

# Automatic filtering of Russian scientific content using Machine Learning and Topic Modeling

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- International Conference on Computational Linguistics • Dialogue 2015 (May 27–30, Moscow)

## 1 Exploratory Search

- Fingertip knowledge and exploratory search
- The elements of exploratory search
- Requirements for topic modeling

## 2 Topic Modeling

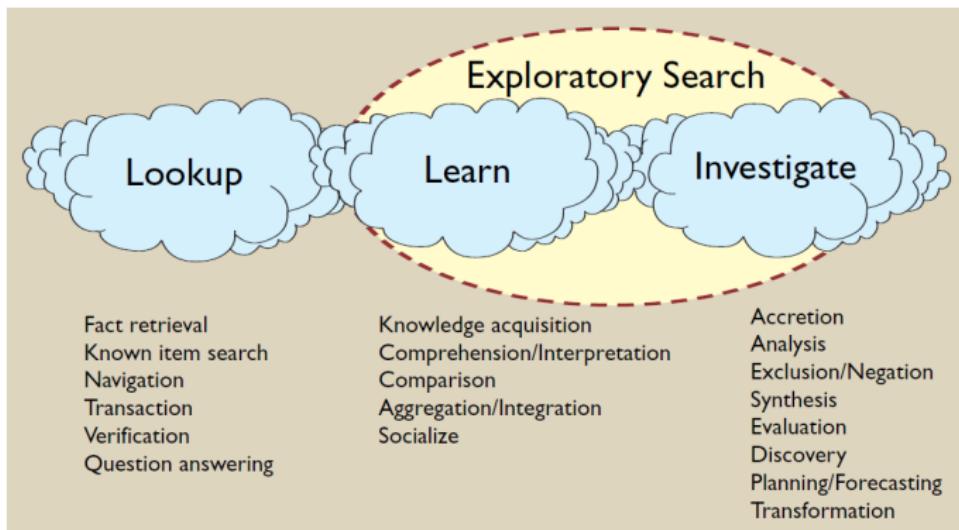
- Theory
- Implementation
- Experiments

## 3 Content Filtering

- Active learning
- Topic modeling for genre classification
- Results

## Exploratory Search for learning and investigation

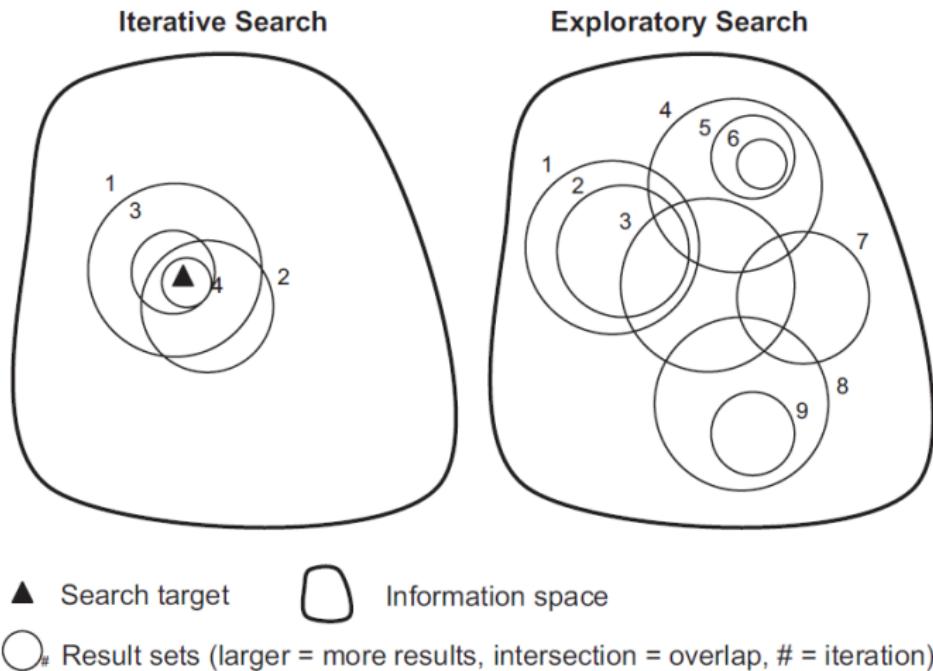
- what if the user doesn't know which keywords to use?
- what if the user isn't looking for a single answer?



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

## Iterative “query-browse-refine” search vs Exploratory Search



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R.W.White, R.A.Roth. Exploratory Search: beyond the Query-Response paradigm. San Rafael, CA: Morgan and Claypool, 2009.

## Exploratory search scenario

### Search query:

- a document of any length or even a set of documents

### Search intents:

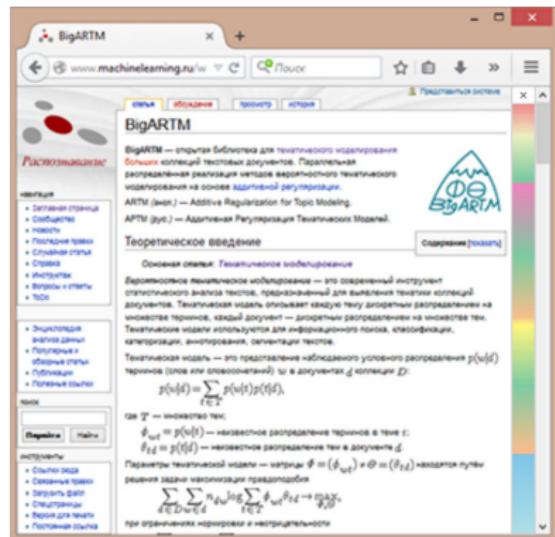
- what topics does it contain?
- what else is known on these topics?
- what is the structure of this domain area?
- what is most important, useful, popular, recent here?

### Search scenario:

- ① given a text (of any length) at hand (in any application)
- ② identify topics and sub-topics it contains
- ③ show textual and graphical representations of these topics

# Exploratory search: the prototype of graphical user interface

Color topic bar is a starting GUI element for exploratory search



# Exploratory search: the prototype of graphical user interface

Click on the color topic bar is a topic query

BigARTM – открытая библиотека для тематического моделирования. Большой коллекцией текстовых документов. Параллельная разработанная реализация метода вариационного тематического моделирования на основе аддитивной регуляризации.

ARTM (артм) – Additive Regularization for Topic Modeling.

ARTM (артм) – Аддитивная Регуляризация Тематической Модели.

**Теоретическое введение**

Основная статья: Техническое моделирование

Бероятностное тематическое моделирование – это современный инструмент статистического анализа текстов, предназначенный для выявления тематики коллекций документов. Тематическая модель определяет каждую тему документом разпределением на множество терминов, каждый документ – документным разпределением на множестве тем. Тематические модели используются для информационного поиска, классификации, категоризации, аннотирования, сегментации текстов.

Тематическая модель – это представление наблюдаемого условного разпределения  $p(w|d)$  термина ( слова или словосочетания)  $w$  в документах  $d$  коллекции  $D$ :

$$p(w|d) = \sum_{t \in T} p(w|t)p(t|d),$$

где  $T$  – множество тем;

$\phi_{wt} = p(w|t)$  – неизвестное разпределение терминов в теме  $t$ ;

$\theta_{t|d} = p(t|d)$  – неизвестное разпределение тем в документе  $d$ .

Параметры тематической модели – матрицы  $\phi = (\phi_{wt})$  и  $\theta = (\theta_{t|d})$  находятся путем решения задачи максимизации правдоподобия:

$$\sum_{d \in D} \sum_{w \in d} n_{dw} \log \sum_{t \in T} \phi_{wt} \theta_{t|d} \rightarrow \max,$$

при ограничениях нормировки и неотрицательности



# Exploratory search: the prototype of graphical user interface

## Topics of the query document

**BigARTM**

BigARTM — открытая библиотека для тематического моделирования больших коллекций текстовых документов. Параллельная реализация алгоритма метода вариационного тематического моделирования на основе аддитивной регуляризации.

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ARTM (рус.) — Аддитивная Регуляризация Тематического моделирования.

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Параметры тематической модели — матрицы  $\phi = (\phi_{wt})$  и  $\theta = (\theta_{t,d})$  находятся путем решения задачи максимизации правдоподобия:

$$\sum_{d \in D} \sum_{w \in d} n_{dw} \log \sum_{t \in T} \theta_{t,d} \phi_{wt} / d \rightarrow \max_D$$

при ограничениях нормировки и неотрицательности.

Topics in «BigARTM» [English] [Russian]

- Natural language processing
  - Statistical text analysis
    - Probabilistic topic modeling
- Probability theory
  - Likelihood maximization
- Mathematical programming
  - Nonconvex optimization
    - Constrained nonconvex optimization
- Machine Learning
  - Topic Modeling
    - Probabilistic Topic Modeling
- Matrix Factorization
  - Nonnegative Matrix Factorization
    - Probabilistic Topic Modeling
- Parallel computing
- Big Data

# Exploratory search: the prototype of graphical user interface

## Documents and objects ranked by relevance

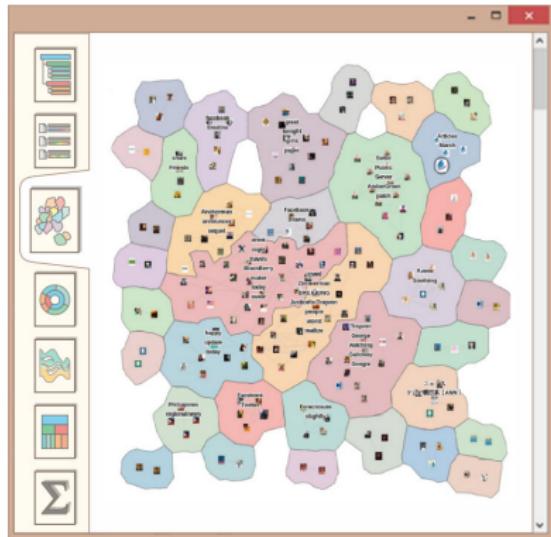
The screenshot shows the BigARTM application window. On the left, there's a sidebar with navigation links like 'Распознавание', 'Теоретическое введение', 'FAQ', and 'Архив'. The main area displays a list of documents with their titles and relevance scores. To the right of the list is a large heatmap with a color gradient from red to green, representing the distribution of topics across documents. A legend at the bottom of the heatmap identifies the topics by color.

The screenshot shows the BigARTM documentation website. It features a sidebar with icons for different sections: MachineLearning.ru, BigARTM FAQ, Tutorial, BigARTM FAQ, bigartm.readthedocs.org, GitHub, and Releases. The main content area contains several sections with text, code snippets, and links to external resources. For example, the 'MachineLearning.ru' section has a link to 'www.machinelearning.ru/wiki/index.php?title=BigARTM'. The 'Tutorial' section includes a figure showing how to call BigARTM methods directly on atm.dll (Windows) or BigARTM from other programming languages (not Python). The 'bigartm.readthedocs.org' section provides links to the BigARTM API and developer guide. The 'GitHub' section links to the BigARTM repository on GitHub, and the 'Releases' section links to the releases page.

# Exploratory search: the prototype of graphical user interface

## Topic roadmap: clustering of relevant documents

The screenshot shows the BigARTM web interface. On the left, there's a sidebar with navigation links like 'Распознавание', 'Теоретическое введение', 'Эксплоратор', and 'Аддитивная регуляция'. The main content area has tabs for 'статьи', 'обзоры', 'презентации', and 'источники'. A large text block explains BigARTM as a library for topic modeling, mentioning ARTM (Additive Regularization for Topic Modeling) and APTM (Additive Regularization for Topic Modeling). It also defines 'Тематическая модель' (Topic Model) as a representation of a document's topic distribution. Below this, there's a mathematical formula for the probability of a term  $t$  in a document  $d$ :  $p(v_t|d) = \sum_{\ell \in T} p(v_\ell|t)p(t|d)$ . A legend on the right shows a color gradient from red to blue with the text 'Фон' (Background).



# Exploratory search: the prototype of graphical user interface

## Topic hierarchy: topical structure of the domain area

**BigARTM**

**Распознавание**

**Теоретическое введение**

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Большинство языковых моделей — это специальный инструмент статистического анализа текстов, предназначенный для выявления тематики коллекций документов. Техническая модель описывает каждую тему дзиретным распределением на известных терминах, каждый документ — дзиретное распределение на известных темах. Технические модели используются для информационного поиска, классификации, категоризации, аннотирования, сегментации текстов.

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Параметры тематической модели — матрицы  $\phi = (\phi_{vt})$  и  $\theta = (\theta_{t,d})$  находятся путем решения задачи нахождения максимальных правдоподобий:

$$\sum_{d \in D} \sum_{v \in d} n_{dv} \log \left( \sum_{t \in T} \delta_{vt} \theta_{t,d} \right) \rightarrow \max_{\phi, \theta}$$

при ограничениях нормировки и неотрицательности

**Справка | Наши**

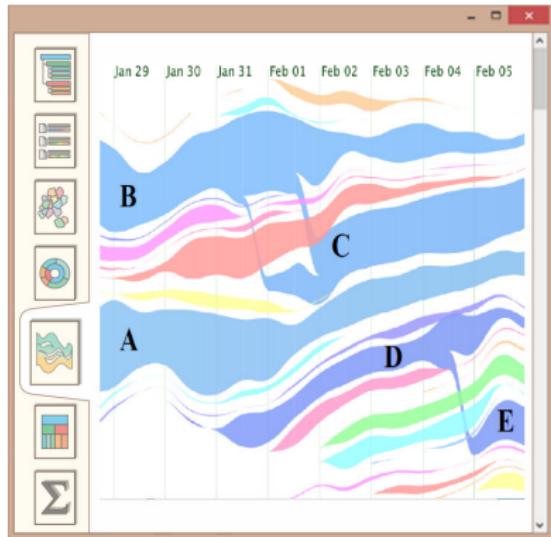
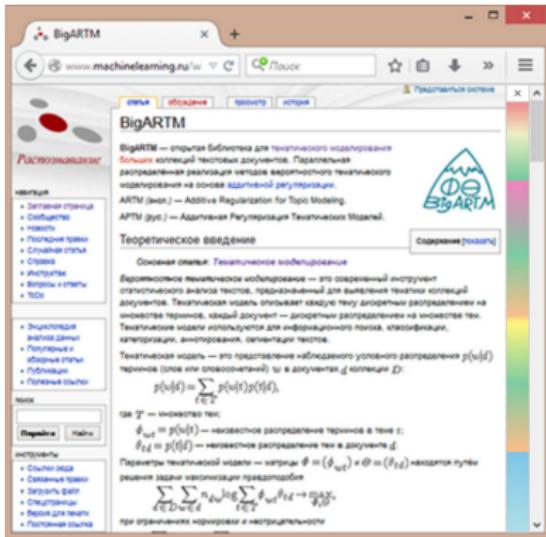
**Алгоритмы**

• Сточные задачи  
• Сокращенные тренинги  
• Загрузка файлов  
• Специальные алгоритмы  
• Помощник пользователя  
• Постановка задачи



# Exploratory search: the prototype of graphical user interface

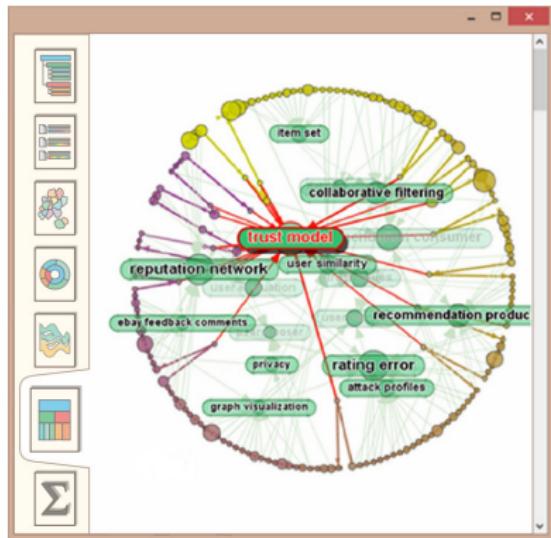
## Topic river: evolution of the domain area



# Exploratory search: the prototype of graphical user interface

## Topic bar: segmentation of the query document

The screenshot shows a web browser window for 'BigARTM' at [www.machinelearning.ru/w](http://www.machinelearning.ru/w). The main content area displays a 'Topic bar' with a color gradient from red to blue. Below the bar, text explains the BigARTM library for topic modeling, mentioning ARTM (Additive Regularization for Topic Modeling) and APTM (Adaptive Regularization for Topic Modeling). It also describes the 'Theoretical introduction' section, which includes a diagram of a pyramid labeled 'ФАБ' (Fab) and a color wheel. The sidebar on the left contains sections like 'Распознавание' (Recognition), 'Теоретическое введение' (Theoretical introduction), and 'Эксперименты' (Experiments). The bottom navigation bar includes links for 'Помощь' (Help) and 'Наши' (Our).



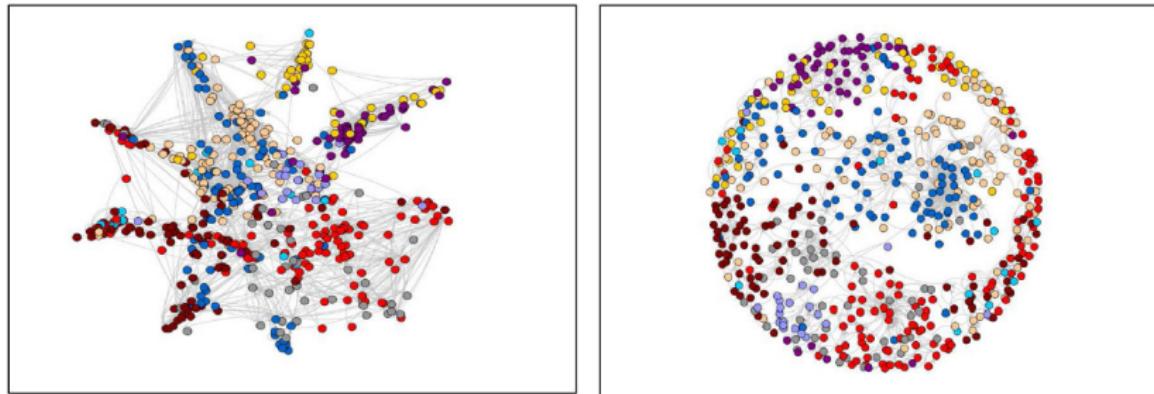
# Exploratory search: the prototype of graphical user interface

## Summarization of the query document

The screenshot shows a web browser window for 'BigARTM' at [www.machinelearning.ru/w](http://www.machinelearning.ru/w). The main content area displays a summary of a query document. The summary is presented in a grid format with three columns: 'Тематическое моделирование' (Thematic modeling), 'Большие коллекции текстовых документов' (Large text document collections), and 'Параллельная разработке' (Parallel development). Below this, there is a section titled 'Теоретическое введение' (Theoretical introduction) containing text and mathematical formulas related to topic modeling. A color bar on the right side of the summary grid indicates the topic distribution for each term.

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## Topic roadmap: clustering of relevant documents

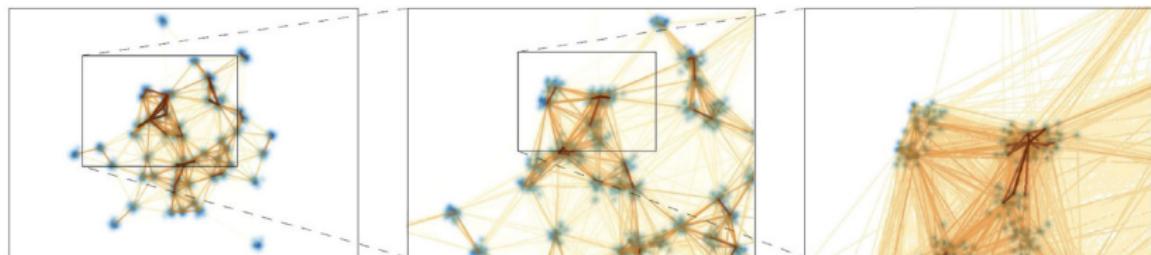


- Points represent documents
- Clusters represent groups of similar documents
- The most convenient shape of a cloud may be adjusted

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Tuan M. V. Le, Hady W. Lauw Probabilistic Latent Document Network Embedding. IEEE International Conference ICDM. 2014.

## Topic roadmap: clustering of relevant documents

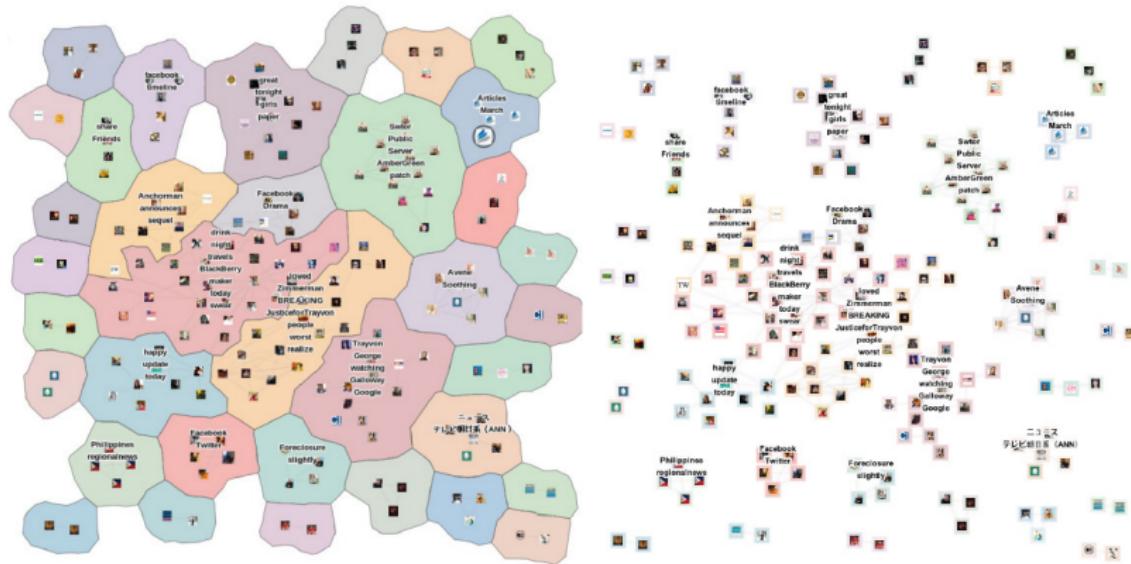


- Clusters
  - of clusters
  - of clusters
  - of clusters ...

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*M.Zinsmaier, U.Brandes, O.Deussen, H.Strobelt. Interactive level-of-detail rendering of large graphs. IEEE Trans. Vis. Comput. Graph. 2012.*

## Topic roadmap: clustering of relevant documents

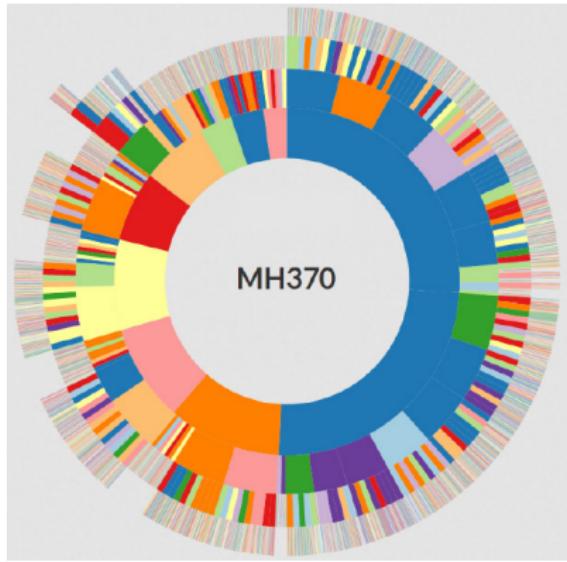


A map metaphor visualization (left) seems more appealing than a plain graph layout (right), and clusters seem easier to identify.

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E.R.Gansner, Y.Hu, S.North. Visualizing Streaming Text Data with Dynamic Maps. 2012.

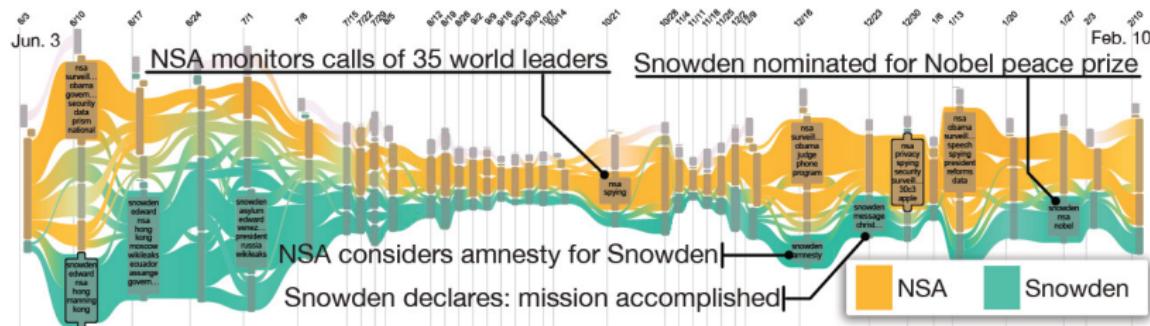
## Topic hierarchy: topical structure of the domain area



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*Smith A., Hawes T., Myers M.. Hiérarchie: interactive visualization for hierarchical topic models. Workshop on Interactive Language Learning, Visualization, and Interfaces, ACL, 2014.*

## Topic river: evolution of the domain area



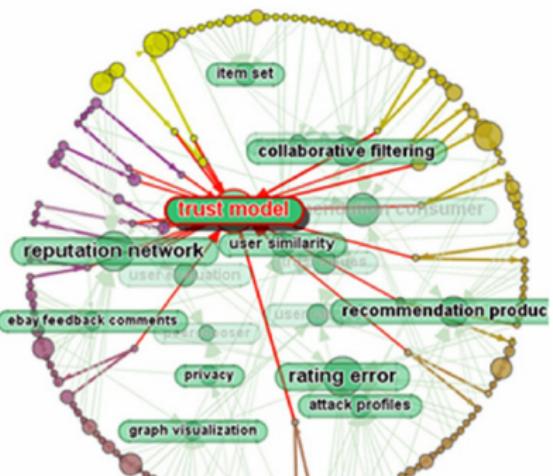
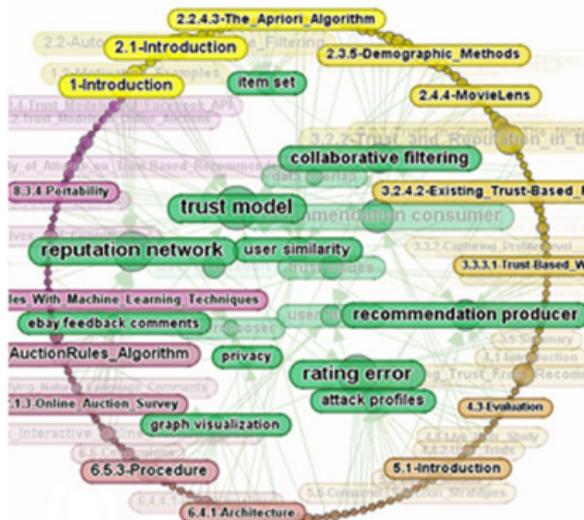
Evolving hierarchical topics in the Prism dataset (2013/06/03 – 2014/02/09).

- An expert chooses the cut of the tree hierarchy,
- marks events interactively,
- then generates a report.

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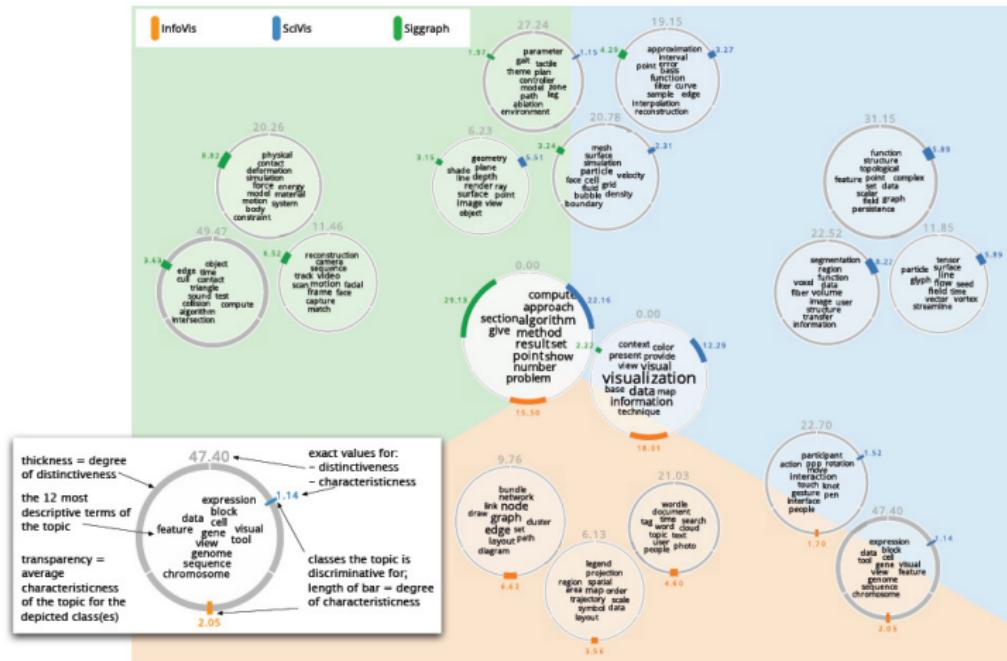
Weiwei Cui, Shixia Liu, Zhuofeng Wu, Hao Wei. How hierarchical topics evolve in large text corpora. IEEE Trans. Vis. Comput. Graph. 2014.

# Topic bar: segmentation of the query document



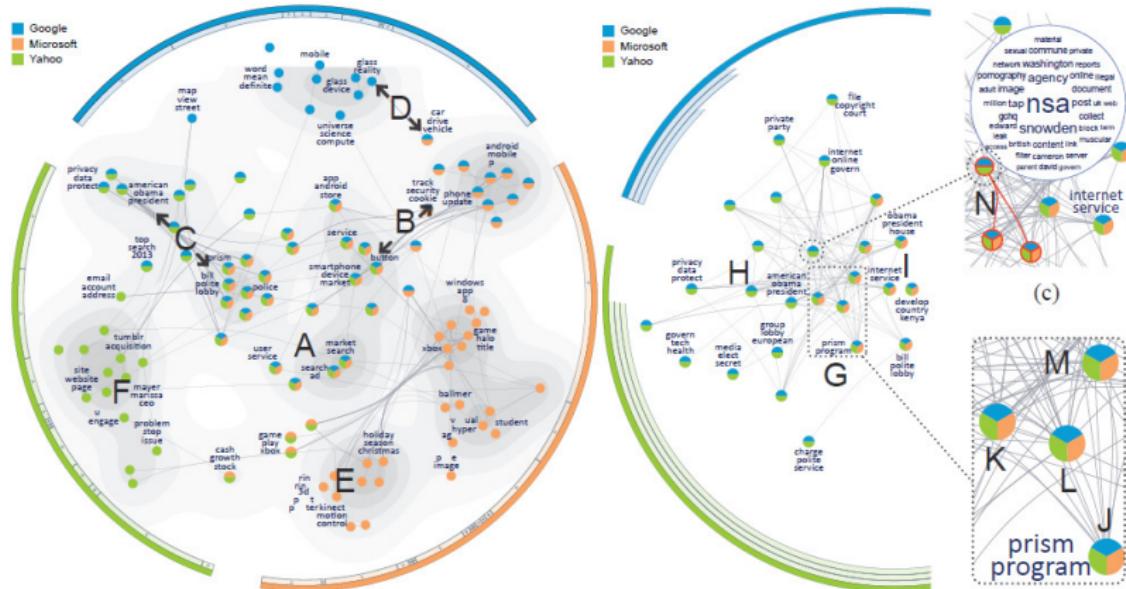
Gretarsson B., O'Donovan J., Bostandjiev S., Hollerer T., Asuncion A.,  
Newman D., Smyth P. TopicNets: visual analysis of large text corpora with  
topic modeling. ACM Trans. on Intelligent Systems and Technology. 2012.

# Topic sources: common topics and source-specific topics



Oelke D., Strobelt H., Rohrdantz C., Gurevych I., Deussen O. Comparative exploration of document collections: a visual analytics approach. EuroVis. 2014.

## Topic sources: common topics and source-specific topics



*Shixia Liu, Xiting Wang, Jianfei Chen, Jun Zhu, Baining Guo.* TopicPanorama: a full picture of relevant topics. IEEE Symp. on Visual Analytics Science and Technology. 2014.

<http://textvis.lnu.se>

A visual survey of 170 text visualization techniques



# The elements of Exploratory Search

- ① Web crawling
- ② Content filtering
- ③ Topic modeling
- ④ Building the inverted index
- ⑤ Ranking
- ⑥ Visualization

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- ⑥ Visualization ..... ready-made solutions

# The elements of Exploratory Search

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- ❸ Topic modeling ..... **in this presentation**
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- ❺ Ranking ..... ready-made solutions
- ❻ Visualization ..... ready-made solutions

## What is “topic”?

- *Topic* is a specific terminology of a particular domain area.
- *Topic* is a set of coherent terms (words or phrases) that often co-occur in documents.

More formally,

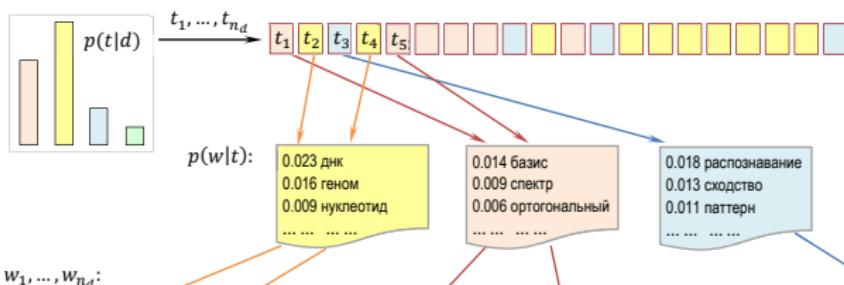
- *topic* is a probability distribution over terms:  
 $p(w|t)$  is (unknown) frequency of word  $w$  in topic  $t$ .
- *document profile* is a probability distribution over *topics*:  
 $p(t|d)$  is (unknown) frequency of topic  $t$  in document  $d$ .

When writing term  $w$  in document  $d$  author thinks of topic  $t$ .  
*Topic model* tries to uncover latent topics in a text collection.

# Probabilistic Topic Model (PTM)

Topic model explains terms  $w$  in documents  $d$  by topics  $t$ :

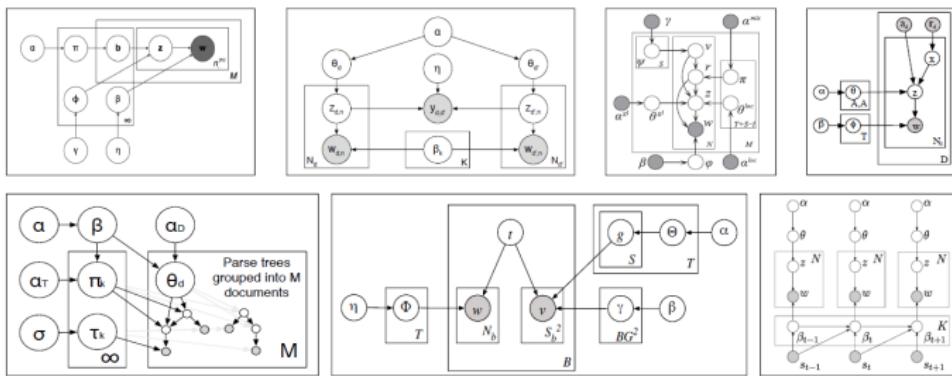
$$p(w|d) = \sum_t p(w|t)p(t|d)$$



Разработан спектрально-аналитический подход к выявлению размытых протяженных повторов в геномных последовательностях. Метод основан на разномасштабном оценивании сходства нуклеотидных последовательностей в пространстве коэффициентов разложения фрагментов кривых GC- и GA-содержания по классическим ортогональным базисам. Найдены условия оптимальной аппроксимации, обеспечивающие автоматическое распознавание повторов различных видов (прямых и инвертированных, а также tandemных) на спектральной матрице сходства. Метод одинаково хорошо работает на разных масштабах данных. Он позволяет выявлять следы сегментных дупликаций и мегасателлитные участки в геноме, районы синтезии при сравнении пары геномов. Его можно использовать для детального изучения фрагментов хромосом (поиска размытых участков с умеренной длиной повторяющегося паттерна).

## Probabilistic topic modeling: milestones and mainstream

- ➊ PLSA — Probabilistic Latent Semantic Analysis (1999)
  - ➋ LDA — Latent Dirichlet Allocation (2003)
  - ➌ 100s of PTMs based on Graphical Models & Bayesian Inference



*David Blei.* Probabilistic topic models // Communications of the ACM, 2012. Vol. 55. No. 4. Pp. 77–84.

## Topic model for exploratory search should be...

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- ⑥ **Hierarchical:** granularity of topics should be user-adjustable

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- ⑤ **Temporal:** topic dynamics over time should be identified
- ⑥ **Hierarchical:** granularity of topics should be user-adjustable
- ⑦ **Segmented:** the topical text segmentation should be supported beyond the bag-of-words (BoW) model

## Topic model for exploratory search should be...

- ① **Interpretable:** each topic should be well interpretable by humans and labeled
- ② **Multigram:** keyphrases should be extracted automatically
- ③ **Multilingual:** cross-language and multi-language search should be supported
- ④ **Multimodal:** authors, categories, sources, links, tags, named entities, users, etc. should be involved in the model
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- ⑦ **Segmented:** the topical text segmentation should be supported beyond the bag-of-words (BoW) model
- ⑧ **Semi-supervised:** the corrections from experts should be used to improve the model

## What prevents usage of topic modeling for exploratory search?

- ➊ Lack of techniques for combining topic models

How are we going to solve these problems:

- ➋ ARTM — Additive Regularization for Topic Modeling

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- ②
  - Automatic multigram term extraction
  - Using external linguistic resources (thesaurus, ontologies)
  - Automatic revealing of topic lexical kernels  
(via sparsity, diversity and coherence maximization)

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  - Using external linguistic resources (thesaurus, ontologies)
  - Automatic revealing of topic lexical kernels
    - (via sparsity, diversity and coherence maximization)
- ③ Linguistic regularization of topic models
  - (sentence TM, syntactic TM, segmentation TM, etc.)

## ARTM: Additive Regularization for Topic Modeling

**Given:**  $W$  is a set (vocabulary) of terms

$D$  is a set (collection) of documents  $d = \{w_1 \dots w_{n_d}\}$

$n_{dw}$  = 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

The problem is to maximize the *regularized* log-likelihood:

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

$$\phi_{wt} \geq 0, \quad \sum_{w \in W} \phi_{wt} = 1; \quad \theta_{td} \geq 0, \quad \sum_{t \in T} \theta_{td} = 1.$$

## Solution: the regularized EM algorithm

**Input:** collection  $D$ : each  $d = \{w_1 \dots w_{n_d}\}$  also as BoW  $\|n_{dw}\|$ ;

**Output:** matrices  $\phi_{wt} = p(w|t)$ ,  $\theta_{td} = p(t|d)$ ;

- 1 initialize  $\phi_{wt}$ ,  $\theta_{td}$ ;
- 2 repeat
  - 3 estimate topic distribution for each term  $w$  in each document  $d$ :  
$$p(t|d, w) = \text{norm}_t(\phi_{wt} \theta_{td});$$
  - 4 count the frequency of each term  $w$  in each topic  $t$ :  
$$n_{wt} = \sum_d n_{dw} p(t|d, w);$$
  - 5 count the frequency of each topic  $t$  in each document  $d$ :  
$$n_{td} = \sum_w n_{dw} p(t|d, w);$$
  - 6 apply **regularization** and normalize conditional probabilities:  
$$\phi_{wt} = \text{norm}_w(n_{wt} + \phi_{wt} \frac{\partial R}{\partial \phi_{wt}});$$
$$\theta_{td} = \text{norm}_t(n_{td} + \theta_{td} \frac{\partial R}{\partial \theta_{td}});$$
- 7 until convergence;

## ARTM: available regularizers

- topic smoothing (equivalent to LDA)
- topic sparsing
- topic decorrelation
- topic selection via entropy sparsing
- topic coherence maximization
- supervised learning for classification and regression
- semi-supervised learning
- using documents citation and links
- modeling temporal topic dynamics
- using vocabularies in multilingual topic models
- and many others

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Vorontsov K. V., Potapenko A. A. Additive Regularization of Topic Models // Machine Learning. Special Issue "Data Analysis and Intelligent Optimization with Applications". Springer, 2014.

## Summary of ARTM approach

**EM-algorithm is computationally efficient:**

- It has linear time complexity  $O(n \cdot |T| \cdot \text{nlter})$
- Its online version passes only once through a big collection
- Parallelism is possible for both multi-core CPUs and clusters

**ARTM reduces barriers to entry into PTM research field:**

- PLSA, LDA, and 100s of PTMs are covered by ARTM
- Combining multiple regularizers is easy
- No complicated Bayesian inference and graphical models
- Fast parallel online implementation BigARTM ([bigartm.org](http://bigartm.org))

## Next step: making topic models more linguistic

- Syntactic topic models
- Sentence and discourse topic models
- Text segmentation topic models
- Automatic multigram term extraction
- ARTM: post-processing of topic–term matrix  $p(t|d, w)$

---

*J.Boyd-Graber.* Linguistic extensions of topic models. PhD thesis. 2010.

*N.Aletras.* Interpreting document collections with topic models. PhD thesis. 2014.

*M.Yang, T.Cui, W.Tu.* Ordering-sensitive and semantic-aware topic modeling. 2015.

*M.Riedl, C.Biemann.* How text segmentation algorithms gain from topic models. 2012.

*S.Remus, C.Biemann* Three knowledge-free methods for automatic lexical chain extraction. 2013.

*A.Lazaridou, I.Titov, C.Sporleder.* A Bayesian model for joint unsupervised induction of sentiment, aspect and discourse representations. 2013.

# BigARTM project

## BigARTM features:

- Parallel + Online + Multimodal + Regularized topic modeling
- Out-of-core processing of Big Data
- Built-in library of regularizers and quality measures

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## BigARTM community:

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



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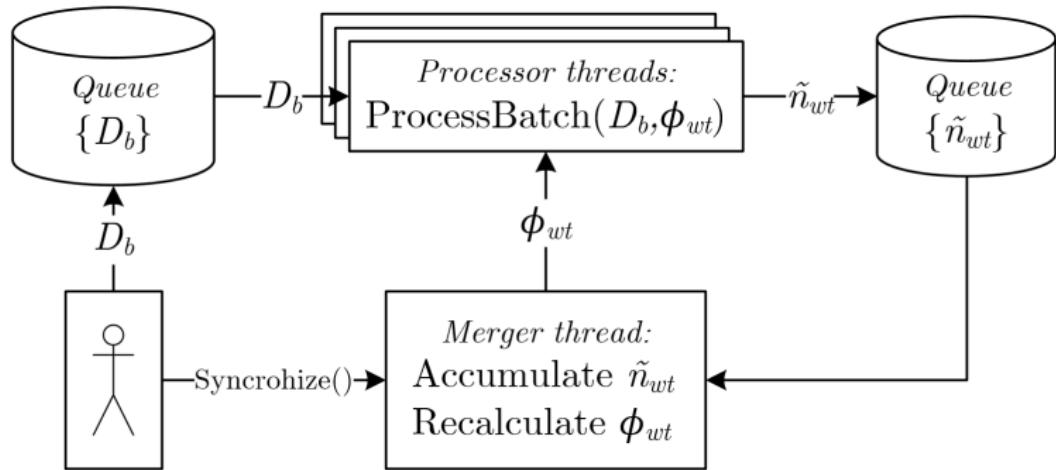
- Open-source <https://github.com/bigartm>  
(discussion group, issue tracker, pull requests)
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## BigARTM license and programming environment:

- 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

# The BigARTM project: parallel architecture



- Concurrent processing of batches
- Simple single-threaded code for *ProcessBatch*
- User controls when to update the model in online algorithm
- Deterministic (reproducible) results from run to run

## Experiment 1. BigARTM vs Gensim vs Vowpal Wabbit

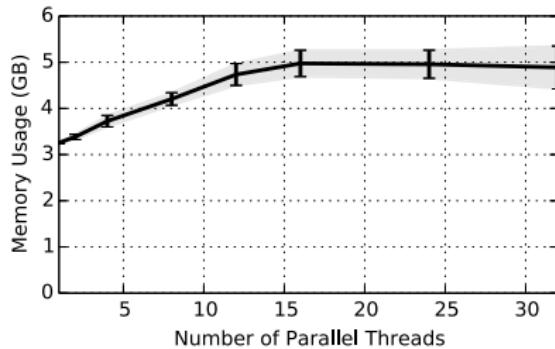
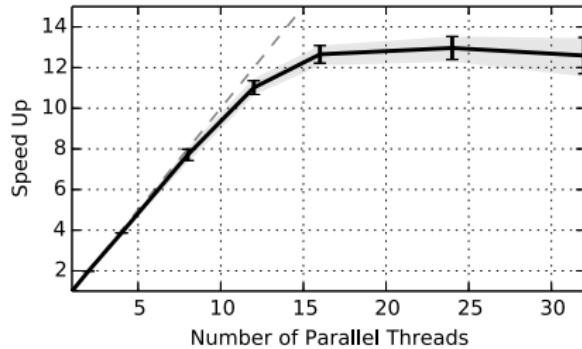
- 3.7M articles from Wikipedia, 100K unique words

	procs	train	inference	perplexity
BigARTM	1	35 min	72 sec	4000
Gensim.LdaModel	1	369 min	395 sec	4161
VowpalWabbit.LDA	1	73 min	120 sec	4108
BigARTM	4	9 min	20 sec	4061
Gensim.LdaMulticore	4	60 min	222 sec	4111
BigARTM	8	4.5 min	14 sec	4304
Gensim.LdaMulticore	8	57 min	224 sec	4455

- procs* = number of parallel threads
- inference* = time to infer  $\theta_d$  for 100K held-out documents
- perplexity* is calculated on held-out documents.

## Experiment 1. Running BigARTM in parallel

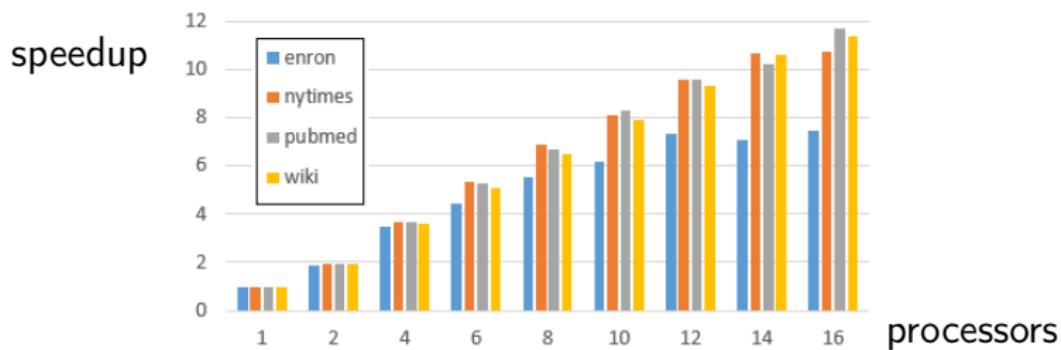
- 3.7M articles from Wikipedia, 100K unique words



- Amazon EC2 c3.8xlarge (16 physical cores + hyperthreading)
- No extra memory cost for adding more threads

## Experiment 2. Running BigARTM on large collections

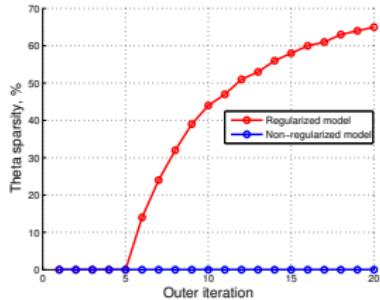
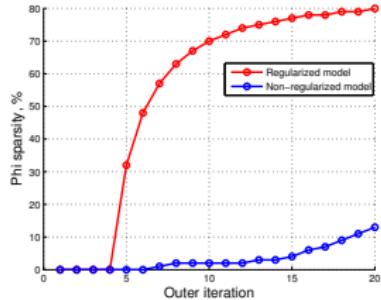
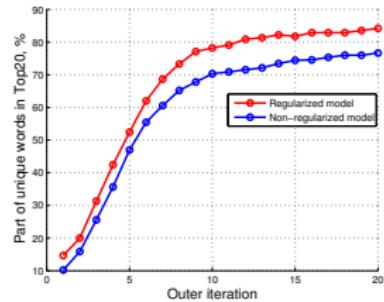
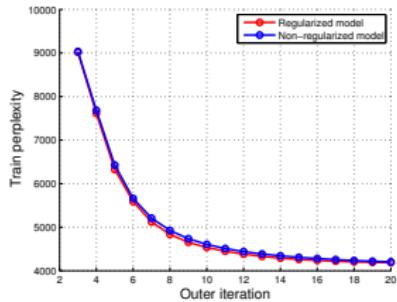
collection	$ W , 10^3$	$ D , 10^6$	$n, 10^6$	size, GB
enron	28	0.04	6.4	0.07
nytimes	103	0.3	100	0.13
pubmed	141	8.2	738	1.0
wiki	100	3.7	1009	1.2



Amazon EC2 cc2.8xlarge instance:  
16 cores + hyperthreading, Intel® Xeon® CPU E5-2670 2.6GHz.

## Experiment 3. Additive regularization

ARTM combines regularizers to improve multiple criteria (sparsity, number of unique words) without a loss of the perplexity.



## Experiment 4. Interpretability of Multilingual ARTM

We consider languages as modalities in Multimodal ARTM.

Collection of 216 175 Russian–English Wikipedia articles pairs.

Top 10 words with  $p(w|t)$  probabilities (in %):

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

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Top 10 words with  $p(w|t)$  probabilities (in %):

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

All  $|T| = 400$  topics were reviewed by an independent assessor,  
and he successfully interpreted 396 topics.

## Experiment 5. Interpretability of Multigram ARTM

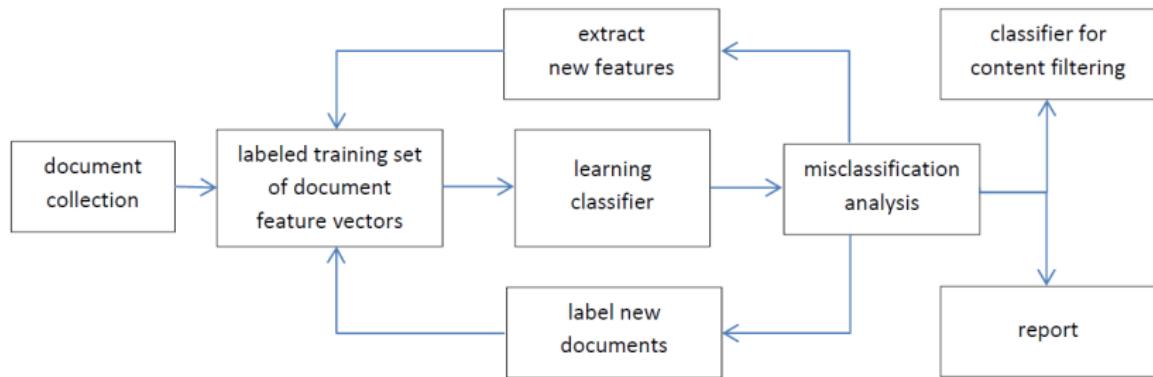
We consider *n*-grams as modalities in Multimodal ARTM.

Collection: 1000 articles from Russian conference [www.mmro.ru](http://www.mmro.ru)

распознавание образов в биоинформатике		теория вычислительной сложности	
unigrams	bigrams	unigrams	bigrams
объект	задача распознавания	задача	разделять множества
задача	множество мотивов	множество	конечное множество
множество	система масок	подмножество	условие задачи
мотив	вторичная структура	условие	задача о покрытии
разрешимость	структура белка	класс	покрытие множества
выборка	распознавание вторичной	решение	сильный смысл
маска	состояние объекта	конечный	разделяющий комитет
распознавание	обучающая выборка	число	минимальный аффинный
информационность	оценка информативности	аффинный	аффинный комитет
состояние	множество объектов	случай	аффинный разделяющий
закономерность	разрешимость задачи	покрытие	общее положение
система	критерий разрешимости	общий	множество точек
структура	информационность мотива	пространство	случай задачи
значение	первичная структура	схема	общий случай
регулярность	тупиковое множество	комитет	задача MASC

# Learning the Content Filter

- ① the principles of filtering are communicated to the experts
- ② experts label the training set as «good» and «bad» documents
- ③ the learned classifier is used for *uncertainty sampling*



The problem of unbalanced classes: 1 : 50 in our collection

# Topic modeling for scientific genre classification

## Collection:

850K documents from 2000 sites of Russian universities,  
no more than 2% of them are «good» i.e. scientific.

**Labeled:** 3K documents, 40% of them are «good».

## Expert instructions:

- «**good**» **document** is a primary source of scientific information that carries scientific knowledge
- «**bad**» **documents**: commercial and organizational content, home pages, courses, annotations, bibliographies, etc.

## Topic model for semi-supervised classification

learns **positive** and **negative** words for text genre classification from a small labeled training set.

## Examples of topics

← less scientific				more scientific →
0.000	0.099	0.203	0.755	1.000
образование	который	страна	прямая	процесс
студент	ряд	Россия	быть	результат
социальный	оценка	производство	точка	модель
учебный	человек	экономика	значение	среда
современный	параметр	который	множество	зависимость
университет	источник	год	движение	различный
российский	система	орган	состояние	структура
научный	помощь	государство	система	позволять
формирование	связь	проблема	время	являться
вуз	этот	развитие	рис	поверхность
конференция	комплекс	период	коэффициент	расчет
организация	наличие	федеральный	тогда	технический
проект	изменение	закон	исследование	обработка
история	труд	хозяйство	свойство	качество
место	мир	такой	граница	данный
вуз	знание	власть	вектор	моделирование
кафедра	высокий	стоимость	уровень	сигнал
личность	величина	весь	коэффициент	следующий
субъект	число	условие	вероятность	основа

## Content filtering results

F1, Recall, Precision (in %) for balanced and unbalanced data:

features	F1	Recall	Prec	F1	Recall	Prec
A1	76.57	62.08	99.90	77.40	71.48	84.39
A1 T	93.27	91.54	95.07	77.38	72.35	83.13
A1 A2	93.18	90.63	95.87	81.86	83.33	80.06
A1 A2 T	92.62	90.13	95.24	81.95	80.21	83.76
A1 A2 T8	95.12	95.52	94.72	82.24	78.54	86.31
A1 A2 B	96.24	95.92	96.57	90.37	91.00	89.75
A1 A2 B T	96.50	96.22	96.78	90.51	93.21	87.95
A1 A2 B T8	97.33	97.47	97.20	90.85	93.42	88.41

### Groups of features:

- A1** Greek letters, math symbols, document length
- A2** digits, short text indicator, grant phrase words
- B** bibliography lines, references
- T** 25 topics
- T8** 8 topics selected manually from several runs

- Topic modeling & content filtering are key technologies for exploratory search
- ARTM (Additive Regularization for Topic Modeling) is a general framework, which makes topic models easy to design, to infer, to explain, and to combine.
- BigARTM is an open source project ready for parallel online multimodal topic modeling of large text collections.



<http://bigartm.org>  
Join BigARTM community!