Research Article
Exploring the Emotional Factors in College English Classroom Teaching Based on Computer-Aided Model

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In order to improve the effect of emotional factor analysis in college English classroom teaching, this paper analyzes the emotional factors of college English classroom teaching combined with computer technology and proposes an attribute-level emotional analysis method based on lifelong learning. Moreover, while solving the sparseness of short texts, this paper integrates the three tasks of topic recognition, emotional tendency judgment, and separation of general emotional words and attributes emotional words under the same model framework. In addition, this paper combines lifelong learning to improve the coherence and correctness of topic mining. Finally, this paper improves the teaching process by analyzing students’ emotional intelligence. The data analysis verifies that the computer-aided model based on the emotional factor analysis model of college English classroom teaching has a good effect in the analysis of emotional factors in English classroom teaching and the improvement of classroom teaching effect.

1. Introduction

With the change and development of the times, education is constantly exploring new concepts and ways to adapt to social development. In order to realize the harmonious and sustainable development of human society, the talents cultivated by education should not only be manifested in their intelligence, but also in their extraordinary emotions and good personal qualities. Moreover, the development of society requires not only talents with corresponding knowledge and skills, but also healthy physique, healthy psychology, and sound personality. Therefore, emotion is particularly important in the composition of talent quality. A true talent must have a high level of emotion, that is, a good moral outlook, values, outlook on life, always optimistic, aggressive, have ideals, pursuits, firm beliefs, good self-awareness, and self-evaluation ability, and have team spirit and sense of cooperation.

The new curriculum standard elevates emotional education to an unprecedented height and believes that “knowledge and ability, process and method, and emotion, attitude, and values” are the three dimensions that together constitute a class. We must point out that this three-dimensional goal is not three blocks, not adding emotions, attitudes, and values to knowledge and skills. Because abilities, emotions, attitudes, and values are rooted in the occurrence and development of knowledge and are formed and developed in the process of continuously exploring knowledge and mastering skills, students always have an emotional and attitude tendency in the learning process, and this tendency may be positive or negative [1]. The responsibility of teachers is to make students develop positive learning emotions and attitudes and gradually develop correct values in the process of imparting knowledge. The cultivation of ability and the experience of emotion all need teachers to implement through the learning of knowledge and skills [2]. Similarly, only through ability development and emotional experience can we help students learn knowledge and skills more effectively, that is to say, the three-dimensional goal emphasized by the new curriculum is a whole. Therefore, in the process of educational work, especially in the future education and teaching, teachers should focus on integrating the learning of knowledge and skills with the cultivation of ability, and the education of
emotions, attitudes, and values [3]. Emotion, which is the core of nonintellectual factors, is a kind of inner experience, and it is a reflection of human beings on the relationship between objective things and the needs of the subject. In the process of personality development, emotion plays the function of a reconnaissance agency and a driving force, monitoring the flow of information and arousing the internal conditions of the subject’s pursuit of belief. Our educational objects are college students, who have special emotional characteristics [4]. College students are in a period of semi-naive and semi-mature, in which independence and dependence, self-consciousness, and childishness are intricately contradictory. Their psychology is immature, and their emotions are very fragile. Open, this is an objective reality that cannot be ignored [5]. With the onset of puberty, the closed mental state brings the ununderstood loneliness and the desire to be understood at the same time, while the pressure of society, parents, oneself, and the increasingly onerous learning tasks and various kinds of various tasks. The psychological pressure brought about by such exams makes this emotional confusion (or hunger) state unavoidable. Therefore, if teachers want to be successful in teaching, in addition to their love for education and the subjects they teach, they must also attach importance to emotional investment and use their sincere love to enhance the emotional exchange between teachers and students, so that students can develop a sense of intimacy and trust is the so-called “close to his teacher and believe his way” [6]. Emotional education means that in teaching activities, teachers focus on cognitive factors, with the help of corresponding teaching methods and through language, attitude, behavior, and other teaching variables that load teachers’ positive emotions, to stimulate, mobilize, and meet students’ positive emotional needs and needs: cognitive needs to promote the optimization of teaching process, the enhancement of teaching effect, and the perfect education of teaching goals [7]. To understand this concept accurately, we need to grasp the following meanings [8]: from the shallow form of teaching, emotional education is a bilateral activity between teachers and students in teaching and learning; from the deep sense of teaching, emotional education is both a relationship between teachers and students. The process of emotional communication between teachers and students is also the process of information conversion and exchange between teachers and students. Emotion is a kind of psychological experience produced by people after being affected by objective things to see whether this effect is in line with their own needs [9]. Psychologists’ research shows that when people’s emotional experience is positive and pleasant, the pituitary gland will make the endocrine system active, metabolism will be accelerated, the whole nervous system will be in a state of excitement, people’s emotions will be in a positive state, and the response will be flexible. The efficiency of study and work is high [10]; on the contrary, when people are tired of study and work, their emotions are in a depressed state, their response is slow, and the efficiency of study and work will be greatly reduced. The theory of learning motivation holds that motivation is of great significance in students’ learning activities. Students who are the main body of learning can achieve excellent results only if they are interested in learning and willing to learn [11]. Learning motivation can arouse students to produce a certain learning activity to stimulate their learning-related stimulation, show eagerness to seek knowledge, and arouse their exploration activities, and emotion has the effect of increasing or decreasing a person’s behavior [12]. When a person’s emotional experience is positive and pleasant, the pituitary gland will make the endocrine system active, the human body's metabolic process will be accelerated, and the excitement level of the entire nervous system will be enhanced, so that people form a dominant excitation center in the cerebral cortex, and people’s emotions are in a positive state; the efficiency of learning is high [13]. When students’ emotions are resisting and disgusting, their interest and motivation to learn will decline, which will cause people to have anxiety and burden on learning and reduce the efficiency of learning [14].

The process of student learning is a process in which both cognitive and noncognitive psychological factors participate and influence each other. In this process, cognitive factors are the main body’s processing system, while noncognitive factors are the main body’s dynamic control system. The success of students’ learning depends on the coordinated activities of the two systems. The two work closely together and are indispensable. The cognitive operating system has no motivation, and the noncognitive system is a dynamic system that generates enthusiasm. We can imagine that without the participation of the dynamic control system, it is impossible for students to learn actively, and there will be no good learning outcomes.

Subjective learning theory holds that students are the subjects of cognitive activities. To implement subjectivity education, it is necessary to give full play to the subjectivity of students in the education process to develop the subjectivity of students and to promote the full and healthy development of students’ personalities while promoting the full development of students’ potential [15]. Affective education is to affirm the subject status of students, opposes students as containers for passively receiving knowledge, pays attention to students’ autonomy and initiative, and regards students’ development as the result of the joint action of the two systems of cognition and emotion. Affect education respects the leading role of teachers more, and it puts forward higher requirements for teachers. If teachers want to carry out affection education freely, in addition to possessing extensive and refined knowledge, they also need to be very knowledgeable about the cause of education and the subjects they teach. Students are full of enthusiasm and are good at arousing the emotional resonance of students with intuitive and vivid images [16]. In addition, modern education is not an industry that replicates similar products with fixed methods and models. It should be an education that recognizes individual differences and has different goals for individual development, that is, respects individuality and guides the formation of positive and healthy individuality. Personality education is centered on the uniqueness of individual emotional world. The implementation of emotional education fully considers the
individual emotional characteristics and needs of the educated, enhances the subject consciousness of the educated, forms the pioneering spirit and creative ability of the educated, improves the personal value of the educated, and enables the free development of the personality. Therefore, emotional education is also a way to achieve the goal of individual education [16].

Emotional education focuses on the harmonious development of irrational factors such as human emotions and rational factors. Through the central link of “emotion,” it connects “cognition” and “moral will” and adjusts the contradiction between them. It is an education aimed at cultivating students’ noble moral sentiments and healthy aesthetic tastes by comprehensively shaping students’ personalities from the three aspects of knowledge, emotion, and intention [17]. Only the emotional education that is close to the reality of students’ lives and thoughts can strike the heartstrings of students and receive practical results. Emotional education under the new curriculum standard system, in layman’s terms, means that teachers, while paying attention to the teaching of systematic knowledge and the development of students’ rational thinking ability, create situations to guide students to fly freely in a rich and colorful emotional space. Students’ emotional thoughts can arouse students’ emotional resonance, thereby promoting the comprehensive and harmonious development of students’ comprehensive quality education [18].

This paper analyzes the emotional factors of college English classroom teaching combined with computer technology, improves the teaching process and improves the effect of English classroom teaching through the analysis of students’ emotional intelligence.

2. Emotional Mining Model

2.1. Topic Model. In the field of natural language processing, topic models are statistical models used to discover hidden topics in text corpora. It is a form of text mining, an “unsupervised” machine learning technique used to automatically discover topic distributions in document sets.

The LDA model is a generative probabilistic modeling method that gives the topic of each document in a document set in the form of a probability distribution. Briefly, in the LDA model, each document has a set of topics that are assigned to the document using LDA, and the words in the document are generated from one of a random mix of topics. This idea is basically similar to Probabilistic Latent Semantic Indexing (PLSI), except that the topic distribution in the LDA model is assumed to obey a Dirichlet prior distribution. That is to say, the LDA model is a generalization of the PLSA model. Under the uniform Dirichlet prior distribution, the PLSA model is equivalent to the LDA model. A graphical representation of the LDA model is shown in Figure 1. Grey circles represent observable variables, white circles represent latent variables, arrows represent conditional dependencies between two variables, boxes represent repeated sampling, and the number of repetitions is to the right of the box.

In the LDA model, both the parameter document-topic distribution $\theta$ and the topic-term distribution $\varphi$ are regarded as random variables, and both probability distributions are assumed to be multinomial distributions. Therefore, the topic distributions in all documents have a common Dirichlet prior $\alpha$, and the word distributions of topics have a common Dirichlet prior $\eta$. The LDA model is based on the assumption of the bag-of-words model, which states that in the model a document is a collection of words, regardless of the grammar or order between words. The generation process of the LDA model simulation document is as follows:

1. For each document, the algorithm generates a “document-topic” distribution $\theta_d \sim Dir(\alpha)$
2. For each topic, the algorithm generates a “topic-term” distribution $\varphi_k \sim Dir(\eta)$
3. For each position of the current document:
   a. The algorithm generates the subject $z_{m,n} \sim \theta_m$ to which it belongs
   b. The algorithm generates the current position term $w_{m,n} \sim \varphi_{z_{m,n}}$ according to the selected topic

In the LDA model, when given a set of documents, $w$ terms are known variables that can be observed, and $\alpha$ and $\eta$ are empirically given prior parameters for multinomial distributions of topics and terms. The other variables $z, \theta, \varphi$ are unknown hidden variables, which need to be learned and estimated according to the observed variable $w$.

Specifically, in the Gibbs sampling algorithm to solve the LDA method, $\alpha$ and $\eta$ are known prior inputs. The goal is to obtain the probability distribution of the overall $z, w$ corresponding to each $z_{m,n}, w_{m,n}$, that is, the distribution of the document-topic and the distribution of the topic word. Then, corresponding to the required target distribution, we need to obtain the conditional probability distribution corresponding to each feature dimension of the distribution. According to the graphical model of LDA, the joint distribution of all variables can be written:

$$P(\bar{w}, \bar{z}) = \prod_{d=1}^{D} \prod_{m=1}^{M} \prod_{n=1}^{N} p(\bar{w}_{d,m} | \bar{z}_{m,n}, \bar{\theta}_d)^{N_{d,m}} p(\bar{z}_{m,n} | \bar{\alpha}) p(\bar{\theta}_d | \bar{\alpha}) p(\bar{\alpha}).$$ (1)

According to the Dirichlet prior distribution and the conjugate of the multinomial distribution, the topic sequence probability of the entire corpus can be obtained:

$$p(\bar{z}_{d} | \bar{\theta}_d) = \int p(\bar{z}_{d} | \theta_d) p(\theta_d | \bar{\alpha}) d\theta_d = \frac{\Delta(\sum_{d}^{D} N_{d,m} + \bar{\alpha})}{\Delta(\bar{\alpha})}. \ (2)$$

After being given the topic sequence $z$, the probability of the term sequence $w$ is
The required for Gibbs sampling can be derived:

\[ P(\overline{w}, \overline{z}) \propto P(\overline{w}, \overline{z} | \alpha, \beta) = \prod_{d=1}^{M} \Delta (\nu_d + \alpha) \prod_{k=1}^{K} \Delta (\nu_k + \beta) \]

Combining formulas (2) and (1), the joint probability of the term and topic sequence is obtained:

\[ P(\overline{w}, \overline{z}) = \prod_{d=1}^{M} \Delta (\nu_d + \alpha) \prod_{k=1}^{K} \Delta (\nu_k + \beta) \]

With the joint distribution, the conditional distribution required for Gibbs sampling can be derived:

\[ P(z_i = k | \overline{w}, \overline{z}^i) = \frac{\nu_{d,j}^k + \alpha_k}{\sum_{j=1}^{V} \nu_{d,j}^k} \]

where \( i \) is a two-dimensional subscript corresponding to the \( n \)-th word of the \( d \)-th document. After obtaining formula (5), we can use Gibbs sampling to sample the topics of all words. When Gibbs sampling is harvested, we can get the sampling topics of all words.

2.2. Text Emotional Analysis Method Based on Topic Model.

The JST model considers the connection between the subject and emotion and thinks that people have a certain emotion first and then have the theme that they want to describe under the expression of this emotion. Therefore, it assumes that the topic of the document is bounded by emotional labels, and each word in the document is bounded by topic and emotion. In order to simultaneously detect emotions and topics from text, JST adds an emotion layer to the LDA model. The graphical representation of the model is shown in Figure 2. Among them, \( \alpha, \gamma, \beta \) control the hyper-parameters of topic, emotional label, and word prior distribution, respectively; \( \theta, \pi, \varphi \) denote topic distribution, emotional distribution, and word distribution; \( i \) denotes topic; \( l \) denotes emotional label; \( w \) denotes word.

The JST model is improved on the basis of the LDA model, so it is also based on the bag-of-words hypothesis; that is, there is no sequence relationship between words. The generation process of the JST model simulation document is as follows:

1. The algorithm generates an emotion distribution \( \pi_d, \pi_d \sim \text{Dir}(\gamma) \)
2. The algorithm generates a topic distribution \( \theta_{d,l} \sim \text{Dir}(\alpha) \) for each emotional label \( l \) under the document
3. The algorithm generates a word distribution \( \varphi_{t,z} \sim \text{Dir}(\lambda_z \times \beta_{t,z}) \) for each topic \( z \) under each emotional label \( l \)
4. For each word \( \omega_i \):
   i. The algorithm selects an emotional label \( l_i \sim \text{Mult}(\pi_d) \)
   ii. The algorithm selects a topic \( z_i \sim \text{Mult}(\theta_{d,l}) \)
   iii. The algorithm selects a word \( \omega_i \sim \text{Mult}(\varphi_{t,z}) \)

The parameter estimation of the JST model also uses the Gibbs sampling algorithm, and the joint probability of all variables can be obtained according to Figure 2:

\[ p(w, z, l) = p(w|z, l)p(z, l) = p(w|z, l)p(z|l)p(l) \]

The sampling conditional probability formula is obtained according to the D-M conjugate:

\[ p(z_i = j, l_i = k|w, z^{i-1}, \Gamma^{i-1}, \alpha, \beta, \gamma) \]

\[ \frac{N^{-1}_{t,j} + \beta}{N^{-1}_{t,j} + \gamma} \frac{N^{-1}_{d,k} + \alpha}{N^{-1}_{d,k} + \gamma} \frac{N^{-1}_{t,j} + \sum_{j=1}^{V} \alpha_{k,j}}{N^{-1}_{d,k} + \sum_{j=1}^{V} \beta_{t,j}} \]

The final generated word distribution is

\[ \varphi_{t,z} = \frac{N_{t,j,k} + \beta}{N_{t,j} + \gamma} \]

The topic distribution is

\[ \theta_{d,l} = \frac{N_{d,l} + \alpha}{N_{d,k} + \gamma} \]

The emotional distribution is

\[ \pi_d = \frac{N_{d,k} + \gamma}{N_d + \gamma} \]

This paper proposes an attribute-emotional unification model similar to JST, namely, the aspect and emotional unification model (ASUM model). The difference is that ASUM assumes that different words of the same sentence have the same theme and emotional. A graphical representation of the ASUM model is shown in Figure 3.

The ASUM model, like the SLDA model, believes that the constituent units of documents should not be unrelated words. Because according to the habit of language expression, there are often words expressing emotional tendencies around the feature words describing product attributes. Therefore, although the ASUM model believes that topics and words are limited by emotions like the JST model, it assumes that the emotional labels and topics of words in the same sentence are the same, and the emotional tendencies...
and topics of different sentences are different. The generation process of ASUM model simulation document is as follows:

1. The algorithm generates a word distribution $\phi_{sz} \sim \text{Dir}(\beta_s)$ for each emotional label $s$ and the corresponding topic $z$.

2. For each document $d$:
   a. The algorithm generates an emotional distribution $\pi_d \sim \text{Dir}(c)$
   b. The algorithm generates a topic distribution $\theta_{ds} \sim \text{Dir}(\alpha)$ for each emotional label
   c. For each sentence:
      i. The algorithm selects an emotional label $j \sim \text{Mult}(\pi_d)$
      ii. The algorithm selects a topic $k \sim \text{Mult}(\theta_{dj})$ for a given emotional label $j$
      iii. The algorithm selects the word $w \sim \text{Mult}(\phi_{jk})$

The ASUM model parameter estimation also uses the Gibbs sampling algorithm. In each transition step of the Markov chain, the conditional probability formula for sampling the emotional and feature of the $i$-th sentence is:

$$p(s_i = j, z_i = k | s_{-i}, z_{-i}, w) \propto C_{dj}^{DS} + y_j \cdot \frac{C_{djk}^{DST} + \alpha_k}{\sum_{k=1}^{T} C_{djk}^{DST} + \alpha_k}. \Gamma \left( \sum_{w=1}^{V} C_{jkw}^{STW} + \beta_{jw}' \right) \prod_{w=1}^{V} \Gamma \left( C_{jkw}^{STW} + \beta_{jw} + m_{iw} \right) \Gamma \left( C_{jkw}^{STW} + \beta_{jw}' \right)$$

(11)

The probability that the emotional label $j$ in document $d$ is as follows:

$$\pi_{d,j} = \frac{C_{dj}^{DS} + \gamma_j}{\sum_{j=1}^{S} C_{dj}^{DS} + \gamma_j}$$

(12)

The probability of feature $k$ under emotional label $j$ in document $d$ is as follows:

$$\theta_{d,j,k} = \frac{C_{djk}^{DST} + \alpha_{jk}}{\sum_{k=1}^{T} C_{djk}^{DST} + \alpha_{jk}'}$$

(13)

The probabilities of words in each emotional feature $(j, k)$ are as follows:

$$\phi_{jkw} = \frac{C_{jkw}^{STW} + \beta_{jw}}{\sum_{w=1}^{V} C_{jkw'}^{STW} + \beta_{jw}'}$$

(14)

2.3. Attribute-Level Emotional Analysis of Short Texts Based on Lifelong Learning. This paper proposes a short text attribute-level emotional analysis method based on the lifetime topic model. The specific implementation process is shown in Figure 4.

It includes the following steps:

1. The maximum entropy model classifier learns the training set that has marked the word pair type in advance and obtains the weight $\lambda$ value when selecting the word pair type.
2. The algorithm performs data preprocessing on the corpus $C$, performs part-of-speech tagging on each word, and then converts $C$ into a word pair bag $B = \{b_{m}\}_{m=1}^{M}$, where $b_m = (w_{m}^l, w_{m}^r)$.
3. The algorithm simulates the generation process of word pairs and establishes the Maxent-JAWSTM model for the word pair package $B$.
4. The algorithm adopts the Gibbs sampling method to estimate the parameters of the Maxent-JAWSTM model.
(5) The algorithm uses SKL divergence to match the topics sampled in Step 4 with the topics obtained from all previous mining tasks and find a similar topic set S for the topics sampled in Step 4.

(6) The algorithm uses the method of frequent itemsets to mine useful prior knowledge from the similar topic set S in step five. Prior knowledge is represented by word pairs of length 2 (that is, the length of frequent itemsets), and the mined knowledge is stored in a knowledge base to generate a knowledge set K.

(7) The algorithm combines the knowledge set K in Step 6 with the Maxent-JAWSTM model and uses the GPU model to embed the knowledge set into it. The control matrix is used to sample the current word and improve other words at the same time. Moreover, the algorithm uses the improved Gibbs conditional formula to iteratively sample the word pair package B and finally obtains a posterior distribution of emotional distribution, topic distribution, and word type. By combining the posterior distribution with prior knowledge, the emotional distribution of the current corpus C, the topic distribution, and the type of each word are finally estimated.

There are disordered pairings between general emotional words and opinion words. The graphical representation of the Maxent-JAWSTM model is shown in Figure 5.

The Maxent-JAWSTM model simulates the word pair generation process. It is assumed that all words belonging to the same sentence have the same emotional polarity, two words in a word pair belong to the same topic, and there are S emotional labels, S ∈ {1, 2, ⋯ S}. Moreover, there are T related topics under each emotional label l, and the model simulates the generation process of word pairs as follows:

1. The algorithm generates an emotional distribution \( \pi_l \sim \text{Dir}(\gamma) \) for each document d.
2. The algorithm generates a topic distribution \( \theta_{dl} \sim \text{Dir}(\alpha) \) for each emotional label l under document d.
3. For each emotional label l, the algorithm generates the general emotional word distribution \( \phi_{l} \sim \text{Dir}(\beta_l) \) under emotional l.
4. The algorithm generates two types of word distributions \( \phi_{l}^0 \sim \text{Dir}(\beta_l) \) for each emotional tendency l and topic z:
   a. Feature word distribution under emotional l and topic z.
   b. The distribution \( \phi_{l}^0 \sim \text{Dir}(\beta_l) \) of specific emotional words under emotional l and topic z.
5. For each sentence M in document d:
   a. The algorithm selects an emotional label l ∼ Multi(\( \pi_l \))
   b. The algorithm selects a topic \( z \sim \text{Multi}(\theta_{dl}) \)
6. For each word pair \( b_t \in B \):
   a. The algorithm assigns it the emotional label l of the sentence it belongs to
   b. The algorithm selects a topic \( z_t \sim \text{Multi}(\theta_{dl}) \)
   c. The algorithm selects a word pair type \( r_t \) according to the feature vector x of the word pair type and the training result of the maximum entropy model
   d. The algorithm selects the types \( y_t \) and \( y_j \) of two words according to the word pair type \( r_t \)
   e. The algorithm selects words \( w_t \) and \( w_j \): (i) According to the type \( y_i \) of the word, the algorithm selects a word \( w_t \sim \text{Multi}(\phi_{l}^0_{i, z_t}) \) or \( w_j \sim \text{Multi}(\phi_{l}^0_{j, z_t}) \)
   (ii) According to the type \( y_j \) of the word, the algorithm selects a word or \( w_j \sim \text{Multi}(\phi_{l}^0_{j, z_t}) \)

To model the separation of attribute words, general emotional words, and attribute emotional words, word type \( y_i \) and word pair type \( r_t \) are introduced. The word type \( y_i \in \{0, 1, 2\} \) represents attribute word A, general emotional word G, and attribute emotional word O, respectively. The word pair type \( r_t \in \{0, 1, 2, 3, 4, 5\} \) represents the word class combination \( \langle A, G \rangle, \langle G, A \rangle, \langle A, A \rangle, \langle A, O \rangle, \langle O, A \rangle, \langle G, G \rangle, \langle O, O \rangle \), respectively. The maximum entropy model can flexibly set constraints, and the model can be adjusted to adapt to unknown data through the number of constraints.

In the sampling process, a word pair type \( q \in \{0, 1, 2, 3, 4, 5\} \) is first sampled for each word pair. g represents the word class combination \( \langle A, G \rangle, \langle G, A \rangle, \langle A, A \rangle, \langle A, O \rangle, \langle O, A \rangle, \langle G, G \rangle, \langle O, O \rangle \), respectively. The selection of word pair types is controlled by the maximum entropy model, which is related to the trained category weights and feature functions. Therefore, based on the training results of the maximum entropy model, the probability of the t-th word pair type will be calculated according to

\[
p(r_t = q) = \frac{\exp(\lambda_q x_{l_t})}{\sum_{q'} \exp(\lambda_q x_{l_t})} \tag{15}\]

\( \exp(\lambda_q x_{l_t}) \) is the feature of the t-th word pair type q, which is related to the trained category weights and feature functions.
After the type of each word pair is generated, the topic and emotional are sampled by the word pair type case by case:

(1) If \( q = 0 \) or 3 or 4, each word in the word pair is sampled separately, and the sampling condition formula of the \( t \)-th word is

\[
p(l_{i} = l, z_{i} = k|W, l_{-i}, z_{-i}),
\]

\[
\text{co} \left\{ \left( \frac{N_{k,l,w_{t-1}} + \beta_i}{N_{k,l} + V\beta} \right) \left( \frac{N_{k,l} + a_{k}}{N_{d} + Sy} \right) \right\}
\]

(16)

(2) If \( q = 1 \) or 2 or 5, sampling is performed based on word pairs, and the sampling condition formula of the \( t \)-th word pair is

\[
p(l_{t} = l, z_{t} = k|B, l_{-t}, z_{-t}),
\]

\[
\text{co} \left\{ \left( \frac{N_{k,l,w_{t-1}} + \beta_i}{N_{k,l} + V\beta} \right) \left( \frac{N_{k,l} + a_{k}}{N_{d} + Sy} \right) \right\}
\]

(17)

Finally, the types of words are sampled. If \( q = 1 \) or 2 or 4, the type of the \( t \)-th word is 0 or 1 or 2, respectively. If \( q = 0 \) or 2 or 3, the probability of the type of the \( t \)-th word is calculated according to

\[
p(y_{t} = c) = \frac{\exp(\lambda_{c} x_{b})}{\sum_{c'} \exp(\lambda_{c'} x_{b})} \left( \frac{N_{k,l,w_{t-1}} + \beta_i}{N_{k,l} + V\beta} \right)
\]

(18)

The current task is defined as \( i \), while the past task is defined as \( -i \). For all tasks, we learn topics through the Maxent-JAWSTM model training, and topics are represented by some high-frequency topic words. Therefore, we can use Symmetries KL Divergence (SKL) to measure the similarity between two topics. For given two topics \( A_{x} \in D_{(i)} \) and \( A_{y} \in D_{(-i)} \), the formula for calculating the difference between the two topics is

\[
\text{SKL}(A_{x}, A_{y}) = \frac{KL(A_{x}, A_{y}) + KL(A_{y}, A_{x})}{2}
\]

(19)

A threshold \( \pi \) is set, and if the calculated value of formula (19) is less than \( \pi \), then \( A_{y} \) is included in the similarity set \( S_{x} \) of subject \( A_{x} \). For each topic \( k_{(i)} \) trained by the Maxent-JAWSTM model, a similar topic set \( S_{(i)} \) is obtained by the above method. All \( S_{(i)} \) are grouped together to form a topic set \( S \) that matches the current task.

Corresponding to the topic sampling, that is, after sampling a word, other words related to the word are improved accordingly. The boost ratio is controlled by matrix \( \delta_{k}(i, w_{i}, w_{j}) \). The matrix \( \delta_{k}(i, w_{i}, w_{j}) \) is defined as follows:

\[
\delta_{k}(i, w_{i}, w_{j}) \left\{ \begin{array}{ll}
1 & \text{if } PR(w_{i}, w_{j}) \in K'_{k}(i) \\
0 & \text{otherwise}
\end{array} \right.
\]

(20)

Among them, \( PR(w_{i}, w_{j}) \) represents the degree of association of these two words in the current task. The commonly used Pointwise Mutual Information (PMI) is used as a measure. Its calculation formula is as follows:

\[
PR(w_{i}, w_{j}) = \mu * \frac{p(w_{i}, w_{j})}{p(w_{i})p(w_{j})}
\]

(21)

\[
p(w) = \frac{\#D(w)}{\#D}
\]

(22)

\[
p(w_{i}, w_{j}) = \frac{\#D(w_{i}, w_{j})}{\#D}
\]

(23)

where \( p(w) \) represents the probability that the word \( w \) appears in the current corpus, and \( h p(w_{i}, w_{j}) \) represents the probability that the word \( w_{i}, w_{j} \) appears in the current corpus at the same time. \( D(w) \) represents the number of documents containing the word \( w \) in the current corpus, \( D(w_{i}, w_{j}) \) represents the number of documents containing the word \( w_{i}, w_{j} \) in the current corpus at the same time, and \( D \) represents the total number of documents.

The conditional formulas for sampling topics and emotions at this time as are as follows:

(1) If \( q = 0 \) or 3 or 4, each word in the word pair is sampled separately, and the sampling condition formula of the \( t \)-th word is

\[
p(l_{t} = l, z_{t} = k|B, l_{-t}, z_{-t}),
\]

\[
\text{co} \left\{ \left( \frac{\sum_{w} \delta_{k, w_{t-1}, w_{i}} + \beta}{\sum_{w} \delta_{k} + V\beta} \right) \left( \frac{\sum_{w} \delta_{k} + a_{k}}{\sum_{w} \delta_{k} + Sy} \right) \right\}
\]

(24)

(2) If \( q = 1 \) or 2 or 5, sampling is performed based on word pairs, and the sampling condition formula of the \( t \)-th word pair is

\[
p(l_{t} = l, z_{t} = k|B, l_{-t}, z_{-t}),
\]

\[
\text{co} \left\{ \left( \frac{\sum_{w} \delta_{k, w_{t-1}, w_{i}} + \beta}{\sum_{w} \delta_{k} + V\beta} \right) \left( \frac{\sum_{w} \delta_{k} + a_{k}}{\sum_{w} \delta_{k} + Sy} \right) \right\}
\]

(25)
The formulas for other sampling conditions remain unchanged. This paper uses formulas (14), (23), (24), and (17) to iteratively sample the word pair bag B and finally obtain a posterior distribution of emotional distribution, topic distribution, and word type. By combining the posterior distribution with prior knowledge, the emotional distribution of the current corpus C, the topic distribution, and the type of each word are finally estimated. In this way, three tasks of topic recognition, emotion tendency judgment, and separation of general emotion words and attribute emotion words are realized.

3. Exploring of Emotional Factors in College English Classroom Teaching

After long-term research, psychologists have pointed out that emotional function has two sides, both positive and negative. The functions of emotion mainly include motivation, migration, reinforcement, grooming, health care, coordination, infection, signal, and regulation. In the long-term educational practice, the importance of emotion to education was found, and the specific embodiment of emotional function in English teaching was summarized, as shown in Figure 6.

The intelligent emotional English teaching evaluation system is to quantify the students’ emotions in the classroom environment and evaluate the students’ learning situation from the perspective of emotion. The analysis results can not only assist teachers to complete classroom English teaching in real time, but also serve as a basis for educators to analyze the effect of English teaching for a long time. Emotion quantification results refer to the use of statistical analysis methods to quantify students’ emotions and use scientific data to reflect the emotional state of individual students or the attention, participation, and difficulty of students in the classroom. Moreover, it provides a reliable basis for teachers to change English teaching strategies in a timely manner. The design idea of the intelligent emotional English teaching evaluation system is shown in Figure 7.

The data augmentation method designed in this paper and the random data augmentation method for comparison
**Figure 7:** Design ideas of the intelligent emotional English teaching evaluation system.

**Figure 8:** Continued.
Figure 8: Text emotional data enhancement. (a) Method for calculating the relevance weight of text words and classification labels. (b) Data augmentation process.

Table 1: The effect of the system on the recognition of emotional factors in college English classroom teaching.

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</table>

are based on the strong word replacement, and the augmentation that changes the overall structure like back translation is not considered. The idea of data enhancement in this paper is to use text segmentation to obtain independent words and exclude punctuation. The substitution of punctuation marks does not make much sense; otherwise, it will affect the coherence of the semantics. The method for calculating the relevance weight of text words and classification labels is shown in Figure 8(a).

The random replacement enhancement method uses a random equal probability screening mechanism to randomly select replacement words from tokens. The weighted replacement enhancement method uses the sample weights converted from the model weights (see Sampling Weight 1 and Sampling Weight 2 in Figure 8(b)).

On the basis of the above system model, this paper combines Matlab to verify the recognition effect of the system proposed in this paper on the emotional factors of college English classroom teaching, and the verification results shown in Table 1 are obtained.

On the basis of the above research, the effect of the model proposed in this paper is verified, and the effect of improving
the teaching effect of college English classroom is calculated, and the results shown in Figure 9 are obtained.

From the above data analysis, it is verified that the computer-aided model based on the emotional factor analysis model of college English classroom teaching has good effects in the analysis of emotional factors in English classroom teaching and the improvement of classroom teaching effect.

4. Conclusion

The emotion emphasized in emotional education is the positive emotion of both teachers and students. In teaching, teachers should pour their own positive emotions into teaching variables, so as to arouse students’ corresponding positive emotional activities and trigger students’ corresponding emotional experience, so as to form a harmonious emotional communication field between teachers and students. The so-called positive emotions refer to the emotions in the teaching situation that are conducive to promoting students’ learning, including both positive emotions such as joy and happiness, and some negative emotions such as sadness and anger. In addition, it also includes some complex emotions such as love and hate. This paper analyzes the emotional factors of college English classroom teaching combined with computer technology and improves the teaching process through the analysis of students’ emotional intelligence. The data analysis verifies that the computer-aided model based on the emotional factor analysis model of college English classroom teaching has a good effect in the analysis of emotional factors in English classroom teaching and the improvement of classroom teaching effect.

Data Availability

The labeled data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares no conflicts of interest.

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References


