Eng Int Syst (2019) 3: 111–119

Engineering
Intelligent Systems

Evaluation of Web-Based Teaching Based on Machine Learning and Text Emotion

Lifang Wang*

Physical Education College Xi'an Physical Education University, Xi'an, Shaanxi 710068, China

In the era of big data, the analysis of text sentiment is an effective means of mining text data, which has strong practicability. In this paper, the author analyzes the evaluation of web-based teaching based on machine learning and text emotion The core of the machine learning method is the selection of an effective feature combination and the use of a classifier to classify emotion. The method of evaluating teachers' teaching quality by means of a network saves data processing time, makes the evaluation more comprehensive, gives a more detailed evaluation of the data, and indicates teachers' actual teaching situation more fairly and impartially. This paper introduces the main technologies used in the system, and conducts a detailed demand analysis for each subsystem, designs important modules and technologies such as a database and, finally, it summarizes the system design process and its shortcomings . At the same time, combining word vector and emotion, a vector matrix and hash table index are constructed, which significantly improve the efficiency of the model. This data preprocessing method can be widely used in other natural language processing tasks.

Keywords: Machine Learning; Text Emotion; Database; Hidden Markov models; Deep semantic objects

1. INTRODUCTION

With the development of information technology, the Internet is attracting more and more attention. China's Internet development report shows that more than half of China's population uses the Internet (Petersen et al., 2015). The current technology era is characterised by artificial intelligence, big data, cloud computing and other concepts, and these areas are also informing future Internet innovations (Dahl, 2011; Tasan et al., 2014). Every day on the Internet, a great volume of user-generated content (UGC) is produced, comprising users' comments about online shopping experiences, users' views on entertainment programs and hot spots, to name a few. Underlying the user's original content, there is often a less obvious user attitude, including the user's emotional state at the time of writing. Teaching evaluation is one of the important means of self-monitoring teaching quality in colleges and universities (Edgren, 2017; Isomoto et al., 2017). Not only do students have the opportunity to provide feedback on the effectiveness of their teachers' pedagogical practice; it also encourages teachers to improve their teaching methods, teaching quality and teaching management. It is an indispensable and important aspect of teaching activities (Hammond, 2010). The methods used to evaluate teaching quality mainly include the traditional teaching evaluation in the form of written questionnaires, answering cards, and the modern teaching evaluation via computer technology.

Within the broad and complex spectrum of human psychology, human emotions can be divided into three basic categories: positive, neutral and negative. For example, happiness is a positive emotion, indifference is a neutral or negative emotion, sadness is a negative emotion and so on. There are many external manifestations of human emotions, including the content of user comments posted on the Internet (Ma & Cheng, 2016). Comments such as "this thing works well" and "this product is too bad", enable readers to clearly discern the opposite attitudes of the two writers. The various emotions underlying written texts have given rise to the research field known as text sentiment analysis. Sometimes

*E-mail: lifangwang963@163.com

referred to as text sentiment classification, this is an important branch of the field of NLP. It can help people understand the hidden emotions and viewpoints in text information, so it is often analyzed with point mining. In the era of big data, text sentiment analysis can effectively mine text data, which has strong practicability (Ngobi et al., 2011). For example, through the analysis of user comments, e-commerce platforms can know and understand consumers' attitudes to certain products. This can help businesses to find product defects and subsequently modify the design and the marketing strategies Government departments through real-time analysis of public opinion, can help staff quickly respond to crucial events, improve administrative efficiency and so on. Reinforcement learning is an important branch of machine learning (Zhu et al., 2016) owever, compared with other machine learning algorithms, reinforcement learning has been ignored by researchers for a long time.

Written questionnaires and card-based evaluations of teaching usually require several tasks such as designing sample forms, printing and distributing, students filling in information, and obtaining statistical results either manually or by machine. The process is very complex, requiring a lot of manpower and financial resources, and is restricted by many factors such as time and space (Tao et al., 2016). It may take weeks, even months, to complete the whole process. Considering the task of receiving and sending, statistics and other work, many schools have to control the number of participants in the evaluation of teaching by means of evaluation, and even set up several teaching informants in each class to be responsible for teaching evaluation (Petersen et al., 2015). Doing so will undoubtedly result in untrue evaluation results, seriously affecting the quality and purpose of teaching evaluation. It can be seen that the traditional means of conducting teaching evaluation not only consumes a lot of resources, but also wastes the time of teachers and students, and increases the workload of all staff involved. Moreover, manually-obtained statistics often contain errors, which will directly affect the accuracy and objectivity of the evaluation results. Hence the increasing trend to apply computer and network technology to the evaluation of teaching quality. These tedious tasks are handled by computer, which not only completes them accurately and quickly, but also provides fair and impartial feedback information. It can be said that online teaching evaluation based on machine learning and text emotion is an extension of traditional teaching evaluation. It not only shares the purpose and main functions of traditional teaching evaluation, but also offers several functions that paper-based teaching evaluations do not have.

2. RELATED WORK

This paper summarizes the four factors that affect learners' participation in online learning: instructors, learners, online courses and learning environment. Zhang Jiahua believes that these four factors are interrelated and have a positive impact on learners' motivation and performance during online learning. In addition, the theory of network learning effect impact regards learners as the core factor, teachers as the key factor, network courses as the basic factor, and learning environment as the guarantee factor. This theory provides a reference for evaluating the effect of teaching based on network environment (Tasan et al., 2014)

The teacher's method of teaching is the key factor in the model. Firstly, in terms of teacher quality it is a new attempt to organize virtual community teaching in the Mu Course Platform environment, which also has new requirements for teachers' teaching quality, including the application quality of the Mu Course Platform, the cognitive quality of virtual community teaching theory, the application quality and collection of virtual community teaching theory and practice, and the evaluation quality of teaching data, etc (Tanwar and Kumar 2015). Teachers should conscientiously self-monitor in the early stage, update teaching concepts promptly, master the application skills of the teaching platform, and improve the comprehensive quality of self-teaching. Secondly, in terms of teaching design (Fan & Xiao 2015; Esteva et al., 2017) the research of scholar Liu Aiqin has proved that instructional design will have an impact on the quality of online learning.

The basic research ideas regarding text emotion classification can be divided into two categories - based on expert system method, mainly using prior knowledge such as emotional dictionary and lexicon to analyze the special structure of text sentences and emotional tendency words, giving different weights to emotive words with different emotional intensity, and judging the emotional tendencies of text according to the calculation results. Secondly, based on machine learning, the text is represented as feature vectors by specific methods, and the manual annotated corpus is used as training set (Liang et al., 2016; Kaneko 2017). Then, the machine learning model is trained by adjusting the parameters, and the model is used to determine the underlying emotion(s) in the text.

Of these, the rule-based expert system does not need a large amount of corpus for training, and has a high level of interpretability (Wang, 2015) Accuracy is high in specific areas. However, the disadvantage is that the established rules cannot cover all the knowledge, so the prediction ability of cross-domain corpuses is poor; moreover, the rules change quickly, and the maintenance cost is high (Benzaoui et al., 2014). With the development of computer technology, the machine learning algorithm has gradually become the mainstream method used for emotional classification tasks. Compared with expert systems, the machine learning algorithm has stronger learning ability. Before the emergence of the deep learning algorithm, scholars used traditional machine learning methods to conduct emotional analysis and achieved some promising results (Bharadi et al., 2010). For example, Pang et al. used a support vector machine, maximum entropy model and other algorithms to study the emotion classification task of movie reviews. Bengio and others use the neural network method to build language models, leading to the application of neural networks in the Natural Language Processing field (Dubey et al.,012).

With the development of deep learning technology, the effect of deep learning algorithms on text sentiment analysis has been verified many times. The concept of deep learning stems from the research on artificial neural networks, which is a relatively young research field. At the initial stage of the algorithm, because of the limitations of technology, a too complex neural network structure cannot be effectively learned. However, with G.E. Hinton and others proposing a new gradient descent algorithm in 2006, the problem of model training is solved. This method effectively promotes the development of deep learning. Kim et al. use word vector technology to express text as vector, so that the convolution neural networks commonly used in image recognition and other fields are migrated to the field, proving that depth learning has wide applicability. Reinforcement learning is another important branch of machine learning. Compared with traditional machine learning and deep learning algorithm, reinforcement learning is more in line with the human learning process (Eskander et al., 2013).

3. OPTIMAL MODEL OF INFORMATION DEVELOPMENT

Definition 1 (large data technology) Given a time series $T = \langle t_1, t_2, \cdots t_i \cdots \rangle$, data dimension d and node number n. A large data technology is defined as $S = \langle r_1, r_2, \cdots, r_i, \cdots \rangle$, where each $S_k = (k = 1, 2, \cdots, n)$ is a single data stream, is a multidimensional data tuple sequence $S_k = \langle r_1, r_2, \cdots, r_i, \cdots \rangle$, $r_i = \left\langle r_i^1, r_i^2, \cdots, r_i^d \right\rangle$ collected on T.

Definition 2 (historical window) Given a time series $T = \langle t_1, t_2, \cdots, t_i, \cdots \rangle$ and a data flow $S = \langle r_1, r_2, \cdots, r_i, \cdots \rangle$ on it. Suppose $t_i, t_k \in T, i \langle k, H_k = [t_i, t_k)$ is called the historical window of the S corresponding to k, and k belongs to a mining point. The data $chunk_k = \langle r_i, r_{i+1}, \cdots, r_{k-1} \rangle$ from the H_k is called the data block of the historical window.

Definition 3 (large data) Assuming the d dimension data set $X = \{x_1, x_2, \cdots x_n\}$, which is A = B, the large data structure of the data set contains the following 5 tuple $M = \langle n, c, s, d, f \rangle$ definitions.

(1) M.n: represents the total number of data (here is n).

(2) M.c: mean value, equivalent to the center point, that is

$$M.c^j = \left(\sum_{i=1}^{n} x_i^j\right) \Big/ n, \; j = 1, 2, \cdots, d \tag{1}$$

(3) M.s: square sum statistics (to prevent overflow radicand)

$$M.s^j = \sqrt{\sum_{i=1}^{n} \left(x_i^j \times x_i^j\right)}, \; j = 1, 2, \cdots, d \tag{2}$$

(4) M.d: Statistical value of variance

$$M.d^j = \left(\sum_{i-1}^{n} \left(x_i^j - M.c^j\right)^2\right) \Big/ n, \; j = 1, 2, \cdots, d \tag{3}$$

(5) M.f: The class identifier of the data set.

Algorithm 1 micro–cluster–abstractor.

Input:the mining time is set to t; at this time the corresponding data block is D; its data dimension is d; k represents the number of large data.

Output:M is a large set of data at t

divideD intok clustersC by Algorithmk–means;
$FOR\ each p \in C$
$p.n \leftarrow |p|;$
FOR $i = 1$ to d
$p.c^i \leftarrow \left(\sum_{q \in p} q^i\right) \Big/ n;$
$p.s^i \leftarrow \sqrt{\sum_{q \in p} q^i \times q^i};$
$p.d^i \leftarrow \left(\sum_{q \in p} (q^i - p.c^i)^2\right) \Big/ n;$
$ENDFOR$
$p.c \leftarrow (p.c^1, p.c^2, \ldots, p.c^d);$
$p.s \leftarrow (p.s^1, p.s^2, \ldots, p.s^d);$
$p.d \leftarrow (p.d^1, p.d^2, \ldots, p.d^d);$
$flagp.f$ *with the most label in instances ofp*;
$integratep.n, p.c, p.s, p.d and p.f into microclusterm;$
$M \leftarrow M \cup \{m\};$
$ENDFOR$
$returnM$

Definition 4 (teaching management informatization of university education model) The optimal model for education and teaching management information in colleges and universities with the main technical features of distributed and fluidity is defined as $M = \langle T, D, O, P \rangle$. Among them, $T = \langle t_1, t_2, \cdots \rangle$ is the sequence of time points for data collection, and $D = \{S_1, S_2, \cdots S_n\}$ is determined by the structure of big data technology composed of n strips and data streams collected from T data at some single nodes of the data set. This is also the source of data mining. Operator operations for D are performed by O, and special algorithms are needed. P is the optimer of the dataset.

4. INFORMATION PROCESS OF TEACHING MANAGEMENT

4.1 Big Data Extraction Algorithm

The purpose of this system is to analyze the big data mining after the system receives the corresponding data blocks of teaching management information. For example, algorithm 1 shows the extraction of large data from the implementation of teaching management informatization.

The algorithm uses the k-means in the first steps of the clustering operation. The time complexity of the algorithm can be expressed as $o(l \times m)$, l and m indicate the number of iterations to be completed under the premise of obtaining the optimal partition and the total amount of data needed to be mined. $m = k \times n$, so the time complexity of the algorithm depends on the k-means algorithm.

4.2 Data Maintenance Algorithm of Teaching Management Information

Based on the characteristics of distributed educational management information in colleges and universities, the author selects the "variance and minimum" analysis method to get the best combination cluster. A large data set M is given, in which two large data m_1 and m_2 that are merged should meet the following conditions:

$$min\left\{\sum_{i=1}^{d} unite(m_1, m_2).d^i | m_1, m_2 \in M\right\} \tag{4}$$

$*.d^i$ is the i dimension value of the variance of a large data; unite (m_1, m_2) represents the large data after the combination of m_1, m_2.

Definition 5 (the process of merging large data) For the two d dimension big data m_1 and m_2, assuming that the two big data have the same class identities, it can be merged into new big data by a merging operation, unite (m_1, m_2), and is labeled m_3 = unite (m_1, m_2), thus obtaining the statistical process of the m_3 statistics.

$$m_3.n \leftarrow m_1.n + m_2.n \tag{5}$$

$$m_3.c^i \leftarrow \frac{m_1.n \times m.c^i + m_2.n \times m_2.c^i}{m_3.n} \tag{6}$$

$$m_3.s^i \leftarrow \sqrt{\left(m_1.s^i \times m_1.s^i + m_2.s^i \times m_2.s^i\right)} \tag{7}$$

$$m_3.d^i \leftarrow \frac{m_1.s^i \times m_1.s^i + m_2.si \times m_2.s^i}{m_3.n} - 2 \times m_3.c^i \tag{8}$$

$$\times \frac{m_1.c^i \times m_1.n + m_2.c^i \times m_2.n}{m_3.n} + m_3.c^i \times m_3.c^i \tag{9}$$

$$m_3.f \leftarrow m_1.f \tag{10}$$

Theorem 1 For $m_3 = unite(m_1, m_2)$, the statistical values corresponding to the large data m_3 can be calculated by using the formula (5)~(9) in the definition 5. According to the calculation results, the data distribution features before the merger can be obtained.

It is proved that under general conditions, m_1 and m_2 are all one-dimensional data sets, which are written as $c_1 = \{x_1, x_2, \cdots, x_p\}$ and $c_2 = \{y_1, y_2, \cdots, y_q\}$ (since both are one dimensional dataset, they are not marked dimensions).

For $m_3 = unite(m_1, m_2)$, the original data set of the m_3 cluster is $c_1 \cup c_2 = \{x_1, x_2, \cdots, x_p, y_1, y_2, \cdots, y_q\}$.

Combined with the statistical method of large data point number defined by 3, we can get it $m_3.n = p + q = m_1.n + m_2.n$

Therefore, the definition of (5) in 5 is established.

The calculation process of the large data center point corresponding to 3 is defined.

$$\begin{aligned} m_3.c &= (x_1 + \cdots + x_p + y_1 + \cdots + y_q)/(p+q) \\ &= (x_1 + \cdots +_p + y_1 + \cdots + y_q)/m_3.n \end{aligned} \tag{11}$$

$$\begin{aligned} m_1.c &= (x_1 + x_2 + \cdots + x_p)/m_1.n, \\ m_2.c &= (y_1 + y_2 + \cdots + y_q)/m_2.n \end{aligned} \tag{12}$$

Add the formula (12) to formula (11) and get

$$m_3.c = (m_1.c \times m_1.n + m_2.c \times m_2.n)/m_3.n \tag{13}$$

The formula (6) in the definition 5 can be judged to be established.

We further analyze the large data square of the definition of 3 and its statistical results.

$$m_3.s = \sqrt{x_1^2 + \cdots + x_p^2 + y_1^2 + \cdots + y_q^2} \tag{14}$$

$$\begin{aligned} m_1.s &= \sqrt{x_1^2 + x_2^2 + \cdots + x_p^2}, \\ m_2.s &= \sqrt{y_1^2 + y_2^2 + \cdots + y_q^2} \end{aligned} \tag{15}$$

Add the formula (15) to formula (14) and get

$$m_3.s = \sqrt{m_1.s \times m_1.s + m_2.s \times m_2.s} \tag{16}$$

Hence, the formula (7) in definition 5 is established.

Calculate according to the statistical values of variance of the large data defined in definition 3.

$$\begin{aligned} m_3.d &= \frac{\sum_{i=1}^{p}(x_i - m_3.c)^2 + \sum_{i=1}^{q}(y_i - m_3.c)^2}{p+q} \\ &= \frac{\sum_{i=1}^{p} x_i^2 + \sum_{i=1}^{q} y_i^2 - 2 \times m_3.c \times \left(\sum_{i=1}^{p} x_i + \sum_{i=1}^{q} y_i\right)}{p+q} + m_3.c^2 \end{aligned} \tag{17}$$

Add the formula (15) and (12) to formula (10) and (17), get

$$\begin{aligned} m_3.d &= \frac{m_1.s \times m_1.s + m_2.s \times m_2.s}{m_3.n} - 2 \times m_2.c \\ &\times \frac{m_1.c \times m_1.n + m_2.c \times m_2.n}{m_3.n} + m_3.c \times m_3.c \end{aligned} \tag{18}$$

It can be proved that the formula (8) in definition 5 is established, and

$$m_3.f \leftarrow m_1.f \tag{19}$$

Combined with the above results, we can see that for the one-dimensional data set, theorem 1 is established. When data set is multidimensional, we need to calculate every dimension separately.

Through algorithm 2, we can see that the time cost is determined by the number of large data merging. It can be found that the big data extraction algorithm based on k-means can form k big data in the existing data blocks, so algorithm 2 can carry out the unite operation of big data at most k times.

4.3 A Sample Reconstruction Algorithm for Teaching Management Information Processing Center

When a big data mode corresponding to teaching management information is updated, it can be transmitted to the teaching management information processing center by network. As

Algorithm 2 micro–cluster–maintainer.

Input: set the mining time t; M^* is the large data set extracted from the current data block; its dimension d; L is the largest number of data that can be carried out for teaching management informatization; M is the big data set for maintaining the last mining point.

Output: a large data set M that is updated at time t

$M \leftarrow M^* \cup M$;
$L_M \leftarrow |M|$;
$WHILE\ L_M >$ L DO
$b \leftarrow$ *the largest number of machine*;
$FOR\ each\ m_1 \in M$
$FOR\ each\ m_2 \in M$
$IF\ \sum_{i=1}^{d} unite(m_1, m_2).d^i \langle b\ THEN$
$s_1 \leftarrow m_1$; s2$\leftarrow m_2$;
$b \leftarrow \sum_{i=1}^{d} unite(m_1, m_2).d^i$;
$ENDIF$
$ENDFOR$
$ENDFOR$
$p \leftarrow unite(s_1, s_2)$;
$M \leftarrow M \cup \{p\};\ M \leftarrow M - \{s_1\} - \{s_2\}$;
$L_m \leftarrow L_M - 1$;
$ENDDO$
$return\ M.$

shown below, it shows the following code in algorithm 3 to form a global training data sample set.

It can be found that the time complexity of algorithm 3 is $O(n)$ when the influence of the data dimension is excluded, where the n represents the number of the recovered samples. The actual memory space depends on the size of the data of these samples.

Theorem 2 If the data in the large data technology are in the form of normal distribution, the data set constructed by algorithm 3 will be equivalent to the original statistical results of the mean and variance of the large data. Theocument analysis approach only analyzes one-dimensional data, assuming that the big data set M contains only one big data m, where μ and σ are the mean and variance of m respectively, and the algorithm 3 is used to compute m, and the sample set $X = \{x_1, x_2, \cdots x_n\}$ can be obtained.

According to the definition of the mean value of large data, the X center point X_c can be expressed as:

$$X_c = 1 \Big/ n \times \sum_{i=1}^{n} x_i \tag{20}$$

At the same time, the point of X is obtained with algorithm 3.

$$\forall x_i \in X, x_i \leftarrow \mu + \sqrt{3n\sigma/2} \times rand(-1, 1) \tag{21}$$

Add the formula (21) to formula (20) and get

$$\begin{aligned} X_c &= 1 \Big/ n \times \sum_{i=1}^{n} \left(\mu + \sqrt{3n\sigma/s} rand(-1, 1)\right) \\ &= \mu + 1 \Big/ n \times \sqrt{3n\sigma/2} \times \sum_{i=1}^{n} rand(-1, 1) \end{aligned} \tag{22}$$

Algorithm 3 Sample–remaker.

Input: set the mining time t; at this time, M is a large data set consisting of the data for the teaching management; the dimension of the data set is d.

Output: the set of data samples reconfigured at t is S

$FOR\ each\ m \in M$
$n \leftarrow m, n$;
$FOR\ i = 1$ to n
$FOR\ j = 1$ to d
$r \leftarrow rand\ (-1.1)$; the random numbers in the $-1 \sim 1$ interval are obtained.
$l \leftarrow \sqrt{3 \times n \times m.d^j/2}$;
$x^j \leftarrow m.c^j + l \times r$;
$ENDFOR$
$x \leftarrow (x^1, x^2, \ldots, x^d)$; the multidimensional data point x is obtained.
$flag\ x\ with\ m.f$
$insert\ x\ into\ S$;
$ENDFOR$
$ENDFOR$
$returnS.$

In the normal distribution, A=B. So according to the formula (22),

$$X_c \sim \mu \tag{23}$$

In addition, according to the definition of variance in definition 3, the variance A of X_d is

$$X_d = 1 \Big/ n \times \sum_{i=1}^{n} (x_i - X_c)^2 \tag{24}$$

Add the formula (21) to formula (24) and obtain

$$\begin{aligned} X_d &= 1 \Big/ n \times \sum_{i=1}^{n} \left(\mu + \sqrt{3n\sigma/2} \times rand(-1, 1) - X_c\right)^2 \\ & 1 \Big/ n \times \sum_{i=‘}^{n} \left((\mu - X_c) + \sqrt{3n\sigma/2} \times rand(-1, 1)\right)^2 \end{aligned} \tag{25}$$

According to equation (23) $X_c \sim \mu$, the formula (25) and the following formula is equivalent:

$$\begin{aligned} X_d &\sim \frac{\sum_{i=1}^{n} \left(\sqrt{3n\sigma/2} \times rand(-1, 1)\right)^2}{n} \\ &= \frac{3n \times \sigma \times \sum_{i=1}^{n} rand(-1, 1)^2}{2n} \\ &= 3\sigma/2 \times \sum_{i=1}^{n} rand(-1, 1)^2 \end{aligned} \tag{26}$$

Because of $\sum rand(-1, 1)^2 \sim \int_{-1}^{1} x^2 dx = 2/3$, then

$$X_d \sim \sigma \tag{27}$$

According to the above formula (23) and the formula (27), it is found that theorem 2 is suitable for single large data and single-dimension data space types. For multidimensional data or large data, it is necessary to use only the above method to reason each dimension or large data in turn.

Table 1 Exam Paper.

Key	Name	DataType	Notnull	Description
primary key	Paperld	Integer		Text paper ID
	PaperNo	NVarChar[100]		Text paper number
	PaperName	NVarChar[100]	Notnull	Text paper name
	Reserved			Reserved field 1

Table 2 Examination task record table PaperRecord.

Key	Name	DataType	Notnull	Description
primarykey	PaperRecordld	Integer		ID of the test paper record
	PaperNo	NVarChar[100]		ID of the test paper
	taskld	NVarChar[100]		ID of the task

Algorithm 4 Ensemble–Updater.

Input: set the mining time t; at this time, the training sample set is S; the previous mining point maintains large data scale to E; the largest number of weak optima can exist in the big data scale is Q.

Output: Get large data scale E after update at t.

$p \leftarrow |S|/Q$;
$FOR\ each\ e \in E$
$e.error \leftarrow 0$;
$FOR\ s \in S$
$f \leftarrow e(s)$; Using the weak optimer e to realize the prediction
$IFf = s.fTHEN\ delete\ s$ from S
$ELSEe.error \leftarrow e.error + 1$;
$ENDFOR$
$IFS = \phi$ *THEN break*
$ELSE$
$K \leftarrow$ *randomly select psample from S*
$e* \leftarrow C4.5(K)$; New optimer learing
$E \leftarrow E \cup \{e*\}$;
$ENDIF$
$IF\ |E| > QTHEN$
$c \leftarrow 3$ *that satisfies max*$\{e.error|e \in E\}$
$c \leftarrow E - \{c\}$; Deleting the worst optimer over the bound condition
$ENDIF$
$ENDFOR$
$returnE$

4.4 The Optimal Updating Algorithm of Large Data in Teaching Management Information

A base optimer is used as a large data scale structure in this paper. Given a large data scale $E = \{e\}$. Algorithm 4 is the optimal device code for the learning of the teaching management information processing center.

In algorithm 4, the three steps above must be completed separately for each worst optimer. At the same time, the number of worst optimers depends on the Q value. Through the analysis, the algorithm time complexity is Max$\{O(Q \times n)$, $O(Q \times c)$, $O(Q^2)\}$.

5. EXPERIMENT AND RESULT ANALYSIS

In this experiment, KDD (CUP) 99 data set is used to evaluate the effectiveness of the information development strategy for education and teaching management in colleges and universities. The DS-means algorithm is compared. Exam Paper, as shown in Table 1, contains the ID, number, and names of the test paper fields. Among them, Paperld is the primary key.

The paper test record table PaperRecord is shown in Table 2, including the ID of the test paper record, the ID of the test paper, and the ID of the task. The PaperRecordId is the primary key.

Experiment 1 (accuracy test under different historical window). Combined with the application of the LDTC method and the contrast algorithm DS-means, the global optimer is obtained. After that, the accuracy is tested on a dataset from KDD99. Figure 1 shows that the LDTC error rate is significantly lower than DS-means (about 10%). As the historical window increases, the accuracy of the LDTC is gradually increasing and the DS-means is fluctuating.

Experiment 2 (the optimal precision test for different large data scales). In 1000s, error rate tests are performed every additional 100s performs 1 time LDTC and DS-means to generate global optimer. From Figure 2, we can see that, compared with DS-means algorithm, the optimal accuracy of our method is obviously better. From Figure 3, we can see that LDTC will increase with the increase of training time, and the DS-means will fluctuate.

Experiment 3 (test execution time and memory space). The time spent in the teaching management information processing center is executed by tracking LDTC and DS-means. As seen in Figure 4, the two algorithms increase with the time of the history window, and the time cost of each update is increased. The execution time of the LDTC is not as much as for the DS-means.

As shown in Figure 5, the memory size of LDTC and DS-means is basically the same. This is because when LDTC calls the C4.5 algorithm, only one of the numbers

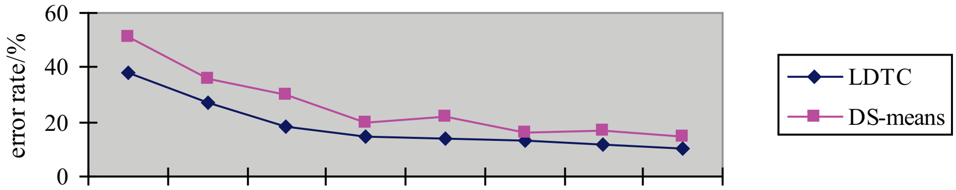

Figure 1 The change in error rate when the length of the time window increases.

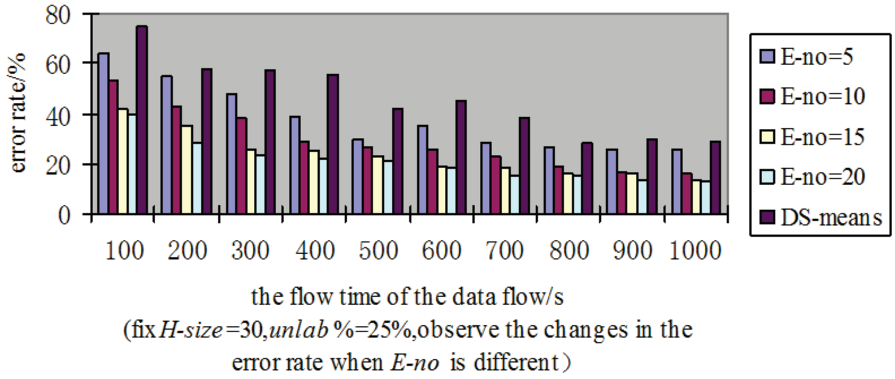

Figure 2 Error rate of the corresponding flow data under each integrated optimal condition.

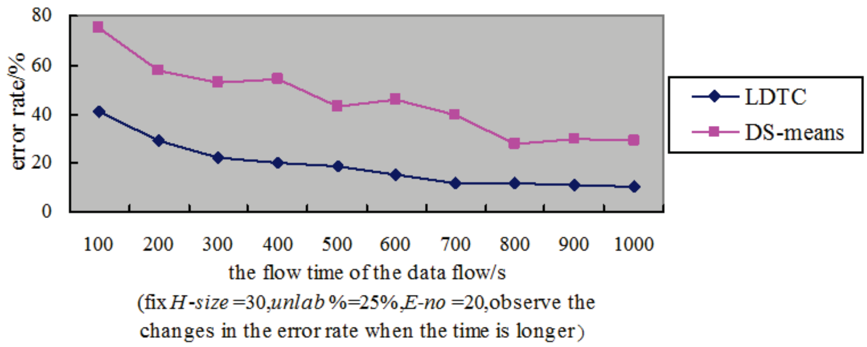

Figure 3 The corresponding error rate state under the condition that E-no is 20.

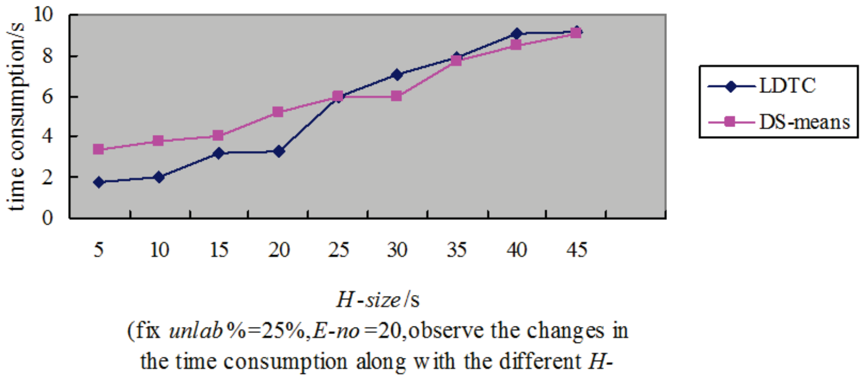

Figure 4 The relationship between the execution time and the length of the time window.

of training samples is selected. Therefore, the memory is slightly lower than the memory size in experiments 1, 2 and 3 of DS-means. The security of data is very important in the teaching evaluation system. Whether it is traditional teaching evaluation or online teaching evaluation, the school is responsible for ensuring the confidentiality of (and archiving)

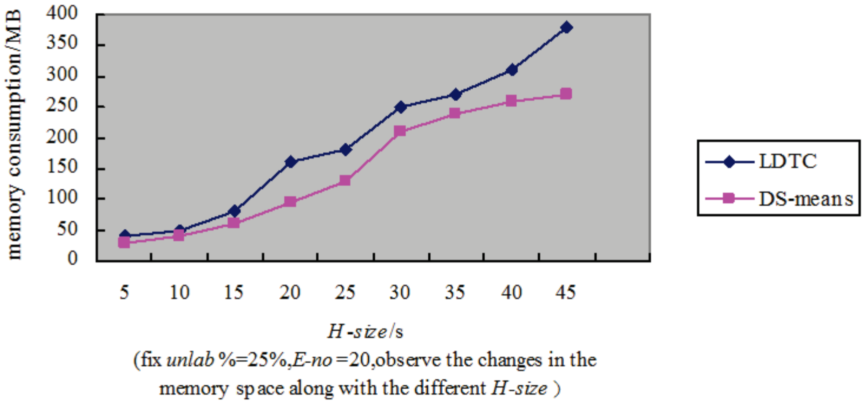

Figure 5 The relationship between the memory space and the length of the time window.

much of the information – only a limited amount of evaluation information can be made public. Firstly, the system uses a firewall for security protection, which is placed between the client browser and the Web server. Users can access the server but only through the firewall, and then the server accesses the database. Secondly, the user rights are controlled, and appropriate rights are assigned to each role; hence, each role can operate only on its own relevant modules. At the time of login, the identity of each user is confirmed. Only legitimate users can enter the system and perform related operations. Administrators will assign permission to users according to the requirements of the system and the functions required by the roles. In addition, the system administrator also maintains the server regularly and establishes the working log of the system.

6. CONCLUSION

With the continuous development of society, colleges and universities are offered enormous opportunities, but are also facing challenges. How to improve the management of schools and the quality of teaching is a very important issue. As a vital part of daily teaching management, the evaluation of teaching quality leads to the ongoing exploration of new methods and ideas. The use of computer and network technology in teaching evaluation is recognized for its high efficiency and scientific basis. In recent years, the construction of digital campus in colleges and universities has gradually been attached importance to and studied by schools. Sharing resources and software docking of all systems are important prerequisites for realizing digital campus. The evaluation of teaching via a network is also an indispensable part of the digital campus. How to realize the data docking and data integration between this system and other systems needs further research and development.

REFERENCES

1. Benzaoui, A., Hadid, A. and Boukrouche, A. (2014) ‘Ear biometric recognition using local texture descriptors’, IET Biometrics, Vol. 23, No. 3, pp.9–17.
2. Bharadi, V.A. and Kekre, H.B. (2010) ‘Off-line signature recognition systems’, International Journal of Computer Application, Vol. 1, No. 27, pp.48–56.
3. Dubey, R. and Agrawal, D.K. (2012) ‘Comparative analysis of off-line signature recognition’, Proc. – 2012 Int. Conf. Commun. Inf. Comput. Technol. ICCICT 2012, pp.1–6.
4. Dahl, K. K. B. (2011). Becoming a health education professional in Kenyan teacher training colleges: professional identity, everyday life and health education practices. Annals of Internal Medicine, 2(2), 289–290.
5. Esteva A., Kuprel B., Novoa R., Ko J., Swetter S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. Nature, 542 (7639), pp. 115–118.
6. Edgren, H. (2017). Abstract 2596: Medisapiens explorer technology platform - integrated solution for big biomedical data. Cancer Research, 77(13 Supplement), 2596–2596.
7. Eskander, G.S., Sabourin, R. and Granger, E. (2013) Hybrid Writer-Independent Writer-Dependent Offline Signature Verification System, IET Biometrics, DOI: 10.1049/iet-bmt.2013.0024.
8. Fan C., Xiao F. (2015). A framework for knowledge discovery in massive building automation data and its application in building diagnostics. Automation in Construction, 50, pp. 81–90.
9. Hammond, M. (2010). What the literature says about continuing professional development and the use of learning platforms in schools and in initial teacher education. Swiss Medical Weekly, 140(19–20), 286–292.
10. Isomoto, Y., Nakano, U., Yamasaki, H., & Itoh, S. (2017). Examination and problems in development of a simulation teaching matrial for information processing education. Physics Today, 35(8), 60–61.
11. Kaneko H. (2017). A new measure of regression model accuracy that considers applicability domains. Chemometr. Intell. Lab., 171 (2), pp. 1–8.
12. Liang X., Hong T., Shen G. (2016). Occupancy data analytics and prediction: A case study. Build. Environ., 102 (2), pp. 179–192.
13. Ma, J., & Cheng, J. C. P. (2016). Estimation of the building energy use intensity in the urban scale by integrating gis and big data technology. Applied Energy, 183, 182–192.
14. Ngobi, D. H., Otaala, J., Maani, J., & Bakaira, G. (2011). The role of universities in teacher education and professional development: Kyambogo University: A Case Study. Systematic Entomology, 35(1), 19–58.
15. Petersen K., Vakkalanka S., Kuzniarz L. (2015). Guidelines for conducting systematic mapping studies in software engineering: an update. Information & Software Technology, 64 (1), pp. 1–18.

16. Tasan C., Diehl M., Yan D., Bechtold M. (2014). An overview of dual-phase steels: advances in microstructure-oriented processing and micromechanically guided design. Annual Review of Materials Research, 45 (1), pp. 391–431.
17. Tao J., Wen S., Hu W. (2016). Multi-source adaptation learning with global and local regularization by exploiting joint kernel sparse representation. Knowledge-Based Systems, 98 (2), pp. 76–94.
18. Petersen K., Vakkalanka S., Kuzniarz L. (2015). Guidelines for conducting systematic mapping studies in software engineering: an update. Information & Software Technology, 64 (1), pp. 1–18.
19. Tasan C., Diehl M., Yan D., Bechtold M. (2014). An overview of dual-phase steels: advances in microstructure-oriented processing and micromechanically guided design. Annual Review of Materials Research, 45 (1), pp. 391–431.
20. Tanwar S., Kumar N. (2015). A systematic review on heterogeneous routing protocols for wireless sensor network. Journal of Network & Computer Applications, 53 (2), pp. 39–56.
21. Wang E. (2015). Benchmarking whole-building energy performance with multi-criteria technique for order preference by similarity to ideal solution using a selective objective-weighting approach. Appl. Energy, 146, pp. 92–103.
22. Zhu X., Li X., Zhang S., Ju C. (2016). Robust joint graph sparse coding for unsupervised spectral feature selection. IEEE Transactions on Neural Networks & Learning Systems, 26 (6), pp. 1263–1275.