etc.

But. . .

Many documents do not have associated keyphrases.

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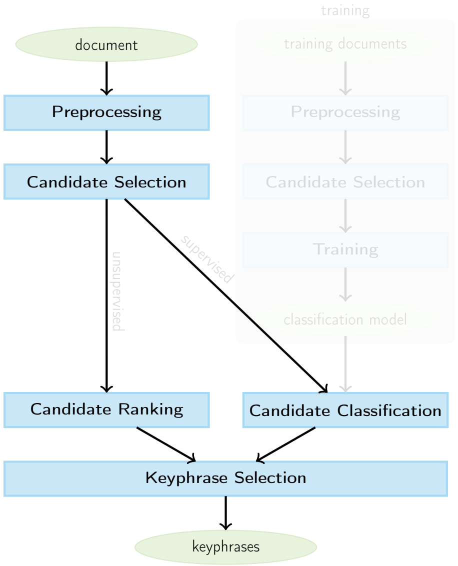

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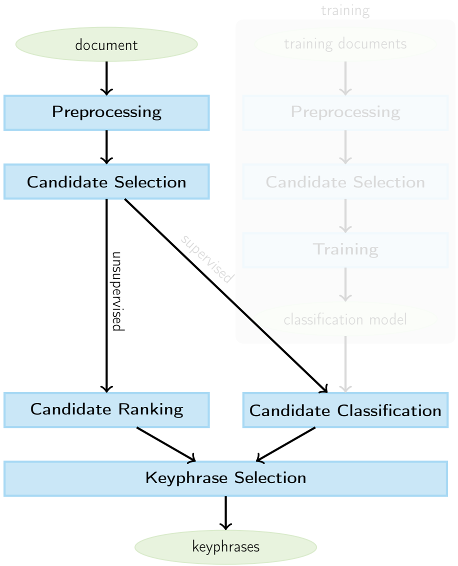

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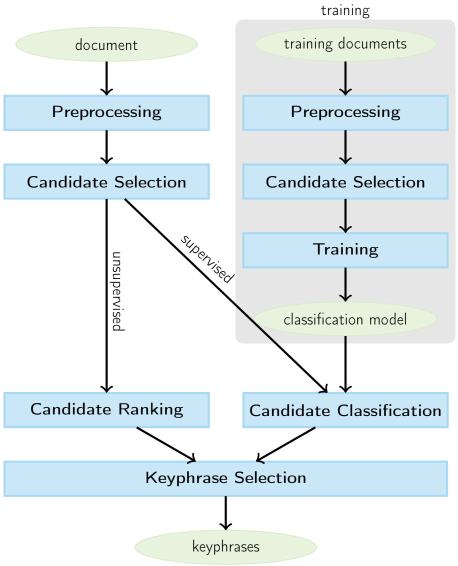

Introduction

Our work

Combining unsupervised and supervised methods:

1. Clustering candidate keyphrases into topics
2. Ranking topics **in an unsupervised way**
3. Selecting keyphrases from the best topics **in a supervised way**

Outline

1. State-of-the-art
2. Supervised TopicRank
3. Evaluation
4. Conclusion

Outline

State-of-the-art

Unsupervised methods

Mostly ranking techniques that use:

- language models
- clusters
- or **graphs** of word co-occurrences
  - weighted with co-occurrence number or semantic measures
  - refined with similar documents
  - biased with topic probabilities
  - modified to rank topics instead of words

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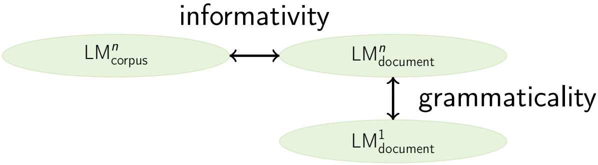

(Tomokiyo and Hurst, 2003)

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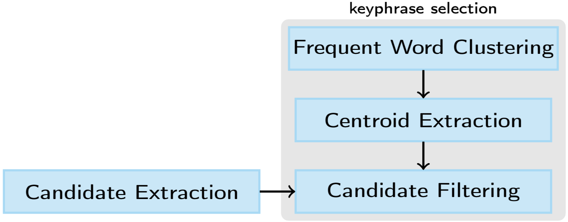

(Liu et al., 2009)

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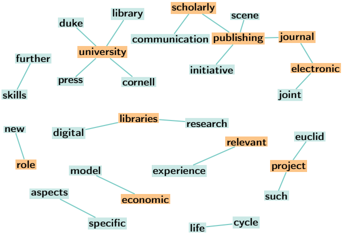

(Mihalcea and Tarau, 2004)

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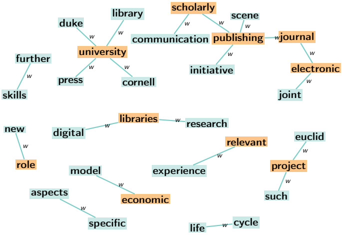

(Wan and Xiao, 2008; Tsatsaronis et al., 2010)

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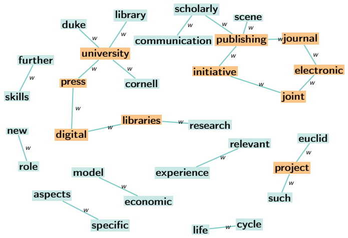

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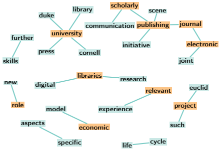
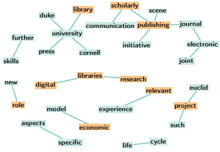
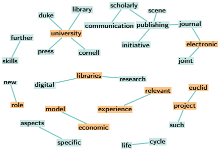


topic 1



topic 2

. . .



topic n

(Liu et al., 2010)

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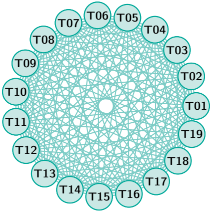

(Bougouin et al., 2013, TopicRank)

State-of-the-art

Supervised methods

Train various classifiers:

- Naive Bayes (Witten et al., 1999)
- MaxEnt (Sujian et al., 2003)
- Support Vector Machines (SVMs) (Zhang et al., 2006)
- Decision trees (Ercan and Cicekli, 2007)
- Multilayer perceptrons (Sarkar et al., 2010)

with many different features:

- Length
- First position
- Part-of-Speeches
- Frequency (TF)
- Inverse document frequency (IDF)
- $TF \times IDF$
- Generic sections

$\Rightarrow$ Currently the best performing methods

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Two categories / Two visions

Unsupervised vision

How important is a given phrase regarding the others?
$\Rightarrow$ extract the most important phrases

Supervised vision

How does a given phrase fit the keyphrase caracteristics in a global context?
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Then...

Why not combining both supervised and unsupervised approaches?

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TopicRank: brief overview

1. Select the `(<NOUN>|<ADJ>)+` as candidates
2. Cluster candidates that "belong to the same topic"
   - stem overlap similarity
3. Build a complete graph of topics
   - edges weighted by a sementic strength
4. Apply PageRank's "voting concept"
   - Important topics contribute more to the importance of the topics they are strongly connected to
5. Extract keyphrases from the most important topics
   - one keyphrase per topic → the first candidate in the document

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Supervised TopicRank

Motivations

TopicRank's results are encouraging:

- Significant improvement over state-of-the-art graph-based methods
- Possible improvement from 12.1% to 30.3% of f-score
  - find a better strategy to identify the keyphrase of a given topic

A new vision (???):

- Combination of local importance and global likelyhood
- Bigger granularity for the importance: topic
- Superised classification on smaller sets: topics

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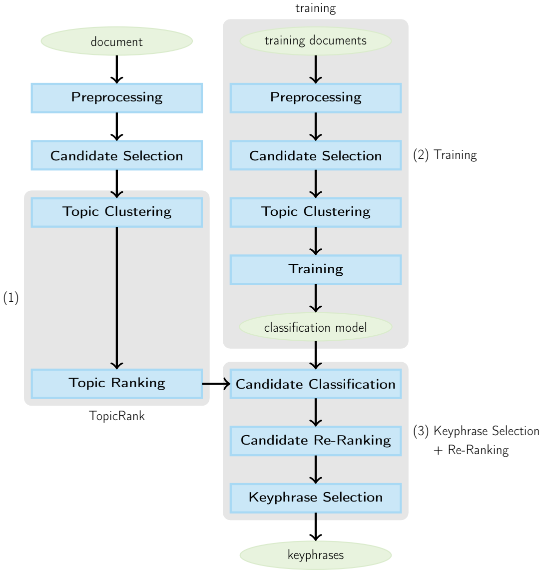

Supervised TopicRank

Training

Classifier

SVM:

- Learns a separating hyperplane between positive and negative examples
- Supports a large number of features
- Does not consider each feature to be independent

Samples

Only relevant clusters
⇒ clusters where a discrimination can actually be done

Features

Two categories of features:

- Topically independent features
- Topically dependent features

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Supervised TopicRank

Training (next)

Topically independent features

- Lenght
- Structural features:
  - First position
  - In the 1st third?
  - In the 2nd third?
  - In the 3rd third?
- Distributional features:
  - TF-IDF
  - GDC (phraseness)

    $$\text{GDC}(c, d) = \frac{|c| \times \textbf{count}(c, d) \times \textbf{log}_{\textbf{10}}\textbf{count}(c, d)}{\sum_{w \in c} \textbf{count}(w, d)}$$
  - Keyphrase frequency (keyphraseness)

Topically dependent features

- Average stem overlap similarity
- Average number of completely disimilar candidates

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Supervised TopicRank

Keyphrase selection

- Apply the SVM classifier
- For each topic:
  - Select the candidate with the best confidence

Supervised TopicRank

Keyphrase re-ranking

Formerly, TopicRank ranks keyphrases by their topic's importance, but the topic ranking is not perfect.

$\Rightarrow$ we combine the TopicRank score to the probability that the keyphrase is actually a keyphrase

$$S(c) = \alpha \times \text{topicrank}(c) + (1 - \alpha) \times p(c)$$

$\alpha = 0.75 \Rightarrow$ more importance is given to the unsupervised topic ranking

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$\alpha = 0.75 \Rightarrow$ more importance is given to the unsupervised topic ranking

Supervised TopicRank

Keyphrase re-ranking

Formerly, TopicRank ranks keyphrases by their topic's importance, but the topic ranking is not perfect.
$\Rightarrow$ we combine the TopicRank score to the probability that the keyphrase is actually a keyphrase

$$S(c) = \alpha \times \text{topicrank}(c) + (1 - \alpha) \times p(c)$$

$\alpha = 0.75 \Rightarrow$ more importance is given to the unsupervised topic ranking

Outline

Evaluation

Dataset

SemEval

- 244 scientific papers
  - 144 training documents
  - 100 test documents
- author- and reader-assigned keyphrases

Evaluation

Baselines

Derived baselines

Method	Features		
	Independent	Dependent	All
TopicRank+SVM	✓	✓	our method
Clustering+SVM	✓	✓	✓
SVM	✓	✗	✗

Classic baselines

- KEA
  - Naive Bayes
  - Two features: first position et TF-IDF
- TF-IDF
- TopicRank

Evaluation

Baselines

Derived baselines

Method	Features		
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TopicRank+SVM	✓	✓	our method
Clustering+SVM	✓	✓	✓
SVM	✓	✗	✗

Classic baselines

- KEA
  - Naive Bayes
  - Two features: first position et TF-IDF
- TF-IDF
- TopicRank

Evaluation

Measures

- Cut-off at 10 keyphrases
- Precision
- Recall
- F-score

$$\text{f-score} = (1 + \beta^2) \times \frac{\text{precision} \times \text{recall}}{(\beta^2 \times \textit{precision}) + \textit{recall}}$$

$$\beta = 1$$

- Problem of dealing with gold standard

$\Rightarrow$ Stemmed form comparisons

Evaluation

Results

Method	Features								
	Independent			Dependent			All		
	P	R	F	P	R	F	P	R	F
TopicRank+SVM	21.5	15.1	17.6	9.0	6.5	7.5	24.2	16.7	19.6
Clustering+SVM	13.3	9.3	10.8	0.2	0.1	0.2	11.9	8.4	9.7
SVM	15.0	10.5	12.2						

- Low performance of dependent features
- Best performance overall derived baselines

Evaluation

Results

Method	Features								
	Independent			Dependent			All		
	P	R	F	P	R	F	P	R	F
TopicRank+SVM	21.5	15.1	17.6	9.0	6.5	7.5	24.2	16.7	19.6
Clustering+SVM	13.3	9.3	10.8	0.2	0.1	0.2	11.9	8.4	9.7
SVM	15.0	10.5	12.2						

- Low performance of dependent features
- Best performance overall derived baselines

Evaluation

Results (next)

Method	P	R	F
KEA	18.8	13.3	15.4
TF-IDF	13.2	8.9	10.5
TopicRank	14.9	10.3	12.1
TopicRank+SVM	24.2	16.7	19.6
$\text{TopicRank}_{\text{max}}$	37.6	25.8	30.3

- Best performance over state-of-the-art methods
- The dream is not fulfilled...

Evaluation

Results (next)

Method	P	R	F
KEA	18.8	13.3	15.4
TF-IDF	13.2	8.9	10.5
TopicRank	14.9	10.3	12.1
TopicRank+SVM	24.2	16.7	19.6
$\text{TopicRank}_{\text{max}}$	37.6	25.8	30.3

- Best performance over state-of-the-art methods
- The dream is not fulfilled…

Outline

Conclusion

- Extension of TopicRank
- Supervised keyphrase selection with TopicRank's best topics
- Results show improvement over TopicRank
- There is still a huge gap between the current performance and the best possible ones

Perspectives

- Apply topic modeling to improve TopicRank's topic clustering (LDA, etc.)
- Experiment with topic labelling methods proposed for LDA

Thank you

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