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The Literary Features of Shakespeare's Plays Based on Natural Language Processing and Its Influence and Analysis on British Drama Literature

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Abstract The development of Shakespeare's dramatic literature is a turning point in the development of the history of English dramatic literature and an important period in the development of the English language. Based on a self-constructed corpus of Shakespeare's dramatic literary works, this paper combines BERT and attention mechanism to establish a SMLCL model for literary feature extraction of Shakespeare's drama. Based on the literary feature extraction results of this model, the lexical feature situation of Shakespeare's dramatic literary works is explored. Then a multiple linear regression model was constructed with Shakespeare's dramatic literature features as the independent variable and the level of British dramatic literature development as the dependent variable, which was used to explore the influence of Shakespeare's dramatic literature on British dramatic literature. It was found that the F@6 index of the SMLCL model was 67.62%, which was 3.31 percentage points higher than that of the MIEnhance-KPE model. The lexical densities of the observed and reference pools of Shakespeare's dramatic literature were 76.02% and 77.97%, respectively, and there was a significant difference in the use of lexical densities (LLR=-84.72***, P<0.01). There is a significant positive effect of Shakespeare's dramatic literary features on the level of development of English dramatic literature. Relying on Shakespeare's dramatic literary features, it makes the lexical transformations in British dramatic literature more flexible, the sentence expressions more varied, and the use of foreign words and hyphenation, all of which make the expressions of British dramatic literature more figurative and compatible.

Index Terms Shakespearean dramatic literature, BERT, SMLCL model, literary feature extraction, multiple linear regression

I. Introduction

Shakespeare is the most representative playwright of the English Renaissance movement, and his plays can be said to represent the highest achievement of English dramatic literature at that time [1], [2]. In-depth analysis of the literary characteristics of Shakespeare's plays, as well as analyzing the influence of Shakespeare's plays on the development of later generations of British drama, which is of great significance to deepen the knowledge of drama [3]-[5].

The literary features of Shakespeare's plays are mainly embodied in the distinctive humanist color, possessing a strong realism style and displaying a deep romanticism style [6]-[8]. Shakespeare is the greatest English dramatist, and the plays he created have had a significant impact on English theater, and even on world theater [9], [10]. Shakespeare's tragedy has had a significant impact on English literature, one of which is to influence the concept of the creation of tragedy, Shakespeare's tragedy is expressed in the trend of humanism, as well as the thinking of the value of life, and these concepts have directly influenced the creation of tragedy in England later [11]-[14]. Secondly, it influences the method of British tragedy creation, and at the same time makes British literature occupy an important position in the history of world literature [15]. Although Shakespeare used English writing, his works have been translated into many languages popular all over the world, and Shakespearean tragedies are the most active content performed on the theater stage [16]-[19]. Shakespeare, as the most influential dramatist in the history of England, the development of English literature is not only reflected in the concept as well as the artistic expression, but also in the use of language, Shakespeare's contribution to the development of language is enormous, which not only creates more vocabulary, but also influences the language, especially the norms for the use of the language of English writing [20]-[23].

In this paper, a corpus of Shakespeare's dramatic literary works is established through the steps of collection, cleaning and processing, using electronic texts and website data as data sources. This paper proposes a SMLCL model for Shakespearean dramatic literature feature extraction based on BERT and attention mechanism, which consists of four modules: semantic feature extraction, adaptive local thresholding, cross-labeling, and boundary interval loss as a way to improve the accuracy of feature extraction for Shakespearean dramatic literature. Based on the extraction results of Shakespeare's dramatic literature features, a quantitative analysis of its vocabulary richness and difficulty level is carried out. A multiple linear regression model was established with Shakespeare's dramatic literature features as the independent variable and the development level of British dramatic literature as the dependent variable, aiming at exploring the influence of Shakespeare's dramatic literature on British dramatic literature.

II. Shakespeare's Dramatic Literature Corpus

William Shakespeare's literary and artistic achievements in his life are unsurpassed, and he not only expanded the techniques of characterization and plot content, but also made revolutionary innovations in the effects of language expression and literary genres. The purpose of establishing a corpus of Shakespeare's dramatic literature is to better explore the characteristics of Shakespeare's dramatic literature and further understand the cultural connotation of Shakespeare's dramatic literature.

II. A. Data Acquisition and Preprocessing

II. A. 1) Data collection and cleaning

The main corpus sources of Shakespeare's Dramatic Literature Observatory in this paper are divided into two categories, the first one is the electronic text in PDF, Fb2, epub and other formats, whose text format cannot be directly included in the text library due to the special nature of non-editable. Therefore, it is necessary to identify and process the text with the help of ABBYY FineReader and iLovePD tools, and after manual checking for accuracy, the text is named and saved in plain text txt format. The other category is the text that can be directly copied and pasted on the website of Shakespeare's works, so it can be directly copied and pasted on the webpage, but it is necessary to delete the redundant information such as advertisements, navigations, URLs and so on that are not about the content of the works itself, and name and save it in txt text format.

After the formation of txt plain text format is to clean the text, clean text, the main purpose of which is to delete the blank lines, line breaks, the realization of half-whole-width symbols, as well as special symbols, such as conversion, in order to avoid the next step in the text retrieval of garbled code. Clean text is the main tool used to clean the Text Editor, it should be noted that the use of this tool before the need to save a good UTF-8 text format with the help of the Replace Pioneer tool to achieve batch transcoding, and will be converted to ANSI format after the text is saved and imported into the Text Editor for cleaning.

II. A. 2) Corpus processing and handling

Tree Tagger is English lexical annotation software that performs English word splitting and lexical annotation, and batch processing of text. Finally, the processed text is manually proofread, and at the same time formatted and re-encoded for easy storage and retrieval, ultimately generating a corpus of cooked text that can be used for research. Lexical annotation refers to adding a mark consisting of a number of characters to each word in the corpus text to indicate the lexical category of the word. It is also a more sophisticated form of markup that can be automatically labeled by computer software. This paper adopts the lexical annotation set designed and created in the relevant research, according to the lexical annotation set, combined with the actual situation of the original Shakespearean dramatic literature text, the Shakespearean dramatic literature text can be labeled as the first level of the 12 categories.

The software has a relatively high rate of correctness for participle, lexical annotation and lexical reduction, but there are still a small number of errors and problems. We need to use the draft specification of the annotation set to correct the participle and lexical errors, perform manual proofreading, and at the same time fill in the prototypes of the words in the positions that are not recognized and the software is unable to perform lexical reduction showing as <unknown>. Based on the processing of the text, deeper processing is performed for research needs. Use Editplus to replace "t" with "_" in batches, use the regular expressions "_.*$" and "^([^_]*)_", extract the part-of-speech annotation column and the reduction column, and save them as part-of-speech annotation text and part-of-speech reduction text respectively. The part-of-speech annotation text is labeled according to the first-level English part-of-speech annotation set, which is used for the statistics of word classes, N-element sequence structure and sentence construction block model. Morphological text is used to extract high-frequency words and keyword lists.

II. B.Shakespeare's Dramatic Literature Corpus

II. B. 1) Corpus construction process

Shakespeare's dramatic literature, which carries the British dramatic literature, shows high literary value, in order to realize the effective extraction and analysis of Shakespeare's dramatic literature features, this paper constructs a Shakespearean dramatic literature corpus, and its specific library construction process is shown in Figure 1. It mainly contains five steps: data collection, data cleaning and labeling, data integration and alignment, data storage and management, and data analysis and application, in order to realize the construction of Shakespearean dramatic literature corpus.

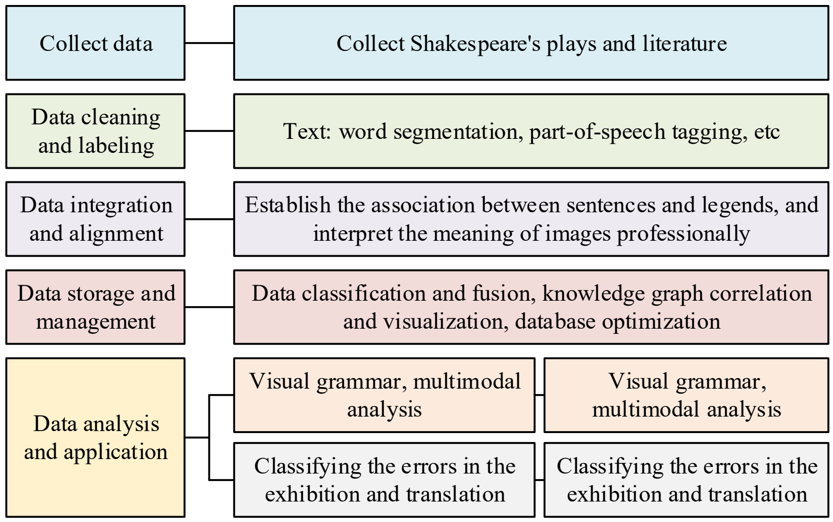

Figure 1: The construction process of Shakespeare's drama literature

II. B. 2) Dramatic Literature Corpus

There are two corpora used in the study of this paper, a self-constructed observational corpus and a reference corpus learned from the comparison data.

(1) Macrodata of Observation Corpus

After text collection, cleaning and processing, the Shakespearean drama literature corpus is initially built, which can complete the function of searching and extracting data. The overall macro data of the corpus is visible through the Statistics software page, the library capacity of the Observation Library is 385,661 words, the number of class symbols is 54,589 words, and the class symbol/shape symbol ratio (TTR) is 14.58%, and the class symbol/shape symbol ratio of every 1,000 words is homogenized to get the value of Standardized Class Symbol/Shape Symbol Ratio (STTR) 62.79%, and the total number of sentences is 40517 sentences.

(2) Macro data of reference library

The reference library is built with the help of the British Dramatic Literature Corpus built by the Center for Literature Studies of H Polytechnic University, which mainly consists of the relevant dramatic works of several British authors. The library capacity of the reference library is 1585741 words, the number of class symbols is 154237 words, the TTR is 10.31%, the STTR is 61.56%, and the total number of sentences is 164827 sentences. Overall, the capacity of the reference library is 4.11 times of the capacity of the observation library, which is comparable. Both the reference and observation library texts consist of British dramatic literature, with a high degree of analogy and research feasibility.

III. Shakespeare's Dramatic Literary Features Extraction

Shakespeare's dramatic literature expresses the spiritual connotation of contemporary British era, and the study of its literary features helps to better understand the development of British dramatic literature and lays the foundation for further exploration of the spiritual connotation of British dramatic literature. Based on this, this paper establishes a Shakespearean dramatic literature feature extraction model based on natural language processing technology, and carries out a validation and analysis of Shakespearean dramatic literature features for the model, aiming at laying a foundation for exploring the influence of Shakespearean dramatic literature on British dramatic literature.

III. A. Natural language processing techniques

III. A. 1) Pre-training the BERT model

BERT is an unsupervised pre-trained language model for natural language processing tasks, which draws on the design ideas of EMLO, BERT adopts the Transformer structure while using a two-way attention mechanism. Therefore, it can consider the context of all positions in the input sequence, which also makes it able to utilize the contextual information more fully, instead of simply splicing the left and right directions of the language model as ELMO does.

In the BERT model structure, [CLS] labels denote the corresponding output vectors as the semantic representation of the sentence as a whole, which is used for category prediction, and [SEP] denotes the separator, which is used to distinguish between two sentences.BERT adopts the NSP training method, which makes the input utterance consist of two sentences, and there is a probability of 50% that two semantically coherent sentences will be taken as the training sample, and 50% that two sentences will be taken as training samples in a completely randomized way. Two sentences are drawn as training samples, and the model will make a judgment on whether they are true continuous utterances or not, which can enable the model to learn how to capture the semantic links between sentences [24].

III. A. 2) Attention mechanisms

The attentional mechanism recognizes and focuses on the important parts of a large amount of information, filtering out the key information and leaving out the less important content.

The way the attention mechanism works can be likened to an addressing process. Given an element in the target Target as the query Query, the model determines the weight coefficients for each corresponding value $\{Value_i\}$ by calculating the similarity or correlation between the Query and each key $\{Key_i\}$, and then performs a weighted summation of $\{Value_i\}$ in order to calculate the final Attention value [25]. The computation process can be represented by the following equation:

$$Attention(Query, Source) = \sum_{i=1}^{L_x} Similarity(Query, Key_i) * Value_i \tag{1}$$

where $L_x = \| Source \|$ is the length of the source.

In this way, Attention is able to selectively filter a small amount of important information from a large amount of information, and focus on this information while ignoring most of the unimportant information. The process of focusing is reflected in the calculation of weight coefficients, the larger the weight coefficients are, the more important the information corresponding to Value is.

In the field of natural language processing, the attention mechanism was initially introduced to solve the problems of proximity context bias and fixed context size limitation inherent in recurrent neural network (RNN) models. The attention mechanism enables the target RNN to depend on all hidden vectors of the source RNN, not just the last one.

III. B. Dramatic Literature Feature Extraction

In order to realize the effective extraction and classification of literary features of Shakespeare's plays, this paper proposes a semi-supervised text classification model (SMLCL), which combines the semantic feature extraction module and the interval loss module to solve the problem of pseudo-labeling error accumulation and the underfitting situation of the decision boundary. The structure of the SMLCL model is shown in Fig. 2, which consists of four main modules, i.e., the semantic feature extraction module, the adaptive local thresholding module, the cross-labeling module, and the boundary interval loss module.

For the raw data we divide it into two parts, i.e., labeled data and unlabeled data, and for each batch of unlabeled and labeled data we apply two data enhancement techniques, i.e., weak data enhancement and strong data enhancement. Subsequently, these data are passed through a BERT model that combines the Attention and TextCNN layers to capture the semantic features. After being processed by the adaptive local thresholding module, the predicted values whose confidence exceeds the adaptive local threshold are selected as the corresponding category pseudo-labels. Then the interval between the preset boundaries and the true values is used to make the predicted values move closer to the true labeling direction and away from the false labels. The two models then cross iteratively train each other by exchanging their generated pseudo-label predictions.

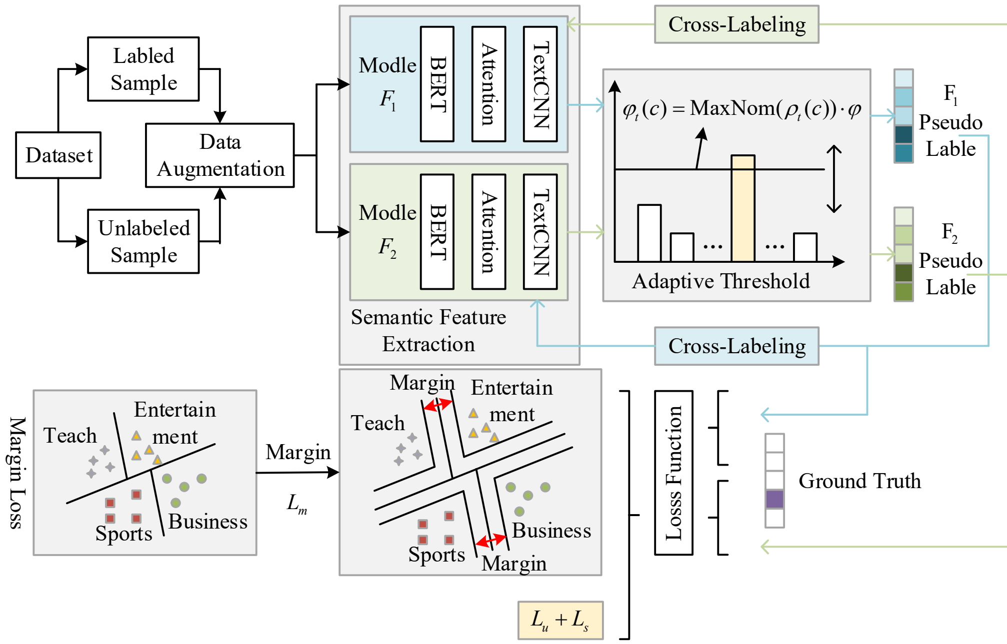

Figure 2: Illustration of the SMLCL Model

III. B. 1) Semantic Feature Extraction Module

In order to obtain the initial representation vectors of local features that contain more rich semantic information, the semantic feature extraction module is designed in this paper [26]. First, the initial representation vectors of the contexts of the higher BERT layers are obtained according to the BERT encoder $H_9^l, H_{10}^l, H_{11}^l, H_{12}^l$, and the corresponding aspect word representation vectors are extracted $H_9^a, H_{10}^a, H_{11}^a, H_{12}^a$. In order to enhance the correlation between the representation vectors of each layer and the aspect words, for the context representation vector H_n^l of the nth layer, a gated fusion function G is used to fuse the aspect word representation vectors of the corresponding layers H_n^a into the context representation vectors of each layer to obtain the hidden vectors H_n^{la}. Then the gated fusion method G is used again to fuse the semantically fused representation vectors from the previous layer $H_n^{la'}$ to obtain a new initial representation vector of local features H_{init}^l. The specific procedure is as follows:

$$H_{init}^{la'} = H_{12}^{la'} \tag{2}$$

$$H_n^{la'} = \begin{cases} G(H_n^{la}, H_{n-1}^{la'}), & n = 10,11,12 \\ H_n^{la}, & n = 9 \end{cases} \tag{3}$$

$$H_n^{la} = G(H_n^l, H_n^a) \tag{4}$$

where n is the number of layers of the hidden vector, H_n^{la} is the new context representation vector generated after G fusing the aspect representation vector of layer n with the context representation vector of the corresponding layer. G is the gated fusion function, which utilizes the Sigmoid function to compute the degree of association r_i between two vectors and multiplies it with the vector that needs to be feature fused for feature fusion. The computational procedure for G is:

$$G(H_i, H_j) = r_i \odot H_i \tag{5}$$

$$r_i = Sigmoid(W_1 H_i + W_2 H_j) \tag{6}$$

where r_i is the semantic relevance weight of vectors H_i and H_j, $W_1 \in R^{d_n \times d_n}$, $W_2 \in R^{d_n \times d_n}$ belong to the learnable parameters, H_i and H_j represent the two vectors for which the degree of relevance calculation is required, and $\odot$ represents the element-by-element multiplication operation.

III. B. 2) Adaptive Local Thresholding Module

The adaptive threshold-based pseudo-labeling algorithm draws on the idea of course learning to convert fixed thresholds into dynamic thresholds for each class. That is, different thresholds are assigned according to the learning difficulty of different classes, and these thresholds are dynamically adjusted with different stages of model learning and random data enhancement of samples [27].

First, the algorithm tracks the confidence of the largest category predicted by the sample over a historical time period by setting up a queue. The queue update is temporal in nature, i.e., the earliest data entering the queue is popped from the head of the queue, while the latest predicted values are inserted from the tail of the queue, thus realizing the temporal update of the queue. The data stored within the queue can reflect the extent to which the model has recently confirmed the samples of each category. Then, for each category, the corresponding confidence mean is computed separately as the confidence threshold for the current category, and these thresholds are updated as the model continues to learn, enabling the model to select pseudo-labels more accurately.

When the value of $\sigma_t(c)$ keeps improving with the advancement of model training, it indicates that the model learns better. The adaptive thresholds are calculated as:

$$\sigma_t(c) = \frac{1}{T}\sum_{t=1}^{T}\left\{\max[p_{m,t}(y \mid u_b)] = c\right\} \tag{7}$$

where $\sigma_t(c)$ denotes the temporal confidence of category c at moment t, $p_{m,t}(y \mid u_b)$ denotes the predicted value of the model at moment t for the unlabeled sample u_b, and T denotes the length of the queue of unlabeled data, the maximum value of the confidence of the category prediction of the sample is stored, and the average value of the confidence of each category in the queue is calculated.

The base adaptive threshold describes the average confidence of the samples, and in addition to expecting the predicted values of the samples to be higher than the base threshold, it is also expected that the model maintains a certain level of stability in its predictions of the samples. Often, an additional stability threshold is required for the stability metric. In order to minimize the additional computational time, the two metrics, Timing Confidence and Timing Stability, are linearly summed to form the dynamic threshold. The calculation of the timing stability and the dynamic threshold can be expressed as follows:

$$\beta_t(c) = \sqrt{(\sigma_t(c) - |\max[p_{m,t}(y \mid u_b)] = c|)^2} \tag{8}$$

$$V_t(c) = \beta_t(c) + \sigma_t(c) \tag{9}$$

where $\beta_t(c)$ is the temporal stability of category c at t moments, and $V_t(c)$ is the threshold at t moments.

The smaller the standard deviation value, the more stable the temporal prediction value of the sample is represented, and the higher the temporal stability of the model's prediction of the sample. After comprehensively considering the confidence and stability of the samples, a more reliable sample selection mechanism can be provided for the model, which helps to improve the model performance and robustness.

III. B. 3) Cross-referencing module

Another key problem with pseudo-labeling is error accumulation: if the generated predictions are incorrect, the model generates more and more noisy pseudo-labels and continues to train the model on the wrong samples, and the model becomes worse and worse. Therefore in this paper, given two different initialization networks F_1 and F_2, each network uses the pseudo-labels of the other network as the data it uses for its own next iteration. By cross-validating and labeling the two models, the adaptability of the final model to new data is improved, and it helps to reduce the effects of single-model bias. These pseudo-labels are then used to compute the unlabeled data loss L_u to update the parameters of their peer network, i.e:

$$P_b^{F_2} = (\max(q_b^{F_2}) \geq \varphi_t^{F_2}(\arg\max_b(q_b^{F_2}))) \tag{10}$$

$$P_b^{F_1} = (\max(q_b^{F_1}) \geq \varphi_t^{F_1}(\arg\max_b(q_b^{F_1}))) \tag{11}$$

$$L_u^{F_1} = \frac{1}{\mu B}\sum_{b=1}^{\mu B} Z(P_b^{F_2}) Z(\hat{q}_b^{F_2}, Q_b^{F_1}) \tag{12}$$

$$L_u^{F_2} = \frac{1}{\mu B}\sum_{b=1}^{\mu B} Z(P_b^{F_1}) Z(\hat{q}_b^{F_1}, Q_b^{F_2}) \tag{13}$$

where P_b represents the model generates pseudo labels only if the confidence exceeds a threshold, q_b is the weakly augmented unlabeled data predictive category distribution, q_b is the one-hot labels converted from q_b, Q_b is the strongly augmented unlabeled data predictive category distribution, Z is the cross-entropy loss, and $I(\cdot)$ is the indicator function, which helps in avoiding the accumulation of direct errors within a single network.

III. B. 4) Boundary interval loss module

The final task of Shakespeare's dramatic literature classification model is to predict the label vectors of any text in the test set species, for the above task can be learned by solving the optimization problem for deep prediction model $f(I;\theta)\in R^C$, θ for the parameters. Namely:

$$\min \frac{1}{\theta}\sum_{k=1}^{N} I[f(I_k;\theta), y^k] + R(\theta) \tag{14}$$

where $\min(\cdot)$ is the minimization function, $I[f(I_k;\theta), y^k]$ is the loss function, and $R(\theta)$ is the regularization term. f_c^i denotes the predicted score of the deep network to categorize the image into labels t. The multi-label sorting loss aims to produce a label vector for image I_k whose positive label values are greater than the negative label values, P_k and N_k denote the set of positive labels and the set of negative labels in y^k, i.e., $f_u(I_k) > f_v(I_k), \forall u \in P_k, \forall v \in N_k$, and the sorting loss expression is as follows:

$$l_{rank} = \sum_{veN_k}\sum_{ueP_k} max(0, \alpha + f_v(I_k) - f_u(I_k)) \tag{15}$$

where $\max(\cdot)$ is the maximum function and α is a hyperparameter that determines the interval.

In order to further enhance the classification effect on Shakespeare's drama and literature features, this paper proposes a deep large interval sorting loss (dlmrl) for multi-label text classification, which can impose intervals on any layer of the deep network, and can use any number of paradigms to compute the metric of the label intervals, which is applicable and practical for any network structure.

We define the expression for the sorting interval for each label pair $\{u,v\}$ as follows:

$$D_{\{u,v\}} \square \{I_k \mid f_u^k = f_v^k\} \tag{16}$$

where $\forall u \in P_k, \forall v \in N_k$ By this definition, the distance of image I_k from the sort interval is defined as the minimum displacement point that results in the same score. Then:

$$d_{f,I_k,\{u,v\}} \square \min_{\delta} \|\delta\|_p \tag{17}$$

$$s.t. \quad f_v(I_k+\delta) - f_u(I_k+\delta) \tag{18}$$

When f is nonlinear, d exact computation is intractable, and an d approximation is given in the existing literature by linearizing f it, δ close to the neighborhood of $\delta = 0$ with the following expression:

$$\begin{aligned} &\tilde{d}_{f,I_k,\{u,v\}} \square \min \|\delta\|_p \\ &s.t. \quad f_v^k + \langle \delta, \nabla_{I_k} f_v^k \rangle = f_u^k + \langle \delta, \nabla_{I_k} f_u^k \rangle \end{aligned} \tag{19}$$

where ∇_{I_k} is the Hamiltonian operator.

According to the available literature on the subject, the problem has a closed solution which is expressed as follows:

$$\tilde{d}_{f,I_k,\{u,v\}} = \frac{|f_v^k - f_u^k|}{\|\nabla_{I_k} f_v^k - \nabla_{I_k} f_u^k\|_q} \tag{20}$$

where $\|\cdot\|_q$ is the dual norm of $\|\cdot\|_p$. Specifically, if the distances are l_1-paradigm, l_2-paradigm, and l_∞-paradigm, their pairwise norms will be l_∞-paradigm, l_2-paradigm, and l_1-paradigm, respectively.

Start with a triad (I_k, u, v) and process the displacements of I_k to satisfy the marginal constraints of $f_u^k > f_v^k$. This means using the following loss function:

$$\max\{0, \gamma + d_{f,I_k,\{u,v\}} sign(f_v^k - f_u^k)\} \tag{21}$$

where $sign(\cdot)$ is used to adjust the polarity of the distance.

If constraint $f_u^k > f_v^k$ has been satisfied, then we simply ensure that the distance between it and the sorting interval is γ and penalize in proportion to the distance d, so the penalty is $\max\{0, \gamma - d\}$. However, if the sorting is incorrect, we penalize the labels that have not been correctly sorted by a penalty that consists of the distance I_k required to reach the sorting threshold and the γ distance imposed on the correct side of the sorting threshold to obtain the γ interval, and the penalty becomes $\max\{0, \gamma + d\}$. For image I_k, we accumulate the individual losses generated for each $u \in P_k, v \in N_k$ to obtain the dlmrl formula, and the dlmrl formula expression is as follows:

$$l_{dlmrl} = \sum_{u \in P_k, v \in N_k} max\{0, \gamma + d_{f, I_k, \{u,v\}} sign(f_v^k - f_u^k)\} \tag{22}$$

Substituting (20) into (22), the loss function becomes:

$$l_{dlmrl} = \sum_{u \in B_k, v \in N_k} max\left\{0, \gamma + \frac{|f_v^k - f_u^k| \, sign(f_v^k - f_u^k)}{\| \nabla_{I_k} f_v^k - \nabla_{I_k} f_u^k \|_q}\right\} \tag{23}$$

Therefore, it can be further simplified as:

$$l_{dlmrl} = \sum_{u \in P_k, v \in N_k} max\left\{0, \gamma + \frac{f_v^k - f_u^k}{\| \nabla_{I_k} f_v^k - \nabla_{I_k} f_u^k \|_q}\right\} \tag{24}$$

III. C. Validation of Literary Feature Extraction

III. C. 1) Model comparison experiments

In order to verify the effectiveness of the SMLCL model in feature extraction classification of Shakespearean dramatic literature, the corpus of Shakespearean dramatic literature constructed in this paper is used as a data source, and is compared with existing unsupervised feature extraction methods based on deep learning, feature extraction methods based on deep learning, and feature extraction methods combining deep learning and large language models, respectively. A total of six models are selected, namely, TF-IDF, TextRank, LDA, BiLSTM-CRF, BERT-LSTM-CRF, MIEnhance-KPE, and Qwen.When performing model performance evaluation, this paper mainly uses the accuracy (P), recall (R), and F1 value to evaluate the classification effect of Shakespearean dramatic literature feature extraction. This experiment is based on 64-bit Ubuntu running environment, the optimizer of SMLCL model is Adam, the Dropout ratio is 0.15, and the learning rate is set to 0.0001. The experimental results of performance comparison of different models are shown in Table 1. Where "@2" denotes the case where the model extracts 2 literary features in the corpus, and "@4" and "@6" are the same.

As can be seen from the table, for the unsupervised literary feature extraction model, its due to the lack of relevant data for training, Its literary feature extraction effect in Shakespearean drama literature corpus data is the worst. Among them, the LDA model divides the text data in Shakespearean drama literature corpus into different themes and extracts the representative keywords, which performs well in F@6 indexes, proving that the use of theme information can effectively realize literary feature extraction. And the Qwen big model has the highest indicators, which proves the powerful generative ability of the big model. Among the deep learning-based literary feature extraction models, the MIEnhance-KPE model outperforms other deep learning methods by fusing domain adaptive information and glyph features, using multimodal information to enhance the extraction of text features, and ranking the extracted keywords according to their importance. Compared with the BERT-LSTM-CRF model, the F@6 index is improved by 6.48 percentage points, which proves the effectiveness of the enhanced model's semantic comprehension ability and keyword ranking in the literary feature extraction task. The SMLCL model proposed in this paper captures the semantic features of texts related to Shakespeare's dramatic literature by fusing the attention mechanism and the BERT model of the CNN layer, and after being processed by the adaptive local threshold module, the predicted values whose confidence exceeds the adaptive local threshold are selected as the pseudo-labels of the corresponding categories. Then, through the interval between the preset boundary and the true value, the predicted value is made to move closer to the direction of the true label and away from the false label, and then the Shakespearean dramatic literature features are obtained. It reached 67.62% on the F@6 index, which was 3.31 percentage points higher than that of the MIEnhance-KPE model, and was better than all benchmark models in all indicators, which verified the effectiveness of the proposed method.

Table 1: Experimental results of different models (%)

Model	P@2	P@4	P@6	R@2	R@4	R@6	F@2	F@4	F@6
TF-IDF	30.18	34.37	30.46	4.25	10.75	33.05	7.45	16.31	31.38
TextRank	28.04	31.26	32.81	4.76	9.52	30.82	8.18	14.58	31.79

LDA	36.29	35.78	34.92	4.83	10.38	34.17	8.52	16.04	34.26
Qwen	50.57	52.14	52.06	8.41	20.46	49.51	16.37	38.98	50.07
BiLSTM-CRF	48.62	45.75	46.38	7.37	17.64	48.24	12.64	25.46	48.15
BERT-LSTM-CRF	62.05	63.51	62.53	10.72	32.09	53.89	18.51	43.25	57.83
MIEnhance-KPE	78.36	76.23	65.74	15.89	43.27	64.31	26.79	53.63	64.31
SMLCL	**86.41**	**80.82**	**72.95**	**18.64**	**49.13**	**65.86**	**30.28**	**60.02**	**67.62**

III. C. 2) Model ablation experiments

The SMLCL model established in this paper mainly consists of a semantic feature extraction module (A), an adaptive local thresholding module (B), a cross-labeling module (C), and a boundary interval loss module (D). In order to verify the effectiveness of each module in the model, ablation experiments are carried out, and the experimental results are shown in Table 2.

The experimental results show that compared to the baseline model, the BERT semantic feature extraction module with the addition of the fused attention mechanism and TextCNN improves the accuracy, recall, and F1 score by 3.66%, 1.86%, and 1.08%, respectively. After further adding the adaptive local thresholding module, the three evaluation indexes are further enhanced, but the enhancement is relatively small compared to the semantic feature extraction module, which is due to the fact that the adaptive local thresholding module is mainly responsible for assigning different weights to different types of Shakespearean drama and literature features, and the overall impact on the feature extraction effect is relatively small. After the introduction of the cross-labeling module and the boundary interval loss module, the extraction effect of the model on Shakespeare's dramatic literature features is 88.71%, 72.95%, and 70.19%, respectively, which is improved by 12.13%, 9.03%, and 7.45% compared with the baseline model. This fully demonstrates the effectiveness of each module in improving the model's classification effect of literary feature extraction. Relying on the SMLCL model designed in this paper, the Shakespearean drama literary features can be effectively extracted to provide data support for analyzing the spiritual connotation and cultural charm of Shakespearean drama literature.

Table 2: Model ablation experiment

Model	P/%	R/%	F/%
Baseline	76.58	63.92	62.74
Baseline + A	80.24	65.78	63.82
Baseline + A + B	82.49	67.04	65.97
Baseline + A + B + C	84.63	69.16	67.65
Baseline + A + B + C + D	88.71	72.95	70.19

III. D. Literary Characteristics of Shakespeare's Plays

III. D. 1) Vocabulary richness

Lexical richness is the primary indicator of lexical characteristics of literary texts, which can be divided into lexical density and lexical uniqueness. The above observational variables can be reflected by calculating the ratio of class symbols to form symbols, the percentage of real words, and the use of disposable words, respectively.

Lexical density, which is the percentage of the number of real words in a text out of the total number of words, was tested on the lexical density of the study text to further expand the notable features of Shakespeare's dramatic literature at the level of lexical density. Using the text that has been lexically assigned can be easier to obtain the frequency of the use of each word class in the text, the results of the comparison of the lexical density of Shakespeare's dramatic literature can be obtained as shown in Table 3.

The higher the vocabulary density, the greater the proportion of function words in the vocabulary of the text, to a certain extent, it can reflect the diversity of the text vocabulary presentation, generally speaking, the text with high vocabulary density contains more information. From the table, it can be seen that the vocabulary density of Shakespeare's Dramatic Literature Observation Library and the reference library are 76.02% and 77.97% respectively, and after calculating and verifying the use of vocabulary density based on the log-likelihood ratio test (LLR=-84.72***, P<0.01), it can be found that the information density of the text of the self-constructed Shakespeare's Dramatic Literature Observation Library is slightly lower than that of the reference library. In addition to this, it can be observed through the log-likelihood ratio test that nouns (LLR=--2613.58***, P<0.01), and adjectives (LLR=-1063***, P<0.01) in Shakespeare's dramatic literary texts are significantly lower than those in the reference library text collection, especially in the use of nouns which are characterized by little use in the absolute sense. In contrast, pronouns (LLR=+2724.65***, P<0.01) as well as verbs (LLR=+102.24***, P<0.01) accounted for a broadly significantly higher percentage than the reference pool. The two major word categories, number words (LLR=+4.15, P=0.087) and adverbs (LLR=+4.27, P=0.063), showed no statistically significant difference in overall usage compared to the observation pool, and the difference in usage was relatively small. Through the above analysis can be derived from the vocabulary characteristics of Shakespeare's dramatic literary works, Shakespeare in the dramatic literary works of language expression is more inclined to use the pronouns with the meaning of reference, and not the table of concrete things of the noun. Less use of adjectives with abstract meaning, figurative and descriptive, and more use of verbs with intuitive meaning, expressive and figurative. In the use of adverbs and number words, by and large, there is no significant differentiation in meaning, and the difference in frequency of use is tiny.

Table 3: The vocabulary density comparison of the observation library

-	Word class	Observation library		Reference library		Log-likelihood
		Frequency	Ratio	Frequency	Ratio	
Forward	Verbs	83148	21.56%	327773	20.67%	+102.24***, P<0.01
	Pronoun	72581	18.82%	254511	16.05%	+2724.65***, P<0.01
Reverse	Nouns	89280	23.15%	436714	27.54%	-2613.58***, P<0.01
	Adjective	24373	6.32%	120675	7.61%	-1063***, P<0.01
No Sig.	Numerals	3935	1.02%	15540	0.98%	+4.15, P=0.087
	Adverb	19862	5.15%	81189	5.12%	+4.27, P=0.063
Word number		293179		1236402		-
Total word		385661		1585741		-
Vocabulary density		76.02%		77.97%		-84.72***, P<0.01

In addition to the above ways of detecting vocabulary richness, vocabulary richness can also be examined by counting the proportion of one-time words (also known as single-occurrence words) in the corpus. The frequency of single-occurrence words in the text can reflect the individuality and uniqueness of the text to a certain extent. The more single-occurrence words there are, the higher the degree of differentiation between the text and similar texts or other kinds of texts, the higher the degree of textual vocabulary richness, and a large number of single-occurrence words can reflect distinctive stylistic styles and wording features of the writers. Table 4 shows the frequency of single-occurrence words in Shakespeare's dramatic literature.

Compared with the English dramatic literature library, Shakespeare has a significantly higher frequency of single-occurring words than similar texts, which is contrary to the results obtained through the standard class symbols and form symbols ratio and the proportion of real words. The reason is that the ratio of single-occurrence words is limited by the length of the text, and the larger the amount of words included in the text, the frequency of single-occurrence words will be reduced accordingly. Therefore, some scholars have pointed out that in order to reduce the effect of text length on the lexical uniqueness rate, the quantitative index of number uniqueness can be utilized to examine the lexical uniqueness. By further examining the quantitative index of number uniqueness, it is found that the difference between the observation library and the reference library in terms of the ratio of number uniqueness is relatively small, and the relative frequency difference is -0.06%, and the Shakespearean Dramatic Literature Corpus is slightly lower than the British Dramatic Literature Cluster Reference Corpus in terms of the use of disposable words, with a low degree of linguistic richness, and a narrower range of textual word choice.

Table 4: The frequency rate of the drama literature

Retrieve object	Observation	Reference	Relative frequency difference	Log-likelihood
Simple word frequency	18641	25641	-	-
Total word	385661	1585741	-	-
Simple word frequency rate	4.83%	1.62%	+3.21%	+8241.79***, <0.01
Number uniqueness	3.79%	3.85%	-0.06%	-

III. D. 2) Vocabulary Difficulty

In order to illustrate the vocabulary difficulty of Shakespeare's dramatic literature more comprehensively and intuitively, this paper will quantitatively grade the vocabulary of the two corpora with the help of Ant Word Profiler, which is used to analyze the vocabulary difficulty level and complexity of the texts, and present the percentage of vocabulary at each level in the form of a table, so that we can obtain the basic information of the vocabulary of both corpora. Adopting this method can enrich this paper's research on the vocabulary difficulty level of Shakespeare's dramatic literature corpus. Since Ant Word Profiler comes with a list of commonly used words in English, the first

1200 words in the list of commonly used words are defined as Level 1 vocabulary, the 1,201th to 3,600th words in the list of commonly used words are defined as Level 2 vocabulary, and the remaining 2,200 words are defined as Level 3 vocabulary. Before lexical quantification with the help of Ant Word Profiler, the Shakespearean Dramatic Literature Corpus Observational Library and Reference Library need to be processed for word form reduction. Table 5 shows the results of vocabulary difficulty comparison of Shakespeare's dramatic literature.

From the table, it can be seen that the coverage rate of Level 1 and Level 2 vocabulary in the Shakespearean Dramatic Literature Corpus (65.06% and 12.08%) is higher than that of Level 1 and Level 2 vocabulary in the Reference Corpus (63.18% and 10.83%), the coverage rate of Level 3 vocabulary (harder vocabulary) (4.39%) is lower than that of Level 3 vocabulary in the Reference Corpus (5.27%), and the Shakespearean Dramatic Literature Corpus' overall word list coverage (81.29%) was higher than the overall word list coverage of the reference corpus (78.95%), and the difference between the data was significant ($p<0.01$).

The data suggest that more than 80% of the words in Shakespeare's dramatic literature are the most commonly used and most frequently used words in English, and that the lexical difficulty and complexity of the texts in this corpus are lower than those in the reference corpus, with a relatively high degree of legibility. It should be emphasized that the influence of disposable words on vocabulary length should not be underestimated, and the difference in the size of the two libraries is 1,200,080 words, and the mean value is inevitably subject to its factors, so there are greater limitations in judging the degree of difficulty by looking at the mean value of vocabulary length alone. Therefore, when quantifying or quantifying abstract linguistic features into a certain feature value, we should pay attention to the dimensionality, and the multi-dimensional extraction and analysis of linguistic feature values are of great significance in revealing or describing their "authenticity". Based on the above analysis, Shakespeare's dramatic literature has a lower vocabulary difficulty level than the reference library, and is more readable. Moreover, the overall style of Shakespeare's dramatic literature is comparatively less different from that of English dramatic literature, which to a certain extent indicates that Shakespeare's dramatic literature has a certain influence on the English dramatic literature.

Table 5: Comparison of vocabulary difficulty

Glossary	Observation library		Reference library		Chi-Square
	Shape number	Ratio	Shape number	Ratio	
Level1	250911	65.06%	1001871	63.18%	+263.51***, P<0.01
Level2	46588	12.08%	171736	10.83%	+84.47***, P<0.01
Level3	16930	4.39%	83569	5.27%	-124.35***, P<0.01
Others	77826	20.18%	354572	22.36%	-413.51***, P<0.01
Coverage	313503	81.29%	1251943	78.95%	+278.69***, P<0.01

IV. Analysis of the Impact on British Dramatic Literature

Shakespeare can be called a contemporary literary giant, and his works are typical of European Renaissance literature, which has been popular and widely read for centuries. His vivid vocabulary, imaginative metaphors and brilliant puns have breathed life into his works. Shakespeare's dramatic literature has had a profound influence on English literature and even world literature. This chapter analyzes the influence of Shakespeare's dramatic literature characteristics on British dramatic literature based on multiple regression, in order to better understand the unique literary charm of Shakespeare's masterpieces.

IV. A. Variable selection and model construction

IV. A. 1) Variable selection

Living in the Elizabethan era, Shakespeare witnessed the evolution and development of Middle English to Early Modern English, and his linguistic style is also characterized by a combination of tradition and innovation. Based on this, this paper chooses Shakespeare's dramatic literary features as the independent variable and the level of development of British dramatic literature as the dependent variable from the Shakespearean dramatic literature corpus constructed in the previous paper, so as to explore the influence of Shakespeare's dramatic literary features on British dramatic literature.

For the independent variable of Shakespeare's dramatic literary features, this paper mainly starts from the English word formation of Shakespeare's dramatic literature, i.e., the three indicators of Compound (Cop), Cov and Derivative (Der) are quantitatively counted, so as to obtain Shakespeare's dramatic literary features. For the English Dramatic Literature Development Level (EDLD), this paper mainly counts the number of all Shakespeare-related dramatic literatures from the reference library, and defines its development level by the number.

Besides, this paper also chooses the number of foreign plays (FP), the vocabulary expression (VE), the number of foreign writers (FW), the technological development (TD), and the artistic development (AD) as the control variables, the quantification of which are all based on the data records of the relevant literature of the period Shakespeare lived in as the data source.

IV. A. 2) Model construction

Based on the independent, dependent and control variables selected in the previous section, combined with the multiple linear regression model, a fixed effects model was constructed as follows:

$$EDLD_{it} = \beta_0 + \beta_1 Cop_{it} + \beta_2 Cov_{it} + \beta_3 Der_{it} + \beta_4 \sum Control_{it} + \varepsilon_{it} \tag{25}$$

where, $EDLD_{it}$ represents the level of development of English dramatic literature, $Cop_{it}, Cov_{it}, Der_{it}$ represents the composite, transclassification and derivation of Shakespeare's dramatic literature features, respectively, $Control_{it}$ is each control variable, ε_{it} is the random disturbance term, β_0 is the constant term, and $\beta_1 \sim \beta_4$ is the regression coefficient of each variable.

IV. B. Empirical results and data analysis

IV. B. 1) Benchmark regression results

Based on the multivariate linear regression model established in the previous section, the multivariate linear regression analysis was carried out on the data related to the literary features of Shakespeare's dramatic literature corpus by using STATA software, and the benchmark regression results were obtained as shown in Table 6. Where models (1)~(3) are the regression results of time fixed, individual fixed and double fixed effects models respectively. *, **, *** indicate the significance level of 10%, 5%, 1%, respectively, and the value in parentheses indicates the standard error of the regression coefficients, reflecting the uncertainty of the coefficient estimation, and the smaller the value indicates that the estimation of the regression coefficients is more accurate.

As can be seen from the table, whether under the time fixed, individual fixed or double fixed effects model, the composite, transclassification and derivation of Shakespeare's dramatic literature features will have a positive and significant effect on English dramatic literature at the 1% or 5% level. That is, the three techniques of compounding, transclassification and derivation of English word construction in Shakespeare's dramatic literary features all contribute to the development of English dramatic literature, which is more consistent with the results of the previous analysis of the lexical features of Shakespeare's dramatic literature. Shakespeare carries out dramatic narratives through diverse lexical constructions, fully expresses the character traits of the characters in dramatic literary works, and shows the charm of diverse literary works. Under the double fixed-effects model, the compound words of Shakespeare's dramatic literary features have the greatest influence on British dramatic literature, and its regression coefficient reaches 0.149, i.e., for every 1 percentage point increase in the compound words of Shakespeare's dramatic literary features, the level of development of British dramatic literature will be significantly and positively increased by 0.149 percentage points. And the coefficient of determination of the model, R^2, reaches 0.9683, which indicates that the explanatory strength of the variables in the model designed in this paper for the development level of English dramatic literature reaches 96.83%. It can be seen that Shakespeare's dramatic literature works through multiple types of compositional techniques to achieve a clearer narrative of the work, but also to provide a new direction for the development of British dramatic literature.

Table 6: The benchmark regression results of the model

Variable	Model (1)	Model (2)	Model (3)
Cop	0.182**(0.034)	0.173**(0.028)	0.149***(0.051)
Cov	0.075***(0.015)	0.064***(0.031)	0.059***(0.027)
Der	0.032***(0.006)	0.027***(0.004)	0.038***(0.009)
FP	0.113*(0.031)	0.101**(0.035)	0.121**(0.027)
VE	0.527(0.065)	0.526*(0.073)	0.247***(0.069)
FW	0.279*(0.028)	0.227**(0.025)	0.215**(0.023)
TD	0.134**(0.053)	0.131**(0.042)	0.135**(0.041)
AD	0.084***(0.021)	0.079***(0.018)	0.083***(0.019)
(Con_)	0.428***(0.013)	1.247***(0.241)	0.659*(0.342)
R^2	0.7931	0.9512	0.9683

IV. B. 2) Robustness Tests

In order to further verify the reliability of the model, this paper launches the model robustness test from the following aspects:

(1) Changing the measurement method of the development level of British dramatic literature, adopting the number of writers of British dramatic literature (NUM) to calculate its development level of dramatic literature, and including it as a dependent variable in the model, and re-conducting regression analysis.

(2) Add control variables, add two control variables, the level of urbanization in the UK (UL) and people's enjoyment of dramatic works (PD), and re-run the regression analysis.

Both use double fixed effect model, then get the regression results of robustness test as shown in Table 7. As can be seen from the table, the composite, transclassification and derivation bases of Shakespeare's dramatic and literary features have a positive and significant effect on the level of British theater development at the 5% level, and the coefficient of determination, R^2, is more than 0.8, indicating that the model has a good fitting effect. The overall measurement results are consistent with the previous regression results, so the regression results have good robustness.

Table 7: Regression results of robustness test

Variable	Model (1)-NUM	Model (2)
Cop	0.137**(0.051)	0.142**(0.021)
Cov	0.083***(0.027)	0.059***(0.043)
Der	0.029***(0.008)	0.025***(0.008)
FP	0.105*(0.035)	0.084**(0.021)
VE	0.419(0.033)	0.319*(0.056)
FW	0.261*(0.042)	0.163**(0.038)
TD	0.128**(0.036)	0.106**(0.027)
AD	0.075***(0.029)	0.065***(0.022)
UL	-	1.241***(0.001)
PD	-	0.137**(0.025)
(Con_)	0.573***(0.005)	1.852***(0.014)
R^2	0.8127	0.8238

V. Conclusion

This paper proposes a Shakespearean dramatic literature feature extraction and classification model (SMLCL) based on BERT and attention mechanism, carries out a validation analysis for the model, and introduces multiple regression to analyze the influence of Shakespeare's dramatic literature features on British dramatic literature.

(1) The SMLCL model is 67.62% on the F@6 index when extracting the features of Shakespeare's dramatic literature, which is 3.31 percentage points higher than the second-best MIEnhance-KPE model, and is better than all benchmark models in all indicators.

(2) Shakespeare's dramatic literature features contain three kinds of features, namely, compound, transitive and derivative, all of which have a significant positive impact on the level of development of British dramatic literature, and under the double fixed-effects model, the degree of influence of compound constructions on British dramatic literature is relatively the greatest, and its regression coefficient reaches 0.149.

Although this paper has achieved certain research results in the research process, there are still areas that need to be improved on the whole. For example, the changes in the syntactic features of Shakespeare's dramatic literature and the different influences of Shakespeare's dramatic literature on the development of English dramatic literature at different stages. These issues will be further explored in the subsequent research, aiming to further explore the cultural connotation and spiritual charm of Shakespeare's dramatic literature.

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