My first scientific paper
in Machine Learning

Vadim Strizhov

m1p.org

This course produces students' research papers

Machine learning projects to

- state the problem
- run the computational experiment
- share and deploy results

Science requires community

- The student is a project driver, plunges into scientific research
- The consultant conducts research and helps the student
- The professor states the problem and enlightens the goal

History

- It starts in February, ends in May, and goes 14 weeks
- For the past ten years, 500+ projects have been made
- Awarded in 2020 for its significant impact on the scientific community development

Step-by step weekly instructions and support

Lectures

- Theory: Machine learning for researchers
- Practice: The routine of scientific research

Seminars

- Collective games
- Analysis of projects
- Talks

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6	The message
9	Computational experiment
12	Conference talk

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Roadmap

1. Set the toolbox
2. Select your project
3. Read papers
4. Write introduction
5. State the problem
6. Set your experiment
7. Develop your theory
8. Make error analysis
9. Paper draft
10. Share your results
11. Finalize your paper
12. Present your talk

Deliveries are scheduled

- LinkReview with references and the literature review
- GitHub with the code and computational experiment
- Paper is ready for submission
- Slides for the presentation
- Video of the conference talk

Table of deliveries and weekly scores

Author	Problem	Links	Supervisor	Scores
Pilkevich Anton	Existence conditions for hidden feedback loops in recommender systems	GitHub , LinkReview , Paper , Slides , Video , Video	Khritankov	AIL[B]P-X+RB-H1CV[O]T-EM.H1WJSF
Orlov Alexey	Model distillation on multi-domained datasets	GitHub , LinkReview , Paper	Grabovoi	AIL[B]PXRBCV[O][M]
Gorbulev Alexey	Iterative improvement of the topic model with user feedback	GitHub , LinkReview , Paper , Slides , Code	Alekseev	AIL[B]PX>RBCV>[O]T>[M]

New

News

- Every your project is welcome!
- Your experts and consultants are highly appreciated!
- The number of students is not limited.

Challenges

- Every student should work with the society!
- The project should be welcome to disseminate.
- The peer-review must be continuous.

A student's paper example

Topic Models Selection for Reading Orders Generation over Document Collections 1

Topic Models Selection for Reading Orders Generation over Document Collections

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This paper investigates an impact of topic models on the quality of reading orders. A reading order organizes a collection of documents in a tree from general to more specific documents. It allows a user to choose a reading sequence over the documents. We evaluate the impact of ARTM technique and its variations, hierarchical ARTM and additive ARTM, on the quality of reading orders. Such alterations enhance the quality of reading orders as well as reducing its construction time. We propose a new metric named hierarchical entropy to measure document generality. The experiments were conducted with Russian Wikipedia hierarchies of categories in Mathematics and Machine Learning. The problem to solve gives a novel way to content consumption that is significant for learning or editorial purposes.

Keywords: *reading order, probabilistic topic modeling, reading sequence.*

1 Introduction

Search engines like Google or Yahoo rank the search results based on the relevance to the provided query. That requires the user to know the area and to be able to formulate the query using specific terms. As for users wanting to explore a new topic, this kind of search and ranking approaches do not work effectively.

The exploratory search [20, 30] is a paradigm of information retrieval. This paradigm is useful when user intends to learn the subject domain better. As the user does not know the main concepts of the domain, he needs a hint to determine which of the found documents to read first, gradually moving from simple to more complex documents.

The reading order optimization is an alternative way to content consumption. It departs from the lists of documents ranked based on their relevance. Given a document collection, existing systems allow users to browse the collection or perform search. This search return the sequence of documents ranked based on their relevance to the user query. Google-like approach work fine when the user has to locate specific documents. However, they are insufficient when a user need to access the pertinent documents in some logical reading order. For example, it is crucial for learning or editorial purposes. Reading order ranking technique helps to achieve more accurate content consumption significantly faster.

Attempts to convert document collection into some meaningful structure have already been in [11, 23]. However, this attempts are applicable only for some specified document collections. Our aim is to develop a ranking technique for arbitrary collections. The paper [17] explores a possible solution to Reading Order problem, which we elaborate in this paper. The proposed method is based on two techniques. Firstly, the clustering technique that is more flexible than used previously in label tree learning methods [3, 18, 19]. Secondly, the vector representations of documents, obtained by topic modeling [13]. The authors of [17] suppose that the reading order is not a list, but a set of trees. To explore a topic, a user sometimes has to make a decision of what subtopic to dive into, as the amount of information is vast.

Another kind of meaningful structure over a document collection is the curriculum. The automatic curriculum generation is discussed in [16] and [22]. However, they do not provide any scalable solution, only tailored variations.

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Multiple approaches on counting document generality and complexity were proposed in [10, 24]. In order to solve the Reading Order problem, they count simple characteristics and sort the documents by them. The complexity of the document is calculated effectively [10]. But sorting does not provide a tree structure, plain lists only.

The paper [14] explores methods of deriving document collection using variations of the PageRank [8] algorithm. The explored methods are query-based. It means that the user has to provide a query to get a sorted sequence of documents. These algorithms cannot be applied to sort an arbitrary document collection without a given query.

Probabilistic topic modeling [13] is a technique used to build the probabilistic document embeddings with the interpretive components. Our paper extends the method proposed in [17], by varying topic models, which are the core of the method. We scrutinize the ARTM [27, 29] approach, which is proved to outperform LDA [5] in many tasks due to the wide choice of regularizers [26]. We compare different types of models, including hierarchical models [2, 7] with diverse combinations of regularizers, as well as with different text preprocessing methods like terms and bigrams extractions.

There is a lot of approaches to model the hierarchical nature of topics. For example, hLDA [4] presents a topical hierarchy as a tree with only one parent for each sub-topic, hPAM [21] overcomes this limitation and represents hierarchies as multilevel acyclic graphs, hHDP [31] additionally estimates the number of levels and number of topics on each level of hierarchy and uses a multilevel graph model. In this work, we use hARTM because of the better results shown in experiments [2].

We analyze possible drawbacks of the algorithm, proposing extensions to overcome them. For example, we introduce hierarchical entropy, successfully upgrading accuracy of generality estimation.

2 Problem statement

A reading order $R(V, E)$ over a document set D is a directed acyclic graph whose nodes correspond to the input documents. Its edges correspond to specificity relations among the documents. In particular, a node $v_i \in V$ maps a non-empty set $D_i \subseteq D$ of equivalent documents. An edge $v_i \to v_j$ between nodes v_i and v_j signifies that documents belonging to the corresponding document set D_i precede documents belonging to the respective set D_j.

A complete reading tree over a document set D is a reading graph $R(V, E)$ with the following properties:

(a) For each node $v_i \in V$ with D_i being its corresponding set of documents, it holds that: a document $d \in D$ maps to $v_i \Leftrightarrow d \leftrightarrow d_i$, for all $d_i \in Di$.

(b) For each pair of nodes $v_i, v_j \in V$ with D_i and D_j being their sets of documents, and an edge $v_i \to v_j$, it holds that: For each pair of documents $d_i \in D_i$ and $d_j \in D_j$, it is $d_i \to d_j$.

(c) For each pair of nodes $v_i, v_j \in V$ with D_i and D_j being their sets of documents, and an edge $v_i \to v_j$, it holds that: there is no other node v_k, such that: $v_i \to v_k \to v_j$.

A reading sequence $d_{m1} \to d_{m2} \ldots \to d_{mk}$ of documents $d_{mi} \in D, i = 1 \ldots k$, maps to a path $v_{i1} \to v_{i2} \ldots \to v_{ik}$ on the graph with $v_{ti} \in V, i = 1 \ldots k$ such that $d_{mi} \in D_{ti}$ of node $v_{ti}, i = 1 \ldots k$.

In order to compare the reading orders, we need a way to compare trees. The editor distance metrics, initially introduced for string comparison, have been used to compare ordered trees [25]. The ordered labeled trees are trees in which the left-to-right order among siblings is significant. The distance between two trees is computed by an optimal mapping between two trees as the

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minimum cost of a sequence of elementary operations that converts one tree into the other. An alternative to mapping and tree edition is tree alignment [15].

The editor distance metric was extended for Reading Order problem. We are not interested in how identical two trees are. We care for the relative ordering of each pair of documents. To evaluate the tree difference based on the pairwise document orderings, we first build the adjacency matrix A for a tree structure using the following formula:

$$A_{ij} = \begin{cases} \frac{1}{\text{man of hope}(d_i \to d_j)} & \text{if there is a directed path } d_i \to d_j, \\ 0, & \text{otherwise.} \end{cases} \quad (1)$$

To measure the difference of two tree represented by matrixes A and $\hat{A}$, we use the mean squared error (MSE), which is defined as:

$$\frac{1}{n} \sum_{i,j=1}^{n} (A_{ij} - \hat{A}_{ij})^2. \quad (2)$$

3 Model Relationships Between Documents

The foundation of the method from [17] is document embeddings. For example, it is the semantic vector representation [1]. Each component i of the document d representation is the probability of the document d belonging to the topic i. Hence, the topic model simultaneously calculates document embeddings and performs soft clustering.

3.1 Topic Modeling

The central assumption of topic modeling is that the probability of the word w occurs in the document d:

$$p(w \mid d) = \sum_{t \in T} p(w \mid t) p(t \mid d) = \sum_{t \in T} \varphi_{wt} \theta_{td}, \quad (3)$$

where matrix Φ contains distributions of word w in document d (φ_{wt}), and matrix Θ are the probabilities θ_{td} of topic t occurs in document d, T is the total number of topics in the model.

The primary model (4) proposed in [13] is the **Probabilistic Latent Semantic Analysis (PLSA)**. It obtains the solution matrices by maximizing the likelihood:

$$L(\Phi, \Theta) = \sum_{d \in D} \sum_{w \in d} n_{wd} \log p(w \mid d) \to \max_{\Phi, \Theta}, \quad (4)$$

with the constraints on Φ and Θ:

$$\sum_{w \in W} \varphi_{wt} = 1, \varphi_{wt} \geqslant 0, \quad (5)$$

$$\sum_{t \in T} \theta_{td} = 1, \theta_{td} \geqslant 0. \quad (6)$$

The optimization problem is successfully solved with the EM algorithm.

The paper [6] introduces the Bayesian approach to extend the PLSA by adding the prior distributions to the and matrices. This approach is called **Latent Dirichlet Allocation**

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(LDA) and acknowledged the state-of-the-art method. The [17] uses the LDA model in experiments.

Additive Regularization of Topic Models (ARTM) scrutinized in [29], [28] and [26] brought vast diversity into topic modeling techniques. Still aiming to solve (4), ARTM uses regularizers to manage the topic model quality, and the optimization problem has the form:

$$L(\Phi, \Theta) + \sum R(\Phi, \Theta) \to \max_{\Phi, \Theta}. \quad (7)$$

There are many useful regularizers, the following three are the most widely used ones:

1. Sparsity Φ: In order to make the φ_{wt} distributions more sparse, the sparsity regularizer is used. Having the following form:

$$R(\Phi) = \sum_{t \in T} \sum_{w \in W} \beta_{wt} \log \varphi_{wt},$$

it makes each topic to contain lesser number of tokens from the vocabulary, making them, therefore, more distinct. The only parameter β is to be set up.

2. Sparsity Θ: Alike the Φ sparsity, the Θ sparsity regularizer ensures each document belongs to fewer topics.

$$R(\Theta) = \sum_{d \in D} \sum_{t \in T} \alpha_{td} \log \theta_{td}.$$

3. Decorrelation: To make topic even more diverse the regularizer

$$R = -\frac{\tau}{2} \sum_{t \in T} \sum_{w \in W} \sum_{s \in T} \varphi_{wt} \varphi_{ws}.$$

The regularizers are combined to acquire more precise and valuable models. Important indicators of the model's value are Φ and Θ sparsity values. However, the interpretability of topics is the most accurate measure, which cannot be estimated analytically, only by assessors.

In addition, ARTM brings new methods in handling the modalities. Modalities are various parts of text besides raw words (e.g. authors, terms, collocations), and their extraction can help in building a better model.

Multimodal ARTM solves the following optimization problem with old constraints:

$$\sum_m L_m(\Phi_m, \Theta) + \sum R(\cup_m \Phi_m, \Theta) \to \max_{\Phi, \Theta}, \quad (8)$$

where m stands for different modalities can be obtained from the texts or their meta data.

Finally, the **Hierarchical ARTM (hARTM)** combines two or more distinct ARTM models for each level of the hierarchy, linked with each other. To tailor next-level topics to the topics of the previous level, the regularizer, discussed in [7] is used:

$$R = \sum_{t \in T} \sum_{w \in W} n_{wt} \log \sum_{s \in S} \varphi_{wt} \psi_{st}, \quad (9)$$

where T is the number of topics on the previous level, S is the number of topics on the next level, Ψ is the stochastic matrix. It consists of probabilities of next-level topics in previous-level ones. This probabilities are obtained by solving the following problem:

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Figure 1 Entropy on a document collection

$$\sum_{t \in T} n_t KL_w \left(\frac{n_{ts} t}{n_t} || \sum_{s \in S} \varphi_{ws} \psi_{st} \right) \to \max_{\Phi, \Psi}. \quad (10)$$

The regularizer ensures that each previous-level topic is the convex sum of the next-level topics, while the Ψ matrix can be valuable in further applications. All regularizers and modalities extensions are applicable to the hARTM models.

In our paper, we compare all of these models in terms of their performance in building reading orders.

3.2 Generality

When starting to explore the novel topic and choosing what to read, it is preferable to start with general documents, covering basic terms and ideas of the domain. Measuring generality is the primary problem in reading orders generation.

Entropy. We can measure the document generality based on the document's entropy over the topics [17]. The basic intuition behind the entropy is that the higher a document's entropy is, the more topics the document covers hence the more general it is. Using the Shannon entropy, the generality score $g(d)$ of document d is computed as follows:

$$g(d) = -\sum_{t \in T} \theta_{td} log(\theta_{td}). \quad (11)$$

Hierarchical entropy. The entropy value has a significant problem that makes it unstable: if the document includes tailored topics from different domains, then its entropy is large, whereas the document is not general. A view of the chart of this entropy on a document collection is shown in Figure 1.

Using hierarchical topic models alleviates this problem. We introduce a hierarchical entropy, that can be calculated using a two-level hierarchical model. Hence, each document d has two embeddings - θ_d^1 and θ_d^2 on first and second level respectively.

Consider the document d is fixed. Let's denote the $h_{st} = -\psi_{st} \times \theta_{td}^2 d \times \log \theta_{td}^2 d$ - element of classical entropy of the second-level topic vector multiplied by the probability of the second-level topic s in the first-level topic t. Thus, obtain the matrix H.

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Finally, the hierarchical entropy score is a convolution of the matrix with first-level document embedding:

$$g_h(d) = -\sum_{t \in T} \theta_{td}^1 \sum_{s \in S} \psi_{st} \theta_{sd}^2 \log \theta_{sd}^2. \quad (12)$$

Such score is more stable in terms of above-mentioned example. Its effect is explored in the experiments.

3.3 Distance

Distance is the second vital parameter in reading order construction. It defines what documents could be read at the same time independently and what documents are not equal and should be read one after the other.

Document overlap. The overlap of two documents can be computed as their weighted Jaccard score [12]. The classic Jaccard index defined as the size of the intersection divided by the size of the union of the topic sets assigned to each document. The weighted Jaccard extends the classic Jaccard index by taking into account their topic probabilities. The overlap score can be computed as follows:

$$o(d_i, d_j) = \frac{\theta_{td}^1 \cdot \theta_{td}^1}{|\theta_{td}^1|^2 + |\theta_{td}^1|^2 - \theta_{td}^1 \cdot \theta_{td}^1}. \quad (13)$$

4 Computational Experiment

4.1 Data

We use Russian Wikipedia documents and hierarchy of categories to fit and validate our models. Both the Wikipedia texts and categories descriptions are accessible through the Wikimedia Resource. However, the categories hierarchy in Wikipedia is neither the tree nor the set of trees. It is a connected acyclic graph, meaning that from any category we can reach any other.

Since we need the trees only, we use Depth Full Search (DFS) algorithm with limited depth to construct trees fitting our needs.

To validate the model we use the tree with the «Mathematics» as root category and depth 8, containing 9500 documents. On this set, all topic models were fitted and trees validated. Additionally, to compare our results with the initial [17], and explore the scalability of tuned hyperparameters, we gathered the tree with the root of «Machine Learning» and depth 5.

4.2 Data processing

Several steps of processing were performed: we lemmatized the documents, all formulas were replaced with special «FORMULA» token.

Moreover, to try the multimodal ARTM, we extracted bigrams from the texts via the TopMine algorithm [9].

4.3 Topic models construction

For words from Wikipedia documents collection, there were constructed four topic models: LDA, ARTM, PLSA, Hierarchical ARTM. After that, each document was divided into bigrams and monograms and submitted as input to ATM and Hierarchical ARTM. Overall, six topic models were designed with Sparsity Φ and Sparsity θ that are shown in Table 1

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Type	Sparsity θ	Sparsity Φ for monograms	Sparsity Φ for bigrams
LDA	0.76	0.93	-
ARTM	0.77	0.93	-
PLSA	0.74	0.93	-
hARTM	0.87	0.95	-
ARTM with bigrams	0.82	0.90	0.75
hARTM with bigrams	0.90	0.93	0.81

Table 1 Topic models scores

4.4 Reading Tree Generation

The tree generation process progressively weaves the reading order for a set of documents by determining the specificity relations among the documents. It takes as input the set of documents, the document-topic assignments F, and two parameters: τ , which defines the minimum overlap between two equivalent documents, and k, which defines the maximum difference of their generality scores, n, which defines the dynamic decline of τ during algorithm execution. All parameters are used to define the specificity relations. We use the formulas (11) and (13) for computing document generality and overlap, respectively, but the algorithm is really independent of how document overlap and generality are estimated.

The algorithm builds a complete reading tree in an iterative way [17]. At each round, it handles a subset of similar documents that need to be connected to the tree already created. The algorithm's intention is to grow a sub-tree out of this set of documents and connect it to the existing tree. For this purpose, it first creates the root of this new sub-tree by putting together the most general documents from the set in consideration that are also equivalent. The remaining documents of this set are clustered such that they have some overlap with the root and among them. Each cluster becomes a new set of documents out of which the algorithm will further create new nodes and edges. This process repeats until no more tree growing is possible and there are no documents unprocessed. Initially, the set of documents under consideration contains all documents and the current root node is a dummy node.

The algorithm starts by computing the generality score for each input document $g(d_i)$. All documents are then ordered in descending order of their generality score. A dummy node is created and this node becomes the root of the tree. It is also the first node from where the tree will start to expand (called expansion node). The core operations of the algorithm are described as the function *GetOrder*, which is executed repeatedly but for a different subset of the input documents and growing the tree from a different expansion node each time. Its objective is to build a tree out of its input documents and connect it to the expansion node v_e. Steps 1–4 are responsible for the creation of the root node of this tree. This node, v_r, groups the more general documents from the current set of documents that have the required topic overlap and generality closeness based on the equivalence condition.

To build this node, the process starts with the most general document d. Subsequently, it considers documents in descending order of generality. As long as a document d_j has a close generality score to d, and its overlap with all the documents already selected for the node v_r satisfies the equivalence criterion, this document d_j is also added to the set of documents for

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Algorithm 1 Get Order

0: **procedure** GetOrder(doc set D, doc-topic matrix F, generality difference threshold k, overlap threshold τ, expansion node v_e)
0: **while** $D \neq 0$
0: 1. Create a set S containing the most general d in D
0: 2. Select the next most general document d_j in D
0: **while** $o(d, d_i) > \tau$ and $g(d) - g(d_i) < k$
0: **If** $o(d, d_i) > \tau$ **then** add d_j to S
0: Select the next most general document d_j in D
0: 4. S contains the most general equivalent documents
0: and it is mapped to a new node v_s
0: 5. Connect node v_s to the expansion node v_e
0: 6. Remove from D all documents belonging to S
0: 7. $C \leftarrow \{d_i \in D | o(d, d_i) > 0\}$
0: 8. Divide C into clusters D_i s.t.:
0: for each D_i it holds $o(d_i, d_j) > 0, \forall d_i, d_j \in D_i$
0: **for all** cluster D_i
0: GetOrder(D_i, F, k, $\frac{\tau}{2}$, v_s)

the node v_s. The node v_s becomes the root node for the remaining documents in the current set and it is connected to the node v_e at step 5.

The remaining steps are responsible for re-organizing the rest of the documents in groups such that each group will be used to further grow the tree in a different direction. Step 7 creates a set C of all documents that have non-zero overlap with at least the most general document d of the node v_s just created. The reason is that any document in any node at any level under v_s should have even a distant relation to the documents of v_s. Step 8 clusters C into sets D_i, such that the documents contained in each set have non-zero overlap among them. The reason is that the nodes of a tree should have some relatedness. The node v_s becomes the new expansion node. The function *GetOrder* is called for each set D_i to grow a new reading tree. Each of these trees is connected to v_e.

For simplicity in presentation, Algorithm 1 shows the case of constructing one reading tree. The algorithm builds more than one tree if required. The critical point is the output of step 7. If this is an empty set but there are still documents whose reading order has not been determined, then the algorithm starts a new set of rounds building a new tree that is connected to the dummy root node for the remaining documents.

5 Results of Experiments

5.1 Machine Learning Catalog of Wikipedia

Due to the small size of this dataset, it could be used for parameter selection. In Table 2 the optimal parameters are shown. There was revealed that optimal parameters depend only on Entropy Type instead of Topic model as we assumed, also parameter n is not mostly useful in the algorithm. Moreover, having optimal parameters τ and k and changing value of parameter n, mostly the quality of the constructed reading order does not depend on n when it is less than one, whereas the greater than one value could have adversely affect on the score, for example, Table 3 shows the dependence of the quality of the constructed reading order with LDA topic model with respect to the n parameter value for optimal parameters τ and k.

A student's paper example

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Figure 2 Reading Order Graph with PLSA topic model

	Entropy	Hierarchical Entropy
τ	0	0.1
k	0	0
n	1	1

Table 2 Optimal parameters

n	MSE
1	0.0746
2	0.0942
3	0.0911
4	0.1012
5	0.0917
6	0.0898
7	0.1066
8	0.1012
9	0.1011

Table 3 MSE values of reading orders with LDA w.r.t. n

The sample of the reading order graph with PLSA topic model is shown in Figure 2. The results of experiments for reading orders with monograms topic models are shown in Table 4. Comparing with results from [17], where entropy, as the measure of document generality, and LDA, as the only topic model, were used for English Wikipedia hierarchies of ML categories, we got approximately twice better results and revealed that applying LDA and entropy does not give the best score.

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Figure 3 Results for Machine Learning Catalog of Wikipedia

Topic model	MSE value	Execution time (sec)
hARTM	0.07967	6.96
PLSA	0.07969	10.1
ARTM	0.07980	6.91
hARTM with Hierarchical Entropy	0.07983	5.71
LDA	0.07987	6.32
ARTM with bigrams	0.07996	5.84
hARTM with bigrams	0.0799970277	4.75
hARTM with bigrams and Hierarchical Entropy	0.08018838538	2.96

Table 4 Results for Machine Learning Catalog of Wikipedia

5.2 Mathematics Catalog of Wikipedia

We tested how our approach and optimal parameters for τ, k, n scales with the number of documents. This dataset contains many more articles than the previous one and it was decided to apply bigrams selection and topic models that used them. In Table 5 the results of experiments for reading orders with optimal parameters and different topic models are presented. Unfortunately, we couldn't wait for the algorithm to finish working with the PLSA model and optimal parameters, we estimated the results according to execution times and MSE values with this topic model for fewer document collections.

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Figure 4 Results for Mathematics Catalog of Wikipedia

Topic model	MSE value	Execution time
ARTM with bigrams	0.003534	1h 5min
ARTM	0.003533	2h 28min
LDA	0.003533	2h 28min
hARTM with bigrams	0.003532	42min
hARTM	0.003531	1h 8min
hARTM with bigrams and Hierarchical Entropy	0.003529	22min
hARTM with Hierarchical Entropy	0.003528	38min
PLSA (estimation)	0.003510	$3\text{-}10^{6}$min

Table 5 Results for Mathematics Catalog of Wikipedia

6 Conclusion

Overall, there is scalability for optimal parameters of the algorithm with different topic models. Moreover, it is unnecessary to find the optimal parameters each time you change the topic model of the algorithm. They depend only on the type of entropy that you use. However, scaling does not save the rating of reading orders with different topic models. Reading orders with PLSA topic model give one of the smallest error but it is applicable only for small document collections because of its long execution time for construction. Hierarchical Entropy improves the quality of reading orders on large document collections (more than 1000 documents). For arbitrary document, it is better to use the reading order with hARTM in both execution time and MSE value. Bigrams selection worsens the MSE value of reading order but reduces construction time instead.

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Timing

- Student: 48+ hours — day weekly
- Consultant: one hour a week
- Professor: 30' to set, 30' to harvest

Profit

- Student publishes a paper, gets the proof of qualification
- Consultant gains mentorship
- Professor expands the team

The project topics

Any topic is welcome on the open access basis!

- Analysis of wearable devices' data
- Brain computer interface modelling
- Image and symbol recognition
- Synchrotron image analysis
- CERN LHCb data analysis
- Receptor-ligand docking
- Chemical reaction forecasting
- Multiscale time series forecasting
- Expert learning and knowledge distillation
- Neural architecture search
- Hyper-networks for model selection
- Model generation, processes
- Stochastic model selection
- Metaparameter optimisation
- Stochastic optimisation
- Spatial and time series alignment

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My first scientific paper