

Label generation

Two experts who are well familiar with the above short texts are invited to label the

generated topics.

Specifically, two tasks ("Topic Labeling" and "Word Labeling") are conducted by the two

judges.

For the first task "Topic Labeling", the experts are asked to label "coherent" if more than

half of the topN terms in a topic are semantically related; otherwise "not coherent".

[Additionally, at this stage the concept represented by the topic is identified]

Then for the second task "Word Labeling", the topics that are labeled as "coherent" by

both judges are used for word labeling.

Particularly, each topical word is labeled as "correct" if it is coherently related to the

concept represented by the topic (identified in the "Topic Labeling"); otherwise

"incorrect".

After labeling, we can compute the number of the coherent topics for different methods

and the average Precision for the first topN topical words.

Finally, the overall performances are averaged by the evaluation measures from two

experts.

Motivation

"Here we also evaluate the quality of learned topics based on human judgements" (topic

coherence)

Topic modeling

LDA, NMF, NMF-based method (with external knowledge)

Topic modeling parameters

Nr. of topics: {20, 40, 60, 80 and 100}

a: 1

β: 0.1

**NMF** 

## Nr. of topics

20

### Label

Concept associated with the topic.

Coherent / not coherent depending on whether more than half of the topN terms in a topic are semantically related.

Correct / Incorrect depending on whether each topical word is coherently related to the concept represented by the topic.

### Label selection

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## Label quality evaluation

No quality evaluation on the label itself, but:

"After labeling, we can compute the number of the coherent topics for different methods and the average Precision for the first topN topical words. Finally, the overall performances are averaged by the evaluation measures from two experts."

Table 2: Average coherent topics evaluated by experts given topic number K=20 for different short text datasets between NMF and LDA methods.

Datasets \ Methods	NMF	LDA
Snippet	18	17
XinlangNews	20	19
News	19	18
StackOverFlow	19	19
TMNtitles	19	18

Additionally, the Cohen's Kappa is used to measure agreement between experts

#### Assessors

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### **Domain**

Domain (paper): Short text topic modeling

Domain (corpus): Miscellaneous (Google), News, Online Q&A

#### Problem statement

Learning topics from short texts has become a critical and fundamental task for understanding the widely-spread streaming social messages.

In this context, the basic LDA and NMF are compared with different experimental settings on several public short text datasets;

In the second part, we propose a novel model called "Knowledge-guided Non-negative Matrix Factorization for Better Short Text Topic Mining" (abbreviated as KGNMF), which leverages external knowledge as a semantic regulator with low-rank formalizations, yielding up a time-efficient algorithm.

### Corpus

Origin: Google

Nr. of documents: 12.284

Details: Snippet dataset drawn from Google

Origin: Sina website

Nr. of documents: 8966

#### Details:

XinlangNews dataset with news crawled from 8/23/2016 to 9/7/2016

• Composed by news titles from 6 domains, "entertainment", "Finance", "Sci Tech", "Society", "Sports" and "Military".

Origin: Various newspaper websites

Nr. of documents: 32.592 (or 29.487 when considering only the title fields)

### Details:

 Title and description fields of english news extracted from RSS feeds of popular newspaper websites (nyt.com, usatoday.com, reuters.com)

 Categories are: "Sport", "Business", "U.S.", "Health", "Sci Tech", "World" and "Entertainment".

Origin: StackOverFlow

Nr. of documents: 19.783

Details: Short text dataset collected from an online question-and- answer site

(StackOverflow.com) for programmers.

Table 1: Statistics of datasets. (#Docs: the total number of documents; #Words: the average number of words per document; #Vocabulary: the total number of distinctive terms in the dataset; #Label: the number of ground-truth labels or categories.)

Datasets	#Docs	#Words	#Vocabulary	#Label
Snippet	12,284	14.34	4,045	8
News	32,592	11.82	7,771	7
StackOverFlow	19,783	7.25	2,437	20
XinlangNews	8,966	4.38	2,631	6
TMNtitles	29,487	3.46	4,015	7

#### **Document**

- 1. Each snippet is on each line and each one consists of a list of words/terms plus a class label at the end in the data files. Overall, there are 8 categories marked "Business", "Computers", "Culture-Arts-Entertainment", "Education- Science", "Engineering", "Health", "Politics-Society", and "Sports".
- 2. News title
- 3. News title and description
- 4. StackOverflow thread

# Pre-processing

- Tokenisation
- Filtering the short texts that has less than two terms
- Discard the terms, of which the IDF (Inverse Document Frequency) is less than 5

 $\verb|@article{chen_2019_experimental_explorations_on_short_text_topic_mining_between_lda_and_nmf_based_schemes||}$ 

abstract = {Learning topics from short texts has become a critical and fundamental task for understanding the widely-spread streaming social messages, e.g., tweets, snippets and questions/answers. Up to date, there are two distinctive topic learning schemes: generative probabilistic graphical models and geometrically linear algebra approaches, with LDA and NMF being the representative works, respectively. Since these two methods both could uncover

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the latent topics hidden in the unstructured short texts, some interesting
doubts are coming to our minds that which one is better and why? Are there any
other more effective extensions? In order to explore valuable insights between
LDA and NMF based learning schemes, we comprehensively conduct a series of
experiments into two parts. Specifically, the basic LDA and NMF are compared
with different experimental settings on several public short text datasets in
the first part which would exhibit that NMF tends to perform better than LDA;
in the second part, we propose a novel model called ``Knowledge-guided Non-
negative Matrix Factorization for Better Short Text Topic Mining' (abbreviated
as KGNMF), which leverages external knowledge as a semantic regulator with low-
rank formalizations, yielding up a time-efficient algorithm. Extensive
experiments are conducted on three representative corpora with currently
typical short text topic models to demonstrate the effectiveness of our
proposed KGNMF. Overall, learning with NMF-based schemes is another effective
manner in short text topic mining in addition to the popular LDA-based
paradigms.},
  author = {Yong Chen and Hui Zhang and Rui Liu and Zhiwen Ye and Jianying
Lin},
  date-added = \{2023-03-11 \ 11:37:41 +0100\},
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  doi = {https://doi.org/10.1016/j.knosys.2018.08.011},
  issn = \{0950 - 7051\},
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  keywords = {Short text mining, Topic modeling, Latent dirichlet allocation
(LDA), Non-negative matrix factorization (NMF), Knowledge-based learning},
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  title = {Experimental explorations on short text topic mining between LDA and
NMF based Schemes},
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  year = \{2019\}\}
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