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RESEARCH OF THE TEXT DATA VECTORIZATION AND CLASSIFICATION ALGORITHMS OF MACHINE LEARNING

Abstract: *The article includes information about different classification algorithms and vectorization methods. We give the advantages and disadvantages of classification methods. Also in this paper we observe not only usual classification algorithm, but classification with using neural network, specifically with convolutional neural networks. In addition to description of these methods we discuss metrics which can be used to rate the quality of trained classification models.*

Key words: *text classification, vectorization, neural networks, machine learning.*

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Introduction

Solving problems using machine learning is a very popular task in the modern IT community. You can see a large number of competitions at Kaggle, courses at EdX, Coursera and Stepik. For machine learning, there are also a large number of different tools and platforms, for example, Scikit-learn, Tensor-flow, Keras and others.

One of the classic and popular tasks is the classification of various data (texts or images). The basic algorithm for solving such problems:

–Create a dataset and label it.

– Split a dataset to train and test datasets

– Fit vectorizer sand choose classifiers.

– Fit classifiers with training dataset and calculate accuracy with test dataset.

– Choose the most accurate classifier.

– Use it.

We talked about how to create and prepare a dataset in a previous article [1]. Using the prepared dataset, we can train a model that will predict which category the input message belongs to. And now let's talk in detail first about vectorization, and then about classification.

Vectorization

Machine learning algorithms operate in a space of numerical attributes, that is, they expect that a two-dimensional array will be presented at the input, the rows of which are concrete instances, and the columns are attributes or features. Thus, in order to perform machine learning on the text, it is necessary to convert the source documents into vector representations, to which numerical machine learning will subsequently be applied. This process is called vectorization and it is the first step towards analyzing natural language data.

Converting documents to their numerical form makes it possible to analyze them and create instances with which the machine learning algorithm we choose will work. Documents (or sentences) can have different sizes, but the vectors that we define for them will

always be the same length. Each property in a vector representation is a feature. In our case, these will be the words that are included in the sentence. Together, all these features will describe a multidimensional feature space to which machine learning methods can be applied.

Thus, we must move from individual sentences and words to points in a multidimensional semantic space. These points can be located far or close to each other, distributed evenly or vice versa randomly. Based on this, we can conclude that sentences that are close in meaning will be located nearby, and different, on the contrary, far.

Frequency vectorizer

One way to vectorize the source text is to calculate the frequency of occurrence of each word in each sentence and associate this value with the entire set of words of the original data set. You can start by creating a dictionary of all words in all sentences of your dataset. A dictionary in this case is a list of words that occur in texts where each word has its own index. This allows us to create a vector for any sentence - just take the sentence that we want to vectorize and count the occurrence of each word. The length of the resulting vector will be equal to the size of our dictionary and contain the value of the number of occurrences of the word from the dictionary in each specific sentence.

Consider a concrete example — there is a collection of a sentence (see Listing 1).

```
sentences = ['Сломалась кофемашина на нашем этаже',
             'Лопнула лампочка на восьмом этаже',
             'Кофемашина отремонтирована и работает',
             'Лампочка упала и разбилась']
```

Listing 1. The sentences for demonstration

Then we can use the method CountVectorizer from the scikit-learn [2] library to vectorize our sentences. The result of the CountVectorizer() vectorizer you can see below (see Listing 2).

```
from sklearn.feature_extraction.text import CountVectorizer

vectorizer = CountVectorizer()
vectorizer.fit(sentences)
vectorizer.vocabulary_

Output:
{'восьмом': 0, 'кофемашина': 1, 'лампочка': 2, 'лопнула': 3, 'на': 4,
'нашем': 5, 'отремонтирована': 6, 'работает': 7,  'разбилась': 8,
'сломалась': 9, 'этаже': 11, 'упала': 10}
```

Listing 2. Demo of how CountVectorizer() works

As the output we get a dictionary of all unique words that are available in all sentences that we passed as the input to our vectorizer.

We can also take all our sentences and transform them using CountVectorizer() to get vectors for each sentence that will display the number of occurrences of each word from the dictionary in a specific sentence (see Listing 3).

```
vectorizer.transform(sentences).toarray()

Output:
array([[0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0, 1],
       [1, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 1],
       [0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0],
       [0, 0, 2, 0, 0, 0, 0, 0, 1, 0, 1, 0]])
```

Listing 3. Vector presentation of example sentences

The output shows that, for example, in the fourth element of array (which means sentence) the word “лампочка” was encountered twice, so in the corresponding position for the word “лампочка” the value is equal to 2.

This approach is called Bag-of-Words and it is a common way to create vectors from text. Each document, in our case, a sentence, is presented as a separate vector.

The disadvantages of this approach are follows. With the increase in the size of the dictionary, vectors will grow and become sparser, and will have in their view a large number of zeros due to the fact that each document will contain only a small number of words from the dictionary. Such vectors require more memory and computational resources, which can have a significant impact on the performance of models. But this can be solved by the following techniques:

– You can ignore the case of words, and then the word “хороший” from the phrases “Хороший день” and “Он дал мне хороший совет” will appear in our dictionary exactly once.

– Delete stop words – unnecessary words. Stop words are words that do not carry any particular meaning, and their exclusion may not affect learning in any way, except cases when all words are important.

– Format words to their normal form - the use of stemming and lemmatization algorithms.

– Correct words that are written with an error.

Also, in addition to applying text preprocessing methods to reduce the size of the dictionary, you can use HashingVectorizer() for large cases. It uses memory more economically and is great for processing large sets of text data, since it does not completely store the entire dictionary, and due to this there is an acceleration of saving and learning.

Also, with this approach, the word order is lost, that is, after vectorization the sentence vectors, for example, “Она не поет” and “Не, она поет” will be identical, but their meaning is completely different. To solve this problem, you can use N-grams (sequences of N entities, for example, words, numbers, letters, etc.) at the tokenization stage.

An example sentence and its bigrams is as follows (Listing 4):

```
Лампочка не работает на восьмом этаже

- лампочка не
- не работает
- работает на
- на восьмом
- восьмом этаже
```

Listing 4. Bigrams of source sentence

Direct coding

In addition to counting the number of occurrences of a particular word in a sentence, there is a simpler vectorization approach - direct coding. Direct (or binary) coding is a logical vectorization method that writes true or 1 to the corresponding vector element if the given word from the dictionary is present in the sentence, or false (or 0) if there is no such word. In other words, each element of the vector with this approach indicates either the presence or absence of a word in the described sentence. Thus, we simplify the document to its constituent components. This method is very effective for short documents, such as, for example, tweets that contain a small number of repeating elements. The direct coding approach is also often used in neural networks, where activation functions require input values from the ranges [0, 1] or [-1, 1].

The result of this vectorizer will be the following (Listing 5). Thus, it can be noted that in the fourth sentence, the value in the third position of the vector is no longer 2, but 1, which means that the given word from the dictionary is present in this sentence.

```
vectorizer = CountVectorizer(binary=True)

vectorizer.transform(sentences).toarray()

Output:
array([[0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0, 1],
       [1, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 1],
       [0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0],
       [0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 1, 0]])
```

Listing 5. The result of binary mode of CountVectorizer()

TF-IDF

The approach of counting the number of words occurrences in a document has a problem: words that are more likely to occur have a higher rating. But these words can have very little useful information, as can have less frequent words. A more successful approach is based precisely on a comparison of the relative frequency or rarity of words in one particular document with their frequency in other documents. The main idea of this approach is that the main meaning is hidden in those words that are less common.

The TF-IDF (Term Frequency – Inverse Document Frequency) [3] coding method normalizes the word frequency in the document, taking into account the contents in the entire case. Thus, it turns out that if a word is often found in a specific document, but is rarely found in the rest, then this word is of high importance for this document itself and such words will gain more weight compared to other corpus words.

The TF-IDF is calculated as follows. To begin, consider TF - this is the ratio of the number of occurrences of a word in one document to the total number of words in a document (formula 1):

$$TF = \frac{n_t}{\sum_k n_k} \qquad (1)$$

where n_t is the number of occurrences of the word t and in the denominator is the total number of words in the document.

And IDF is calculated as follows (formula 2):

$$IDF = log \frac{N}{DF_t} \qquad (2)$$

where N is the quantity of documents in corpus collection;

DF_t is the quantity of documents from collection where t word is occurred.

Thus, we have two components TF and IDF and we can calculate the value of TF-IDF (formula 3):

$$TF - IDF = TF \cdot IDF \qquad (3)$$

Let's look at an example based on our four-sentence case. As a result of using TfidfVectorizer() from scikit-learn, we get the following matrix of the form (see Listing 6) where each row is our document, the column is words, and the value at the intersection is the TF-IDF score.

	восьмом	кофемашина	лампочка	лопнула	на	нашем	\
0	0.000000	0.401043	0.000000	0.000000	0.401043	0.508672	
1	0.508672	0.000000	0.401043	0.508672	0.401043	0.000000	
2	0.000000	0.486934	0.000000	0.000000	0.000000	0.000000	
3	0.000000	0.000000	0.744450	0.000000	0.000000	0.000000	

	отремонтирована	работает	разбилась	сломалась	упала	этаже
0	0.000000	0.000000	0.00000	0.508672	0.00000	0.401043
1	0.000000	0.000000	0.00000	0.000000	0.00000	0.401043
2	0.617614	0.617614	0.00000	0.000000	0.00000	0.000000
3	0.000000	0.000000	0.47212	0.000000	0.47212	0.000000

Listing 6. The TF-IDF presentation of source sentences

One of the advantages of the TF-IDF approach is that it solves the problem of stop words in a natural way, which most likely are almost always present in all documents of the corpus and for this reason gain a little weight compared to other words that will become more valuable in this method.

Word2vec

The methods of frequency and direct coding described above, as well as the TF-IDF approach, allow you to convert a collection of documents into vector space, for example, present an entire sentence as a single vector of objects. But it is also useful to code the similarity between documents in the context of this very vector space.

The methods described above produce vectors only with positive elements, which does not allow you to compare documents that do not have common words due to the fact that two vectors having a cosine value of the angle between them equal to 1 will still be considered distant in meaning.

If the similarity between documents plays an important role in the application of machine learning algorithms, then the data can be encoded using the distributed representation method. With this approach, a vector is not just a mapping of the positions of words into their numerical value, but a set of features that determine the similarity of words. The complexity of the feature space (and the length of the vector) is determined by the learning features of this representation and is not directly related to the document itself.

The word2vec software was developed in 2013 by a team of researchers from Google, led by Tomaš Mikolov. Tools for creating vector-semantic models existed before [4, 5], but word2vec was the first popular implementation due to its ease of use, speed of work and, most importantly, open source code.

Tomaš's approach is based on one important hypothesis that he wrote in his work [6] - "words that occur in identical environments have similar meanings". Proximity in this context can be understood as the fact that only matching words can stand nearby. That is, for example, it's normal for us to hear the phrase "злой человек", but the phrase "злой холодильник" is completely unusual.

The model that Tomaš proposed is quite simple - the probability of a word will be predicted by its context. That is, we will train the vectorization model so that the probability assigned by the model to a word is close to the probability of meeting this word in this environment in real text. This approach is called the Continuous Bag of Words (CBOW) - it is called continuous, because the sets of words from text are fed sequentially to the input of, and BoW, because the order of words in the context is not important. The input element to the neural network is the set of context vectors w (t - k), ..., w (t - 1), w (t + 1), ..., w (t + k), and the output vector is w (t), where w (t) is the vector of the word predicted based on the context.

Mikolov also proposed a different approach, which is the exact opposite of the CBOW approach, which he called skip-gram. The architecture of Skip-gram differs from a continuous bag of words in that it predicts a set of words around, based on a given word. The input vector is w (t), and the output element is the set of vectors M = {w (t - k), … , w (t - 1), w (t + 1), ..., w (t + k)}. Each word corresponding to vectors from the set M characterizes a word corresponding to an input vector. The working scheme of these two approaches can be seen in Figure 1.

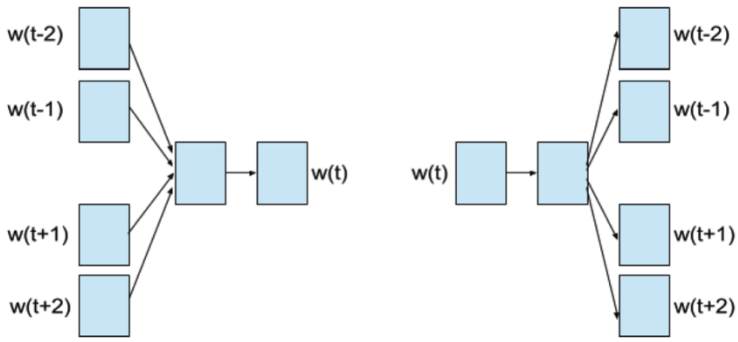

Figure 1. The workflow of the CBOW and Skip-gram algorithms

Classification

Classification of text data by specific topics or classes is the definition of text data belonging to any topic to which the corresponding text is devoted. The most common classification tasks are determining the emotional coloring of a text, otherwise, analyzing tonality and classifying data on predefined topics. Such type of classification is used to cut off those entries that relate to topics that are not of interest for analysis, for example, the classification of input messages as spam and not spam.

There are several methods for classifying texts. The first is to analyze the data and determine the class to which the input text belongs, manually. This method, of course, is absolutely accurate from the point of view

of classification, but its main drawback is the inability to process a large amount of data in a short time.

The second approach is to write some rules based on regular expressions and use them to classify text. In this case, manual verification disappears, which increases the classification speed and the amount of data that can be analyzed in a shorter time. It may also take time to create rules for a deeper study by a specialist of the text and the identification of certain patterns for different classes. In addition, the creation of such rules requires efforts to keep them up to date.

But in the work [7], the authors of Qing Zeng-Treitler and Duy Duc An Bui describe the process of automating the creation and use of regular expressions to classify clinical texts. They write about the development of their own regular expression detection algorithm RED (Regular expression discovery) and the implementation of two text classifiers based on it: the RED + ALIGN classifier - a regular expression detection algorithm in conjunction with an alignment algorithm, and RED + SVM are regular expressions combined with the support vector method. Two of their classifiers achieved an accuracy of 80.9 - 83.0% for two data sets, which is 1.3-3% percent higher than the accuracy of the SVM method. More importantly, RED + ALIGN correctly classified many instances that were erroneously classified by SVM (8.1-10.3% of the total number of instances and 43.8-53.0% of erroneous SVM classifications). Therefore, we can say that the approach to the classification of text data based on regular expressions also has a place to be and shows good results.

Finally, the third approach, to which further research will be devoted, is an approach based on machine learning. With this approach, the classes to which the data belongs are automatically determined, but manual marking of the training data is required. Classification of the text using machine learning is currently the most used and promising approach, since it does not require special time expenditures on the part of the person and allows you to process a large amount of data in a short time.

Before starting to describe the approaches to the classification of text data, we introduce some basic concepts. For starters, machine learning systems or neural networks accept input and output parameters. Input parameters are usually called features. Symptoms are some of the characteristics that we can explore.

When we pass these features to the input of machine learning systems, they try to find a match and notice some patterns between the input parameters. At the output, we get the result of work, which is usually called labels (label), since these output parameters have some label by which you can get ahead of which category the output belongs to.

For example, if you look at fig. 2, one can imagine that ferns, mosses and algae are the input parameters to some machine learning system. In turn, the output parameter or label will be the value "spore-bearing plants". Thus, the abstract system defined the class to which these plants belong.

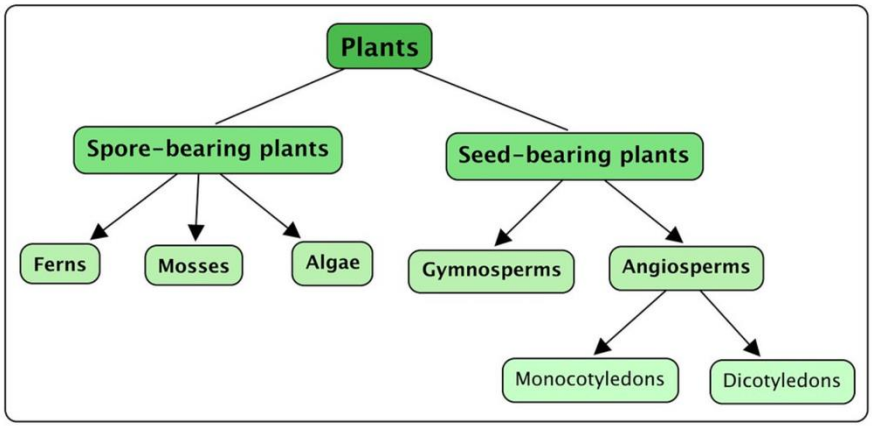

Figure 2. Example of classification

In the context of machine learning, classification is a type of learning with a teacher. This means that the data that we submit to the input is already pre-marked with certain labels or classes, and this means that the training system knows which parts of the input data are important for each class. In addition, the system itself can check the result of its work, as it knows in advance to which class each input object should belong.

What is the process of training a classification model? We provide the input data and their labels, and the machine learning system we choose must learn how to output specific patterns for this data. In the process of testing a trained model, only untagged data is input,

and the model itself must predict which class our object belongs to.

In this paper, we consider several basic classification methods from a wide variety of algorithms, and also consider the use of neural networks to solve the classification problem.

The main classifiers that will be considered in this paper:

– support vector machine;
– naive bayes;
– logistic regrssion;
– decision trees;
– k-nearest neighbors.

Support Vector Machine

Support Vector Machine (SVM) is a discriminating classifier that is widely used for classification tasks. Support vector methods were introduced in the early 1960s, and then improved in the 1990s. However, only now they are becoming extremely popular due to their ability to achieve brilliant results.

The algorithm displays each data element as a point in N-dimensional space, taking the value of each feature as the value of a specific coordinate. Then, in the case of linearly shared data in two dimensions, as shown in Fig. 3, a typical machine learning algorithm tries to find a boundary that separates data so that the classification error is minimal. There may be several boundaries that correctly separate data points. Two dashed lines, as well as one solid line, correctly classify data.

SVM differs from other classification algorithms in that it selects a solution boundary that maximizes the distance from the nearest data points of all classes. SVM does not just find the boundary of a solution; it finds the most optimal boundary for the solution.

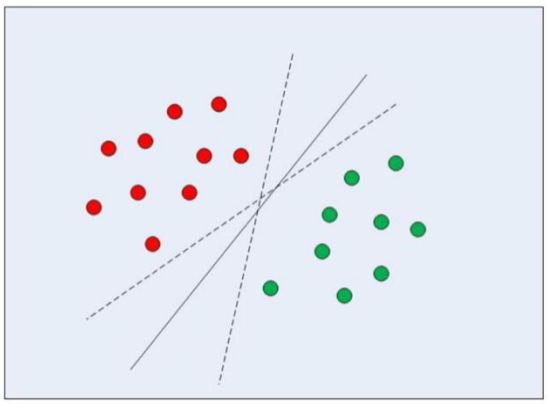

Figure 3. Linearly shared data in two dimensions

The most optimal solution boundary is one that has a maximum separation from the nearest points of all classes. The nearest points from the boundary of the solution that maximize the distance between the boundary of the solution and the points are called support vectors, as can be seen in Fig. 4. The boundary of the solution in the case of the support vector method is called the classifier of the maximum margin or the hyperplane of the maximum margin.

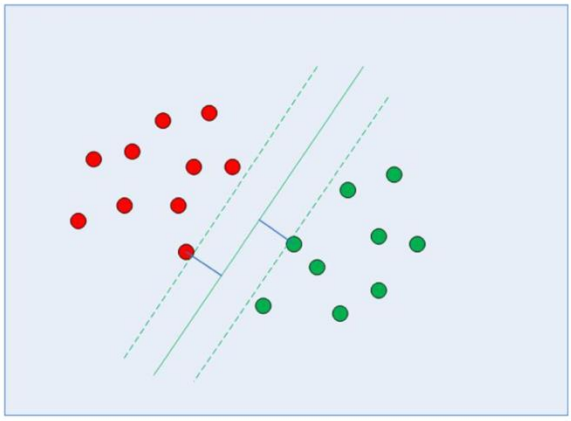

Figure 4. The hyperplane of the maximum margin

The advantages of this approach are:

– works well with a small dataset;

– due to maximizing the distance, finds the optimal solution and allows to achieve minimum classification error;

– works well with the feature space of large size.

And the disadvantages are:

– long training time for large datasets;

– the algorithm is unstable to noise, it means that outliers in the data for training strongly affect the construction of the separating hyperplane.

Naive Bayes

When studying probability and statistics, one of the first and most important theorems that students study is Bayes' theorem (see formula 4). This theorem is the basis of deductive thinking, which focuses on determining the probability of an event on the basis of prior knowledge of the conditions that may be associated with this event.

$$P(A \mid B) = \frac{P(B \mid A) \cdot P(A)}{P(B)}, \quad (4)$$

where P(A|B) – the probability that event A is true if event B is true,

P(B|A) – the probability that event B is true if event A is true,

P(A) – the probability that event A is true,

P(B) - the probability that event B is true.

The naive Bayes classifier brings the power of this theorem to machine learning, creating a very simple but powerful classifier.

Let's look at a simple example. Suppose we want to know if an input message containing the word “купить” is an application. Then, according to Bayes' theorem, the components of the formula will look as follows:

– P(class=ЗАЯВКА|contains=“купить”) – the probability that the input message which is ЗАЯВКА contains the word “купить”.

– (P(contains=“купить”|class=ЗАЯВКА) – the probability that the input message which contains the word “купить” is classified as ЗАЯВКА.

– P(class=ЗАЯВКА) – the probability that the input message is an application (without any knowledge of the words that enter it). This is the percentage of all messages in our training dataset that are marked as ЗАЯВКА. We multiply by this value because we are interested in knowing how important the information is regarding the letters of ЗАЯВКА class.

– P(contains=“купить”) - the probability that the input message contains the word "buy." This is the proportion of those messages in our training sample in which the word “buy” is present. We divide by this meaning, because the more exclusive the word “buy” is, the more important is the context in which it appears. Thus, if a word is very rare, that is, it is small, this can be an excellent indicator that, when it appears, it is an important function for analysis.

Thus, the Bayes’ theorem allows us to make informed conclusions about events occurring in the real world, based on preliminary knowledge about the observations that may imply this.

The main advantages of the naive Bayesian classifier are the simplicity of its implementation and, relative to other classifiers, low computational costs for training and data classification. That is, in those rare cases when the signs are really independent (or almost independent), the naive Bayesian classifier is quite optimal.

The main disadvantage of algorithm is the relatively low quality of classification in most real tasks.

Logistic regression

The next classification algorithm is logistic regression. Logistic regression is a controlled classification algorithm. Unlike conventional regression, logistic regression does not predict the value of a numerical variable based on a sample of the initial values. Instead, the value of a function is the probability that the original value belongs to a particular class.

The main idea of logistic regression is that the space of initial values can be divided by a linear boundary into two regions corresponding to the classes. In the case of two dimensions, the linear boundary is simply a straight line without bends; in case of three - a plane, etc. (see fig. 5). This boundary is set depending on the available input data and the training algorithm. For everything to work, the source data points must be divided by a linear border into the two above-mentioned areas. If the source data points satisfy this requirement, then they can be called linearly separable.

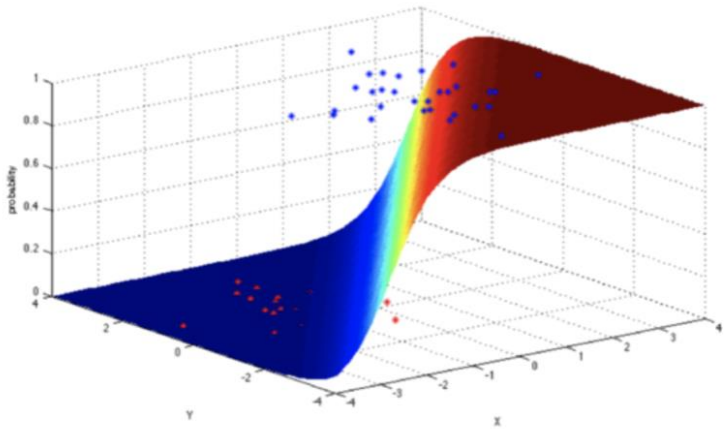

Figure 5. A plane in the case of three dimensions

K-nearest neighbors

The k-nearest neighbor algorithm is a type of supervised machine learning algorithm. KNN is extremely simple to implement in its most basic form but performs quite complex classification tasks.

This is a “lazy" learning algorithm because it does not have a special learning phase. Rather, it uses all the data for training in classifying a new instance. KNN is a nonparametric learning algorithm that means that it does not make any assumptions about the underlying data. This is an extremely useful function, since most of the data in the real world does not correspond to theoretical assumptions, for example, linear separability, uniform distribution, etc.

The KNN algorithm is one of the simplest of all machine learning algorithms with a teacher. It simply calculates the distance of the new data point to all other points from the training dataset. The distance can be of any type, for example, Euclidean or Manhattan, etc. Then, the K-nearest data point is selected, where K can be any integer. Finally, it assigns the data point to the class to which most of the K data points belong.

The advantages of this approach:

– Easy to implement it.

– As mentioned earlier, this is a lazy learning algorithm and, therefore, does not require training before making real-time forecasts. This makes the KNN algorithm much faster than other algorithms that require training, such as SVM, linear regression, etc.

– Since the algorithm does not require training before making predictions, new data can be added without problems.

– To implement KNN, only two parameters are required, that is, the value of K and the distance function (for example, Euclidean or Manhattan, etc.)

The disadvantages are:

– The KNN algorithm does not work well with large data, because with a large number of measurements, it becomes difficult for the algorithm to calculate the distance in each measurement.

– The KNN algorithm has a high prediction cost for large data sets. This is because in large data sets, the cost of calculating the distance between a new point and each existing point becomes higher.

– Finally, the KNN algorithm does not work well with categorical signs, since it is difficult to find the distance between dimensions with categorical features, therefore it is desirable that the signs have a numerical value, such as vectors into which we convert our sentences.

Decisions tree

The decision tree is one of the most frequently and widely used supervised machine learning

algorithms, which can perform both regression and classification tasks. The decision tree algorithm is simple, but also very powerful.

For each attribute in the data set, the decision tree algorithm forms a node where the most important attribute is located in the root node. For evaluation, we start from the root node and go down the tree, following the corresponding node that matches our condition or "solution". This process continues until a final node is reached that contains the forecast or result of the decision tree.

At first, this may seem a little complicated, but it should be obvious that we have been using decision trees to make decisions all our lives, without even knowing about it.

There are several advantages to using the decision tree to analyze forecasts:

– Decision trees can be used to predict both continuous and discrete values, i.e. they work well for both regression and classification problems.

– They require relatively less effort to learn the algorithm.

– They can be used to classify nonlinearly separable data.

– They are very fast and efficient compared to KNN and other classification algorithms.

Neural networks

For a long time, the core technologies of NLP were dominated by machine learning approaches that used linear models, such as support vector methods or logistic regression, which are trained using very multidimensional, but very rare feature vectors. In recent years, deep learning models have achieved remarkable results in computer vision and speech recognition.

As part of natural language processing, most of the work with deep learning methods included studying the representations of word vectors using neural language models and performing composition on the vectors of the studied words for classification.

The word vectors in which words are projected from 1-to-V sparse encoding (here V is the size of the dictionary) into smaller vector space through a hidden layer are essentially extracted characters that encode the semantic properties of words in their dimensions. In such dense representations, semantically close words are also close - at Euclidean or cosine distance - in the vector space of the lower dimension.

And some time ago, in the field of machine learning, success was seen in the transition from linear models to models of nonlinear neural networks. Yoav Goldberg, in his textbook on deep learning [16] about natural language processing, notes that neural networks generally offer better performance than classic linear classifiers, especially when used with pre-trained words embeddings.

He also notes that convolutional neural networks are effective in classifying documents, namely because they are able to distinguish characteristic features (for example, tokens or token sequences) in a way that does not depend on their position in the input sequences.

Convolutional neural networks (CNNs) use layers with convolutional filters that apply to local features. Originally CNN models, invented for computer vision, subsequently showed their effectiveness for NLP and achieved excellent results in the tasks of semantic parsing, search by search query, modeling sentences and other traditional NLP tasks.

The significant reasons why CNN is considered a level higher than other classical models are as follows. Firstly, the key interest for applying CNN is the idea of using the concept of weight distribution, due to which the number of parameters requiring training is significantly reduced, which leads to improved generalization - in essence this means how good our model is in studying data and applying the information received in other places [8]. Due to its smaller parameters, CNN can be trained smoothly and does not suffer from overfitting.

Secondly, the classification stage is combined with the stage of feature extraction [9], both use the learning process. Thirdly, it is much more difficult to implement large networks using common models of artificial neural networks (ANNs) than to implement them in CNN [10]. CNNs are widely used in various fields due to their remarkable characteristics [11], such as image classification [12], object detection [13], face detection [14], speech recognition [15], and much more.

Classification metrics

In machine learning tasks, in order to evaluate the quality of the trained model and to compare various algorithms, metrics are used. Before proceeding to the description of the metrics used, we introduce the concept of a confusion matrix. Suppose we have two classes and some algorithm that predicts which class the input object belongs to, then the classification confusion matrix will look like this (table 1):

Table 1

	class = 1	class = 0
predicted class = 1	True Positive (TP)	False Positive (FP)
predicted class = 0	False Negative (FN)	True Negative (TN)

Table cells are filled with the following values

– True Positive – the number of cases that are recognized correctly and belonging to class 1;

– True Negative – the number of cases that are recognized correctly and belonging to class 0;

– False Positive – the number of cases that are recognized incorrectly and must belong to class 0 but were recognized as objects of class 1;

– False Negative – the number of cases that are recognized incorrectly and must belong to class 1 but were recognized as objects of class 0.

In order to analyze and compare the capabilities of various classifiers, the following metrics were selected:

– accuracy;
– precision;
– recall;
– F-score;

Let's consider them in more detail.

Accuracy is the proportion of correct answers. It is considered as follows (see formula 5):

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN} \qquad (5)$$

This metric is intuitive, but in some cases, it can be useless, for example, in the case of classification on not-balanced training datasets. For example, let there be 100 objects in the sample that belong to the class "заявка". Our classifier defined 90 of them correctly, and 10 defined them as a "вопрос" (True Negative = 90, False Positive = 10). And there are 10 objects of the "вопрос" class, 5 of which the classifier also determined correctly (True Positive = 5, False Negative = 5). Thus, the proportion of correct answers will be calculated as follows:

$$accuracy = \frac{5 + 90}{5 + 90 + 10 + 5} = 86{,}4$$

But at the same time, if all messages from employees are recognized by a "вопрос":

$$accuracy = \frac{0 + 100}{0 + 100 + 0 + 10} = 90{,}9$$

Thus, the algorithm assigns all messages to the "вопрос" class and at the same time has a large share of correct answers, which is actually extremely illogical and does not bear any benefit. Therefore, you can't just rely on the proportion of correct answers, you must use it in conjunction with the following metrics (see formulas 6 and 7).

$$precision = \frac{TP}{TP + FP} \qquad (6)$$

$$recall = \frac{TP}{TP + FN} \qquad (7)$$

Precision can be interpreted as the proportion of objects called positive by the classifier and at the same time really positive, and recall shows what proportion of objects of a positive class from all objects of a positive class are recognized correctly (TP) and wrong (FN) the algorithm has found.

It is understood that the higher the precision and recall, the better. But in real conditions, the maximum values of precision and recall are not achievable at the same time, so you have to look for some balance. Therefore, we would like to have a metric that combines information about the two these metrics. And in this case, it would be much easier to determine which trained model to use for your tasks. Such a metric is an F-measure, which is a harmonic mean between completeness and accuracy (see formula 8):

$$f - score = 2 \cdot \frac{precision \cdot recall}{precision + recall} \qquad (8)$$

Conclusion

In this article we observed different vectorization algorithm such as vectorization method based on occurrence of words in corpus, direct coding (or binary), TF-IDF method and disturbed vector representation method using Word2vec. In addition, we reviewed some of these methods with its implementations in scikit-learn frameworks.

Also, in this article we talked about classification algorithm: support vector machine, naive bayes, logistic regression, decision trees; k-nearest neighbors and neural networks. We observed convolutional neural network as one of the best tools for text classification.

The information in this research will be used in our next paper which will be devoted to experiments with different classification algorithms and vectorization methods to get the model which will show the best classification result according to metrics and which we are going to use in our tasks.

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