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Augmenting College English Teaching with Advanced Semantic Representation and Intelligent Evaluation in E-Learning

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Abstract. In linguistics, psycholinguistics applied linguistics, and second language acquisition theory, "student-centeredness" has emerged as a profound teaching theory. Diverging from the conventional teacher-centered approach, student-centered pedagogy thrives in a teacher-guided environment. This study integrates word2vec, paragraph2vec, pos2vec, and Latent Dirichlet Allocation (LDA) to construct a semantic representation vector tailored for university English teaching. The crux of reform in university English teaching revolves around the need for conceptual and theoretical updates. These updates are vital for enhancing educators' teaching theory and practice, fostering effective university English teaching reform. Ultimately, this research demonstrates the superiority of our proposed intelligent evaluation framework over traditional methods, particularly in the realms of automatic grading and rubric generation for college-level English instruction.

Keywords: Evaluation in E-Learning, Psycholinguistics, Applied linguistics, Word2vec, LDA, Natural language processing
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1 INTRODUCTION

In recent years, English teaching theories and practitioners in China have considered enabling students to master English as a tool of information and communication while learning their major subjects[16]. University English teachers and researchers have searched for the best teaching methods and approaches[25]. The traditional teaching model is no longer fully adapted to the modern teaching requirements, and "a national reform of university English teaching is imminent" [21]. The focus has been on the learner-centered model of teaching, which is popular in Europe and the United States. The traditional teacher-centered teaching model has increasingly shown limitations, inappropriateness, and lag. Both in China and abroad, the teacher-centered teaching model adopts a teaching-oriented teaching method[19],[3],[17],[22],[11],[13]. The theoretical sources of the student-centered teaching model can be summarized as humanistic psychology [18],[20][26].

If different students have different communicative purposes, then these communicative purposes should be reflected in the content (what to teach) and the learning process (how to guide) of the course[6],[2],[23]. In addition, the fact that different students have different communicative purposes also promotes a shift in the concept of teaching and learning from the concentration of teachers and textbooks to students, which to some extent reflects the idea of student-centered teaching[24],[12],[4],[7],[8]. As Cook says, "The communicative approach focuses on the interaction of two people in a situation, what Halliday (1975) calls the 'interpersonal' function of language. Instead of the teacher ruling the classroom, controlling and directing the students at all times, the students are given free rein to talk in pairs or small groups, learning by doing; the students are no longer expected to produce completely error-free discourse; instead, they can use whatever forms and strategies they think will solve the problem, and the teacher can provide some feedback and correction. Correction is also an essential responsibility of the teacher in the classroom[9],[15],[11],[5],[1].

2 THEORETICAL MODEL

2.1 Intelligent College English Teaching Evaluation Framework

Step 1 Organize N documents by ID and use the data cleaning module to check the completeness of the training corpus (each essay should contain essay subjects, comments, scores), consistency of coding, etc. ;

Step 2 For each university English teaching text (X train), the feature vectors of word2vece, paragraph2v, pos2vec, LDA of the university English teaching are obtained in turn $\boldsymbol{U}_{w2v}$, $\boldsymbol{U}_{p2v}$, $\boldsymbol{U}_{\text{pos}2v}$, $\boldsymbol{U}_{\text{LDA}}$;

Step 3 splice all semantic vectors from left to right to get 1×M-dimensional integrated feature vectors, and all the training college English teaching (N pieces) form an N×M-dimensional integrated feature vector space $V^{\text{all}} = \left[V_{w2v}, V_{p2v}, V_{\text{pos}2v}, V_{\text{LDA}}\right]^T$;

Step 4 Normalize the scores corresponding to N university English teaching articles (Y train) to obtain a 1×N-dimensional score vector space W.

Step 5 Input V and W into the XGboost regression algorithm for training and obtain the scoring model;

In step 6, TF-IDF and text rank algorithms are used to calculate the comment tag set of all college English teaching comments respectively, P_1 and P_2 are obtained, and the intersection $P = P_1 \cap P_2$ is taken as the comprehensive comment tag;

Step 7: Based on the kNN algorithm, find the university English language teaching similar to the university English language teaching to be evaluated, and generate the final evaluation labels of the university English language teaching to be considered using the comprehensive evaluation labels of the university English language teaching in the training set.

2.2 Online Evaluation Phase

Step 1 Check the subject text, coding specification, and word count for the university English teaching to be evaluated;

Step 2 Based on the trained vector library, the subject of the university English teaching to be evaluated is represented as a comprehensive feature vector;

Step 3 Input the comprehensive feature vector of the university English teaching to be evaluated into the trained scorer to get the university English teaching score Y online;

Step 4 uses the semantic similarity model based on the kNN algorithm to find the top k university English teaching texts that best match the university English teaching, get the rubric signature, use the rule-based grammar error correction module for grammar errata, and then give the university English teaching rubric after synthesis. The rubric of English teaching.

2.3 Integrated Feature Vector Representation Considering Distributed Features

The core computation principle of Paragraph2vec is the same as that of word2vec, which is based on the MLP model, and the vector of modeling objects is obtained by finding the objective function (1). Still, the difference lies in the selection of modeling objects. To consider the influence of word order on semantics more, paragraph2vec introduces a paragraph ID so that each sentence has a unique ID, as shown in Figure 1. Given the paragraph id, the probability of four words occurring in the context is counted, i.e., the position of the sentence is also taken as an essential feature to record the implied semantics between paragraphs.

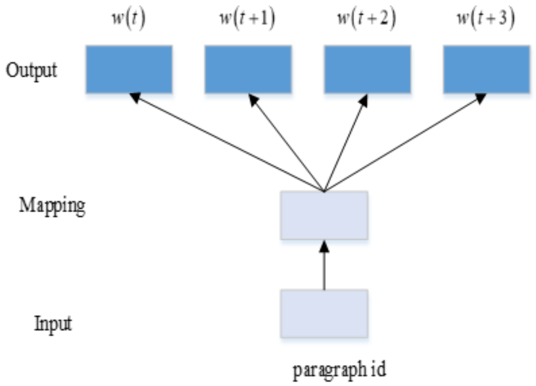

Figure 1: Schematic diagram of paragraph2vec model.

In the training step, only the feature of id, i.e., paragraph id, $w_1, w_2, \ldots, w_T$, is added in front of the word sequence of Eq. (1), and the subsequent parameter-solving steps remain unchanged.

2.4 LDA-Based Chapter Representation

The LDA model is a generative topic model, a three-layer Bayesian probabilistic model consisting of words, topics, and documents, and is centered on calculating the distribution of topic variables (i.e., hidden variables) for a given document [18]. The estimation process of the parameters is shown in Figure 2.

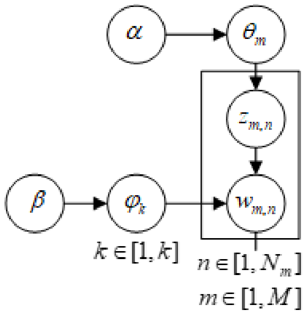

Figure 2: Probabilistic graphical model of LDA.

In Figure 2, the parameters satisfy each other :

$$p(w \mid \alpha,\beta)=\int p(\theta \mid \alpha)\left(\prod_{n=1}^{N} p(w_n \mid \theta,\beta)\right)d\theta=\int p(\theta \mid \alpha)\left(\prod_{n=1}^{N}\sum_{z_n} p(z_n \mid \theta)p(w_n \mid z_n,\beta)\right)d\theta= \frac{\Gamma(\sum_i \alpha_i)}{\prod_i \Gamma(\alpha_i)}\int\left(\prod_{i=1}^{k}\theta_i^{\alpha_i-1}\right)\left(\prod_{n=1}^{N}\sum_{i=1}^{k}\prod_{j=1}^{V}(\theta_i\beta_{ij})^{w_n^j}\right)d\theta \tag{1}$$

Where,

$$p(\theta \mid \alpha)=\frac{\Gamma(\sum_i \alpha_i)}{\prod \Gamma(\alpha_i)}\theta_1^{\alpha_1-1}\cdots\theta_k^{\alpha_k-1} \tag{2}$$

3 PRINCIPLE OF XGBOOST ALGORITHM

Compared with the traditional GBDT (gradient-based decision tree) method, XGBoost has improved error approximation and numerical optimization and has become one of the most popular methods in various machine learning-based applications and competitions in recent years. Assume that k trees are composing the model :

$$\hat{y}_i=\sum_{k=1}^{K} f_k(x_i), f_k \in F \tag{3}$$

Solve for the objective function of each parameter in the tree :

$$Loss=\sum_i l(\hat{y}_i,y_i)+\sum_k \Omega(f_k)=\sum_i(y_i-\hat{y}_i)^2+\sum_k\left(\gamma T+\frac{1}{2}\lambda\|w\|^2\right) \tag{4}$$

Among them, $\Omega(f_k)$ includes two parts: parameters γ Reflect the influence of the number of leaf nodes t on the error; Parameters λ Reflects the impact of leaf node weight W on the error; L2 regularization is adopted here to prevent overfitting phenomenon due to too many leaf nodes. See the literature for the detailed solution process of the objective function (5) [20].

The general idea of the kNN algorithm-based rubric generation method for university English teaching is as follows: firstly, several typical rubric labels for each university English teaching in the training set are filtered by TF-IDF method and Text Rank method; then, the university English teaching to be evaluated and all university English teaching in the training set are represented by the comprehensive feature vector in Section 1.2, and the cosine similarity between the university English teaching to be evaluated and each university English teaching in the training set is compared. Finally, the kNN algorithm is selected, and the typical rubric labels of the first k university English language teaching in the training set with higher similarity to the university English language teaching are de-weighted to form the rubric labels of the university English language teaching to be considered. The steps are as follows :

Step 1 The TFIDF method (equation (4)) is used to calculate the TF-IDF weights of each comment phrase for the ith college ELT comment c_i, and a set of comment phrases is obtained in descending order $K_i^{\text{TF-IDF}}$:

$$\text{TF-IDF}=tf_{i,j}\times idf_i=\frac{n_{i,j}}{\sum_k n_{k,j}}\times lg\frac{|D|}{|\{j:t_i\in d_j\}|}。 \tag{5}$$

Step 2: Using the Text Rank method (equation (5)), the TR weights of each comment phrase are calculated and ranked in descending order to obtain a set of comment phrase sequencesK_i^{TextRank}

$$\text{TR}=(1-d)+d\times\sum_{V_i\in\{V_i\}}\frac{w_{ji}}{\sum_{V_k\in\text{Out}\{V_j\}} w_{jk}}\text{TR} \tag{6}$$

Step 3: The top n TF-IDF phrases are$K_{i(n)}^{\text{TF-IDF}}$, the top n TR phrases are $K_{i(n)}^{\text{TextRank}}$, and the intersection is taken to obtain the sequence of integrated phrases for university English teaching $K_i=K_{i(n)}^{\text{TF-IDF}}\cap K_{i(n)}^{\text{TextRank}}$, and so on.

Step 4 In Figure 1, when calculating the rubric online, the composite vector$\boldsymbol{v}_i^{\text{all}}$ of the essay i to be evaluated is compared to the composite vector $\boldsymbol{v}_j^{\text{all}}$ of each university English teaching in the training library (equation (7)) and ranked in descending order:

$$Similarity_{ij} = cosin\left(\boldsymbol{v}_i^{\text{all}}, \boldsymbol{v}_j^{\text{all}}\right) = \frac{\boldsymbol{v}_i^{\text{all}}\,\boldsymbol{v}_j^{\text{all}}}{\sqrt{\sum_{m=1}^{M}\left({}_{i,m}^{\text{all}}\right)^2}\sqrt{\sum_{m=1}^{M}\left(\boldsymbol{v}_{i,m}^{\text{all}}\right)^2}} \tag{7}$$

Step 5 Finally, based on the idea of the kNN algorithm, the comment phrases with the top k similarity are selected, and the duplicate phrases are removed and combined into the final comment of the university English teaching.

4 EXPERIMENTAL RESULTS

To ensure the accuracy and fairness of the original labels, two teachers were asked to rate each piece of college English teaching, and the average score of the college English teaching was obtained by summing up the comments of the two teachers. The comments of the two teachers were summed up to get a comprehensive comment. The final number of essays in each score range was obtained, as shown in Table 2, with an average of 7.2 comment phrases per college English teaching essay.

Theme	*Number of compositions*
online shopping	*191*
online learning	*166*
Importance of invention	*192*
a part-time job in college	*178*
choice of career	*173*

Table 1: Number of university English teachers teaching various topics.

Score range/point	*Number of compositions*
[0,60]	*54*
[60,70]	*219*
[70,80]	*296*
[80,90]	*273*
[90,100]	*63*

Table 2: Number of university English teaching in each score range.

According to the technical route in Figure 1, the 900 university English language teaching items were divided into five equal parts (i.e., 180 items each), 4 of which (i.e., 80%) were randomly selected as the training sample, and the remaining one as the test sample. The evaluation index was obtained each time, and the average of the five times was used as the score. The comparison between the scoring effect of this method and several previous scoring methods is shown in Table 3.

Scoring method	*Mean square error*	*Pearson correlation coefficient*
Paper method	*10.40*	*0.955*
This paper synthesizes eigenvector + SVM	*18.91*	*0.924*
This paper synthesizes eigenvector + gbdt	*12.81*	*0.945*
Word2vec, LDA+XGBoost	*15.12*	*0.937*
Word2vec +XGBoost	*16.18*	*0.933*
LDA+XGBoost	*21.91*	*0.909*
LDA+SVM	*27.72*	*0.888*

One-hot+GBDT	*24.48*	*0.901*

Table 3: Scoring effects of various college English teaching scoring methods.

The comprehensive feature vector of the i-th university English teaching is $\boldsymbol{v}_i^{\text{all}} = [\boldsymbol{v}_{w2v}, \boldsymbol{v}_{p2v}, \boldsymbol{v}_{\text{pos2v}}, \boldsymbol{v}_{\text{LDA}}]$, i.e., 1× 270-dimensional vector, for word2vec, paragraph2vec, pos2vec and LDA with 50, 100, 20 and 100 dimensions, respectively. Compared with other methods, this method has the minorest mean square error and the most significant Pearson correlation coefficient, which means that this method has the minorest error and the highest correlation with teachers' ratings[14].

In the process of rubric generation, the top 5 comprehensive rubric phrases of TF-IDF weight and Text Rank weight are intersected and used as a sequence of complete rubric phrases with k=3 using the KNN algorithm to give the university English teaching rubric to be evaluated. The average accuracy, recall, and F-score of the university English teaching rubrics and teacher comments generated by the new method were compared with those of the TF-IDF and Text Rank methods alone, and the results are shown in Figure 3.

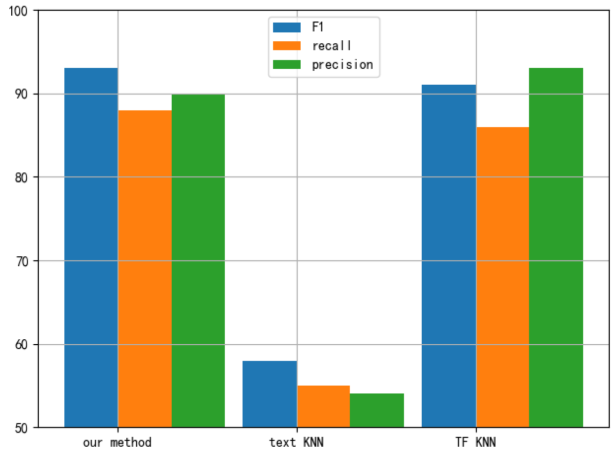

Figure 3: Comparison of the effects of the methods for generating English language teaching rubric labels in college.

As can be seen from Figure 3, the method in this paper effectively selects typical English college EFL rubrics by combining the TF-IDF method and the Text Rank method, which has a more significant advantage than using a single tag extraction algorithm and achieves a high level of accuracy (F-score over 0.8) in generating English college EFL rubrics by using the kNN algorithm. The main rubrics (more than three occurrences) were clustered according to 5 rating levels, i.e., [0, 60), [60, 70), [70, 80), [80, 90), [90, 100].

Many minor errors, poor language flow, and problems with vocabulary use or spelling characterize the clustering of students' college English teaching in different score levels. There is some overlap in the labels of the comments between adjacent score areas, and the comments vary more across score areas.

5 CONCLUSIONS

This theory of teaching and learning developed in the study of second language acquisition theory. The "student-centered" teaching theory and model differs from the "teacher-centered" traditional teaching theory and model but is implemented in a teacher-led teaching environment. In this study, the semantic representation vector of college English teaching is combined with the word vector; the focus of college English teaching reform is to update the concept and theoretical understanding to improve the teachers' English teaching theory and teaching practice and to do an excellent job of college English teaching reform. Integrating advanced semantic representation and intelligent evaluation into e-learning for college English education marks a groundbreaking advancement. This fusion enriches language comprehension, offering contextual insights and practical language usage. Tailored learning paths and instant feedback elevate language proficiency, creating immersive online experiences.

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