Unsupervised learning for news summarization

how to automatically extract the most important information

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Agenda

Introduction

Why unsupervised learning?

- Lack of pre-trained models for Polish

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- Shortage of training data

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Why unsupervised learning?

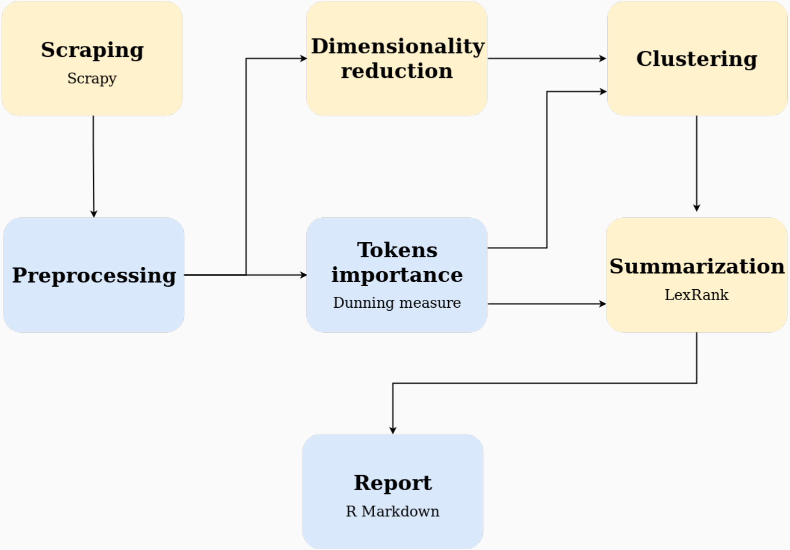
- Lack of pre-trained models for Polish
- Shortage of training data
- Low computing resources
- Multi-document problem - hundreds articles every day

Definition of key words

- **Token** - word
- **Lemmatization** - reducing word to its base grammar form
- **TF matrix** - matrix that describes the frequency of terms occuring in a collection of documents
- **IDF** - Inverse Document Frequency
- **Embedding** - numeric (vector) representation of a word
- **Cosine similarity** - a measure of similarity of two vectors

$$cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\| \, \|\mathbf{B}\|}$$

Model's overview



Words importance

Dunning’s measure

General information

- Measures whether token’s **frequency** in a particular day is statistically different from that in a reference period
- Likelihood ratio test
- No normality assumption - **binomial** distribution
- Proper measure for **rare** events

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Equation

$$\lambda = \frac{L(p, k_0, n_0)\, L(p, k_1, n_1)}{L(p_0, k_0, n_0)\, L(p_1, k_1, n_1)} \tag{1}$$

$$L(p, k, n) = p^k (1 - p)^{n-k} \tag{2}$$

where, $p = \frac{k_0 + k_1}{n_0 + n_1}$, $p_i = \frac{k_i}{n_i}$ and **-2** $\boldsymbol{log \lambda}$ has χ^2 distribution with one degree of freedom. k_0 is the number of word's occurrences **without** a particular day, k_1 is the word's count **in** a particular day.

Model's implementation

Modification of Dunning measure

- Multiplication by -1, when $p_1 < p_0$
- Counteracting logarithm of zero: $p = max(eps, p)$

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Selecting words for clustering

- $-2log\lambda \geq 10$
- Token count (k_i) larger than the value of 90^{th} percentile of all counts

Embeddings

Latent Semantic Analysis (LSA)

- Singular Value Decomposition (**SVD**) of TF matrix composed of both **paragraphs** and **articles**
- Dimensionality reduction
- Capturing **semantic** relation between words

Clustering

Clustering

Agglomerative hierarchical clustering

- Start with N topics
- Find two the most similar topics - cosine between embeddings
- Merge the two topics - set new embedding as a **sum** of the two
- Stop when there is 1 topic
- Return clustering optimal according to the **silhouette** algorithm

Silhouette algorithm

It aims to find clusters such that objects inside groups are **similar** to each other and **dissimilar** to objects from other clusters.

Equation

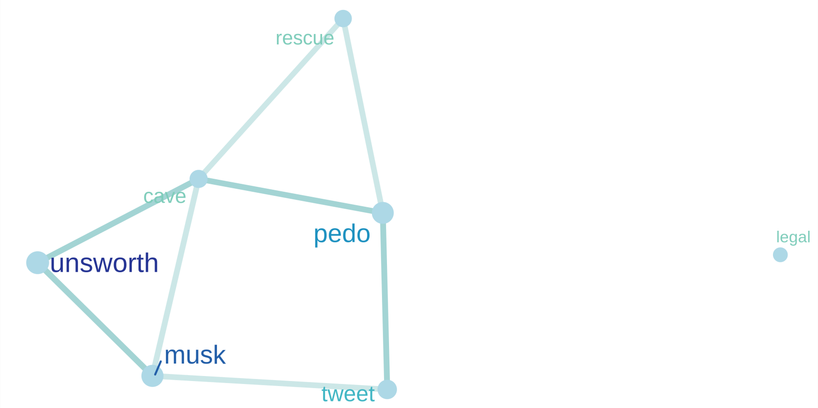
$$a(i) = cos(e_i,\, e_{C_k} - e_i)$$

$$b(i) = \min_{l \neq k} cos(e_i,\, e_{C_l})$$

$$s(i) = \begin{cases} \frac{b(i)-a(i)}{max\{b(i),a(i)\}}, & \text{if } |C_k| > 1 \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

where $a(i)$ and $b(i)$ are inner and outer similarity, e_i is an embedding of i^{th} token, e_{C_k} is the topic's embedding where $i \in C_k$.

Example



Summarization

LexRank

An extractive summarization algorithm, based on Google's **PageRank**, aiming to select sentences that are highly linked (by common words) to other higly linked sentences.

- PageRank
  - Used to rank web pages
  - Ranking equal to the **steady state** of Markov chain
  - Markov matrix obtained as a weighted mean of normalized matrix of links between pages and **random** matrix ($\frac{1}{N}$ in every cell)
- LexRank
  - Cosine similarity between sentences
  - Uses **TF-IDF** matrix

Implementation in the model

Modifications

- Articles filtering - minimal topic words frequency

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- Weights of words for cosine similarity
  - **TF**
  - Modified **Dunning** measure
    - $log(D_i + 1)$ when $p_1 \geq p_0$
    - 0 when $p_1 < p_0$
  - Cosine similarity between word and topic embeddings

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- Ranking scaling - $F_i = \frac{log(w_i^T)}{log(w_i)}$
  - where F_i is a scaling factor, w_i^T is a number of topic words and w_i number of all words in i^{th} sentence
  - Upscale when sentence has more topic words
  - Downscale long sentences

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- Non-duplicated sentences ($cos(\theta) > 0.5$)

Example

Summary

- Mr Unsworth's legal team have described Mr Musk's now-deleted **tweet** as ”vile and false” and are seeking unspecified punitive damages.
- Two days later, Mr Musk wrote a series of tweets including one describing Mr Unsworth as a **”pedo guy”**.
- On Thursday, Mr Unsworth told the **court** that Mr Musk's tweet had left him feeling ”humiliated”.

jkubajek/News_Selector

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