The Initial Study of Term Vector Generation Methods for News Summarization

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Summaries

Type: Abstract and. Extract

Length: Indicative and Informative

Task: Single/Multi-document, Actualization, Comparative...

Why do we want summaries?

Summec - Count Methods

- Heuristic methods
  - remove Stop list
  - sentence position
  - sentence length
  - count of words
- TFxIDF

$$score(sent) = \sum_{t \in sent} tf(t) \times idf(t, D) \qquad (1)$$

  - Extract the best scoring sentences
  - What do they contains? Repetitive information?

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Summec - From Counts to Space

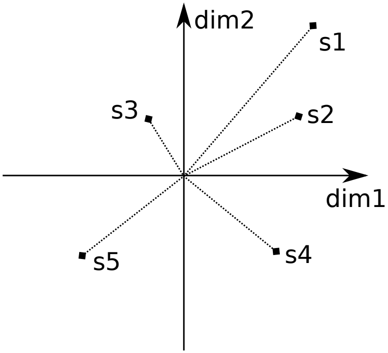
Every dimension represents one term.

Sentence is combination of terms.

$$\vec{s_i} = \sum_{t \in s_i} \vec{v_t}$$

The longest sentence is the most informative.

What is the second best sentence?



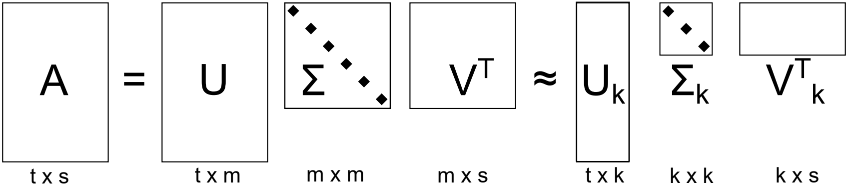
Vector model

The Curse of Dimensionality - spares high dimensional space

- Heuristic selection
  - Stop list
  - Lemmatization
  - Synonyms
- Data transformation
  - Matrix reduction - Latent Semantic Analysis
  - Random projection - Random Manhattan Indexing
- Neural network - Skip-gram model (word2vec)

Latent Semantic Analysis

Term-Document matrix **A** decomposed by SVD.
Dimensions with the lowest variance are throws away.



$\mathbf{U}_k$ - reduced matrix of term vectors
$\mathbf{V}_k^T$ - reduced matrix of sentence vectors

Summarization - Evaluation data

Experiment: Generate Informative Extract of Article

Test data:

- 50 Czech newspaper articles
- 15 annotators
- informative extract (25 % of original text)

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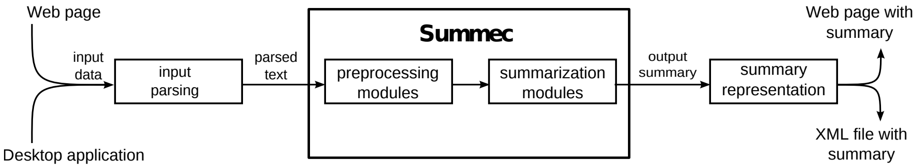
Summec - Scheme & Results



method	ROUGE-1		
	Recall [%]	Prec. [%]	F-score [%]
Heuristic	57.2	54.3	55.3
TFxIDF	62.6	53.3	57.3
LSA	55.4	55.2	55.1

New vector generation methods

Skip-gram model (word2vec)

Mikolov, T., Sutskever, I., Chen, K., Corrado, G., Dean, J.: Distributed representations of words and phrases and their compositionality. In: Advances in Neural Information Processing Systems. (2013)

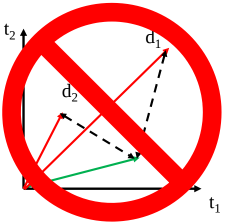
Random Manhattan Indexing

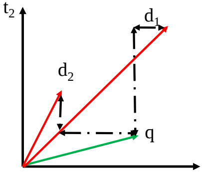
Zadeh, B.Q., Handschuh, S.: Random manhattan indexing. In: Proceedings - International Workshop on Database and Expert Systems Applications, DEXA. (2014) 203–208

Random Manhattan Indexing

Advantage of Random Projection - Euclidian distance

Not suitable for text vectors → Manhattan distance





Random Manhattan Indexing - algorithm

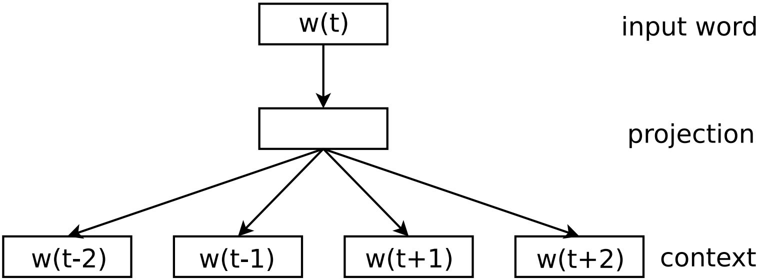
1. Extract index terms from text
2. Generate vector to each index term (2)

$$v_i = \begin{cases} \frac{-1}{U_1} & \text{with prob.} \quad \frac{s}{2} \\ 0 & \text{with prob.} \quad 1-s \\ \frac{1}{U_2} & \text{with prob.} \quad \frac{s}{2} \end{cases} \qquad s = \frac{1}{\sqrt{\beta|\{t\}|}} \tag{2}$$

3. Compute sentence vector (3)

$$\vec{s_j} = \sum_{t \in s_j} \vec{v_t} \tag{3}$$

Skip-gram model



Objective function: maximize value of (4)

$$\frac{1}{T}\sum_{t\in T}\sum_{-c\leq j\leq c, j\neq 0}\log(p(w_{t+j}|w_t)) \tag{4}$$

Results

Training data:
RMI - 706 033 (1 025 815) lemmas
SGM - 8.6 GB lemmatized ASR training data

Table: Comparison of ROUGE-1 score of summarization methods

method	Recall [%]	Precision [%]	F-score [%]
LSA	55.4	55.1	55.2
RMI	50.7	56.7	53.3
SGM	50.7	56.7	53.3
TFxIDF	62.6	53.3	57.3

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Conclusion

- Proposed schemes do not perform better than TFxIDF.
- TFxIDF is still the best performing method.

- RMI - poor results are understandable (random vectors)
- SGM - high expectations - maybe different approach

Current Work, Future Paper?

- Sentences are not sufficient - long and without context.
  Example:
  Title: Věci Veřejné krituzijí akreditační komisi za zveřejnění usnesení.
  Extract: Podle ní má komise povinnost svá rozhodnutí zveřejňovat a u tohoto sledovaného případu chtěla rychlým vyjádřením předejít spekulacím.
- Extracting clauses is more interesting way.
  Podle Dvořákové má komise povinnost zveřejňovat svá rozhodnutí.
  Dvořáková chtěla předejít spekulacím u tohoto sledovaného případu rychlým vyjádřením.
  (Tento případ = Mají se rušit plzeňská práva)

Summec and Aara

Summec + Aara = Sumara

- Evaluate Aara's accuracy.
- How to evaluate abstract? Read and mark vs. automatic

The End

Thank you for attention