Web news content classification method based on evolutionary fuzzy rules

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Abstract

Aiming at the current mining and processing of Web news information, this paper proposes a method based on evolutionary fuzzy rules for Web news content classification. First, the pre-processing of Web news text content, and then combined with mutual information and TF-IDF to filter the terminology of Web news content, forming a streamlined and better descriptive terminology. This topic uses the improved eClass0 classifier, the news text will update the attributes of the fuzzy rules, so that the text category can be better distinguished. Finally, the evolutionary fuzzy classification of Web news text data is realized by the combination of evolutionary fuzzy inference mechanism and cosine distance. Experiments show that the method has good effect and applicability.

Keywords

Evolutionary fuzzy rule, text categorization, BP neural network.

1. Introduction

1.1 The practical significance of web news content classification research

1.1.1 Related introduction

With the development of modern technology and living standards and methods, people's understanding of things is constantly evolving. The existing methods of Web news classification are mostly based on pre-defined categories, which cannot be adapted to the complicated and constantly updated Web news categories. And the status quo and trends of evolution. Therefore, in order to make it easy for users to read news, and it is possible to make the news document search easier by limiting the search scope, a very important research hotspot is the Web news content classification technology based on the evolutionary fuzzy mechanism. Web News Content Categorization is one of the ways of Web News Mining and Analyzing, which is a way to process and analyze information contained in news content [1].

The evolutionary fuzzy system was proposed as early as 1965. It is slowly being refined and researched. Its core idea is to imitate human thoughts. When some things are too complicated and have certain uncertainty, use it to ambiguity. The way to deal with it is a very effective tool today [2]. The fuzzy system is different from the classification system we know. Its uncertainty is the biggest advantage and of course the difficulty of construction.

In recent years, with the rapid increase in the types and volume of Web news sites and news, large-scale Web news data has the characteristics of large amount of data, type, timeliness, and uncertainty. In order to adapt to the analysis and application of social media big data, the corresponding social network analysis and social computing technologies have also become the focus of people's research. One of the most important hotspots is Web news mining analysis based on evolutionary fuzzy mechanism.

1.1.2 Related work

Web news classification is one of the important application techniques of news mining analysis. Since Web news classification is a special form of text classification, many existing Web news classification methods are derived from the previous text classification methods, which are all statistical methods. Commonly used text classification algorithms include SVM (support vector machine), BP (back propagation) neural network [3], ELM (extreme learning machine) algorithm, and these methods often exist. The finite sample or local optimization and over-learning problems are old, and these methods usually reduce the dimensionality of the data in order to avoid dimensional disasters. The results obtained at this time do not reflect the characteristics of the text well, which ultimately leads to low classification accuracy. A deep belief network (DBN) has been proposed very early [4]. It has been used in classification a lot, the main idea is to train neurons to get their parameters to the best, and then classify the data.

In recent years, news classification research has achieved some important results. In [5], a textual classification based on the Naïve Bayes Classifier is used for the text classification of Indonesian language. This method assumes that the news text data is a parametric model and uses Bayer's minimum error rate estimation using training samples. . Literature proposed a news classification method based on genetic algorithm for semantic features. The method is divided into two stages: semantic feature selection and feature transformation. In the feature transformation stage, genetic algorithm is used to realize news document classification. Literature [6] proposes a K-nearest neighbor reference classification and constrained clustering algorithm to construct a Web news text content classification model.

The two best methods that have been proposed so far are neural network fuzzy systems [7] and evolutionary fuzzy systems [8]. These two methods have strong adaptive capabilities, but these two methods are not only difficult to determine the initial value, but also the construction is too complicated, so they need a lot of research for further use. In any case, many years of evolutionary fuzzy systems will be a very important research content in the future.

2. Identification and Extraction of Web News Content

2.1 Characteristics of text information and picture information

Web news pages contain a lot of information, but they also contain a lot of content that is not relevant. Therefore, high-quality news text content can be extracted through the analysis of the results of the website. Currently, HTML is the most commonly used specification for representing web pages. It uses a very standard standard Html tag to define a large number of data elements (such as the body) of a web page, and can also define how the text of the page is displayed, so understanding and utilizing these standard Web tags can be achieved. Locate the central element of the text, such as the title, time, body content, etc. of the news. The news page has more obvious characteristics, and its time view is stronger and very important. Not only that, but it also has the characteristics of multimedia means and multi-modal interaction. Therefore, the obvious characteristics of web news create a good condition for identifying and extracting web content. At the same time, the web page not only contains news content, it also contains a wealth of information. In addition to the content on the topic of web news, there are a number of sections such as "navigation section", "copyright information description", and "advertising" that are not related to the topic content of web news. An example of the newspage is shown in Fig. 1. By extracting the feature analysis of the web news structure to identify the text portion related to the news topic content, thereby excluding the part that interferes with the text content, and providing an effective text resource for the classification of the web news content in the future.

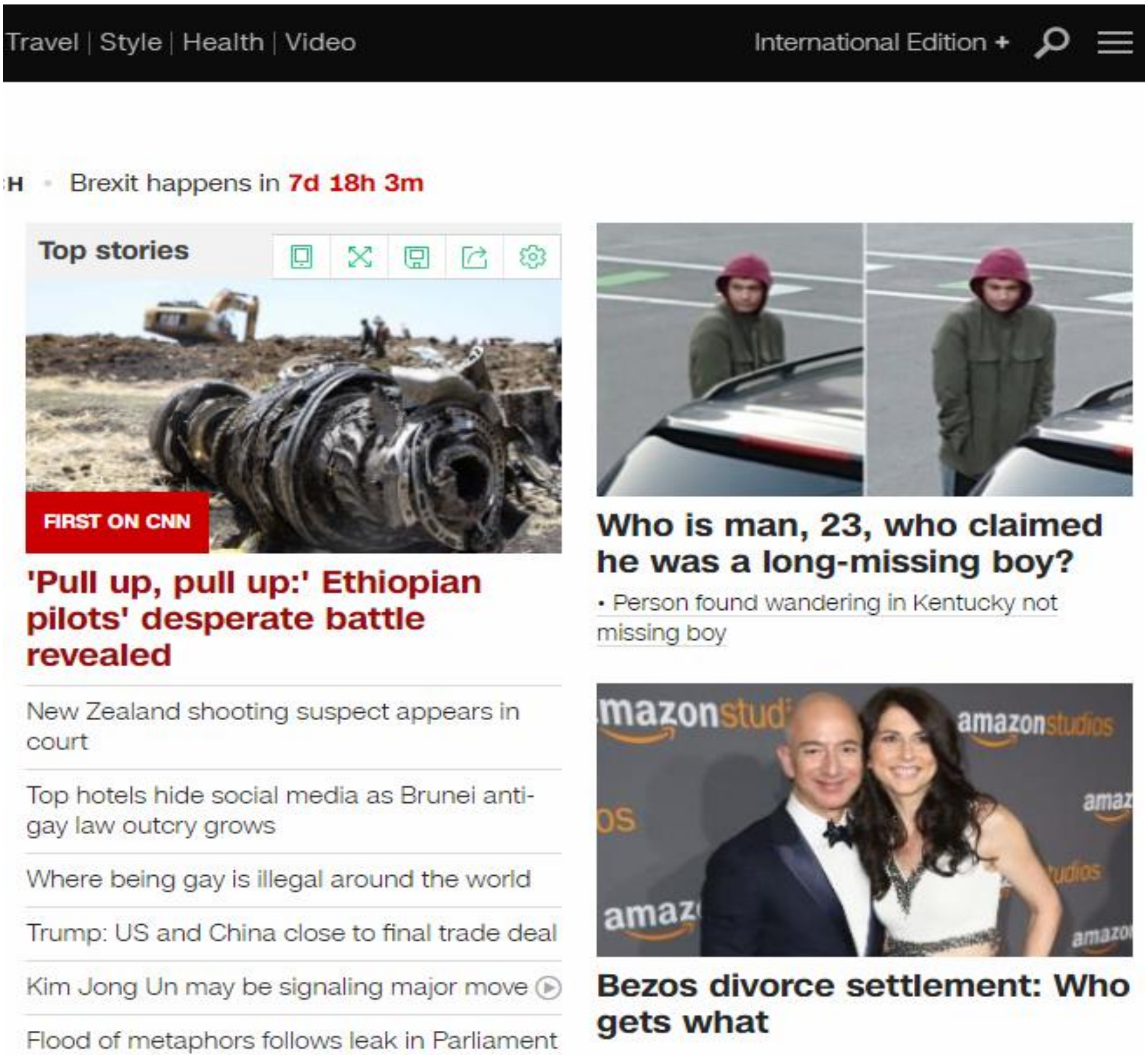

Figure 1. An example of the newspage

2.2 News subject content extraction

Since there are many types of web pages today, their common HTML writing is not necessarily strictly as desired. If you want the subsequent parsing to be well implemented, it is a necessary step to conform to the standard syntax and specification. This article uses the repair tools commonly used on the Internet to fix the incorrect HTML statements, and is standardized and conforms to the standard. Statement document.

Through the above standardization, the next step can be to parse such a web page into a tag tree. This article uses the DOM method to parse the web page, so after parsing it, we get a DOM tag tree with HTML as the root node. All attribute pairs in the web page will be stored in each node in the tree. This paper designs a method combining DOM tree parsing and topic content extraction based on web content segmentation. The basis of these two methods is to analyze the semi-structured nature of web pages, and to segment the web pages according to the HTML markup and the content of the webpage.

The core of the DOM tree parsing method is classified into three steps. First, calculate the weight of each block on each DOM tree sub-node according to the characteristics of the link ratio and punctuation proposed above; second, traverse the entire tag tree and look for their title <title> tag, obviously this tag decoration The content is the title of the news content of this page; finally, through the <table> tag, the sub-trees of the lowest level corresponding to the tags are merged into one block, and then the tree traversal algorithm is started, the specific way is: traversing the HTML, Compare the weight of the first occurrence of the content block in each branch, that is, the <table> block. The largest block is selected by the algorithm, and the <table> block weight of the same layer is deleted. Then re-traverse from the largest value of the <table> block just found, repeat the above method to continue to find the <table> block with the largest weight, so that the purpose of pruning can be achieved, and the pruning is always performed to the lowest layer. The end of the block.

At the same time, the webpage text is represented by the vector space model VSM (Vector SpaceModel). Vectors are often used to represent text, and such models are not only practical but uniform. In this paper, the similarity between the text content and the news headline after segmentation is used as the weight, and the content weights are sorted from large to small, and the weight of the certain size is selected as the module that can extract the content of the extracted text. Because it is the calculation of similarity. Here, the Boolean weight function is used to calculate the weight, that is, the degree of similarity is measured by the same number of words.

2.3 Non-text filtering

This paper constructs a two-layer BP neural network classifier to classify text content through feature calculation and related weights. The two results after classification are text class and non-text class. This classifier model contains an input layer, an implicit layer and an output layer. The number of nodes they contain will certainly be different, and they will change as the input eigenvalues change. The output layer has two nodes, representing the output as a non-text class and a text class. The neural network structure model is shown in Figure 2:

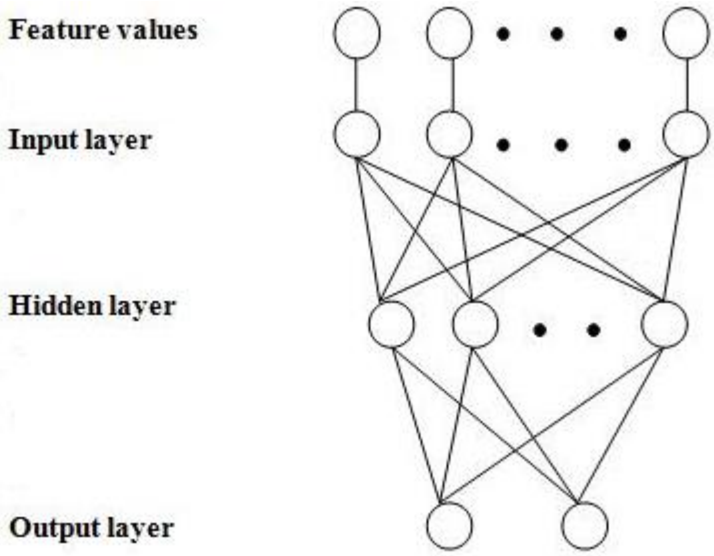

Figure 2. Structure diagram of double-layer bp neural network

We can clearly see that when the value of the output y1 is not greater than the value of y2, it is non-text content. When the value of the output y2 is greater than the value of y1, and the difference has a certain functional relationship, it is often text content.

Where t represents the value and r represents the proportion of the correct classification. The threshold will vary due to differences in data sets and positioning methods. The threshold here should vary from 0.25 to 0.55. As can be seen from the above figure, when the threshold value is too low, many non-text areas cannot be judged, resulting in a decrease in non-text filtering effect. When the threshold value is too high, the text will be filtered out better. The filtered positioning area is the area containing the text, but at the same time, many text areas are also filtered out, which leads to a significant drop in the recall rate. Based on the above experimental results, we chose BP neural network as the classifier, and the threshold value of 0.4 is the best. That is to say, the difference between the output of the true positive region and the difference is greater than 0.4, and the difference between the non-text regions is less than or equal to 0.4. Candidate text areas classified as non-text categories will be filtered out and finally the final location area will be obtained. In order to get a better threshold, we also use the SVM classifier as a comparison, and select the same feature as input, as shown in Fig 3:

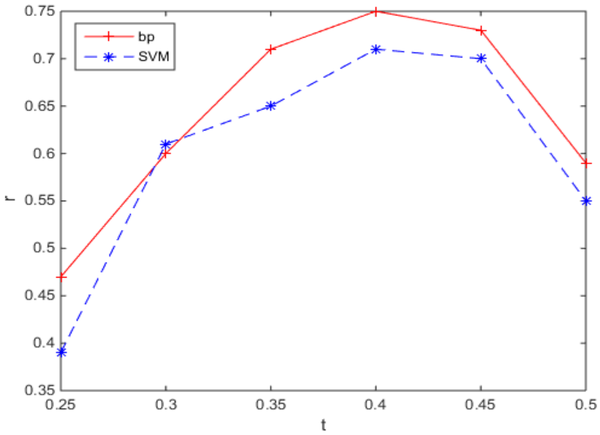

Figure 3. Contrast diagram of BP neural network and SVN effect

3. Evolutionary Fuzzy Classification

3.1 Text Preprocessing

The previously obtained Web news text can not be used directly, it also needs to be pre-processed, that is, to remove the word segmentation stop words [9]. First of all, the words of many features are to be marked, which will be used in the following classifications. Then we need to delete the useless words in the news text that do not make sense. This will not only reduce the dimension, but also improve the efficiency of future classification. There is also the extraction of the most central meaning of the words in the text sentence, for some words that are repeated or semantically ambiguous, we have to find a piece of content that best represents its meaning as text input.

3.2 Term filtering

When the text categories are many and complex, it is cumbersome to classify them according to the feature words, and the effect is not good. Therefore, this paper proposes a method combining the mutual information and TF-IDF to implement term filtering. The mutual information is first used to remove and classify the feature items that are not affected, and then the feature words are filtered using the determined value of the TF-IDF.

We can understand from the formula of TF-IDF that it mainly emphasizes and calculates the relationship between features and news text data, and there is no function value that can be reflected by the interaction between features and classification categories. Mutual information can well calculate the connection and impact between feature items and categories. For example, if the category and the corresponding feature of the calculation do not affect each other, then their mutual information value is equal to 0, which means that the feature has no effect on the text into this category. Then through the experiment to get the experience, set the threshold so that the value of the mutual information is less than each number, then filter out the useless words, and then use TF-IDF to extract less appear in the news text, but has a good Relevant characteristic words. Finally, the output is the weight corresponding to each word in the feature lexicon. This is to achieve a simplified role in the corpus [10].

3.3 Fuzzy rule based classifier

People often distinguish two things clearly, but the so-called fuzzy sets don't do this. This means that it may or may not belong to a collection. This ambiguous transformation requires a theory to describe, that is, membership functions, which make the language of the fuzzy set construction flexible and compatible. This is based on the earliest authors of the concept of "fuzzy collections", using such collections or classes that are not precise, to imitate some abstract ideas in human thinking to solve control, communication, etc. problem. Here we must focus on a solid place. The so-called ambiguity cannot be understood as a fuzzy random nature of the constituent elements in the set according to abstract ideas or undetermined nature.

In fact, the simple understanding is to divide the domain x of continuous space into several so-called fuzzy sets. We choose the membership function that specifies it, which overrides x in a more consistent way. Just like we give these fuzzy sets some names that people can understand, such as "high", "medium", "low", which is the origin of the fuzzy theory language mark. Therefore, the domain x is often referred to as a linguistic variable. In the fuzzy space we define, according to the fuzzy logic proposed and explained above, since we do not set the exact boundary between the two categories, then an object can be divided into two different categories at the same time, which may be The fuzzy set plays a role in making it theoretically true. Below we make a relatively detailed description through Figure 4-1. In this paper, we try to construct a fuzzy rule that has been proposed with multiple category labels and a lot of weights. Although the structure is more complicated, the ability to describe the problem is very good. The description is as follows.

In Fig. 4, the abscissa represents an input variable and the ordinate represents a membership degree. In this paper, each dimension of the input vector is homogenized into the interval [0,1], and then the entire interval is divided into 2N+1 fuzzy partitions, using SN,...,S1,CE,B1,...,BN respectively. To represent, the value of N in this paper is 2, which means that each dimension of the data will have 5 such 5 fuzzy partitions to correspond to, then we can use the Gaussian membership function to specify these five fuzzy partitions. Of course, there are many membership functions, such as the trigonometric membership function, the trapezoidal membership function, and the Gaussian membership function. As shown in Fig. 4, the value represented by the ordinate is the membership degree, and its range is [0, 1] (which will be used later).

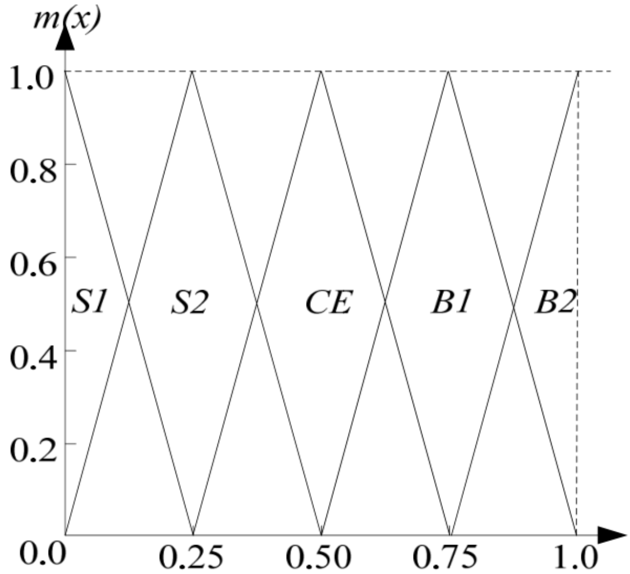

Figure 4. Fuzzy set space

3.4 Eclass0 Classifier

Nowadays, the existing classifiers basically adopt the statistical analysis method of text, and the method of pre-defining categories cannot handle a large amount of data well, and the accuracy of classification is difficult to improve. According to the classical fuzzy theory, the evolutionary fuzzy classifier makes it flexible to model through the membership function.

This paper uses a fuzzy rule (FRB) based classifier eClass0 to create and update fuzzy rules. The structure of the fuzzy rule is defined according to its 0th-order latter term:

$$R_i = IF(\mathrm{A}_t \sim \mathrm{Prot}_n)\,\mathrm{AND}\ldots\mathrm{AND}(\mathrm{A}_n \sim \mathrm{Prot}_n) \Rightarrow \mathrm{C}_j \tag{1}$$

Among them, the fuzzy rule R_i is composed of many weights A_n of features and feature weights Prot_n of a prototype in its corresponding category. Such fuzzy rules are used to describe categories C_j .

3.4.1 Fuzzy cule updat**e**

This article implements the creation of the fuzzy classifier eClass, which automatically initializes the classifier with the first data content. Since it is the first one, it will naturally be treated as a new rule. Then the content of the new spectrum data that is subsequently input will send its corresponding weights to the constructed model to see if it is necessary to change the rules and other operations to learn and change the attributes of the fuzzy rules. As described in [11], then a concept called potential value is proposed, and it is determined whether the prototype needs to be updated by calculating its size.

Assuming the newly entered data sample and his category is, the update of the fuzzy rule is the following four core ways:

Step 1: calculate the xt potential. First, the potential value P of the tth news text is calculated, P is the cumulative function value of the cosine distance of the data and other data, that is, the data density of the data. The formula is as follows:

$$P(\mathrm{x}_t) = (1 + \frac{\sum_{p-1}^{t-1} \mathrm{cosDist}(\mathrm{x}_t, \mathrm{x}_p)}{t-1})^{-1} \tag{2}$$

The cosine value is used in the equation to represent the distance between two vectors, because the cosine distance can better represent the direct relationship between the two vectors, but the calculation is repeated. We use t and p to indicate the number of their respective attributes. Below is the cosine distance formula:

$$\cos Dist(\mathrm{x}_t, \mathrm{x}_p) = 1 - \sum_{j-1}^{n} x_{tj} x_{pj} \Big/ \sqrt{\sum_{j-1}^{n} x_{tj}^2 \sum_{j-1}^{n} x_{pj}^2} \tag{3}$$

Step 2: update all xt prototypes. If it is the first input data, then it is the prototype. If not, the data density will naturally change as the data is continuously entered.

Step 3: a new prototype emerged. After entering a lot of data, if it has the greatest potential value, then its description ability is definitely good, then the classifier needs to be improved to add rules, its rules can be regarded as a new prototype, and then create it:

$$\exists i, i = [1, \mathrm{NumProt}] : \mathrm{P}(\mathrm{z}_k) > \mathrm{P}(\mathrm{Prot}_i) \tag{4}$$

Step 4: delete the existing prototype. Since the new prototype is added, it is necessary to prove that it can describe any other prototype in this class. In this paper, the Gaussian function with better generalization ability is used to calculate the membership function value:

$$\mu_i(\mathrm{x}_t) = e^{-\frac{1}{2}[\frac{\cos Dist|(\mathrm{z}_t, \mathrm{Prot}_i)|}{\sigma_i}]}, \quad i = [1, \mathrm{NumProt}] \tag{5}$$

$$\sigma_i(\mathrm{k}) = \sqrt{\frac{[\sigma_i(\mathrm{k}-1)]^2 + [\cos Dist^2(\mathrm{z}_k, \mathrm{Prot}_i) - [\sigma_i(\mathrm{k}-1)]^2]}{k}} \tag{6}$$

(5) $\cos Dist|(\mathrm{z}_t, \mathrm{Prot}_i)|$ expressed as the cosine distance between the i-th prototype and the $\sigma_i(\mathrm{k})$ description radius that the prototype can affect. Since some data needs to be calculated later, use formula (6) to update it decentralized.

3.4.2 Fuzzy classification

To realize the update of fuzzy rules, we also need to determine the mechanism of fuzzy classification. If we have L fuzzy rules and a new data $x_t = [x_{t1}, x_{t2}, ..., x_{tn}]$ is entered, we will use the following steps to derive the classification process to determine whether it is a text area or Non-text area.

Step 1: Calculate the match between the data xt and each rule.

$$\mu_{A_j}(\mathrm{x}_t) = \mathrm{T}(\mu_{A_j1}(\mathrm{x}_{t1}), ...\mu_{A_{jn}}(\mathrm{x}_{tn})), \mathrm{j} = 1, ..., \mathrm{L} \tag{7}$$

T() is an operation function that repeatedly calculates the membership value. Ajk represents a fuzzy partition, and j is one of the fuzzy rules.

Step 2: Calculate the correlation between the data xt and each rule.

$$b_j = T(\mu_{A_j}(\mathrm{x}_t), RW_j), j = 1, ..., L \tag{8}$$

Where RWj is the weight of the fuzzy rule j.

Step 3: Calculate the degree of association of the data xt on each type.

$$Y_p = \max(b_j, j = 1, ..., L and class h = C_p), p = 1, 2 \tag{9}$$

The maximum value mechanism is used to calculate the degree of association. In the value of p, 1 represents a text area and 2 represents a non-text area.

Step 4: Classify the data xt.

$$Y_l = \max(Y_p, p = 1, ..., M) \tag{10}$$

The last l is the final category of the data xt.

4. Experimental Results and Analysis

4.1 Data set

In order to better verify the performance of the test method, this experiment uses 1000 news texts obtained through the recognition and extraction of Web news content, and online news collection of 2000 news texts and data sets, which are divided into 8 categories. : Sports, fashion, travel, games, science, politics, animation and literature. We guess that as the number of categories will definitely affect the classification effect, this article uses the news text dataset collected by online news to analyze and construct four different types of data sets: (1) fashion, tourism, (2) politics, animation, Literature, (3) sports, games, travel, animation, science, (4) sports, fashion, travel, games, science, politics, animation and literature. Then use the data extracted in Chapter 3 Web News to identify the above four data sets.

4.2 Term Filtering and Threshold Pruning

We performed some column preprocessing on the news text data according to the steps proposed above, such as word segmentation. After the word stop, we got more than 9,000 different terms, so the system is too complicated, so we have taken the filter in this paper. The method filters the terms. To get the best threshold, we need to constantly experiment and analyze. When we adjust the threshold value to about 1, the terminology of the text will probably stabilize at around 600. Below we need to choose the threshold based on the results of the experiment.

The final threshold determination needs to be selected in different data sets and different categories. This article has done a lot of work, and found that there is a certain limit to the filtering of textual terms in news content. For example, if we use the trim threshold = 2 and classify the news text into only two categories (fashion and travel), we will find that the number of terms will drop a lot, from 5871 to 324. On the contrary, it will This will increase the correct classification rate from 59% to 88%, so this pruning process is necessary for this environment. We can set different optimal thresholds for different scenarios. In general, when the trim threshold is higher than 1.5, the experimental results are better. We don't set a lot of categories, we worry that when the categories are too complicated, the classification effect is very poor, we can't draw the conclusions we want.

4.3 Experimental result

The training set and test set were randomly selected in several data sets we constructed in a 1:3 ratio. Here, the commonly used precision and recall rate are selected as the criteria for evaluating the metrics. They are respectively represented by Pp and Pr, and the public display is as follows:

$$P_p = \frac{TP}{TP+FP}100\% \tag{13}$$

$$P_r = \frac{TP}{TP+FN}100\% \tag{14}$$

This paper selects the existing methods for comparative experiments and compares them with the following three methods. Among them, [12] proposed a two-layer BP neural network classification method, [13] proposed an improved K-proximity classification method, and the traditional support vector machine classification method proposed in [14]. We set the threshold of data set 1, 2 to 2.0 by experiment; the same set the threshold of data set 3, 4 to 1.8. The experimental results of the online news data set collected are shown in Table 1:

Table 1. Experimental results on-line data collection

DataSet	Our method		BP neural net work		KNN		SVM	
	Pp	Pr	Pp	Pr	Pp	Pr	Pp	Pr
(1)	88.9%	71.5%	83.6%	71.2%	83.8%	73.36%	89.2%	72.5%
(2)	82.5%	76.6%	80.4%	75.5%	79.1%	80.3%	73.9%	75.1%
(3)	77.2%	80.1%	75.2%	77.1%	76.7%	81.1%	63.8%	76.6%
(4)	75.8%	82.3%	74.7%	81.3%	71.8%	80.5%	55.4%	79.8%

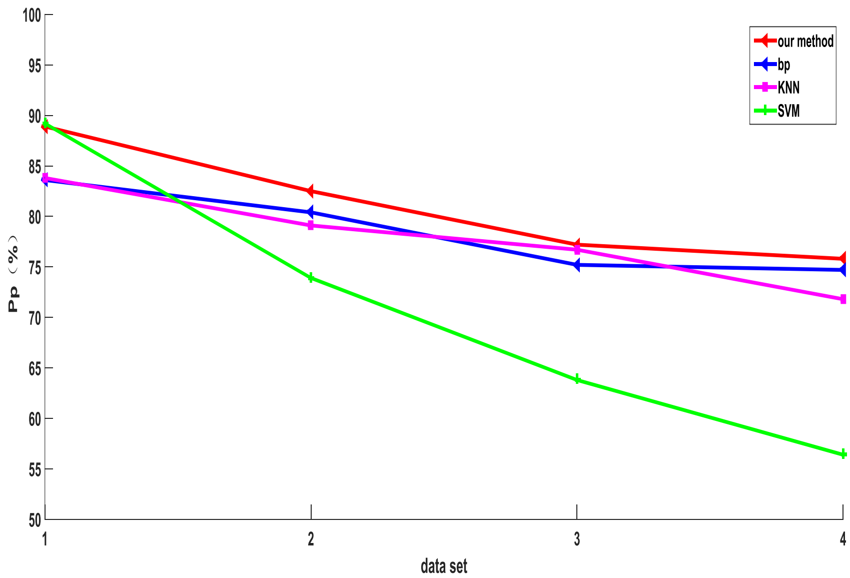

Figure 5. Experimental results on-line data collection

Fig. 5 is a graph showing the precision of comparison with the other three methods in the case where the experimental data set collected online on the website is divided into four data sets. It can be seen from the experimental results that, first of all, due to the increasing number of categories that need to be classified, each method will have an inevitable decline in the accuracy of classification. However, the method used in this article has always been in a better performance. Secondly, since the SVM classification method is a common language classification, it will have a good effect in dividing the data into two categories, but once the classification category increases, its performance decline is the fastest. In addition, because the online news data collected online will be very standardized, although there will be advantages in the precision and accuracy of the classification effect, the text in the web news image and the video frame image is not taken into account, so the data structure Not complicated enough, not very practical.

5. Conclusion

The pre-processed work is done first, and the terminology is filtered by using an improved information retrieval method before the rule is created, so as to achieve the purpose of streamlining and high efficiency. Then the eClass0 evolutionary fuzzy classifier is used to create and change various attributes of fuzzy rules. Finally, the evolutionary fuzzy classification of Web news content is realized by cosine distance combined with fuzzy rule inference, thus achieving the goal of this topic. Although the effect is better than the traditional text categorization method in dealing with complex categories, it is difficult to balance the balance of evolutionary ambiguity and the number of categories. So the next step is to better understand the evolutionary fuzzy rules and achieve a better classification effect on a large amount of data.

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