

Retraction

Retracted: Application of Discriminative Training Algorithm Based on the Improved Gaussian Mixture Model in English Translation Evaluation

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

In addition, our investigation has also shown that one or more of the following human-subject reporting requirements has not been met in this article: ethical approval by an Institutional Review Board (IRB) committee or equivalent, patient/participant consent to participate, and/or agreement to publish patient/participant details (where relevant).

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] S. Wang, "Application of Discriminative Training Algorithm Based on the Improved Gaussian Mixture Model in English Translation Evaluation," *International Transactions on Electrical Energy Systems*, vol. 2022, Article ID 8021240, 11 pages, 2022.

Research Article

Application of Discriminative Training Algorithm Based on the Improved Gaussian Mixture Model in English Translation Evaluation

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English translation, also a kind of language conversion, refers to the activities of expressing each other in English to express another language or another language to express English. This paper aimed to evaluate and research methods of English translation based on the improved Gaussian mixture model (GMM). The paper proposed a simple evaluation and analysis of English translation using a discriminative training algorithm. In the experimental part, on the one hand, taking students, teachers, and translators as case study objects, through a questionnaire survey, it can be known that the number of students who scored more than 80 points in the English translation test is increasing every year, from 11.30% in the first year to 21.13% in the fourth year, an increase of nearly 10%. On the other hand, it can be seen from the speech translation experiment that the correct translation rate was 46.18% by using intelligent technology to distinguish translation. The experimental results showed that the discriminative training algorithm under the improved GMM algorithm is effective in the research of English translation evaluation.

1. Introduction

Due to the continuous progress of science and technology, the English translation evaluation system based on artificial intelligence has been widely used in English teaching and testing. The computer gives the learners the objective scores of English translation, so as to know whether their own English translation is standard. English translation assessment is a wide-ranging research topic, including the learning mode of translation and the selection of teaching materials for translation. This paper used the GMM to study English translation assessment, which is helpful to understand the current social situation. It can help students to remove learning obstacles and help teachers to establish a correct translation teaching concept.

This paper mainly studied the evaluation of English translation by mathematical models, which has a huge positive effect on the field of English translation in the future. The innovation of this paper is mainly based on the improved

GMM discriminative training algorithm to conduct evaluation research in English translation. In the experimental part, the model was explored in depth, and the research results show that the method is effective in the experiment.

2. Related Work

In recent years, with the continuous development of the economy, frequent trade exchanges between enterprises in various countries, and a large population flow, the market demand for English translation has continued to rise. Through Pan's research, using data from the Translation Corpus, a corpus of learners developed for the study of lexical cohesion, through case studies, the results showed the complexity of a learner's language and its relationship to various factors such as learner, text, and task [1]. Through Li's research, some advantages of Hu's ecological translation theory were explained, the translation was used to minimize translation problems, and corpus linguistics method was

used, which excels in quantitative and qualitative analysis [2]. Zhao et al. aimed to explore how narrative space can be transferred from one language to another. Studies have shown that selective appropriation is the most commonly used framing strategy [3]. Si and Wang aimed to apply grammatical metaphors from systematic functional linguistics to translation studies. In order to achieve the purpose of translation, an accurate and appropriate method must be selected [4]. Through Tan Z's and Ke research, the purpose was to analyze the formula of English-Chinese translation thinking mode and explore the possible advantages in translation practice [5]. However, due to the extensive use of language, English can be translated into many languages, and relevant mathematical models are used for statistical analysis, and the above studies are all in-depth analysis of this.

With the development of science and technology, Gaussian mixture model is applied in many fields, and many scholars have studied it. Through Yang J et al.'s research, based on GMM, an efficient GNH approximation method was proposed and used as a preconditioner for the mismatch gradient to speed up its convergence [6]. Through the research of Gao G et al., a new method was proposed to increase the complexity by adding a large number of Gaussian components and then check the accuracy of the GMM approximation of PDF [7]. Through Xu Y et al.'s research, the Gaussian mixture model was used for state estimation, and the main problem was that the number of Gaussian components increases exponentially [8]. After Han J et al.'s analysis, in order to obtain the effective user's actual emotional state and promote a harmonious human-machine interactive experience, combined with emotional space and personality theory, an incremental emotion mapping model based on Gaussian mixture model was proposed [9]. Through the research of Sagratella S, a new algorithm was proposed to calculate the approximate equilibrium of generalized latent games with mixed integer variables. The behavior of approximate equilibrium relative to exact equilibrium was analyzed, and finally, the effectiveness of the method was demonstrated through numerous numerical experiments [10]. However, the above scholars have studied the original GMM and have not conducted a thorough study of the improved GMM.

3. Method of English Translation Assessment Based on Discriminative Training Algorithm

3.1. English Translation Assessment. English translation refers to a way of language conversion, which includes Chinese-English translation, Japanese-English translation, English-Korean translation, and translation between English and other languages [11]. English translation also includes some translation skills, such as two basic methods of literal translation and meaning, as well as other techniques such as provincial translation, positive translation, and reverse translation. English translation can be used in many occasions, such as warning signs and learning courseware. The specific situation is shown in Figure 1, which is an illustration related to English translation.

English translation evaluation refers to the test and score after language translation. It is a specific expression of translation ability by numbers or other standards that people can generally understand, and it has scoring standards [12]. Translation assessment is required in many cases, such as translation majors and employees engaged in translation work, both need to assess English translation ability. Figure 2 shows scenes related to English translation evaluation.

3.2. Gaussian Mixture Model (GMM). Gaussian mixture model (GMM) aims to use Gaussian probability density function to quantify things accurately [13]. The features of each pixel in the image are represented by K Gaussian models. After a new frame of image is obtained, the Gaussian mixture model is updated, and each pixel in the current image is matched with the Gaussian mixture model. Figure 3 is a GMM diagram.

GMM can be regarded as a continuous hidden Markov model (CHMM) with a state of 1. It can better display the probability distribution of multi-category observation data in the sample space using GMM [14]. The probability density function of a K-order GMM is obtained by the weighted summation of K Gaussian probability density functions:

$$P(M|\lambda) = \sum_{i=1}^K w_i b_i(M). \quad (1)$$

In (1), M represents a D-dimensional random vector; $b_i(M)$, $i = 1, 2, \dots, K$, is the sub-distribution; and w_i is the mixing weight. Each sub-distribution is a D-dimensional joint Gaussian probability distribution, which can be expressed as follows:

$$b_i(M) = \frac{1}{(2\pi)^{D/2} |\sum_t|^{1/2}} \exp\left\{-\frac{1}{2}(M - \eta_i)^T \sum_t^{-1} (M - \eta_i)\right\}. \quad (2)$$

Among them, η_i is the mean vector, \sum_t is the covariance matrix, $(M - \eta_i)^t$ is the transpose of the vector $(M - \eta_i)$, $|\sum_t|$ is the determinant, and \sum_t^{-1} is the inverse of the matrix \sum_t . The mean vector η_i is the expected value of the eigenvector M , and the covariance matrix \sum_t represents the cross-correlation and variance of the eigenvector elements.

Let

$$\sum_{i=1}^K w_i = 1. \quad (3)$$

This ensures that the mixing density can represent a true probability density function [15]. Therefore, the parameter set of the complete model θ contains the GMM mean η_i , covariance \sum_t , and weight w_i ; namely,

$$\theta = \{w_i, \eta_i, \sum_t\}, \quad i = 1, 2, \dots, K. \quad (4)$$

GMM can be explained; it is a functional expression of probability density function. As a linear combination of Gaussian probability density functions, GMM can approximate any density function as long as there are a sufficient number of mixed components [16]. Language

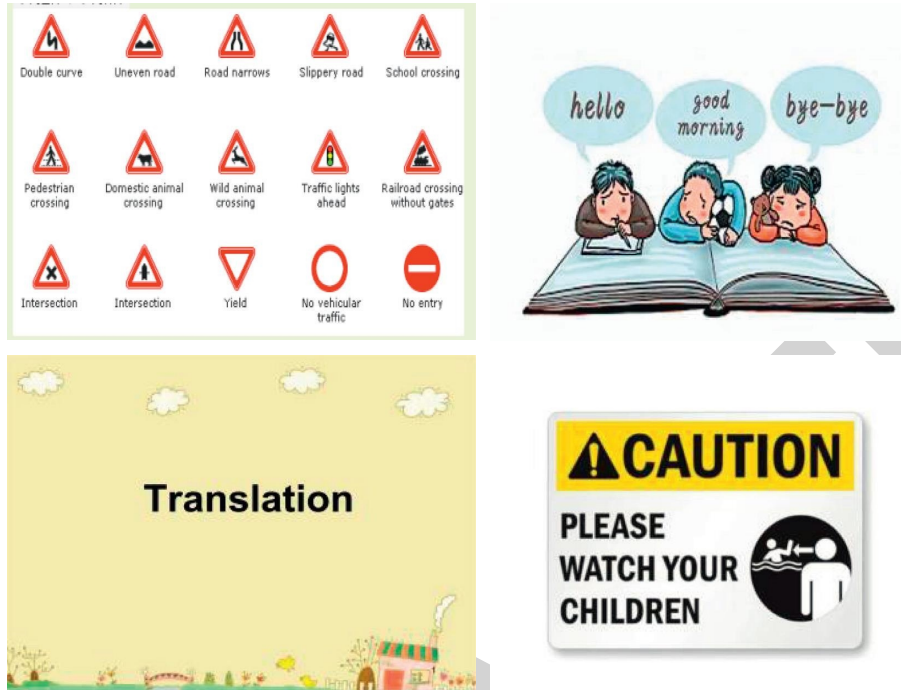


FIGURE 1: Diagrams related to English translation.



FIGURE 2: Scenarios related to English translation assessment.

translation usually has a smooth probability density function, so a finite Gaussian density function is sufficient to form a smooth approximation to the density function of English translation features [17].

The method used to estimate the GMM parameters is the maximum likelihood estimation method; that is, with respect to θ , the conditional probability $P(M|\theta)$ is maximized [18]. The expectation maximization (EM) algorithm improves the

parameter estimates of the GMM in iterations, increasing the matching probability of the model estimate θ and the observed feature vector at each iteration, and at each iteration, there is $P(M|\theta^{k+1}) > P(M|\theta^k)$, where k is the number of iterations.

Figure 4 is a step diagram of the expectation maximization algorithm.

It is assumed that feature vectors are independent of each other; there are

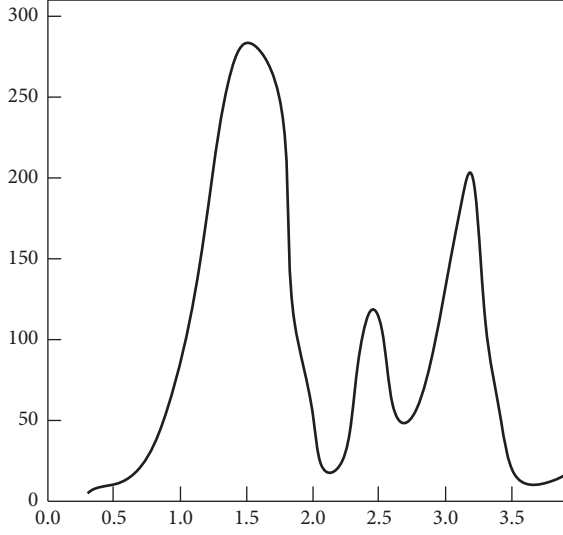


FIGURE 3: Gaussian mixture model fitted image histogram.

$$P(|M|\theta) = \prod_{t=0}^{T-1} P(|M|\theta). \quad (5)$$

It is assumed that $P(M_t|\theta)$ is differentiable to θ ; when $P(M_t|\theta)$ takes the maximum value, it satisfies the following:

$$g = \frac{d[\ln P(|M|\theta)]}{d\theta} = 0. \quad (6)$$

Through (5) and (6), the estimated iterative algorithm is obtained.

Take η_i as an example:

$$\begin{aligned} g &= \frac{d[\ln P(|M|\theta)]}{d\eta_i} \\ &= \sum_{t=0}^{T-1} P(|M|\theta)^{-1} \frac{d[\sum_{i=1}^M w_i P(M_t, i|\theta)]}{d\eta_i} \\ &= \sum_{t=0}^{T-1} P(M_t|\theta)^{-1} w_i P(M_t, i|\theta) \sum_t (M_t - \eta_i) = 0. \end{aligned} \quad (7)$$

Then, we get the following:

$$\eta_i = \frac{\sum_{t=0}^{T-1} P(i|M_t, \theta) M_t}{\sum_{t=0}^{T-1} P(i|M_t, \theta)}. \quad (8)$$

Similarly, we can also get the following:

$$w_i = \frac{1}{T} \sum_{t=0}^{T-1} P(i|M_t, \theta), \quad (9)$$

$$\sum_t = \frac{\sum_{t=0}^{T-1} P(i|M_t, \theta) (M_t - \eta_i) (M_t - \eta_i)^T}{\sum_{t=0}^{T-1} P(i|M_t, \theta)}. \quad (10)$$

In (10),

$$P(i|M_t, \theta) = \frac{w_i b_t(M_t)}{\sum_{j=1}^K w_j b_j(M_t)}. \quad (11)$$

Then, we change the symbols in (8), (9), (10), and (11), and the iterative algorithm expression of θ can be obtained as follows:

$$w_i^{k+1} = \frac{1}{T} \sum_{t=0}^{T-1} P(i|M_t, \theta^k), \quad (12)$$

$$\eta_i^{k+1} = \frac{\sum_{t=0}^{T-1} P(i|M_t, \theta^k) M_t}{\sum_{t=0}^{T-1} P(i|M_t, \theta^k)}, \quad (13)$$

$$\begin{aligned} \sum_t^{k+1} &= \frac{\sum_{t=0}^{T-1} P(i|M_t, \theta^k) (M_t - \eta_i) (M_t - \eta_i)^T}{\sum_{t=0}^{T-1} P(i|M_t, \theta^k)} \\ &= \frac{\sum_{t=0}^{T-1} P(i|M_t, \theta^k) M_t M_t^T}{\sum_{t=0}^{T-1} P(i|M_t, \theta^k)} - \eta_i^{k+1} (\eta_i^{k+1})^T. \end{aligned} \quad (14)$$

In (14), the superscript T in the covariance matrix represents the transpose of the matrix.

Among them,

$$P(i|M_t, \theta^k) = \frac{w_i^k b_i^k(M_t)}{\sum_{j=1}^K w_j^k b_j^k(M_t)}. \quad (15)$$

Among them is the mixture component of the i th Gaussian probability density function in the k th iteration.

In a given sample of translated speech, the purpose of identifying the language is to determine which language the speech belongs to [19]. The block diagram of the language recognition system based on GMM is shown in Figure 5.

By Bayesian theory, maximizing the verification probability can be expressed as follows:

$$P(\theta_i|M) = \frac{P(M|\theta_i)P(\theta_i)}{P(M)}. \quad (16)$$

Among them,

$$P(M|\theta_i) = \prod_{t=0}^{T-1} P(M|\theta_i). \quad (17)$$

Its logarithmic form is as follows:

$$\ln P(X|\theta_i) = \sum_{t=0}^{T-1} \ln P(X_t|\theta_i). \quad (18)$$

Because of the prior probability of θ_i ,

$$P(\theta_i) = \frac{1}{X}, 1 \leq i \leq. \quad (19)$$

For a certain eigenvector M , $P(M)$ is a certain constant, equal for all languages. Therefore, the maximum value of the posterior probability can be obtained by calculating $P(M|\theta_i)$ so that the recognized language in the phonetic database can be expressed as follows:

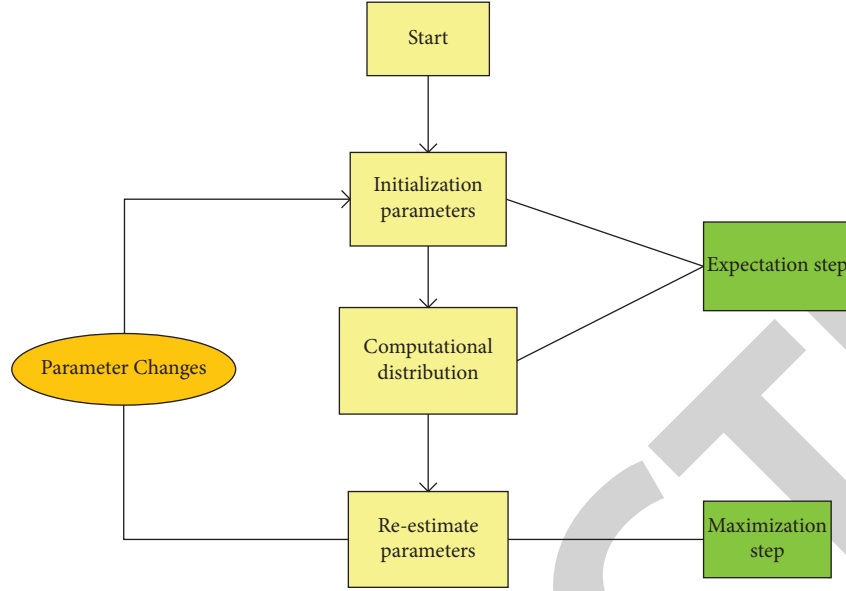


FIGURE 4: Expectation maximization algorithm steps.

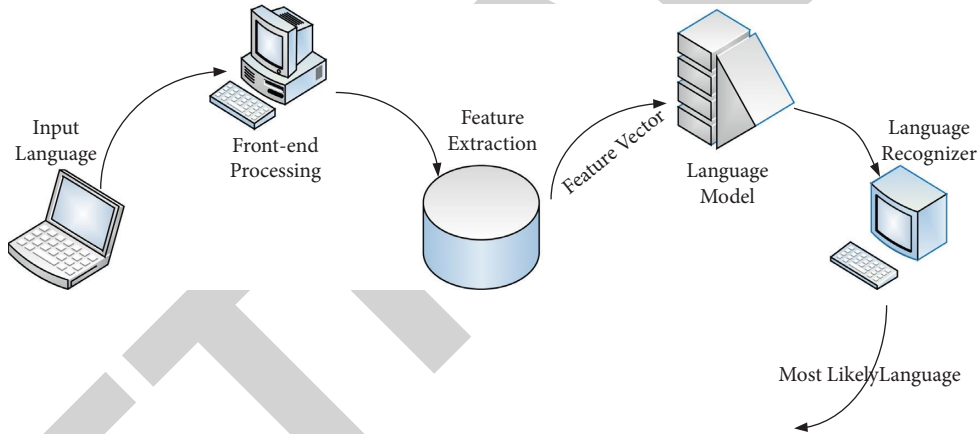


FIGURE 5: Language recognition system based on GMM.

$$i^* = \arg \max P(M|\theta_i). \quad (20)$$

The i^* here represents the recognized language.

3.3. Discriminative Training Algorithm. Discriminative training is proposed to improve language recognition rate. Different from the maximum likelihood algorithm that emphasizes the training data, the language model based on the discriminative training algorithm emphasizes the optimal discrimination of the training data [20]. After several consecutive recognitions, similar languages can be distinguished by using this algorithm, and the language model based on the discriminative training algorithm is more conducive to improving the recognition rate of test data than the traditional maximum likelihood algorithm. Figure 6 is a scene graph related to the discriminative training algorithm.

For a corpus with N training sentences, label each sentence with $r = 1, 2, \dots, R$. Its objective function is defined as its mathematical expectation:

$$G_{GR}(\Gamma) = \sum_{r=1}^R \sum_{x=1}^{X_r} \sum_{n=1}^{N_{rx}} P_{\theta}(w_{rx}(n)|Q_{rx})^k \zeta(w_{rx}(Q) = t_{rx}). \quad (21)$$

Among them, Γ represents the parameter set of the hidden Markov model; t_{rx} is the text of the x th word in the r th training sentence; and the posterior probability is as follows:

$$P_{\theta}(w_{rx}(n)|Q_{rx}) = \frac{L_{\theta}(Q_{rx}|w_{rx}(n))P(w_{rx}(n)|w_{rx}(Q))}{\sum_v L_{\theta}(Q_{rx}|v)P(v|w_{rx}(Q))}. \quad (22)$$

Among them, Q_{rx} is the speech output vector of the x th word in the r th training sentence; v is the possible wrong translation given $w_{rx}(Q)$; and $L_{\theta}(Q_{rx}|v)$ represents the likelihood probability function of Q_{rx} given v .

Similarly, “misaccepted” means that although the identification is wrong, it is wrongly regarded as a correct judgment; its objective function is as follows:

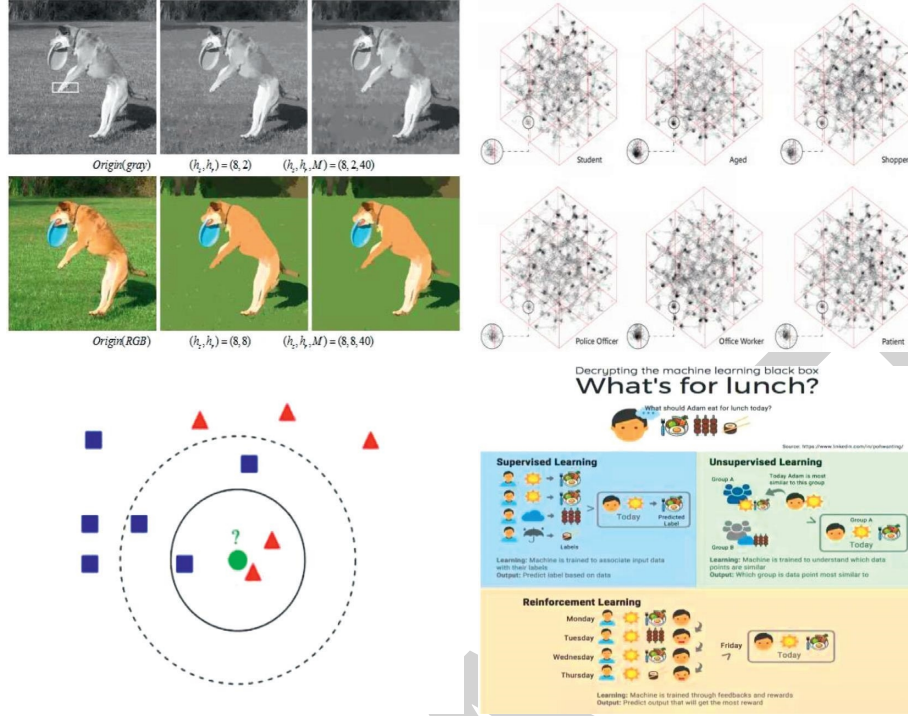


FIGURE 6: Scenario diagram related to the discriminative training algorithm.

$$G_{GT}(\theta) = \sum_{r=1}^R \sum_{x=1}^{X_r} P_{\theta}(w_{rx}(Q)|Q_{rx}) \zeta(w_{rx}(Q) \neq t_{rx}). \quad (23)$$

Corresponding to the correct diagnosis under the true rejection category, the mathematical expectation of the wrong diagnosis is as follows:

$$G_{DE}(\theta) = \sum_{r=1}^R \sum_{x=1}^{X_r} \sum_{n=1}^{N_{rx}} P_{\theta}(w_{rx}(n)|Q_{rx})^x \cdot \zeta(w_{rx}(Q) \neq t_{rx}, w_{rx}(n) \neq t_{rx}). \quad (24)$$

In order to minimize the error, consider the new objective function $G(\theta)$ obtained by summing the three error objective functions. When the scaling factor $k=1$, the derivation result is as follows:

$$\begin{aligned} G(\theta) &= G_{GR}(\theta) + G_{GT}(\theta) + G_{DE}(\theta) \\ &= \sum_{r=1}^R \sum_{x=1}^{X_r} \sum_{n=1}^{N_{rx}} P_{\theta}(w_{rx}(n)|Q_{rx}) \zeta(w_{rx}(Q) = t_{rx}) \\ &= \sum_{r=1}^R \sum_{s=1}^S P_{\theta}(s|Q_r) \text{Raw Word Error}(s, t_r). \end{aligned} \quad (25)$$

Among them, Q_r is the observation vector; t_r is the translated text of a given text sentence; s is the competing text identified according to Q_r ; and the function Raw Word Error(s, t_r) is the number of mismatches between s and t_r translations.

$$P_{\theta}(s|Q_r) = \frac{L_{\theta}(Q_r|s)P(s|t_r)}{\sum_h L_{\theta}(Q_r|h)P(h|t_r)}. \quad (26)$$

In (26), h is any possible wrong translation given t_r .

4. Experiments in English Translation Assessment Based on Gaussian Mixture Model

4.1. Evaluation Plan for English Translation. By collecting the existing research results in the field of English translation, the importance of language translation in various fields can be further understood. This paper randomly selected 500 students majoring in English translation, 200 teachers majoring in English translation, and 300 white-collar workers who work in English translation as the research objects. A total of 1,000 copies of the ‘‘English Translation Assessment Questionnaire’’ were distributed, and 979 copies were recovered. There were 972 valid questionnaires, and the effective recovery rate was 97.2%.

Among the valid questionnaires collected, there are 478 students, accounting for about 49.18% of the total number; 196 teachers, accounting for about 20.16% of the total number; and 298 white-collar workers majoring in English translation, accounting for about 30.66% of the total.

In this questionnaire, a total of 4 questions about English translation were raised, namely, as to whether translation software is used in daily study or work, opinions on using translation software, self-evaluation of English translation, and translation proficiency test situation in daily work or study.

4.2. Evaluation Results of English Translation

4.2.1. Questionnaire

(1) *Whether Translation Software is Used in Daily Study or Work.* Translation software is created to facilitate people’s

daily work and study. Even people with high achievements in English translation will have unskilled words, sentences, etc. and will also use translation software [21]. Table 1 shows the frequency of using translation software in the daily life of the three types of people.

It can be seen from Table 1 that in daily work and life, 386 students frequently use translation software, accounting for about 80.75%; 58 students use the software occasionally, accounting for about 12.13%; and 34 students hardly use translation software, accounting for about 7.12%. It can be seen from this set of data that most of the students' translation foundation is still relatively weak, they are still studying, and relying on translation software is still relatively high. From this part of the data of teachers, it can be found that there are 79 teachers who hardly use translation software, accounting for about 40.31%; 111 who use it occasionally, accounting for about 56.63%; only 6 who use the software regularly, accounting for about 3.06%. From this part, it can be seen that the teachers' job is to contact the students, and their English foundation is solid, so they are less dependent on translation software. However, there are still unfamiliar words or sentences in daily work, and translation software is also needed, so the number of people who use it occasionally accounts for more percentage. Looking at corporate white-collar workers, the English translation ability of this kind of staff is often exercised in their daily work, so their translation ability is strong; therefore, 58 workers hardly use translation software, accounting for about 19.46%. However, due to too many unexpected situations at work, 81 use the software frequently and 159 use it occasionally, accounting for 27.18% and 53.36%, respectively.

(2) *Opinions on the Use of Translation Software.* Translation software has advantages and disadvantages in work and study. The advantage is that it facilitates work and study, facilitates word search, and saves time. The disadvantage is that frequent use will rely on it, resulting in lazy emotions and reluctance to learn new words [22]. Table 2 shows three types of respondents' opinions on translation software.

It can be seen from Table 2 that 405 students think that the translation software is very convenient and greatly saves time. In daily learning, there is no need to look up dictionaries or do direct online search. Those students account for about 84.73%. 40 students maintained a neutral attitude, thinking that translation software has both an advantage and disadvantage. The advantage is that it is convenient to query vocabulary and quickly solve translation problems. The disadvantage is that this software may replace the English translation major, which is a bad phenomenon for people with this major. Those students account for 8.37%. And 33 think that the software is very bad. Many words have too many translation results on the software, and it is difficult to distinguish which translation is the answer they need. Those students account for about 6.90%. From the data of teachers, it can be seen that 56 teachers, accounting for about 28.57%, think that translation software is very convenient. 93 people think that the software has an advantage and disadvantage; the advantage is that it saves time, and the disadvantage is

TABLE 1: Frequency of using translation software in daily life.

	Students	Teachers	Corporate white-collar workers
Used frequently	386	6	81
Occasionally used	58	111	159
Hardly ever used	34	79	58

TABLE 2: Opinions of three categories of people on translation software.

	Students	Teachers	Corporate white-collar workers
Very convenient	405	56	146
Having pros and cons	40	93	150
Very bad	33	47	2

that students' use of translation software may make them dependent on it, so that they will not memorize words. Learning English is limited to learning knowledge from translation software, which is bad for both teachers and students. It can be seen from the data of enterprise white-collar workers that 146 people, which account for about 48.99%, think this kind of software is very convenient, because they encounter too many problems in their daily work. The use of translation software not only helps them solve problems but also saves them a lot of time. And 150 people think that translation software is a double-edged sword, their reasons are the same as those of the students, and they account for about 50.34%.

(3) *Self-Evaluation of English Translation.* As the saying goes, the person who knows oneself best is oneself. Although the evaluation of one's English translation ability includes subjective factors, it also has certain reference value [23]. Table 3 shows the self-evaluation of the English translation ability of the three categories of people.

From the data in Table 3, 117 students in this group of data, accounting for about 24.48%, think their English translation ability is relatively good; 238 students think their English translation ability is average, and the proportion is about 49.79%; and 123 students think their translation level still needs to be improved, and the proportion of this group is about 25.73%. The biggest reference for students' self-evaluation is their usual assessment scores. Better grades are considered excellent, average grades are considered ordinary, and poor grades are considered very poor. It can be seen from the data of teachers that 97, accounting for about 49.49%, think their translation ability is excellent; 96 think that their translation ability is average, and the proportion is about 48.98%; and some teachers think that their translation ability still needs to be improved. This happens mainly because teachers evaluate themselves from their own teaching ability. Among the white-collar workers in the third part, 156, accounting for about 52.35%, think their translation ability is relatively good; 140, accounting for about 46.98%, think that their English translation level is average; of course, some people think that their translation level is very poor, and those account for about 0.67%. The main

TABLE 3: Self-evaluation of English translation ability of three categories of people.

	Students	Teachers	Corporate white-collar workers
Excellent	117	97	156
Ordinary	238	96	140
Very poor	123	3	2

reason for this kind of situation is that the daily work of the company is both difficult and easy. According to this part of the data, it can be concluded that the ability to subjectively judge oneself cannot be limited to only one condition. It is recommended that many aspects are considered, so that the possibility of subjective judgment is smaller.

(4) *Translation Proficiency Test in Daily Work and Study.* Whether students or staff, in order to objectively understand their English translation level, they need to be tested. Students' tests are mainly daily tests, as shown in Figure 7, which compares and analyzes the final exams of students of the same major in the past four years. The teachers' test is mainly about the passing rate of English proficiency, as shown in Figure 8, which is based on the passing rate after graduation. The test of corporate white-collar workers is mainly about the accuracy of translation at work and the time to translate a paragraph. The specific situation is shown in Figure 9.

Figure 7 shows the distribution map of the number of students in each grade of final grades in the past four years.

It can be seen from Figure 7 that in the past four years, the number of students in low grades has decreased year by year, and the number of students in high grades has increased year by year. Among them, the number of people below 60 was decreasing year by year, from 38 in the freshman year to 3 in the senior year, and the population below 60 in the English translation subject test was decreasing. The number of students with scores above 80 was increasing every year, from 54 in the first year, accounting for 11.30% of the total, to 101 in the fourth year, accounting for 21.13% of the total, an increase of nearly 10%. This showed that with the deepening of learning content, the level of translation of students is gradually rising.

Figure 8 shows the number of teachers who have passed the English translation proficiency test in the past four years.

It can be seen from Figure 8 that in the past four years, teachers have participated in the English translation proficiency test with a high pass rate, but there are also people who fail. The number of teachers who pass and perform well also increased every year. From 2018 to 2021, the pass rate was above 98%. The lowest year was 2019, and the pass rate was also 98.47%. Among them, the number of teachers who have passed with excellent grades has increased year by year. In 2018, there were 92 teachers, accounting for about 46.94%. Looking at 2021, we find that the number was 107, accounting for more than 50%. This showed that with the increase of working years, the professional level of these teachers also maintains an upward trend.

Figure 9 shows a survey of corporate white-collar workers' translation capabilities in the past four years.

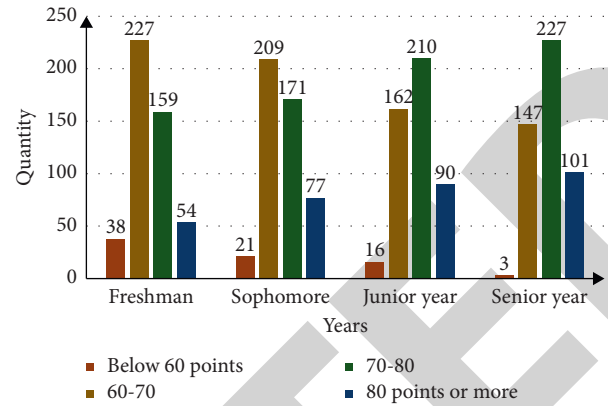


FIGURE 7: Students' final test scores for the past four years.

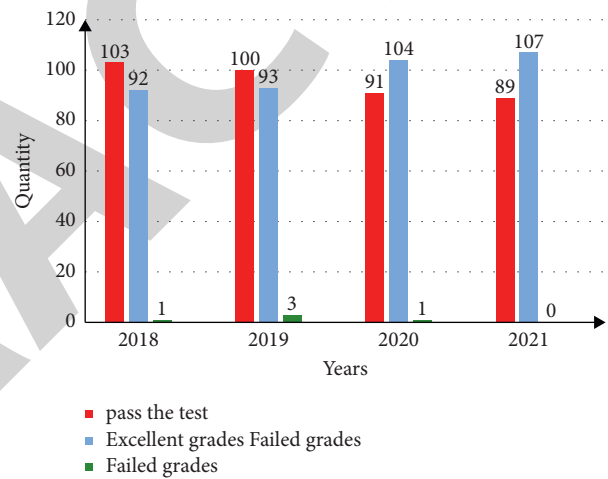


FIGURE 8: The number of teachers who passed the English translation proficiency test.

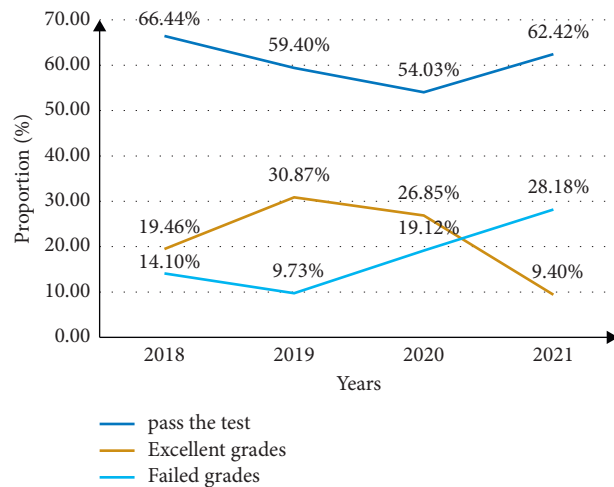


FIGURE 9: Enterprise white-collar workers' survey of their translation capabilities in the past four years.

As can be seen from Figure 9, the test requirements of enterprises for English translators have increased year by year. It can be seen from the data that the failure rate in the four years from 2018 to 2021 has almost doubled from 14.1% to 28.18%. Although there were small changes in the middle, the overall failure rate was on the rise. Of course, during this period, there are still many workers who are constantly improving their strength and professional level. In the work test, their scores are also improving year by year.

4.2.2. Language Recognition Experiment Based on Gaussian Mixture Model. English translation includes not only text translation, but also voice translation. The first part of the questionnaire survey was mainly based on text translation, and then experiments were conducted on voice translation.

In this experiment, four languages were selected for translation results experiment, which are Japanese, Chinese, German, and French. The total number of experimental samples is 400 8-second speeches and 400 2-second speeches. After processing through feature parameters, the dimension of each feature vector is 16, and the mixing degree of GMM is 32. Experiments were conducted with speech with a length of one frame and a speech with a length of 2 seconds (188 frames). The details are shown in Table 4.

It can be seen from Table 4 and Table 5 that only the first frame of each 2-second sample was taken to test the translation effect and then the sample was tested. The recognition results obtained are shown in Table 5, and the correct translation rate was only 46.18%. This first-order polynomial contains the information between frames, but only one frame, with 2 seconds of speech segment, was used for sample testing, and its translation recognition result was not high.

To sum up, through the questionnaire survey and GMM experiment, the English translation ability of the three groups of people and the language translation technology of the GMM can be learned. In this regard, there are still some small problems in the experiment that need to be improved, and the evaluation of the English test needs to be carefully analyzed. In terms of written translation and oral translation, the results are diametrically opposite.

4.3. Evaluation Results of English Translation by Improved Gaussian Mixture Model. According to the analysis of this paper, the application of the discriminative training algorithm of GMM in English translation is relatively perfect. With the advancement of science and technology, intelligent translation technology has gradually been recognized and used by the public. The use of GMM's discriminative training algorithm to collect the opinions of English translation professionals on the profession greatly facilitates the research of this experiment. However, because the research in this field is not comprehensive enough, there are some small problems, which need to be corrected. The details are as follows: First, in the questionnaire survey, three groups of people were selected for experimental investigation; the results are better, but in this part of the experiment,

TABLE 4: Confusion matrix of the number of 1-frame speech tests.

Sample size	Recognition result				
	Japanese	Chinese	German	French	
Japanese	98	27	51	7	21
Chinese	96	28	38	15	15
German	90	10	29	36	15
French	88	29	19	31	9

TABLE 5: Confusion matrix for number of 2-second speech tests.

	Recognition result			
	Japanese	Chinese	German	French
Japanese	0.5578	0.0938	0.2263	0.1221
Chinese	0.080	0.6612	0.229	0.0298
German	0.0779	0.2335	0.5321	0.1565
French	0.09	0.05	0.2111	0.6489

the sample size is small, and the results are not accurate; it is recommended that the sample size is increased. Second, in the speech translation experiment, the sample data is large, but the selected sample time period is short, and the sample selection source is single too. By increasing the sample sources, the experimental data can be more complete and the experiments can be comparable. The application of the discriminative training algorithm based on the improved Gaussian mixture model in the English page-turning profession is a field that experts and scholars from all walks of life have been keen in recent years, and many issues still need further research and discussion.

5. Discussion

With the development of economic globalization, the demand for English translation professionals is also increasing, and the requirements for this profession will also increase. To understand the basic level of this profession, it also needs to be tested [24]. This paper firstly integrated the achievements and ideas of English translation professionals in the major and used the discriminative training algorithm of Gaussian mixture model to discuss the problems of 1,000 English translation professionals. Then, it used the GMM to study the related problems of English translation in speech translation. Finally, through a series of analyses, two opposite results were obtained. In the process of written questionnaires, it was found that the English translation ability of all kinds of people was relatively strong, but in the voice translation, their translation ability was still weak.

This paper is devoted to researching the related application of the discriminative training algorithm based on GMM and applying it in the field of English translation evaluation. This is not only an expansion and extension of the application scope of the algorithm, but also a new attempt to evaluate English translation. Through the above case studies, opposite experimental results are obtained in the written translation experiment and the speech translation experiment, which both show the effectiveness of the discriminative training algorithm in this paper under the Gaussian mixture model.

6. Conclusions

In this paper, the discriminative training algorithm of GMM was used as the main analysis method; 1,000 randomly selected people of three types were selected as the research object; and the related problems of students, teachers, and translators in English translation were selected. Through the case study, the following conclusions were drawn: There are subjective evaluation and objective evaluation in English translation professional test; the subjective test needs to comprehensively consider many aspects and cannot determine one's translation ability only by one factor, and the same is true for the objective evaluation. The translation includes voice translation and written translation. It can be seen from the experiment that the written translation survey results are better. All kinds of people are good at written translation, while voice translation is the use of intelligent technology to memorize translation, and the result has certain defects. From one angle of experiment, the reliability of the results is low, so it needs to be analyzed from multiple angles and multiple aspects to better highlight the efficient application of GMM's discriminative training algorithm in English translation evaluation.

Data Availability

The data that support the findings of this study are available from the author upon reasonable request.

Conflicts of Interest

The author declares no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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