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RESEARCH OF TEXT PRE-PROCESSING METHODS FOR PREPARING DATA IN RUSSIAN FOR MACHINE LEARNING

Abstract: The article includes information about pre-processing methods for preparing text data in Russian language for machine learning. The article covers such techniques as tokenization, normalization, named entity recognition, stemming, lemmatization and removing of stop words. Also, this article shows some approaches using morphological analyzers and libraries for NLP tasks.
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Introduction

There is still a huge problem that we can see in the practice of creating and transforming data collections that are large enough, which forces us to pay attention to efficiency in developing data applications.

Pre-processing is the most important step in the data analysis, and if it is not performed, then further analysis in most cases is impossible due to the fact that analytical algorithms simply cannot work, or the results of their work will be incorrect or ineffective. In other words, the GIGO principle is implemented - garbage in, garbage out.

This paper is devoted to an overview of the methods that will be used to pre-process text data in Russian language in order to prepare them for using of machine learning algorithms. And we will also describe the methods that are used in our application "chat bot assistant for organizing employee support".

About a corpus

At present moment natural language is one of the forms of data available today and which are little used in machine learning algorithm in its initial form. Its analysis allows us to increase the usefulness of data and make it more accessible for our lives.

The main task of any machine learning application is to determine what is considered useful from a large flow of information and how to distinguish this useful information from information noise.

The analysis of text data is the splitting of large text into separate fragments - the selection of sentences, unique words, common phrases - with the subsequent application of other processing methods to these fragments. Data analysis is represented by a large number of different methods and practices and can be applied at various levels, and usually all of them are tied to one key element - a corpus.

A corpus is a collection of documents or texts, possibly related to one subject, in a natural language. Size of corpus can be large or small. The corpus can be annotated, that is, the data in them can be pre-marked with certain labels, such cases are used for training with a teacher, or unannotated - such documents are used in

Clarivate
Analytics indexed

clustering algorithms and various modeling tasks, for example, to predict dollar exchange rates.

As mentioned above, the corpus can consist of documents and it can be divided into categories of documents or into individual documents. Documents can be divided into paragraphs, each of which usually expresses one idea - semantic units of speech. Paragraphs are divided into sentences - syntactic units. A completed sentence is one specific expression. Sentences, in turn, consist of words and punctuation marks - lexical units. These units determine the general meaning of the proposal and can be used not only individually, but also in combination, so they can be of greater importance for analysis.

The corpus with which we will work is consisted of data that were taken from ticket systems operating in the company and represent a collection of text messages. First of all, each message is needed to be marked. For our task - the classification of the input message as belonging to a particular class, two classes are selected "question" and "application". A "question" class message is any message that you can try to answer without human's help.

An «application» class message is a message for which additional forces are required. For example, if an employee wrote "I want to buy a teapot," then the bot itself cannot in any way influence the decision of this application, it can only create a ticket in the ticket system and in the future find out the status of this ticket, inform the employee about various changes, and when ticket is solved send employee an answer.

Processing and transformation of a corpus

Any corpus in its initial form is absolutely unsuitable for analysis - it is necessary to pre-process it first.

To begin with, briefly note the components of the corpus. The corpus consists of documents, each document consists of paragraphs, paragraphs of sentences, sentences of words. We will consider paragraphs as structural units of the document. And sentences as semantic units containing a complete thought formulated and expressed by the author of this proposal. At this stage, we need to implement segmentation, i.e., the division of the text into sentences. Then these proposals will be further subjected to various processing methods, which we will discuss later. The paragraphs are segmented into sentences based on punctuation marks: a period (.), a question mark (?), an exclamation point (!). It is also necessary to consider compound punctuation marks, for example "!?". After segmentation, you can directly start to process sentences.

Tokenization

The first thing to do is to remove the punctuation marks and service characters. This can be done "manually", that is, write code yourself that checks the characters and removes those that we don't need, or use the tools from NLTK (Natural Language Toolkit). Also, this process can be combined with the tokenization of the sentence to words - the allocation of individual tokens of each sentence. This is what we are doing for working directly with words. Tokenization of sentences must be carried out with the peculiarities of the language with which you work. For example, if we use the NLTK tools, we can get unexpected results for the Russian language. Suppose we have the word «Санкт-Петербург". With tokenization for all punctuation marks that are possible, we get two separate words "Санкт" and "Петербург", which in some cases after processing simply will not make any sense. So, at this stage, you must be very careful.

Named entity recognition

When a large number of various tickets created in ticket systems were viewed, it was noticed that very often there are human names and surnames, names of organizations, locations, etc., for example, "Organize a workplace for Ivan Ivanov." For training, these data do not carry any useful information and therefore it was necessary to get rid of them. To do this, it was decided to use one of the most popular tasks in NLP - the recognition of named entities (NER - Named-entity recognition). In most cases, the NER task can be formulated as follows: for a given sequence of tokens (words and possibly punctuation marks), it is necessary to provide a tag from a predefined set of tags for each token in the sequence.

For the task of recognizing named entities, there are several general types of objects used as tags:
- people;
- locations;
- organization;
- expressions related to time;
- quantitative data;
- monetary values.

In addition, many applications use the BIO tagging scheme to distinguish adjacent objects with the same tag. Here, "B" indicates the beginning of the object, "I" means "inside" and is used for all words that make up the object except the first, and "O" means the absence of the object.

In order to perform entity recognition, it was decided to take advantage of the open-source conversational AI of the deeppavlov framework [1]. In figure 1 you can see how entity recognition occurs.

Figure 1. Demo of named entity recognition using deeppavlov

At present moment they have two main types of models available: standard based on RNN and BERT. RNN (recurrent neural network) is a class of neural networks in which the output from the previous step is supplied as input for the current step. In traditional neural networks, all inputs and outputs are independent of each other, but in cases where, for example, it is necessary to predict the next word of a sentence, previous words are required and, therefore, it is necessary to remember them. Thus, a recurrent neural network appeared, which solved this problem with the help of a hidden layer. The main and most important feature of RNN is the latent state, which stores some sequence information.

BERT (Bidirectional Encoder Representations from Transformers) is a natural language processing method based on the use of neural networks of a new architecture for working with sequences, better known as "transformers". This technology helps Google better define the context of words in search queries [2].

Deeppavlov has various BERT and RNN models, trained in various languages and able to recognize up to 19 entities. Models for the Russian language are trained on the Collection 3 dataset [8] and are able to recognize three entities, such as ORG - organizations, agencies, institutes, PER - people, including fictional personalities and LOC - locations, mountain ranges, rivers, etc. Models for the English language and multilingual models (104 languages are available in them) can recognize more entities: events, products, numerical values, time, language names, percentages, numerical values, cities, countries and states, etc.

In figure 2 you can see pre-trained models available at deeppavlov.

Model	Dataset	Language	Embeddings Size	Model Size	F1 score
ner_rus_bert	Collection3 [1]	Ru	700 MB	1.4 GB	**98.1**
ner_rus			1.0 GB	5.6 MB	95.1
ner_ontonotes_bert_mult		Multi	700 MB	1.4 GB	**88.8**
ner_ontonotes_bert	Ontonotes		400 MB	800 MB	88.6
ner_ontonotes			331 MB	7.8 MB	86.7
ner_conll2003_bert	CoNLL-2003	En	400 MB	850 MB	**91.7**
ner_conll2003			331 MB	3.1 MB	89.9
ner_dstc2	DSTC2		—	626 KB	97.1

Figure 2. Pre-trained NER deeppavlov models

Stop words

One of the main forms of preprocessing is filtering out unnecessary data. In natural language processing, useless words (data) are called stop words.

A stop word is a commonly used word (such as "и", "на", "или"), which the search engine should ignore both when indexing records to search, and when retrieving them as the result of a search query, for the exception of strict search for a specific phrase. In order to analyze text data and build NLP models, these words do not add special importance to the document.

When to delete such words and when not? In situations where it is necessary to classify the text, for example, filtering spam or generating titles (scripts) to the image or tags, it is possible to use techniques to remove stop words. On the contrary, in such tasks as machine translation, language modeling, a short summary of the text, it is recommended to leave stop words, because they have great importance.

In our work of development chat bot for organizing employee support, we are more interested in the classification of the input message — the definition of which class it belongs to — an application or a question, and therefore we can use the method of removing stop words because we would not like these words to occupy a place in our database or occupy extra

time for processing and interfered with the classification.

There are several different methods.

The first is the removal of stop words using NLTK (Natural Language Toolkit, a natural language toolkit) [3] - a large package of libraries and programs for processing natural language written in the programming language Python. As for stop words, NLTK has lists for 16 different languages. You can see the list of words for the Russian language as follows (listing 1):

```
import nltk
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize

nltk.download("stopwords")
stop_words = stopwords.words('russian')
```

Listing 1. Collection of stop words using NLTK

Consider a usage example, you can see the messages after tokenization:

```
Добрый день , коллеги . Кофемашину на 7-й этаж вернули . Причиной этой поломки
была залитая в кофемолку вода . Будьте бдительны и осторожны . Перед тем как
налить воду в резервуар , снимайте его ! В следующий раз будет большой счет за
ремонт .
```

Listing 2. Input text after tokenization

After applying the algorithm to delete words from the stop words list, we will receive the following message. It may be noted that some words still remained, for example, "будьте," which is the form of the word "быть" while the word "была" was deleted (listing 3). The list of stop words in the NLTK package is not complete and can be expanded depending on your needs.

```
Добрый день , коллеги . Кофемашину 7-й этаж вернули . Причиной поломки залитая
кофемолку вода . Будьте бдительны осторожны . Перед налить воду резервуар ,
снимайте ! следующий большой счет ремонт .
```

Listing 3. Input text after removing stop words

The second method is to remove stop words using spaCy. SpaCy is one of the most versatile and widely used libraries in NLP [4]. In the following way, you can get a list of stop words for one of 48 languages (listing 4). We would also like to note that spaCy has almost two times more words in the list of stop words for the Russian language than in NLTK.

```
from spacy.lang.ru.stop_words import STOP_WORDS
```

Listing 4. Collection of stop words using spaCy

And the third, but not the last - the use of Gensim. Gensim is a pretty handy library for working on NLP tasks [5]. During preprocessing, gensim also provides methods for removing stop words. Using the method from this library is noteworthy in that it can be used immediately throughout the text.

And also there is no need to apply tokenization before that (listing 5).

```
from gensim.parsing.preprocessing import remove_stopwords


text = <...>
remove_stopwords(text)
```

Listing 5. Removing stop words using gensim

In addition to such well-known packages and libraries, there are a large number of open-source projects in which stop-word lists can have different types, and also, as was noted earlier, you can expand any of these lists to your own needs.

Words normalization

In any natural language, words can be written in more than one form, depending on the situation. For example:

- "Я был в Америке трижды".
- "Я буду в Америке 25 мая".
- "Мы бываем в Америке каждое первое число апреля".

In all these sentences, we see that the word "быть" is used in several different forms. For us people, it's really easy to understand that "быть" is some activity. And it does not matter in what form we see this word - "был", "бываем", etc. We know for sure that they mean the same thing.

But this is not the same as with machines. They believe that all these words are different. Therefore, we need to normalize them to the root word, in our example it is "быть" Therefore, normalization is the process of converting a word into a single canonical form. This can be done in two ways, which are called stemming and lemmatization.

Stemming is a method of normalizing a word, which truncates its end or beginning, according to the list of common prefixes or suffixes that can be found in this word. Lemmatization, on the other hand, is an organized and step-by-step procedure for obtaining the root form of a word. It uses vocabulary (vocabulary meaning of words) and morphological analysis (word structure and grammatical relationships).

Why do stemming or lemmatization? Consider the following sentences:

1) "Я буду в этом ресторане в 12 часов".
2) "Я побываю в этом ресторане в 12 часов".

We easily understand that both of these sentences mean the same action, that someone will be at the restaurant at 12 noon in the future. But the machine will handle these sentences in different ways. Thus, in order to make the text understandable for the machine, we need to perform stemming or lemmatization. Another advantage of text normalization is that it reduces the number of unique words in text data. This helps reduce time for execution of machine learning algorithm.

To sum up, the stemming algorithm works by cutting out a suffix or prefix from a word. Lemmatization is a more powerful operation, since it takes into account the morphological analysis of the word. Lemmatization returns a lemma, which is the root word of all its various variations.

We can say that stemming is a quick and "dirty" method of trimming words to their root form, while, on the other hand, lemmatization is an intellectual operation that uses dictionaries created by deep linguistic knowledge. Therefore, lemmatization helps in the formation of the best features.

What are the options for applying the algorithms of stemming and lemmatization.

First, let's consider the features of NLTK. In stock, NLTK has a number of great methods for performing this step - normalization. To stamp English words, you can choose between Porter and Lancaster. The Porter Algorithm is the oldest stemming algorithm supported by NLTK and was published in 1979. The Lancaster algorithm is newer and was published in 1990 and may be slightly more aggressive than the Porter Stemmer. The WordNet Lemmatizer uses the WordNet database to search for lemmas.

For non-English words, you can use the Snowball stemmer. Actually, Snowball is a language for creating stemmers and was added to NLTK version 2.0b9 as a separate SnowballStemmer class. This stemmer supports the following languages: Danish, English, Finnish, German, Spanish, Swedish, most importantly for us Russian and some other languages.

Since NLTK has few features for the Russian language, we'll only consider stemming with SnowballStemmer. Consider the source text and the text obtained after stemming. As we see, after performing word processing using stemming, most of the words were trimmed (listing 6).

```
Добрый день, коллеги.
Кофемашину на 7-й этаж вернули.

Причиной этой поломки была залитая в кофемолку вода.
Будьте бдительны и осторожны.
Перед тем как налить воду в резервуар, снимайте его!
В следующий раз будет большой счет за ремонт.
```

```
добр ден , коллег . кофемашин 7-й этаж вернул . причин поломк залит кофемолк
вод . будьт бдительн осторожн . перед нал вод резервуар , снима ! след больш
счет ремонт .
```

Listing 6. Stemming using SnowballStemmer from NLTK

When two options are available, lemmatization will always be a better option than stemming. Stamming algorithms are an optimized way to identify related words using a relatively short algorithm and without the need for vocabulary data for each language. The disadvantage is that it is not always accurate: sometimes it connects by kinship relations words that do not come from the same word, but on the other hand, does not identify the related forms of a particular word.

In turn, lemmatization will always give a better result, because lemmatizers rely on the correct language data (dictionaries) to identify the word with its lemma. In addition, the result will always be another element of the dictionary (infinitives, singular forms, etc.), and not a "basis", which can sometimes be difficult to determine (especially when working with typologically different languages).

For our tasks, we also decided to choose lemmatization, because we believe that this will help to give a better result in the classification. And besides, we need to highlight keywords that will help us search for answers for questions in the future. And this would not be possible if we normalized using stemming algorithms, because the knowledge base will be filled in by a person (in the future, an algorithm) who will also select keywords for articles, and it will be difficult for them to select them with stemming.

Consider lemmatization using the pymorphy2 morphological analyzer (listing 7) [6].

```
добрый день , коллега . кофемашин 7-й этаж вернуть . причина поломка залить
кофемолка вод . быть бдительный осторожный . перед налить вода резервуар ,
снимать ! следующий большой счёт ремонт .
```

Listing 7. Lemmatization using PyMorphy2

The normal form of the word can be obtained through the attributes Parse.normal_form and Parse.normalized. To get the Parse object, you must first parse the word and select the correct parsing option from the ones proposed. pymorphy2 now uses the algorithm for finding the normal form, which works most quickly (the first form in the token is taken) - therefore, for example, all participles are now normalized to infinitives. This can be considered an implementation detail. At the same time, pymorphy2 returns all valid parsing options, but in practice you usually only need one option, and therefore if you want to normalize words differently, you can use the Parse.inflect() method, into which you can pass parameters for selection, such as part of speech, case, number, genus.

But in some cases, this analyzer may not work correctly. If we consider the text taken as an example, then there were two words "воду" and "вода". In the first case, pymorphy2 recognizes everything correctly and produces a normal "вода" form.

But in the second case, the word "воду" was recognized with the following set of tags: noun, masculine, genitive. And, accordingly, the normal form of such a word is "вод". Although we understand that the word "вода" is already in itself a normal form.

As a result, which we obtained when executing the parse method, we can see that there are two options for

word "вода", and the second variant in the parsed result (listing 8) is more suitable for us. But to understand this will be quite difficult.

```
[Parse(word='вода', tag=OpencorporaTag('NOUN,inan,masc sing,gent'),
normal_form='вод', score=0.5, methods_stack=((<DictionaryAnalyzer>, 'вода', 33,
1),)),

Parse(word='вода', tag=OpencorporaTag('NOUN,inan,femn sing,nomn'),
normal_form='вода', score=0.5, methods_stack=((<DictionaryAnalyzer>, 'вода',
55, 0),))]
```

Listing 8. The result of parsing word "вода" using PyMorpy2

Let's consider another popular morphological analyzer along with PyMorphy2 MyStem - a morphological analyzer of the Russian language with support for the removal of morphological ambiguity, developed by Ilya Segalovich at Yandex [7]. The program works on the basis of a dictionary and is able to form morphological hypotheses about unfamiliar words.

The first version was developed in the 90s [11], but it was not very popular and could not be found in the public domain. Now there is already a version of MyStem 3.1, which fully provides all the functions of morphological analysis. The MyStem morphoanalyzer is based on the NKRL (National Corpus of the Russian Language) dictionary [9], which contains more than 200 thousand lemmas. MyStem source codes are not accessible to ordinary users, so the characteristics of the data structure used are not known.

Like PyMorphy2, MyStem can parse non-dictionary forms and also provides the ability to resolve morphological homonymy. To solve this problem, depending on the input data, MySte allows homonymy in one of the following ways: without considering the context and vice versa.

Removing homonymy without regard to the context is possible due to the training of the naive Bayesian classifier on the marked-out case with the

$$P(para|word) = \frac{P(para|word) \cdot P(para)}{P(word)} = $$

$$\frac{P(stem|para) \cdot P(flex|para) \cdot P(para)}{P(word)} \quad , (1)$$

removed homonymy [10]. The probability of an unknown word stem having a stem basis and the ending flex to belong to the para (paradigm) is calculated by the formula 1 [10]:

where para – paradigm,
stem – base of word,
flex – end of word,
word – our word.

It is assumed that stem and flex are independent and random variables.

In turn, removing context-specific homonymy is pluggable and uses MatrixNet technology. The main idea is to rank parses based on the words (contexts) closest to the parsed.

Consider the same example with the source code used above. To connect to your MyStem project, you can use the wrapper written in the Python programming language - pymystem3 [12]. This tool is publicly available and licensed under the MIT license.

```
добрый день , коллега . кофемашина 7-й этаж вернуть . причина поломка
заливать кофемолка вода . быть бдительный осторожный . перед наливать вода
резервуар , снимать ! следующий большой счет ремонт .
```

Listing 9. Lemmatization using MyStem

As can be seen MyStem did a better job of finding a lemma for the word "вода when pymorphy2 considered the word "вода" to be a masculine word in the genitive and made a conversion to the word "вод" which turned out to be completely wrong.

Conlusion

We examined what basic pre-processing methods are applied to data for their further use with machine learning methods: tokenization, removal of stop words, reduction to the basic form (normalization). We showed different approaches with using NLKT, pymporphy2, spaCy, gensim and MyStem. We also considered an additional method - recognition of named entities with using capabilities of the deeppavlov framework.

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