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Issue **Article**

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THE EXTRACTING METHOD OF AUTOMATIC ANNOTATION OF TEXTS BASED ON ARTIFICIAL NEURAL NETWORKS

Abstract*: The purpose of this article is to develop and study an extracting method for automatically annotating texts in languages with free word order and morphological complexity (for example, in Russian). The proposed method is based on the use of artificial neural networks. The task of the artificial neural network is to determine the key sentences of the text based on the properties of the sentence to decide on the inclusion of sentences in the annotation.*

Key words*: text annotation, neural networks, machine learning.*
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Introduction

The tasks of automatic summarization of texts appeared many years ago, and the growing volume of information on the Internet and not only requires the presentation of this information in a compressed form every day. Since such an amount of information cannot be processed manually by a person, at least this process is very laborious and time-consuming, in recent years work on the creation of automatic summarization of texts in natural language has become more and more in demand.

Thus, the tasks of abstracting texts have recently become more and more relevant both for the Internet and for other repositories of information, for example, libraries or knowledge bases of various organizations.

A summarization text helps to highlight key parts of the text and reduce the amount of information viewed.

The huge amount and large volume of materials makes it difficult to quickly obtain summarization from texts, since the formation of brief, concise summaries manually requires a significant investment of time and human resources.

In connection with the foregoing, the task of implementing effective methods of automatic summarization of texts is becoming increasingly important.

One of the main tasks of working with texts is its compression that is, reducing the volume of the original text and presenting information in the form of a shorter text, but with the preservation of the main idea, meaning. It is necessary, when constructing a secondary text (summarization), to ensure its integrity and coherence.

Analysis of recent research and publications

From the very beginning of the active use of first-generation electronic computers, that is, from the mid-fifties of the last century, attempts have been made to solve natural-language text processing problems. One of the first tasks in processing natural language texts using computers was automatic summarization.

Since then, a lot of research has been done on the development of automated methods and models for summarization [1,2]. Solving the problem involved such researchers as N.V. Lukashevich, R.G. Piotrovsky, P.G. Osminin, S.A. Trevgoda, V.A. Yatsko H.P. Luhn, H.P. Edmundson, R. Mihalcea, J. Kupiec, E. Lloret, G. Salton and others.

Currently, there are two main approaches to automatic summarization:

- extraction - extraction methods based on the extraction of the most informative fragments from primary documents [3];
- abstraction - generating methods involving the creation of a new text summarizing primary documents [4].

Extractive methods work by identifying the most important pieces of text (sentences, paragraphs). At the same time, these fragments do not process, but are extracted in the order and form in which they are given in the text. The main difficulties associated with this approach are to determine the key sentences of the text, and then link these sentences into a single, readable text.

Extractive methods can be divided into two large groups:

- superficial methods that do not resort to complex linguistic analysis, and
- deep methods.
- Surface methods include, for example:
- methods that use statistical characteristics to select proposals [5, 6];
- methods based on the presentation of the document in the form of a graph whose vertices are sentences or words from the text [7];
- methods using decision trees, reference vectors and neural networks [8];
- methods based on hidden Markov models in which the analysis of the proposal takes into account whether the previous proposal is included in the annotation [9].

Deep methods include, for example, methods using latent semantic analysis, which analyze the relationship between text sentences and the terms contained in them, identify topics in the text, and select a certain number of sentences from each topic in the annotation [10].

Generating methods, unlike extracting methods, are aimed at creating new material that is clearly not represented in the text of the source document. In other words, they interpret and examine the text using natural language processing methods to create new structural units of text that convey the most important information from the source document. When using generating methods, the text of the summarization is based on the rules assuming the presence of a linguistic knowledge base.

For generating methods, several directions can be distinguished:

- use of templates,
- compression of offers,
- full abstraction.

Template-based approaches use pre-prepared templates to present a document. Linguistic patterns or extraction rules are used to fill in the gaps in this template.

Compressive methods extract the most important sentences from the text, but either remove excess information from them or combine several sentences while trying to preserve the coherence and meaning of the text.

Existing works on this topic offer various ways to solve this problem, for example, in the source document is presented as a nested tree, which consists of two types of structures: a document tree and a sentence tree [11]. This tree is built on the basis of the theory of rhetorical structure, developed in the 1980s by American linguists William Mann and Sandra Thompson. This theory offers a description of the structure of discourse (text) in the form of networks of discursive units connected by semantic relations [12]. The theory of rhetorical structure is used to construct an algorithm for annotating the text also in [13].

For full-fledged summarization, the encoder-decoder model looks most promising, which is based on the use of recurrent-rent neural networks.

The authors of the articleQicai Wang, Peiyu Liu 1, Zhenfang Zhu, Hongxia Yin , Qiuyue Zhang and Lindong Zhang propose an approach based on combining two methods of abstract and extractive [14].

The abstract method allows you to highlight the main idea and convey the meaning in other words (generates words that are missing in the source text, but the meaning is preserved), this is often more advantageous, since fewer words can be used, unlike the extractive method, which allows you to select important information and combine it into a short text. Each of these methods has its advantages and disadvantages.

The authors proposed to combine these two approaches using BERT. They suggest using BERT as a token encoder for words and sentences. First, they pre-trained their submodels-an abstractor and an extractor, then they trained an end-to-end model using REINFORCEMENT LEARNING, which can connect submodels. In general, the entire model consists of combined submodels, an extraction agent and an abstraction agent.

Abstract methods perform quite well due to the generation of new words, they can cause information loss with large source texts and require a lot of resources for processing.

In another article, the authors Rajeev Kumar Singh, Sonia Khetarpaul, Rohan Gorantla, Sai Giridhar Allada raise the issue of generating selling headlines, which has a huge role in modern realities [15]. To extract the main idea from the article, they propose the following approach, just like the authors of the article discussed above, they propose combining two methods of extractive and abstract, but they suggest using the SHEG methodology, which is a generator that produces both an accurate summary and the title of a news article.

The proposed hybrid model includes: an extractive mechanism for identifying key sentences or phrases from an article and an abstract mechanism that uses key sentences to form a short summary.

Zinovyeva A.Yu., Sheremetyeva S.O., Nerucheva E.D. in their article "Analysis of the ambiguity of the conceptual markup of a Russian-language text" raise the problem of ambiguity arising at the conceptual level of text markup. With this approach, texts are assigned labels related to a specific subject area. This approach allows you to identify different from the general semantic types of ambiguities, which may have characteristics that depend on a particular language, as well as inherent in all natural languages.

The proposed technique includes a combination of statistical and qualitative analysis of the corpus material, as well as the use of pre-created resources [16].

For the automatic summarization of texts, special parser systems are required; today there are a large number of such programs, but most of them work with texts in English.

The main parsers for working with the Russian language today are: AOT, Mystem TreeTagger, Pymorphy2, CrossMorphy, Tomita parser [17].

Tomita parser is a tool for extracting data from natural language texts.

Tomita parser has an open source, works with the Russian language. This tool has proven itself well in working with Yandex-news and Yandex-work, as well as in other projects.

It works on the basis of the GLR parsing algorithm. Also, the big plus of this parser is that it works with Windows, OS X and Linux.

Unresolved parts of a common problem

Despite the many studies conducted, the problem of developing formal methods and models for automatic summarization has not yet been solved, due to the fact that the task of formalizing a natural language is quite laborious, and the language itself is ambiguous, unlimited, and evolutionary.

The above characteristics of the natural language play a particularly important role in the study of texts in languages that are characterized by free word order and morphological complexity (for example, for the Russian language) [18].

In addition to the various difficulties associated with word formation, the construction of sentences, the texts also have different styles. Typically, the following functional styles are distinguished [18]:

- colloquial,
- literary and artistic,
- newspaper and journalistic,
- scientific.

Language is a set of symbols, language is a sign system, that is, it consists of signs that are united into relations within the system, while signs have a definite place in relations and relations lose their meaning if signs are not in their place. The function of the language system is to help in transmitting information, as well as storing information and generating information [18].

The Russian language has a very high inflection point, as well as a large number of exceptions. Also in the Russian language there are 9 cases of nouns, adjectives have short forms, and there is no form of verbs in the present tense.

Another difficulty is the presence of homonyms in the language, that is, words that have the same form (consist of the same sequence of symbols) but at the same time have a different set of morphological characteristics.

Currently, of the methods of automatic summarization of texts in languages with free word order and morphological complexity, the most common are various statistical and graph methods, which are representatives of the extracting approach. Summarization obtained using extracting approaches are often characterized by insufficient text quality and incoherence. Abstracting approaches are potentially capable of providing better text quality for summarization, but they are extremely difficult to implement and are at the level of research.

Since most texts have a fairly pronounced structure, the key parts of the document can be represented by selecting sentences based on their properties and characteristics. A similar approach was proposed and such methods of machine learning with a teacher were considered for solving automatic summarization problems, such as the naive Bayes classifier and the support vector method [19]. The researcher obtained encouraging results, therefore, in this article it was decided to use the aforementioned extractive approach to automatically summarization texts in Russian, only artificial neural networks were chosen as a classifier, unlike [19].

The difficulty of summarization texts in the Slavic languages, such as Russian, Ukrainian, Belarusian, as well as, for example, Czech, Serbian, Romanian, etc., is that the word order in sentences in these languages does not have a clear, fixed sequence, unlike English, where the place of each member of the sentence is clearly defined. In texts written in the languages of the Slavic group, words can stand in different places of the sentence, but the meaning does not change from this.

Such features should be taken into account when developing systems for automatic summarization of texts in natural language. It is these features that the method proposed in this article takes into account. But more than 400 million people speak languages belonging to the Slavic language group.

In the Russian language, endings that can take many forms play an important role, unlike in English, where the verb has the main role. If in English it is enough to know the verb form to determine the meaning of a sentence, then in Russian and other languages of this group, it is often necessary to take into account complementary words, such as:

- "already",
- "now",
- "at the moment (there are even 3 words)", etc.

In English, a predicate cannot exist without a subject, and in Russian it can, can stand in different parts of a sentence without changing the meaning. All this complicates the automatic summarization of texts and requires a special approach.

The purpose of the article

Development of a method for automatic summarization of texts in morphologically complex languages with a free word order based on the extraction of the most significant elements from the text using artificial neural networks.

Statement of the main material

The proposed method assumes that the source document is a set of sentences, and the sentences themselves are considered as a set of properties and characteristics. Among this set, those sentences are selected that the neural network considers more relevant. The result is a subset of the source text sentences.

The first thing to do is:

- determine the considered properties and characteristics of the proposals, the values of which will be the input data for the neural network;
- create a labeled test case of texts for subsequent training of the neural network;
- produce directly the training network itself.

Determination of properties and characteristics of proposals under consideration

Each sentence of the annotated text is represented as a vector consisting of 6 characteristics [f_1, f_2, ..., f_6,]:

- the ratio of the serial number of the paragraph to which the proposal belongs to the total number of paragraphs of the source document (f_1);
- the ratio of the sequence number of the sentence in the paragraph to the total number of sentences in the paragraph (f_2);
- the ratio of the number of characters of the sentence in question to the number of characters of the longest sentence of the text (f_3);
- the ratio of the number of keywords in the sentence to the total number of thematic words of the sentence (f_4);
- the ratio of the number of matching thematic words of the given sentence and the previous one to the total number of thematic words of the considered sentences (f_5);
- the ratio of the number of matching thematic words of the given sentence and the previous one to the total number of thematic words of the two considered sentences (f_5);
- the ratio of the number of matching thematic words of the given sentence and the subsequent to the total number of thematic words of the two considered sentences (f_6).

Properties f_1-f_2 are based on the location of the sentence in the document or in its paragraph. It is expected that these parameters will contribute to the selection of key sentences, since the summarization consisting of the first sentences of the paragraphs are superior to the summarization made using other methods of the article wrote by Brandow, R., Mitze, K., & Rau, L. F. [20]. And the sentences located at the beginning and end of the paragraphs have a high chance of getting into the final text [21].

Property f_3 will help get rid of too short introductory sentences that are unlikely to fall into the summarization [22].

The f_4 property depends on the number of keywords and thematic words in the sentence. Thematic words are obtained as follows: from a document, all nouns, adjectives and verbs are selected, which subsequently reduces to their initial form. For the resulting set of words, their occurrence in the text is calculated. Keywords are considered 25% of thematic words, but not more than 10, which corresponds to the amount of RAM in humans [23]. It is expected that with the help of this property the probability of choosing key sentences will increase, since the terms that are often found in the document are probably related to its theme [5]. To highlight thematic words, Tomita-parser of Yandex was used*.

Properties f_5-f_6 are based on symmetrical summarization, that is, on determining the number of connections between sentences [24].

* Tomita parser Documentation. Developer's Guide. Available: https://tech.yandex.ru/tomita/doc/ dg/concept/about-docpage/

The considered properties can be changed or supplemented. The choice of the proposed properties of the proposals determines which proposals will be included in the final annotation and affect the operation of the neural network.

Neural network training

Neural network training is conducted to study the types of sentences that should be included in the summarization. Training is conducted on the test case of texts, where each sentence is marked as part of the summarization or not.

The neural network is looking for patterns inherent in sentences that should be included in the summarization. A neural network of direct propagation with three layers is used, which, as has been proved, is a universal functional approximator [25]. The network can detect patterns and approximate the function of any data with an accuracy of 100% if there are no contradictions in the data set.

The creation of a neural network was carried out in NeurophStudio (Java neural network framework). The input layer of the developed neural network consists of six neurons, where each neuron corresponds to one of the properties of the proposal, five neurons of the hidden layer and one neuron of the output layer. A sigmoid is used as an activation function, network training is carried out by the method of back propagation of error.

Neurophstudio is a software environment for building and training Java neural networks. Based on the NetBeans Platform. Neurophstudio contains the following neural network architectures, such as: Kohonen, Hopfield, Hebb, RBF, Kosko, Convolutional networks, as well as Adaptive Linear Neuron and perceptrons.

Since Neuroph works with the Java programming language library, the NetBeans IDE, an integrated development environment, was chosen for development.

To create a test case, 62 articles on various topics found on the Internet were used. Each text consisted of 27 to 102 sentences, on average - of 49. In total, 3076 sentences were analyzed. 565 sentences were marked as key, with an average of 9 per text. The neural network was successfully trained in 23 iterations.

The resulting standard error for the test case was 0.16733. The accuracy of the neural network was 88.76% compared to manual sampling for the test case. For a corpus of 10 new texts, the accuracy was 82.31%.

System performance assessment

The task of evaluating the effectiveness of automatic summarization of texts is also extremely important and complex. There is no general algorithm for evaluating annotations based on a finite set of features and rules; therefore, modern approaches to evaluating the results of automatic summarization are based on a comparison of automatically received summarization with model summarization manually created.

To compare automatically received summarization with manually obtained summarization, a set of ROUGE (Recall-Oriented Understudy for Gisting Evaluation) metrics is usually used [26].

All metrics in this set are based on the idea of maximum coverage by automatic summarization of manual ones and vice versa. N-grams are used to calculate coverage. An N-gram is a sequence of N elements, in this case words.

Evaluation of the implemented software system was carried out using the metrics ROUGE-1 and ROUGE-2, based on the analysis of sequences of one and two words, respectively.

For example, for the sentence “мама мыла раму”, one can single out such unigrams (N = 1), such as «мама, мыла, раму», frame. For the same sentence, you can extract the following bigrams (N = 2): «мама мыла, мыла раму». The sentences are presented in Russian, since in this context it is necessary to take into account the possibilities of this language, the features of the construction of sentences, in this case, the order of words is important, since with different order of sequence and their repetition, the meaning of the original text remains the same.

By itself, the number of matching N-grams of automatic and model summarization is not an estimate of the effectiveness of the result of automatic summarization.

To evaluate metrics, the following characteristics are used:

- ROUGE Precision;
- ROUGE Recall;
- F-measure.

The Rouge Precision feature is an assessment of how well model summarization cover automatic summarization. It is calculated by the formula:

$$Precision = \frac{C_N}{M_N},$$

where C_N is the number of matching N-grams;

M_N is the total number of N-grams of model summarization.

Characteristic Rouge Recall (completeness) - assessment of how well the automatic model summarization covers. It is calculated by the formula:

$$Recall = \frac{C_N}{A_N},$$

where C_N is the number of matching N-grams;

A_N is the total number of N-grams of automatic annotation.

Obviously, the higher the accuracy and completeness, the better. But in practice, maximum accuracy and completeness are not achievable, therefore, to combine information on accuracy and completeness, an F-measure is calculated:

$$F = \frac{2 * Precision * Recall}{Precision + Recall},$$

where F is the harmonic mean of accuracy and completeness.

The F-measure acts as the final value of the metric, reflecting the quality of the received summarization.

For example, manual annotation is represented by the sentence “мама мыла раму”, and automatic annotation - “мама мыла наше окно”, the values of the ROUGE-1 and ROUGE-2 metrics calculated by formulas (1) - (3) can be seen in Table. 1.

Table 1. Example of calculating ROUGE-1 and ROUGE-2 metrics

Metrics	Precision	Recall	F-мера
ROUGE-1	2/3 ≈ 0,67	2/4 =0,5	0,57
ROUGE-2	1/2 = 0,5	1/3 ≈ 0,33	0,4

To create a test case for assessing the effectiveness of the implemented system, 10 articles on various topics found on the Internet were used. The selected texts included from 18 to 94 sentences, an average of 35. Model annotations were written manually for each text. In total, 363 sentences were analyzed, 102 of them were marked as sentences included in the summary summarization, on average 10 per text.

The effectiveness of the implemented system was evaluated on a test set of documents by comparing model and automatic summarization using the ROUGE-1 and ROUGE-2 metrics. The maximum possible characteristic value is 1.

The evaluation results can be seen in Table 2.

Table 2. The results of the evaluation of the implemented system

Metrics	Precision	Recall	F- measure
ROUGE-1	0,61	0,32	0,42
ROUGE-2	0,23	0,12	0,16

In accordance with the fact that the F-measure is the final indicator of metrics, it is necessary to analyze this result. Based on the fact that the F-measure of the ROUGE-1 metric is relatively close to 1, we can conclude that automatic and manual summarization were quite close in terms of the set of words.

The readings of the F-measure of the ROUGE-2 metric are slightly worse. The results are justified due to the complexity of teaching a computer to understand natural language. In order to carry out a full-fledged analysis of the effectiveness of the system and formulate conclusions about its applicability, we compared the metrics of the ROUGE-1 and ROUGE-2 metrics obtained in this paper with the metrics of these metrics of existing tools. For comparison, automatic text summarization systems were selected that have shown the best results to date: [27], [28], [19].

The results of the system considered in this paper are presented in the last row of the Table 3.

Table 3. Comparison of indicators of an implemented system with indicators of existing systems

Author, year	ROUGE-1	ROUGE-2
Nallapati, 2017	0,39	0,16
See, 2017	0,39	0,17
Wong K., 2008	0,42	0,12
Proposed system, 2019	**0,42**	**0,16**

As can be seen from the Table 2, the implemented system exceeded the existing ones, showing the highest result for the ROUGE-1 metric and practically the best for the ROUGE-2 metric, which means that our system provides better automatic summarization than other systems. The results obtained allow us to confirm the applicability of the developed method for summarization texts in Russian, as well as to continue further research.

Subsequently, complication of the topology of the neural network is possible, as well as a change or addition of the characteristics of the proposals under consideration to improve the quality of summarization.

The characteristics selected for the analysis of proposals, as well as manually created training and test samples, have a great influence on the operation of the neural network, and, consequently, the entire system. The network is trained in accordance with the reader's style and in accordance with sentences that this reader considers suitable for annotation. You can consider this feature as an advantage of this approach, since any person can train the neural network in accordance with their personal preferences.

The following describes the algorithm of the system.

The algorithm of operation is shown in Figure 1

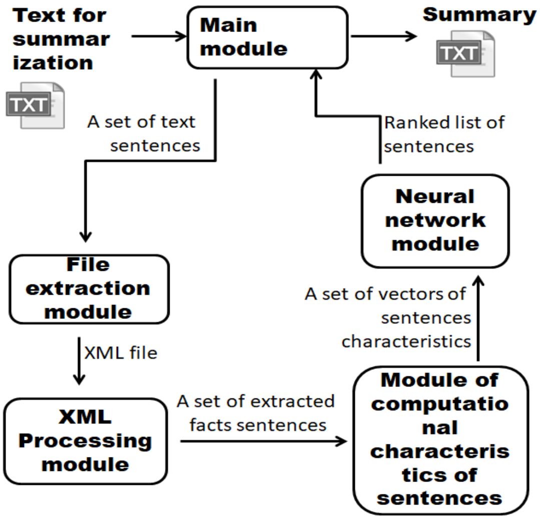

Figure - 1 The algorithm of operation

This section describes the algorithm of the system using the proposed method.

It is assumed that first of all, the user will need to copy the text that is to be annotated to the data entry area, where you also need to specify the percentage that should result from the annotation from the source text.

The second stage is the splitting of the text into paragraphs and sentences, this happens in the main module.

Then, the resulting result is fed to the file extraction module, where the tomita parser is processed, the result of this module is the generation of an XML file that will contain a set of structured facts.

The next stage is the stage of processing the XML file, the output is a set of facts of proposals.

Next, in the module for calculating characteristics, data is generated for feeding to the neural network.

The neural network module receives data and processes it using the described methods of creating, training, and saving a neural network. The output is a ranked list of offers.

In the final stage, an abstract is formed from the set of pre-orders obtained at the previous stage.

Conclusions

In this work, the features of annotating texts related to the Romance language group were considered, using the example of working with texts in Russian, which is difficult for automatic annotation due to such features as free word order, the presence of a large number of cases, etc.

Modern approaches were analyzed and a method of automatic annotation based on the apparatus of neural networks was proposed.

The accuracy of the results of the proposed method of automatic summarization of texts on a test sample was 88.76%. The results were quite satisfactory, which allows further research. The properties selected for the analysis of sentences, as well as the key sentences selected by an independent reader for the test case of texts, have a great influence on the operation of the neural network. The network is trained in accordance with the style of the reader and in accordance with the proposals that this reader considers to be key. You can consider this feature as an advantage of this approach, since any person can train the neural network in accordance with their personal preferences.

This approach takes into account the difficulties of working with such poorly structured languages as Russian, Ukrainian, Moldovan, etc.

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