

Federal Research Center «Computer Science and Control»
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Cross-lingual similar document retrieval methods

Zubarev D.V.
Sochenkov I.V.

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Cross-language plagiarism detection task

- Source retrieval
 - given: a suspicious document and a large collection of sources
 - the task is to retrieve all plagiarized sources while minimizing retrieval costs
- Text alignment
 - given: a pair of documents
 - the task is to identify all contiguous maximal-length passages of reused text between them

Cross-language plagiarism detection methods

- Machine translation approach: use a monolingual methods by translating query document (Barón-Cedeno, 2012; Bakhteev, 2019)
- Cross-lingual similarity detection based on the word embeddings (Ferrero et al., 2017; Kutuzov et al., 2016)
- **Competitions**
 - Translated plagiarism cases were used in PAN 2011 competition as one of an obfuscation type (without Russian)

Training cross-lingual word embeddings

- Russian-English parallel sentences
 - United Nations – first 2 million sentences (opus.nlpl.eu)
 - Wiki – 600K sentences (opus.nlpl.eu)
 - Yandex parallel corpus – 1M sentences
 - Tatoeba – 500k; collection of sentences for foreign language learners (opus.nlpl.eu)
 - QED – 600k; collection of subtitles for educational videos and lectures (opus.nlpl.eu)
 - JW300 – ~1M; texts from jw.org, mainly Watchtower and Awake! (opus.nlpl.eu)

Text Preprocessing

- Tokenization, lemmatization and syntax analysis (aot, udpipeline)
- Stop-words removal (conjunction, pronoun, etc.), and common words (be, the, a)
- syntactic phrases up to 4 words are treated as single “word”:
martial_law, военное_положение,
Организация_объединенных_наций
- Result: pairs of parallel sentences, represented as sequences of lemmas

Training corpus generation

- Generate multiple sentences from a sentence with a phrase:
 - Russian_presidential_election ...
 - Russian_election presidential_election ...
 - Russian presidential election ...
- 10 million sentences
- Dictionary size: 680k unique words/phrases (more than 10 occurrences in the corpus)

Training embeddings

- Learning cross-lingual word embedding mapping
 - Using Vecmap framework (Artetxe et al. 2018)
 - Supervised with dictionary ~20k word pairs (from Muse project)
- Training word2vec model on bilingual corpus (Vulić et al. 2015)
 - Select pairs of sentences that differ in length by less than 5 words
 - Interleave two parallel sentences, e.g.
"Мама мыла раму" + "Mother washed the frame" =
"мама mother мыла washed раму the frame".

Retrieval-based approach: Indexing texts

- Tokenization and lemmatization, syntax analysis (aot, udpipe)
- Extract noun phrases up to 4 words
- Build inverted index of words, phrases:
word_id -> doc_id, weight (LogTF)

Retrieval-based approach: Search

- Represent the query document as a weighted vector
- Use LTF-IDF as the weighting scheme
- Select top words/phrases and map them to N other language keywords with cross-lingual embeddings
- Fetch documents from inverted index based on matched words/phrases
- Measure similarity (cosine or hamming) between query vector and other texts' vectors

Approximate nearest neighbor search

- Represent each document as a vector by averaging vectors of the top K keywords of the document
- Index all vectors with ANN index (Faiss, IVF_SQ16)
- ANN-search at query time for a given document

Cross-Lingual Explicit Semantic Analysis

- Represent a document as a weighted vector of concepts (Wikipedia articles):
 - We used 800k English articles that are aligned with Russian Wikipedia articles
 - Components of a vector are cosine similarity of a given document with each article
- At query time:
 - Document -> weighted vector of articles` identifiers
 - Map identifiers to articles in other language
 - Retrieve the most similar vectors in collection of other language

Dataset

- Russian-English aligned Wikipedia articles (Wikipedia dump of June 2019)
- We sampled article pairs from 10 different groups
- Grouping by:
 - Amount of Russian sentences:
(9, 50], (50, 100], (100, 200], (200, 400], (400, 1000]
 - Comparable/Non-comparable by size
- Sampled 100 document pairs from each group
- 1000 document pairs

Evaluation results

- RBA – retrieval-based approach
- ANN – Approximate nearest neighbor search

Method	Embeddings	DIM	Phrases	Recall	MAP	Rec@1	Rec@10	Rec@20
RBA	Bilingual	300	No	0.831	0.48	0.415	0.622	0.66
RBA	Bilingual	300	4-word phrases	<u>0.845</u>	<u>0.49</u>	<u>0.415</u>	0.635	<u>0.67</u>
RBA	Bilingual	600	4-word phrases	0.856	0.5	0.428	<u>0.629</u>	0.671
RBA	Mapping	300	4-word phrases	0.767	0.336	0.263	0.478	0.533
ANN	Bilingual	300	2-word phrases	0.728	0.398	0.337	0.508	0.548
ANN	Bilingual	600	2-word phrases	0.724	0.433	0.374	0.527	0.577
ANN	Mapping	300	2-word phrases	0.665	0.254	0.197	0.36	0.426
CL-ESA	-	-	4-word phrases	0.833	0.318	0.254	0.453	0.501

Evaluation results per each group for RBA

No	Size in ru sents	Comparable by size?	MAP (Top=100)	Rec (Top=100)	MAP (Top=50)	Rec (Top=50)
1	(9, 50]	False	0.346	0.82	0.346	0.82
2	(9, 50]	True	0.338	0.65	0.338	0.65
3	(50, 100]	False	0.419	0.79	0.419	0.8
4	(50, 100]	True	0.44	0.88	0.445	0.88
5	(100, 200]	False	0.461	0.81	0.453	0.82
6	(100, 200]	True	0.542	0.88	0.535	0.9
7	(200, 400]	False	0.451	0.79	0.473	0.8
8	(200, 400]	True	0.730	0.98	0.742	0.97
9	(400, 1000]	False	0.306	0.85	0.341	0.81
10	(400, 1000]	True	0.87	1	0.871	1

Conclusions and future work

- Retrieval-based approach achieved best recall and MAP on Wiki dataset
- MAP/Recall are generally better for articles from the “Comparable by size” group
- Try combination of various embeddings
Bilingual + Mapping
- Try other retrieval functions

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Dataset - <http://nlp.isa.ru/ru-en-src-retr-dataset/>

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