Use of Topic Modelling for Improvement of Quality in the Task of Semantic Search of Educational Courses

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Abstract—This paper proposes an approach, improving the quality of the original educational course programmes semantic search algorithm, based on vector representations, produced by distributional semantic. The proposed approach works by providing an expert with interpretable topic filtering of courses in search results. Application of probabilistic topic modeling based on additive regularization ensures the interpretability of vector components in representations of texts, allowing the expert, in the process of exploratory search, to narrow down the set of relevant documents found previously by using the vector model. In our experiments, we study the applied task of educational course search, using current requirements of the labor market (requirements described in professional standards serve as search queries). The implementation of topic filtering is based on the open-source BigARTM library. Search for training courses can be performed under the specified requirements of professional standards, which will improve the relevancy of retrieved educational content despite significant differences of vocabularies between the educational field (educational programs, online courses) and the professional field (professional standards, job requirements).

II. APPLICATION OF TOPIC MODELLING TO INFORMATION SEARCH

Topic modeling is one of the applications of machine learning to statistical text analysis. Topic models explore the hidden thematic structure of the corpus, by proposing that topic \( t \) is a probability distribution \( p(w|t) \) over words, while document \( d \) is a probability distribution \( p(t|d) \) over topics \( t \). Simply put, a topic is a collection of words, by looking at which, one could say which subject they describe. Using this approach, the number of topics becomes much smaller than the number of words in the document; therefore, a sufficiently strong compression of the document occurs, while the most essential information about its subject matter is preserved.

Currently, methods based on probabilistic topic modeling (PTM) are being actively developed. PTM defines each topic as a discrete probability distribution over a set of words, and each document, as a discrete probability distribution over a set of topics [2]. The PTM performs joint clustering or “soft-clustering” of documents and words on topics, which means that a document or a word can belong to several topics at the same time with different probabilities.

One of the applications of topic modeling is informational (exploratory) search [3, 4]. According to this concept, a document or a collection of documents acts as a
search query, and information about the subject area is generated as a response. This can be especially useful in a situation where it is not clear how to formulate a search query: in the case of the absence of words or the problem of homonyms. This approach in some cases allows forming a big picture of the subject area.

New approaches to information retrieval, based on topic modeling are currently being actively developed [5-9].

III. OVERVIEW OF TOPIC MODELLING APPROACHES

Currently, two methods and their variations are primarily used for probabilistic topic modeling: pLSA (probabilistic latent semantic analysis) and LDA (Latent Dirichlet allocation).

At the heart of pLSA [10] is an algorithm that associates hidden variables representing topics with each word and document, allowing each to be related to several topics at once, with a certain probability.

This approach is based on the formula of total probability and the hypothesis of conditional independence, according to which the distribution of terms in a document \( p(w|d) \) is described by a probabilistic mixture of distributions of terms over topics \( \varphi_{wt} = p(w|t) \) and topics over documents \( \theta_{td} = p(t|d) \).

\[
p(w|d) = \sum_{t \in T} p(w|t,d)p(t|d) = \sum_{t \in T} p(w|t)p(t|d) = \sum_{t \in T} \varphi_{wt}\theta_{td}
\]

Formula (1) describes the process of generation for a collection of topics, given \( p(w|t) \) and \( p(t|d) \), and searches for \( \varphi_{wt} \) and \( \theta_{td} \), such that the model sufficiently accurately approximates the frequency estimates of conditional probabilities. The model parameters are found by solving the likelihood maximization problem (likelihood logarithm) (2-4):

\[
\sum_{d \in D} \sum_{w \in W} \varphi_{wt} \theta_{td} \rightarrow \max_{\Phi, \Theta} \quad (2)
\]

\[
\sum_{w \in W} \varphi_{wt} = 1; \ \varphi_{wt} \geq 0 \quad (3)
\]

\[
\sum_{t \in T} \theta_{td} = 1; \ \theta_{td} \geq 0 \quad (4)
\]

This method has the following disadvantages:

- The model is prone to overfit and is not applicable to large datasets.
- It is impossible to calculate the probability for a document not from the original dataset.
- The learning process cannot be interpreted.

LDA [11] is a Bayesian version of the pLSA. This approach uses the Dirichlet a priori distribution as the topic distribution over documents and over words, which allows the model to generalize better.

LDA has the following disadvantages:

- It is not grounded in linguistics and does not model any linguistic phenomenon, and its application is dictated solely by the convenience of analytical integration in the Bayesian output;
- The bayesian approach is too complicated to combine more than 2–3 parameters.

The additive regularization approach to topic models (ARTM) [12] is based on the pLSA method. Problem (2) has an infinite set of solutions, and in the general case is solved by using the regularization mechanism, which works by adding weighted sums of regularizers to the optimization criterion. ARTM maximizes the linear combination of the likelihood logarithm (6) and regularizers \( R_i(\Phi, \Theta) \) with non-negative coefficients \( \tau_i, i = 1, \ldots, k \) (5), with consideration for non-negativity and normalization (3, 4):

\[
R_i(\Phi, \Theta) = \sum_{t=1}^k \tau_i R_i(\Phi, \Theta) \quad (5)
\]

\[
\sum_{d \in D} \sum_{w \in W} n_{dw} \ln \sum_{t \in T} \varphi_{wt} \theta_{td} \rightarrow \max_{\Phi, \Theta} + R_i(\Phi, \Theta) \quad (6)
\]

The authors of the ARTM, have proposed various sets of regularizers that increase the interpretability, sparsity, and variation in the topics, produced by the model. In a series of experiments, the level of quality was achieved, comparable if not superior to the common approaches of the word2vec family [13].

In [14], a search of online educational courses for a given text of the discipline’s programme shows that both pLSA and LDA performed worse in the task of semantic search, than the word2vec word vectors, averaged across the document and weighted by IDF (inverse document frequency). However, the neural network language models have a drawback - the lack of interpretability of vector components. In this paper, we propose to use the ARTM algorithm for additional filtering, allowing for thematic interpretation.

\[\text{Begin} \]

- Enter query \( Q \)
- Define thematic course vectors in search \( \text{Results} := \text{Search}(VM, Q, C) \)
- Define training vector model \( \text{Results} := \text{Results} \text{ \ Cr} \)
- Specify thematic filter: set relevant topics \( Tr \)
- Applying thematic filtering to semantic search for educational courses \( \text{Results} := \text{Results} \text{ \ Cr} \)

end

Fig. 1. Algorithm for applying thematic filtering to improve the quality of semantic search for educational courses.
IV. TOPIC MODELING BASED METHOD OF SEMANTIC SEARCH FOR EDUCATIONAL COURSES

Figure 1 describes the proposed method, based on topic modeling as a thematic filter, used to search for training courses according to the queries set by an expert.

Model training stage. We train vector and topic models, using the corpus of educational courses. The vector model allows searching for courses based on cosine similarity with the query [1]. The topic model generates two matrices: word distributions over topics, and topic distributions over documents. Each course is assigned its topic vector—the distribution of the probabilities of assigning topics to the course (matrix td). An example of a thematic vector is presented in Figure 2. Each topic is characterized by its list of keywords that determine the meaning of this topic and allow the expert to assess the relevance of the topic to their search query. This stage is described in more detail in paragraph 4.

Search stage. At this stage, the expert sets the query used to search for semantically similar courses, using one of the vector models [1]. The result of this stage is the ranked list of N courses, most similar to the original query.

Thematic filter preparation stage. For each course in the search results, its topic vector is determined, which, in turn, is used to select a list of key topics—topics, which the topic model considered most likely for this course.

To determine the list of key topics, it is necessary to sort the topic vector in order of decreasing probabilities of topics and select the top N topics.

However, if the variance of the topic vector is not large enough, and the number of topics with a pronounced influence in the thematic vector is less than N, then the topics with relatively small influence could find their way into the list of key topics, which in turn can adversely affect the quality of thematic filtering. To avoid this, we propose the introduction of an additional lower constraint—a k-average of a topic vector. This parameter is determined as the average of the topic vector, multiplied by the coefficient k.

An experiment for the calculation of N and k_avg is described in paragraph 5.2.

As a result, for each query, a list of the most frequently encountered key course topics is compiled, which is displayed to the expert as a list of keywords. The expert can then select a number of the most relevant topics for a given query by keyword, and apply a thematic filter.

Filtering stage. For each course, a list of key topics is compared with a list of the most relevant topics, as selected by the expert. For the final list of search results, only courses, which have at least one relevant topic, are selected.

The described method of thematic filtering allows the expert to influence the final search results, and to order the courses based on the topics he selects. The main advantage of this approach is the interpretability of topics chosen by an expert, which allows for more intelligent and detailed control over the search.

V. TOPIC MODEL CONSTRUCTION

A. Description of the text corpus of educational courses used by the topic model

A text corpus of 3027 educational courses was used to train the topic model. The main characteristics of the dataset are presented in Table 1.

Table 2 presents the detailed data on the MOOC platforms and the corpus of educational course programmes, collected from the websites of 10 large Russian universities for disciplines, related to information technology.

| Corpus                  | Number of sources | Number of documents (training courses) | Number of tokens | Number of unique tokens (vocabulary) |
|-------------------------|-------------------|---------------------------------------|-----------------|-------------------------------------|
| MOOC Corpus             | 4 MOOC-platforms  | 2051                                  | 249k            | 14k                                 |
| Educational Courses     | 10 universities   | 976                                   | 351k            | 16k                                 |
| Total                   | 14                | 3027                                  | 600k            | 23k                                 |

B. Description of topic model training approach

All texts go through a preprocessing stage: deletion of non-textual characters, lowering character’s case, lemmatization using pymorphy2 library, and removal of stopwords. After that, the texts are converted to UCI-Bag-of-words format acceptable by the BigARTM.

In the process of learning, a list of regularizers and a list of results (perplexion and sparsity of the word (Φ) and document matrices (Θ), purity and size of the core, coherence) are selected, which control the quality of the model’s training.

Determining the number of topics

One of the most important parameters of a topic model is the number of topics into which words and documents are to be distributed. The number of topics should be sufficient to provide enough of a variety, yet not too large so that the topics retain enough specificity of the subject area and could be easily interpreted by the expert.
Interpretability is very difficult to formalize. In papers [14-16], the mechanism for assessing interpretability—coherence—is proposed. This estimate is based on a pointwise mutual information formula (PMI) of the k most likely words from a topic, that are found together in documents. This assessment is best correlated with expert estimates of interpretability. Model coherence is thus defined as the average for all topics.

1) Selection of regularizers

Combining and selecting regularizer parameters is a complex empirical task. By selecting a combination of a regularizer and regularization coefficients, it is possible to significantly improve sparseness, contrast, purity, and coherence at the same time with a slight loss of credibility of the model, as well as an improvement of the topic interpretability.

Smoothing and increasing the sparsity of matrices $\Phi$ and $\Theta$ (SmoothSparsePhi, SmoothSparseTheta), as well as decorrelation of terms (DecorrelatorPhi) are recommended as primary and most common regularizers. The increase in the sparsity of matrices $\Phi$ and $\Theta$, leads to the reduction of weak components and an increase in the proportion of stronger ones. DecorrelatorPhi also acts to increase model sparsity, however, it does so in such a way that each topic aggregates words that are not found in other topics, making the topics differ more from each other.

A combination of these regularizers was used for topic exploratory search [17]. It turned out that it significantly improves the overall quality of search results.

To assess the impact of the regularization, 4 thematic models with different regularization parameters were used (Table 3).

Figure 2 describes an example of a topic vector for the course “Computer Science and Programming”. Among the topics, that make the greatest contribution to this vector, are the following topics: 9, 16, 32, 48, 49. The list of keywords for these topics is provided in table 4.

### Table III. Topic Models

| #  | Title                  | Smooth Sparse Phi | Smooth Sparse Theta | Decorrelator or Phi |
|----|------------------------|-------------------|---------------------|---------------------|
| 1  | 60_0_0_0               | 0                 | 0                   | 0                   |
| 2  | 60_-0_02_-0_3_2500    | -0_2              | -0_3                | 2500                |
| 3  | 60_-0_02_-0_5_5000    | -0_2              | -0_5                | 5000                |
| 4  | 60_-0_02_-1_10000    | -0_2              | -1                  | 10000               |

### Table IV. Key Words for Key Topics for the Course “Computer Science and Programming”

| № theme | Russian                      | English                                  |
|---------|------------------------------|------------------------------------------|
| 9       | класс, ориентировать, язык, программа, объектный, среда, java, основа, разработка, объект | class, orient, language, program, object, environment, java, basis, development, object |
| 16      | базовый, основа, изучение, основной, практический, сложный, использовать, программа, студент, практика | basic, basis, learning, basic, practical, complex, use, program, student, practice |
| 32      | алгоритм, структура, сложность, реализация, поиск, дерево, задача, алгоритмический, сортировка, операция | algorithm, structure, complexity, implementation, search, tree, task, algorithmic, sorting, operation |
| 48      | дисциплина, область, метод, навык, студент, цель, умение, вид, основной, формирование | discipline, area, method, skill, student, goal, skill, type, basic, formation |
| 49      | программирование, язык, функциональный, программа, тип, введение, стандартный, пример, выражение, структура | programming, language, functional, program, type, introduction, standard, example, expression, structure |

### Perplexity shows the rate of convergence for the model. It is based on the likelihood logarithm and characterizes how well the corpus is described by the model.

D. Assessing quality of the topic model

To assess the quality of topic models, a combined approach of internal and external metrics is used.

The main internal quality estimates of the model are, the sparsity of matrices $\Phi$ and $\Theta$, and parameters of the topic cores (topic_kerrnel_score).
Figure 3 shows that while learning, perplexity converges fairly quickly. This is because the size of the dataset is relatively small, and the topic model manages to quickly learn a given number of topics. Figure 4 shows a coherence plot for different numbers of topics. Models with the size of topic vector 40 and 60 achieved the best result. According to the aggregate estimation of experts and the average coherence plots, the total size of the topic vector was set to 60. This size of the topic vector allows obtaining sufficiently informative and human-interpretable topics. Examples of keywords are provided in table 4.

Figure 5 presents the evaluation of the sparsity of matrices $\Phi$ and $\Theta$ (SparsityPhi on the left and SparsityTheta on the right). From the results of our experiments, we can note that the value of the SmoothSparsePhi regularizer below -0.02 does not lead to a greater increase in the sparsity of the matrix $\Phi$. At the same time, if SmoothSparsePhi is within the range [0, -1], it allows for the sparsity of the matrix $\Theta$ to reach 49%.

Figures 6 and 7 show that regularization has almost no effect on the average core size of topics, and holds very little improvements to the average contrast and purity of topics. This suggests that even without the regularization of the topic model, we managed to learn quite well from this corpus of text documents.

**External evaluation of the quality of the topic model** include the degree of suitability of the topic model to some “external” task; in our case, this task was the task of the semantic search for educational courses, fitting the requirements of professional standards. The following describes an experiment on the external quality assessment of the topic model applied to this task.
B. Description of the evaluation method

To evaluate the quality of the topic models as a thematic filter, we propose to consider a selection of relevant courses and the filtering of irrelevant courses as an assessment of the quality in the task of classifying courses by relevance for topic models with varying degrees of regularization.

Fig. 7. Average contrast (top) and average purity (bottom) depending on the degree of regularization

VI. EVALUATION OF TOPIC FILTERING IN THE TASK OF SEMANTIC SEARCH FOR COURSES

A. Dataset description

To evaluate the quality of the topic model, we used a dataset, which was assembled in 2 stages.

During the first stage, several vector models were prepared (see Table 1), which were used to determine the list of the most similar courses for each of the queries. The queries were the general functions of the three professional standards (professions): “Programmer”, “Information Systems Specialist”, “Information and Communication Systems Systems Administrator” (hereinafter referred to as queries).

TABLE V. GRADED DATASET

| Model     | Unique queries <90% | Grades course-query |
|-----------|---------------------|---------------------|
| w2v_d300  | 17 / 28             | 536                 |
| tfidf     | 22 / 28             | 472                 |
| fasttext  | 12 / 28             | 407                 |

For the second stage, the experts evaluated the similarity in course-query pairs for each vector model (using a five-point scale: 5 - texts are similar, 1 - texts are very dissimilar). For each query, lists of relevant (with estimates 5, 4, 3) and irrelevant courses (with estimates 2, 1) were formed. To evaluate the thematic filter, we have only used those queries, which had the proportion of relevant courses less than 90%. (see table 5), i.e. queries in which vector models made the greatest number of errors.

Fig. 8. Aggregated query topic vector

Each element of this aggregated topic vector can be assigned one of the 4 classes of topic relevance:

For \(|P_R| \geq |P_I| & |P_I| = 0\) \(\Rightarrow t \in T_{R^+}\), where \(t\) - a topic of a query topic vector, \(T_{R^+}\) - set of topics, consisting mostly of key topics of relevant courses.

For \(|P_R| < |P_I| \& |P_I| \neq 0\) \(\Rightarrow t \in T_{I^{-}}\), where \(t\) - a topic of a query topic vector, \(T_{I^{-}}\) - set of topics, consisting mostly of key topics of relevant courses.

For \(|P_R| < |P_I| \& |P_I| = 0\) \(\Rightarrow t \in T_{I}\), where \(t\) - a topic of a query topic vector, \(T_{I}\) - set of topics, consisting only of key topics of irrelevant courses.

For \(|P_R| \geq |P_I| \& |P_I| \neq 0\) \(\Rightarrow t \in T_{R^{-}}\), where \(t\) - a topic of a query topic vector, \(T_{R^{-}}\) - set of topics, consisting only of key topics of relevant courses.

After this, the courses of the query are clustered based on the clustering of the key topics of the course by the relevance classes of topics (8-11).

\[ c \in C_R \Rightarrow (c, t_c) \in P_R ; c \in C_I \Rightarrow (c, t_c) \in P_I \quad (7) \]

where \(c\) - course query, \(C_R\) - set of relevant courses, \(C_I\) - set of irrelevant courses, \(t_c\) - key topic of the course, \(P_R\) - set of relevant pairs \((c, t_c)\) - for topic \(t_c\) of aggregated query topic vector, \(P_I\) - set of irrelevant pairs \((c, t_c)\) - for topic \(t_c\) of aggregated query topic vector.
TABLE VI.  THE DISTRIBUTION OF COURSES BY TOPIC RELEVANCE 

| Classes          | actual | predicted |
|------------------|--------|-----------|
| Relevant         | $C_R^+$| $C_{R'}$  |
| Irrelevant       | $C_I^-$| $C_{I'}$  |

Then, the main metrics for evaluating the quality of clustering were calculated (12-15):

\[
\text{accuracy} = \frac{(C_R^+ + C_I')/(C_R + C_I)}{(C_R + C_I)} \tag{12}
\]

\[
\text{recall} = C_R' / C_R \tag{13}
\]

\[
\text{precision} = C_R' / (C_R + C_{I'}) \tag{14}
\]

\[
\text{F1-score} = 2 \ast (\text{precision} \ast \text{recall})/(\text{precision} \ast \text{recall}) \tag{15}
\]

As a base evaluation, we used the ratio of relevant courses to the entire set of courses was used:

\[
\text{init}\_\text{precision} = C_R / (C_R + C_I) \tag{16}
\]

C. Determining hyperparameters for the calculation of the number of key course topics

The results of the hyperparameter selection for the topic model, according to the method described in paragraph 5.2.1, for model 3 with average regularization.

From the plots in figure 9 we note optimal criteria for key topics of courses selection: max_themes = 3, k_avg = 3. The described method allows for the selection of the most effective number of key topics for each course.

D. Evaluation of semantic search for educational courses with thematic filtering

Based on the method described in paragraph 5.2. we calculate the quality of topic models with different degrees of regularization in comparison with vector models. The results are presented in Table 7.

From Table 7 we can see the effect regularization has on improving the quality, however, if thematic models 1, 2, and 3 with moderate regularization show a stable quality improvement, then thematic model 4 with high regularization parameters for the TF-IDF vector model shows a slight degradation. It can also be noted that the lower the base estimate of the vector model (init_precision) is, the higher the gain from the use of topic modeling in these models becomes, i.e. it can be said that topic modeling in several cases has corrected the deficiencies of vector models.

Figure 10 shows, using the example of topic models with different degrees of regularization, the effect of regularization on the final quality of the thematic classification of courses according to classes of topics. It can be noted that moderate regularization leads to an improvement in the quality of the topic model, while excessive regularization can lead to a decrease in quality.

![Fig. 9. Average F1-score for different topic models](image1)

Table 8 presents the results of issuing the fasttext vector model and thematic filter for the request “Software Design”.

VII. CONCLUSION

In this paper, a thematic filtering method based on the ARTM topic modeling algorithm is proposed. We show that the use of topic modeling as a thematic filter improves the quality of the semantic search for educational courses for specific requirements of professional standards. Results show that the improvement in the search task occurred for all vector models, and the more the vector model was mistaken before applying the filter, the more tangible was the positive effect of it. The use of moderate regularization during the training of the topic model also has a positive effect on the quality of thematic filtering. In the future, the authors plan to develop a thematic filtering algorithm and add possible ranking of courses in search results by specifying not only relevant but also irrelevant topics.

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TABLE VII. AVERAGE ESTIMATES OF THEMATIC CLASSIFICATION FOR QUERIES

| Topic     | Vector model | F1-score   | Precision | Recall         | Average top query count C来±C允许 |
|-----------|--------------|------------|-----------|----------------|-------------------------------|
| Model 1   | fasttext     | 0.9437 (+0.1526) | 0.9289 (+0.2691) | 0.9673 (-0.0327) | 9.00                          |
|           | tfidf        | 0.8717 (+0.1095) | 0.8432 (+0.2818) | 0.9172 (-0.0828) | 10.14                         |
|           | w2v          | 0.8956 (+0.052)  | 0.8828 (+0.1395) | 0.9484 (-0.0516) | 13.59                         |
| Model 2   | fasttext     | 0.9426 (+0.1516) | 0.9164 (+0.2626) | 0.9792 (-0.0208) | 9.08                          |
|           | tfidf        | 0.8820 (+0.1203) | 0.8304 (+0.2873) | 0.9473 (-0.0527) | 10.32                         |
|           | w2v          | 0.9074 (+0.0861) | 0.8775 (+0.1411) | 0.9614 (-0.0386) | 13.71                         |
| Model 3   | fasttext     | 0.9544 (+0.1634) | 0.9262 (+0.2735) | 0.9896 (-0.0104) | 9.17                          |
|           | tfidf        | 0.8884 (+0.1261) | 0.8619 (+0.3007) | 0.9223 (-0.0777) | 10.18                         |
|           | w2v          | 0.9225 (+0.0789) | 0.8835 (+0.1551) | 0.972 (+0.028)    | 13.76                         |
| Model 4   | fasttext     | 0.9555 (+0.1645) | 0.9163 (+0.2777) | 1.0000 (0.0000)  | 9.25                          |
|           | tfidf        | 0.8753 (+0.1131) | 0.8525 (+0.2872) | 0.9162 (-0.0838) | 10.18                         |
|           | w2v          | 0.9293 (+0.0834) | 0.8876 (+0.1606) | 0.9785 (+0.0215) | 13.82                         |

TABLE VIII. RESULTS OF RUNNING THE FASTTEXT VECTOR MODEL AND THEMATIC FILTER FOR THE REQUEST “ПРОЕКТИРОВАНИЕ ПРОГРАММНОГО ОБЕСПЕЧЕНИЯ” (“SOFTWARE DESIGN”)

| Name_course                        | Filtered |
|------------------------------------|----------|
| Анализ и проектирование систем управления (Analysis and design of control systems) | +        |
| Технологии разработки программного продукта (Software development technologies) | +        |
| Анализ требований к программному обеспечению (Analysis of software requirements) | +        |
| Проектирование программных систем (Design of software systems) | +        |
| Технологии разработки программного обеспечения (Software development technologies) | +        |
| Программная инженерия (Software engineering) | +        |
| Верификация и аттестация программного обеспечения (Software verification and certification) | -        |
| Тестирование программного обеспечения (Software testing) | -        |
| Тестирование и отладка программного обеспечения (Software testing and debugging) | -        |
| Методы тестирования программного обеспечения (Software testing methods) | -        |
| Тестирование программного обеспечения (Software testing) | -        |
| Документирование и сертификация (Documentation and certification) | -        |

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