Applications of topic modeling and non-negative matrix factorization

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Contents

What is a “topic” in a text collection

Intuitively,

- *Topic* is a specific terminology of a particular domain area
- *Topic* is a set of terms that often co-occur in documents

More formally,

- *topic* is a probability distribution over terms (words, tokens):
  $p(w|t)$ is the frequency of term w in topic t
- *document profile* is a probability distribution over *topics*:
  $p(t|d)$ is the frequency of topic t in document d

When writing term w in document d author thought of topic t.

Topic model uncovers the set T of latent topics in a text collection.

Example. Multilingual topic model of Wikipedia

Dataset: 216 175 pairs of parallel Russian–English articles.
Top 10 words and their probabilities $p(w|t)$ in %:

topic #68				**topic #79**			
research	4.56	институт	6.03	goals	4.48	матч	6.02
technology	3.14	университет	3.35	league	3.99	игрок	5.56
engineering	2.63	программа	3.17	club	3.76	сборная	4.51
institute	2.37	учебный	2.75	season	3.49	фк	3.25
science	1.97	технический	2.70	scored	2.72	против	3.20
program	1.60	технология	2.30	cup	2.57	клуб	3.14
education	1.44	научный	1.76	goal	2.48	футболист	2.67
campus	1.43	исследование	1.67	apps	1.74	гол	2.65
management	1.38	наука	1.64	debut	1.69	забивать	2.53
programs	1.36	образование	1.47	match	1.67	команда	2.14

Assessors evaluated 396 topics from 400 as paired and interpretable.

K.Vorontsov, O.Frei, M.Apishev, P.Romov, M.Suvorova. BigARTM: open source library for regularized multimodal topic modeling of large collections. 2015.

Example. Multilingual topic model of Wikipedia

Dataset: 216 175 pairs of parallel Russian–English articles.
Top 10 words and their probabilities $p(w|t)$ in %:

topic #88				**topic #251**			
opera	7.36	опера	7.82	windows	8.00	windows	6.05
conductor	1.69	оперный	3.13	microsoft	4.03	microsoft	3.76
orchestra	1.14	дирижер	2.82	server	2.93	версия	1.86
wagner	0.97	певец	1.65	software	1.38	приложение	1.86
soprano	0.78	певица	1.51	user	1.03	сервер	1.63
performance	0.78	театр	1.14	security	0.92	server	1.54
mozart	0.74	партия	1.05	mitchell	0.82	программный	1.08
sang	0.70	сопрано	0.97	oracle	0.82	пользователь	1.04
singing	0.69	вагнер	0.90	enterprise	0.78	обеспечение	1.02
operas	0.68	оркестр	0.82	users	0.78	система	0.96

Assessors evaluated 396 topics from 400 as paired and interpretable.

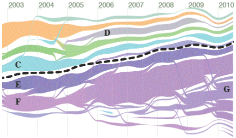
K.Vorontsov, O.Frei, M.Apishev, P.Romov, M.Suvorova. BigARTM: open source library for regularized multimodal topic modeling of large collections. 2015.

Topic modeling applications

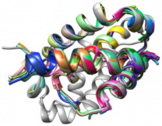
exploratory search in digital libraries

search and recommendation in topical communities

topic detection and tracking in news flows

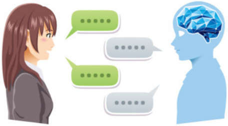


finding patterns in biological sequences



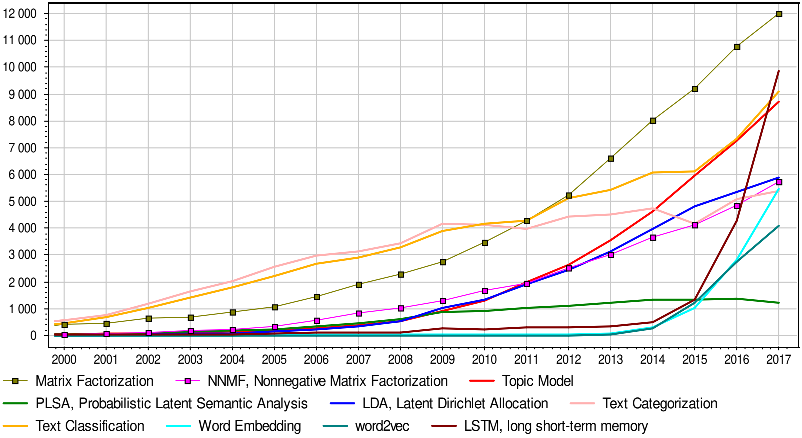
mining the banking customer behavior

dialog management in chatbot intelligence



Topic modeling and related research topics

Number of papers per year, according to Google Scholar:



Topic modeling: the problem setup

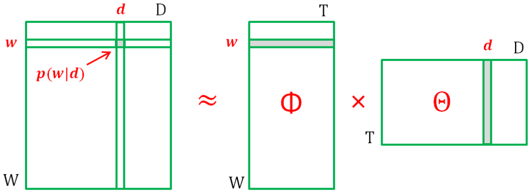
Given: a set of terms (words) W, a set of documents D,
n_{dw} = how many times term w appears in document d

Find: parameters $\phi_{wt} = p(w|t)$, $\theta_{td} = p(t|d)$ of the topic model

$$p(w|d) = \sum_{t \in T} \phi_{wt}\theta_{td} = \sum_{t \in T} p(w|t)p(t|d).$$

subject to $\phi_{wt} \geqslant 0$, $\sum_w \phi_{wt} = 1$, $\theta_{td} \geqslant 0$, $\sum_t \theta_{td} = 1$.

This is a problem of *nonnegative matrix factorization*:



PLSA — Probabilistic Latent Semantic Analysis [T.Hofmann, 1999]

Constrained maximization of the log-likelihood:

$$\sum_{d,w} n_{dw} \ln \sum_t \phi_{wt}\theta_{td} \;\to\; \max_{\Phi,\Theta}$$

EM-algorithm is a simple iteration method for the nonlinear system

$$\begin{array}{rl} \text{E-step:} & \left\{ \begin{array}{l} p_{tdw} \equiv p(t|d,w) = \operatorname*{norm}_{t\in T}\big(\phi_{wt}\theta_{td}\big) \\[2ex] \phi_{wt} = \operatorname*{norm}_{w\in W}\Big(\sum_{d\in D} n_{dw}\,p_{tdw}\Big) \\[2ex] \theta_{td} = \operatorname*{norm}_{t\in T}\Big(\sum_{w\in d} n_{dw}\,p_{tdw}\Big) \end{array} \right. \\ \text{M-step:} & \end{array}$$

where $\operatorname*{norm}_{t\in T}(x_t) = \dfrac{\max\{x_t,0\}}{\sum_{s\in T}\max\{x_s,0\}}$ is vector normalization.

Well-posed and ill-posed problems in the sense of Hadamard (1923)

The problem is *well-posed* if

- a solution exists,
- the solution is unique,
- the solution is stable w.r.t. initial conditions.

Jacques Hadamard
(1865–1963)

Matrix factorization is an *ill-posed* inverse problem.
If (Φ, Θ) is a solution, then (Φ', Θ') is also the solution:

- $\Phi'\Theta' = (\Phi S)(S^{-1}\Theta)$, where $\operatorname{rank} S = |T|$
- $\mathscr{L}(\Phi', \Theta') = \mathscr{L}(\Phi, \Theta)$
- $\mathscr{L}(\Phi', \Theta') \leqslant \mathscr{L}(\Phi, \Theta) + \varepsilon$ for approximate solutions

Additional *regularizing criteria* should narrow the set of solutions.

ARTM — Additive Regularization for Topic Modeling

Maximize log-likelihood with regularization criterion $R(\Phi, \Theta)$:

$$\sum_{d,w} n_{dw} \ln \sum_t \phi_{wt}\theta_{td} + R(\Phi, \Theta) \;\to\; \max_{\Phi,\Theta}$$

EM-algorithm is a simple iteration method for the system

$$\begin{array}{rl} \text{E-step:} & \left\{ \begin{array}{l} p_{tdw} = \operatorname*{norm}_{t\in T}\big(\phi_{wt}\theta_{td}\big) \\ \phi_{wt} = \operatorname*{norm}_{w\in W}\Big(\sum_{d\in D} n_{dw}p_{tdw} + \phi_{wt}\frac{\partial R}{\partial \phi_{wt}}\Big) \\ \theta_{td} = \operatorname*{norm}_{t\in T}\Big(\sum_{w\in d} n_{dw}p_{tdw} + \theta_{td}\frac{\partial R}{\partial \theta_{td}}\Big) \end{array} \right. \\ \text{M-step:} & \end{array}$$

K.Vorontsov. Additive regularization for topic models of text collections. 2014.

ARTM: combining topic models via additive regularization

Maximize log-likelihood with additive combination of regularizers:

$$\sum_{d,w} n_{dw} \ln \sum_t \phi_{wt}\theta_{td} + \sum_{i=1}^{n} \tau_i R_i(\Phi, \Theta) \to \max_{\Phi,\Theta},$$

where τ_i are regularization coefficients.

EM-algorithm is a simple iteration method for the system

$$\begin{cases} \text{E-step:} & p_{tdw} = \operatorname{norm}_{t\in T}\big(\phi_{wt}\theta_{td}\big) \\ \text{M-step:} & \phi_{wt} = \operatorname{norm}_{w\in W}\Big(\sum_{d\in D} n_{dw}p_{tdw} + \sum_{i=1}^{n}\tau_i\phi_{wt}\frac{\partial R_i}{\partial \phi_{wt}}\Big) \\ & \theta_{td} = \operatorname{norm}_{t\in T}\Big(\sum_{w\in d} n_{dw}p_{tdw} + \sum_{i=1}^{n}\tau_i\theta_{td}\frac{\partial R_i}{\partial \theta_{td}}\Big) \end{cases}$$

K.Vorontsov, A.Potapenko. Additive regularization of topic models. Machine Learning, 2015.

LDA — Latent Dirichlet Allocation [D.Blei, A.Ng, M.Jordan, 2003]

Maximize a posteriori probability (MAP) with Dirichlet prior.
The prior can be reinterpreted as cross-entropy minimization:

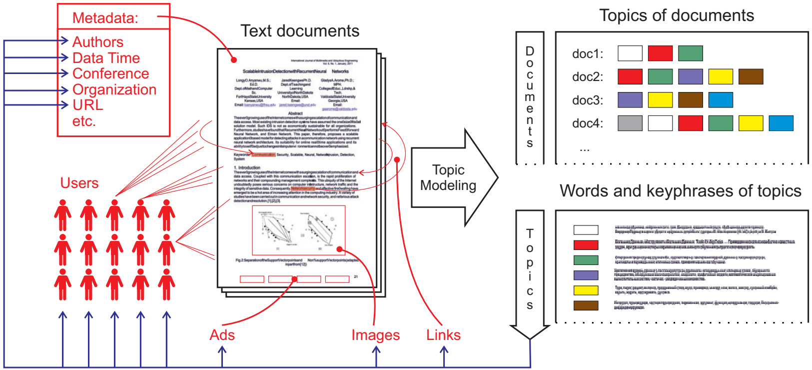
$$\underbrace{\sum_{d,w} n_{dw} \ln \sum_t \phi_{wt}\theta_{td}}_{\text{log-likelihood } \mathscr{L}(\Phi,\Theta)} + \underbrace{\sum_{t,w} \beta_w \ln \phi_{wt} + \sum_{d,t} \alpha_t \ln \theta_{td}}_{\text{cross-entropy regularizer}} \to \max_{\Phi,\Theta}$$

EM-algorithm is a simple iteration method for the system

$$\begin{cases} \text{E-step:} & p_{tdw} = \operatorname*{norm}_{t\in T}\big(\phi_{wt}\theta_{td}\big) \\ \text{M-step:} & \phi_{wt} = \operatorname*{norm}_{w\in W}\Big(\sum_{d\in D} n_{dw}p_{tdw} + \beta_w\Big) \\ & \theta_{td} = \operatorname*{norm}_{t\in T}\Big(\sum_{w\in d} n_{dw}p_{tdw} + \alpha_t\Big) \end{cases}$$

Multimodal Probabilistic Topic Modeling

Multimodal Topic Model finds topic distributions of terms $p(w|t)$ and *tokens* of other *modalities*: $p(\text{author}|t)$, $p(\text{time}|t)$, $p(\text{tag}|t)$, $p(\text{category}|t)$, $p(\text{link}|t)$, $p(\text{object-on-image}|t)$, $p(\text{user}|t)$, etc.



Multimodal extension of ARTM

W^m is a vocabulary of *tokens* of m-th *modality*, $m \in M$.

Maximize the sum of modality log-likelihoods with regularization:

$$\sum_{m\in M} \lambda_m \sum_{d\in D} \sum_{w\in W^m} n_{dw} \ln \sum_t \phi_{wt}\theta_{td} + R(\Phi,\Theta) \to \max_{\Phi,\Theta}$$

EM-algorithm is a simple iteration method for the system

$$\begin{array}{rl} \text{E-step:} & \left\{ \begin{array}{l} p_{tdw} = \underset{t\in T}{\operatorname{norm}}\big(\phi_{wt}\theta_{td}\big) \\ \phi_{wt} = \underset{w\in W^m}{\operatorname{norm}}\Big(\sum\limits_{d\in D} \lambda_{m(w)} n_{dw} p_{tdw} + \phi_{wt}\frac{\partial R}{\partial \phi_{wt}}\Big) \\ \theta_{td} = \underset{t\in T}{\operatorname{norm}}\Big(\sum\limits_{w\in d} \lambda_{m(w)} n_{dw} p_{tdw} + \theta_{td}\frac{\partial R}{\partial \theta_{td}}\Big) \end{array} \right. \\ \text{M-step:} & \end{array}$$

K.Vorontsov, O.Frei, M.Apishev, P.Romov, M.Suvorova, A.Ianina. Non-Bayesian additive regularization for multimodal topic modeling of large collections. 2015.

BigARTM: open source for fast and modular topic modeling

BigARTM features:

- Parallelism + modalities + regularizers + hypergraph
- Out-of-core one-pass processing of large text collections
- Built-in library of regularizers and quality measures

BigARTM community:

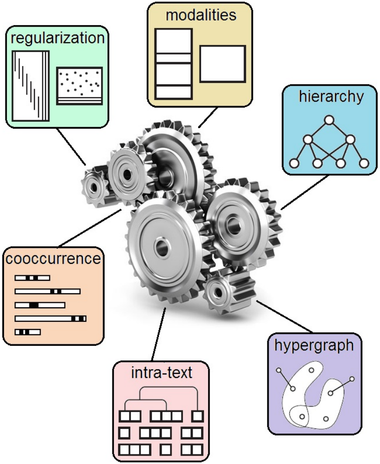
- Open-source https://github.com/bigartm
  (discussion group, issue tracker, pull requests)
- Documentation http://bigartm.org

BigARTM license and programming environment:

- Freely available for commercial usage (BSD 3-Clause license)
- Cross-platform — Windows, Linux, Mac OS X (32 bit, 64 bit)
- Programming APIs: command-line, C++, and Python

Six key mechanisms of BigARTM

1. additive regularization
2. multimodal data
3. topical hierarchy
4. word co-occurrence
5. intratext regularization
6. hypergraph data



Why does BigARTM simplify topic modeling for applications

Stages	**Bayesian Inference for PTMs**	**ARTM**	
Requirements analysis:	Requirements analysis	Requirements analysis	
Model formalization:	Generative model design	predefined criteria	user-defined criteria
Model inference:	Bayesian inference for the generative model (VI, GS, EP)	One regularized EM-algorithm for any combination of criteria	
Model implementation:	Researchers coding (Matlab, Python, R)	Production code (C++)	
Model evaluation:	Researchers coding (Matlab, Python, R)	predefined measures	user-defined measures
Deployment:	Deployment	Deployment	

conventions: ::: not unified stages ::: | ::: unified stages :::

Bayesian modeling requires maths and coding at each stage.

ARTM introduces the modular "LEGO-style" modeling technology, packing each requirement into a *regularization plugin*.

Benchmarking BigARTM vs. Gensim and Vowpal Wabbit

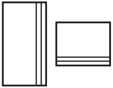
- 3.7M articles from Wikipedia, 100K unique words

	procs	$T = 50$		$T = 200$	
		time, m	perplexity	time, m	perplexity
BigARTM	1	42	5117	83	3347
BigARTM async	1	25	5131	53	3362
VowpalWabbit	1	50	5413	154	3960
Gensim	1	142	4945	637	3241
BigARTM	4	12	5216	26	3520
BigARTM async	4	7	5353	16	3634
Gensim	4	88	5311	315	3583
BigARTM	8	8	5648	15	3929
BigARTM async	8	5	6220	10	4309
Gensim	8	88	6344	288	4263

D.Kochedykov, M.Apishev, L.Golitsyn, K.Vorontsov. Fast and Modular Regularized Topic Modelling. FRUCT ISMW, 2017.

Regularizers for the interpretability of topics

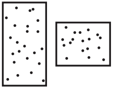
background



LDA: Smoothing background topics $B \subset T$:

$$R(\Phi, \Theta) = \beta_0 \sum_{t \in B} \sum_{w} \beta_w \ln \phi_{wt} + \alpha_0 \sum_{d} \sum_{t \in B} \alpha_t \ln \theta_{td}$$

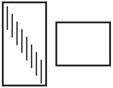
sparse



“Anti-LDA”: Sparsing subject domain topics $S = T \backslash B$:

$$R(\Phi, \Theta) = -\beta_0 \sum_{t \in S} \sum_{w} \beta_w \ln \phi_{wt} - \alpha_0 \sum_{d} \sum_{t \in S} \alpha_t \ln \theta_{td}$$

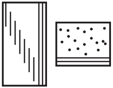
decorrelated



Making topics as different as possible:

$$R(\Phi) = -\frac{\tau}{2} \sum_{t,s} \sum_{w} \phi_{wt} \phi_{ws}$$

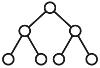
interpretable



Making topics more interpretable
by combining the above regularizers

Many Bayesian PTMs can be reinterpreted as regularizers in ARTM

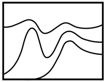
hierarchy



Hierarchical links between topics t and subtopics s:

$$R(\Phi, \Psi) = \tau \sum_{t \in T} \sum_{w \in W} n_{wt} \ln \sum_{s \in S} \phi_{ws} \psi_{st}.$$

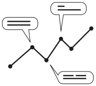
temporal



Topics dynamics over the modality of time intervals i:

$$R(\Phi) = -\tau \sum_{i \in I} \sum_{t \in T} \left| \phi_{it} - \phi_{i-1,t} \right|.$$

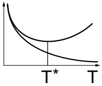
regression



Linear predictive model $\hat{y}_d = \langle v, \theta_d \rangle$ for documents:

$$R(\Theta, v) = -\tau \sum_{d \in D} \Big(y_d - \sum_{t \in T} v_t \theta_{td} \Big)^2.$$

n of topics

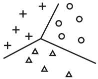


Sparsing $p(t)$ for topic selection:

$$R(\Theta) = -\tau \sum_{t \in T} \frac{1}{|T|} \ln p(t), \quad p(t) = \sum_{d} p(d) \theta_{td}.$$

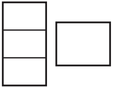
Special cases of the multimodal topic modeling

supervised



The modalities of classes or categories
for text classification and categorization.

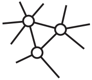
multilanguage



The modalities of languages with translation dictionary $\pi_{uwt} = p(u|w,t)$ for the $k \to \ell$ language pair:

$$R(\Phi,\Pi) = \tau \sum_{u \in W^k} \sum_{t \in T} n_{ut} \ln \sum_{w \in W^\ell} \pi_{uwt}\phi_{wt}$$

graph



The modality of graph vertices v with doc sets D_v:

$$R(\Phi) = -\frac{\tau}{2} \sum_{(u,v)\in E} S_{uv} \sum_{t \in T} n_t^2 \left(\frac{\phi_{vt}}{|D_v|} - \frac{\phi_{ut}}{|D_u|} \right)^2.$$

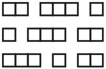
geospatial

The modality of geolocations g with proximity $S_{gg'}$:

$$R(\Phi) = -\frac{\tau}{2} \sum_{g,g' \in G} S_{gg'} \sum_{t \in T} n_t^2 \left(\frac{\phi_{gt}}{n_g} - \frac{\phi_{g't}}{n_{g'}} \right)^2$$

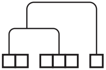
Beyond the “bag-of-words” restrictive assumption

n-gram



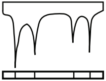
The modalities of n-grams, collocations, named entities

syntax



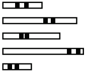
The modality of n-grams extracted by a syntax parser

segmentation



Detecting thematically homogeneous segments in sequential text

coherence



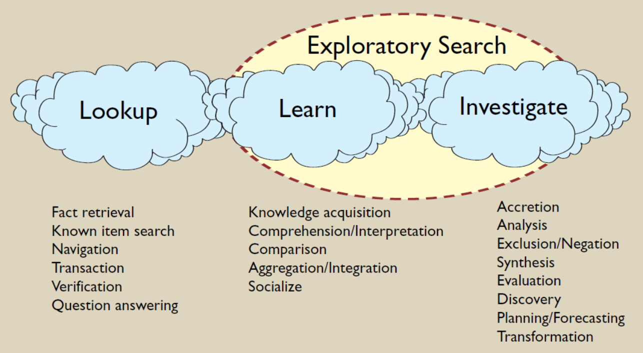
Modeling co-occurrence data n_{uv} of word pairs (u, v):

$$R(\Phi) = \tau \sum_{u,v} n_{uv} \ln \sum_{t} n_t \phi_{ut} \phi_{vt}$$

D.Kochedykov, M.Apishev, L.Golitsyn, K.Vorontsov. Fast and Modular Regularized Topic Modelling. FRUCT ISMW, 2017.

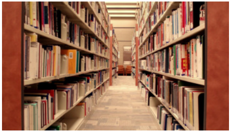
Exploratory Search for learning, knowledge acquisition and discovery

- what if the user doesn't know which keywords to use?
- what if the user isn't looking for a single answer?



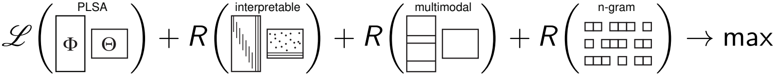
Gary Marchionini. Exploratory Search: from finding to understanding. Communications of the ACM. 2006, 49(4), p. 41–46.

Exploratory search in tech news



Goal: exploratory search by long text queries in digital libraries and tech news.

The bag-of-regularizers:



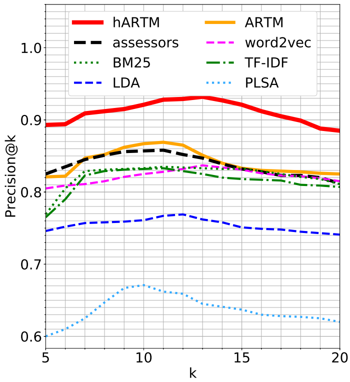
Results:

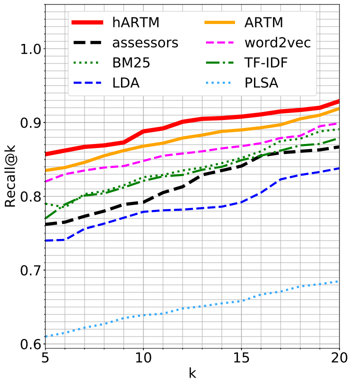
- Precision and Recall $\geqslant 90\%$ on tech news collections, bypassing both assessors and baselines (tf-idf, word2vec).
- The topic-based search engine instantly performs the work that people typically complete in about 30 minutes.

A.Ianina, L.Golitsyn, K.Vorontsov. Multi-objective topic modeling for exploratory search in tech news. AINL, 2017.

Precision and Recall: comparison against baselines

TechCrunch.com text collection, 760K documents
Precision and Recall at top *k* search result positions

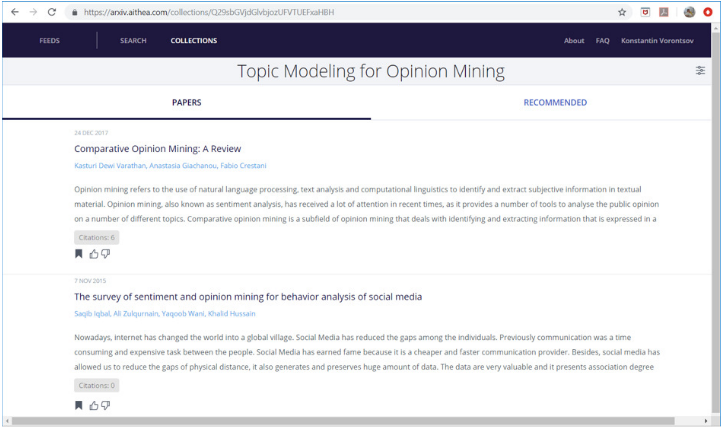




A.Ianina, L.Golytsin, K.Vorontsov. Multi-objective topic modeling for exploratory search in tech news. AINL, 2017.

Exploratory search in scientific literature: arXiv.AITHEA.com

The user makes thematic collections of documents

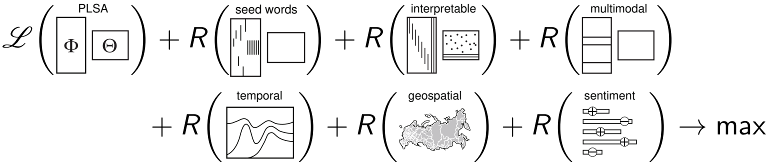


Designed by Digital Decisions (AITHEA)

Mining ethnical discourse in social media

Goal: find ethnical topics for monitoring inter-ethnic relations.

The bag-of-regularizers:



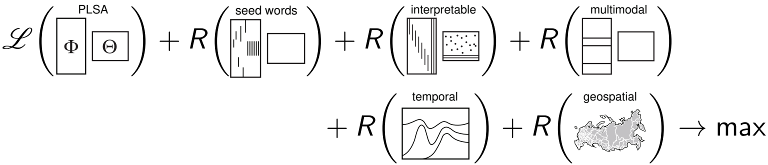
Result: the number of relevant topics augmented from 45% for LDA to 83% for ARTM.

M.Apishev, S.Koltcov, O.Koltsova, S.Nikolenko, K.Vorontsov. Additive regularization for topic modeling in sociological studies of user-generated text content. MICAI, 2016.

Mining health-related discourse in social media

Goal: find ailment related topics discussed in Twitter.

The bag-of-regularizers:

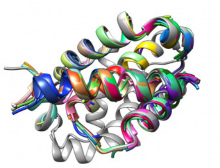


The Ailment Topic Aspect Model (ATAM) can be easily and naturally implemented in BigARTM

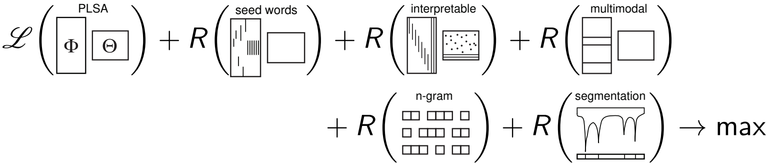
M.J.Paul, M.Dredze. Discovering Health Topics in Social Media Using Topic Models, 2014.

Mining DNA or protein sequences

Goal: finding patterns and motifs in DNA or protein sequences.



The bag-of-regularizers:



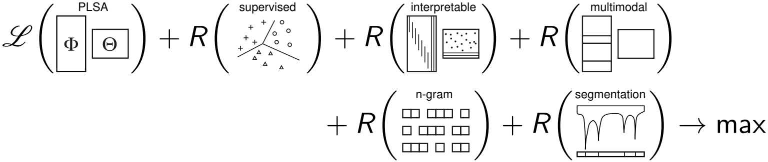
J.B.Gutierrez, K.Nakai. A study on the application of topic models to motif finding algorithms. 2016.

Lin Liu, Lin Tang, Libo He, Shaowen Yao, Wei Zhou Predicting protein function via multi-label supervised topic model on gene ontology. 2017.

Mining gene expression from microarray data

Goal: gene clustering or classification, without assumption of functional independence between genes.

The bag-of-regularizers:

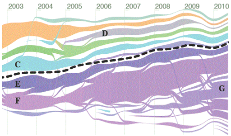


M.Bicego, P.Lovato, et al. Investigating Topic Models' Capabilities in Expression Microarray Data Classification. 2012.

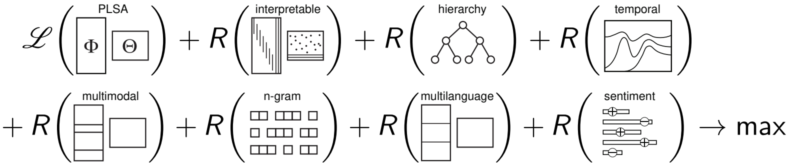
Lin Liu, Lin Tang, Wen Dong, Shaowen Yao, Wei Zhou An overview of topic modeling and its current applications in bioinformatics. 2016.

Topic detection and tracking in news flow

Goal: the development of an interpretable hierarchical temporal dynamic topic model of the news flow.



The bag-of-regularizers:

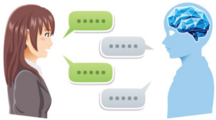


Results:

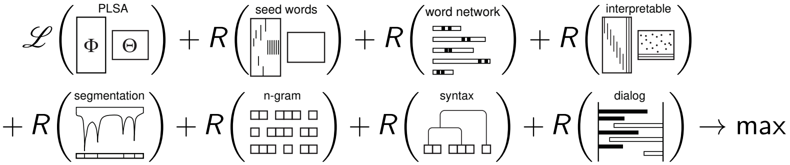
- processing about 50K news per day
- filtering news by topics / companies / events

Scenario analysis of call center records

Goals: determine typical scenarios of dialogues between operators and customers and build the topical hierarchy of customers intents.



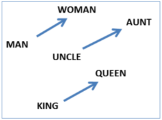
The bag-of-regularizers:



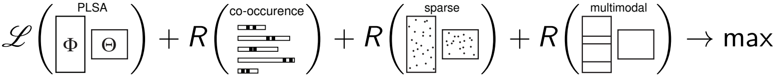
Result: the quality of the topical segmentation augmented from 40% for baselines to 75% for ARTM

Sparse topically interpretable probabilistic word embeddings

Goal: build regularizable embeddings $p(t|w)$ with sparse interpretable topical coordinates and semantic properties similar to word2vec.



The bag-of-regularizers:



Results:

- Performance on word similarity tasks is comparable
- Performance on document similarity tasks is better
- Modalities improve performance on word similarity tasks

A.Potapenko, A.Popov, K.Vorontsov. Interpretable probabilistic embeddings: bridging the gap between topic models and neural networks. AINL, 2017.

Brief summary

- ARTM is a non-Bayesian regularization framework for PTM
- ARTM gives the easy way to formalize and combine PTMs
- ARTM makes it easier to understand and explain PTMs
- ARTM originates the modular "LEGO-style" PTM technology
- BigARTM: open source implementation of ARTM
- Ongoing projects: exploratory search in scientific literature, call-center dialogs, bank transactions.

http://bigartm.org

Welcome to use and make contributions!

ARTM and BigARTM references I

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[4] *K.Vorontsov.* Additive regularization for topic models of text collections. Doklady Mathematics, 2014.

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[12] *N.Chirkova, K.Vorontsov.* Additive regularization for hierarchical multimodal topic modeling. JMLDA, 2016.

[13] *A.Ianina, L.Golitsyn, K.Vorontsov.* Multi-objective topic modeling for exploratory search in tech news. AINL, 2017.

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[17] *A.Belyy, M.Seleznova, A.Sholokhov, K.Vorontsov.* Quality Evaluation and Improvement for Hierarchical Topic Modeling. Dialogue, 2018.

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