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A Study on the Identification of Emotional Tendencies in Huang Tingjian's Poetry Based on Python Text Mining

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Abstract Python's advantages in text mining provide a fast, efficient, and low-cost research path for poetry sentiment analysis. This paper uses Python to design and develop corresponding poetry text sentiment mining software to conduct in-depth sentiment word frequency analysis and visualization of Huang Tingjian's poetry. Additionally, it combines Latent Dirichlet Allocation (LDA) and Non-Negative Matrix Factorization (NMF) to calculate the relationship between high-frequency words and emotional themes, establishing an emotional theme model. The effectiveness of the theme modeling is measured using word vector theme consistency. The results show that the precision, recall, and F_1 scores of the LDA+NMF emotional theme model all exceed 90%, outperforming the six classification models compared in the same period. The model achieved an accuracy rate greater than 0.900 for the classification of three types of poems with different emotional tendencies. The proportion of the three types of emotional tendencies in Huang Tingjian's poems showed an upward or downward trend in the early, middle, and late periods.

Index Terms Python text mining, Huang Tingjian's poems, LDA, NMF, emotional themes

I. Introduction

According to Ren Yuan, Shi Rong, and Shi Jiweng's "Annotated Collection of Shanyu's Poems" from the Southern Song Dynasty, Huang Tingjian left behind a total of 1,343 poems. Judging from the content of Shanyu's poems, very few of them reflect the suffering of the people or expose social contradictions [1]-[3]. The vast majority of his poems are about romantic love, chickens, ducks, insects, birds, and even the names of Chinese herbs. He even used the animals and plants described in the Book of Songs to pile up words and turn them into his own poems, which were both boring and ridiculous to readers [4]-[7]. Nevertheless, Huang Tingjian remains a renowned poet of the Song Dynasty and the founder of the Jiangxi School of Poetry, with a following of admirers. His poetic style and techniques were even referred to by Su Shi as the "Huang Tingjian style" [8]-[10]. Currently, using text mining technology to identify the emotional orientation of Huang Tingjian's poetry not only helps to understand the customs and traditions of the time but also has a positive impact on improving the teaching effectiveness of poetry [11]-[12].

Poetic emotional orientation identification involves analyzing the content of poetic texts to determine the emotional orientation expressed within them, such as positive, negative, or neutral. Python, as a powerful and user-friendly programming language, has widespread applications in text mining and sentiment analysis [13]-[16]. In poetry emotional orientation identification, Python provides various methods and tools to accomplish emotional recognition tasks, offering researchers a solid platform to extract valuable information from Huang Tingjian's poetry [17]-[20].

This paper proposes a Python-based framework for sentiment analysis of Huang Tingjian's poetry texts, providing digital technical support for counting common sentiment words and overall sentiment themes. Using unlabeled Huang Tingjian poetry texts as the research corpus, the framework employs Python-developed multi-type word segmentation software to complete text data preprocessing, word segmentation annotation, sentiment word frequency statistics, and word cloud visualization conversion. For the statistically analyzed emotional words, LDA and NMF topic models are used to estimate parameters and calculate matrix losses between emotional words and emotional themes, determining the optimal modeling method for poetry emotional tendency themes. Based on topic consistency calculations using word vectors, the modeling rationality of the topic models is evaluated.

II. Design of a framework for mining emotions in Huang Tingjian's poetry using Python applications

II. A. Analysis of the Introverted Emotional Tendencies in Huang Tingjian's Poetry

At the semantic level, the uncertainty and ambiguity of Huang Tingjian's poetry mainly stem from its restrained emotions. Unlike Tang poetry, Huang Tingjian's poetry rarely expresses emotions directly. Instead, it uses descriptions of objects, characters, and even allusions to convey emotions. It transforms the author's emotions into various codes within the text, allowing readers to exercise their agency and creativity, each finding their own meaning based on their own emotions.

Huang Tingjian's poems about objects are good at turning objective "things" into symbols or metaphors, projecting human character onto objects, and using this to express his feelings and insights into life. For example, in "Two Poems in Response to Chen Jichang's Gift of Intertwined Pine Branches from the Mountains of Huangzhou," he writes: "An old friend broke off a pine branch and sent it thousands of miles away, thinking of listening to the sound of wind and springs in ten thousand ravines. Who says that the five-lobed pine, shrouded in mist, still harbors the heart of a mortal?" "The intertwined branches of the old pine are but a chance occurrence; after the red and purple blossoms fade, it stands alone, reaching for the sky. The golden sands of the beach may bind its branches, but it need not resist the world's ways." The image of the pine tree has become a symbol of moral character in traditional culture. The first couplet of the poem describes its upright and dignified character, but the poet then takes his imagination a step further: the moral realm of integrity and strictness also encompasses the emotional realm of tender affection. The strength of character and the tenderness of emotion are not mutually exclusive. In the poem "Reflections on Eating Lotus Flowers in Gan," the entire piece uses similes, comparing eating lotus flowers to life. It begins with family affection, the love of a kind mother, and the bond between brothers. Then, it draws on the bitterness of the lotus seed to explore the philosophy of life, explaining that seeking comfort and pleasure only endangers oneself, while embracing simplicity allows one to truly understand the joys and sorrows of life; finally, it draws on the lotus's ability to remain untainted by the mud to suggest that the corrupted world is an excellent place to temper one's character, with each layer of insight building upon the last. The "objects" described in the poem are no longer objective representations of physical objects, but rather concrete and complete artistic images imbued with the poet's emotions. They not only provide artistic enjoyment of natural beauty, but also give people profound insights and inspiration.

Huang Tingjian's poems about people are no exception. Huang Tingjian often wrote about lower-level officials and poor literati who did not hold official positions. He depicted them as people who, despite their poverty, remained committed to their ideals and careers, highlighting the stark contrast between their difficult circumstances and their extraordinary talents. For example, "Chenliu Shi Yin" describes a barber who lives with his daughter. Although he is poor, he is content with his life. Barbering is not only a means of making a living, but also a way for him to cultivate his mind and observe the world, allowing him to be detached and enjoy life. Clearly, this character is a projection of the poet's subjective ideas. Other examples include Zhao Yan in "Gift to Zhao Yan," Li Yanshen in "Playfully Gifting Yanshen," Zhang Zhongmou in "Sending Zhang Zhongmou," Chen Jizhang in "Playfully Gifting Chen Jizhang," and so on. Through vivid descriptions of their images and personalities, the poet reflects his own ideal personality.

The use of allusions was also a means for Huang Tingjian to express his feelings. Among the many allusions in his poems, most were taken from Du Fu's poems. For example, in "Autumn Thoughts Sent to Ziyou," he wrote, "The old pine tree has seen the world lying in the cloud-filled ravine, holding back the blue river with no oxen," which is adapted from Du Fu's poems "Cloud ravines are covered with cloth" and "Ten thousand oxen look back at the heavy hills," comparing himself to an old pine tree lying in the cloud ravines, never compromising with the customs of the times. In "Following the Rhyme of Bo Shi at Changlu Temple," the line "Hand in hand at the end of the frosty trees" is adapted from Du Fu's "Northward Expedition," which says, "I am walking by the water's edge, and my servant is still at the end of the trees." "Yuntao Stone" "All the mountains are covered with fallen leaves in the night" is taken from Du Fu's famous line "Endless fallen leaves fall silently." Through the frequent use of Du Fu's allusions in Huang's poetry, we can see Huang Tingjian's reverence for Du Fu's moral character.

It is evident that the emotions in Huang Tingjian's poetry are expressed through natural imagery, human figures, and even allusions and symbols. The meaning of his poetry in a specific context thus becomes uncertain, allowing readers to interpret Huang Tingjian's poetry from multiple angles and levels of association and aesthetic reflection based on their own expectations, thereby arriving at their own satisfactory judgments; Secondly, regardless of the form in which his poetry is expressed, its emotions all point toward achieving the perfection of one's moral character through tranquility and detachment. The hardships of the world and the frustration of unfulfilled aspirations are common experiences among scholars navigating the vicissitudes of life. External pursuits of achievement inevitably fade away like bubbles, while moral pursuits lie within one's own control. Achieving the perfection of one's character through tranquility and detachment is the sole path for scholars to elevate their existence. It is precisely at this profound emotional level that readers resonate with the poet, gaining deeper aesthetic inspiration.

II. B. Building a Technical Framework for Text Mining Huang Tingjian's Poetry

II. B. 1) Analysis of poetry text data

Although research and achievements in text analysis are relatively mature, to date, there is no professional software capable of conducting comprehensive, multi-perspective analysis of poetry text data. This study utilizes the Python programming language to develop the Rost CM8.0 software, Text Mining text analysis software, NLPIR semantic analysis system, and BLUE-MC word cloud tool to conduct in-depth text mining of Huang Tingjian's poetry emotional tendency data.

Rost CM8.0 software is a poetry text content mining system capable of performing basic operations such as text segmentation, statistical analysis, semantic analysis, and sentiment analysis on poetry text data; Text Mining text analysis software can perform semantic network and sentiment analysis, as well as basic word cloud analysis; the NLPIR semantic analysis system can perform part-of-speech tagging, word frequency statistics, sentiment analysis, entity extraction, and other analyses; it can also visualize analysis results, generating word clouds, entity extraction analysis diagrams, and more.

For this study, we used poetry vocabulary-type text data. Due to the short length of poetry vocabulary-type text data, the limited number of words, and the concise and refined expression of meaning, some meaningless words that affect the analysis results still need to be filtered out after word segmentation. Collect the required text data and perform data preprocessing operations. Figure 1 introduces the specific operation process of poetry vocabulary-type text data analysis. The operational process for analyzing poetic lexical data is as follows: data collection—data processing—format conversion—text segmentation—specific analysis using Python-related software—interpretation of analysis results—drawing preliminary conclusions.

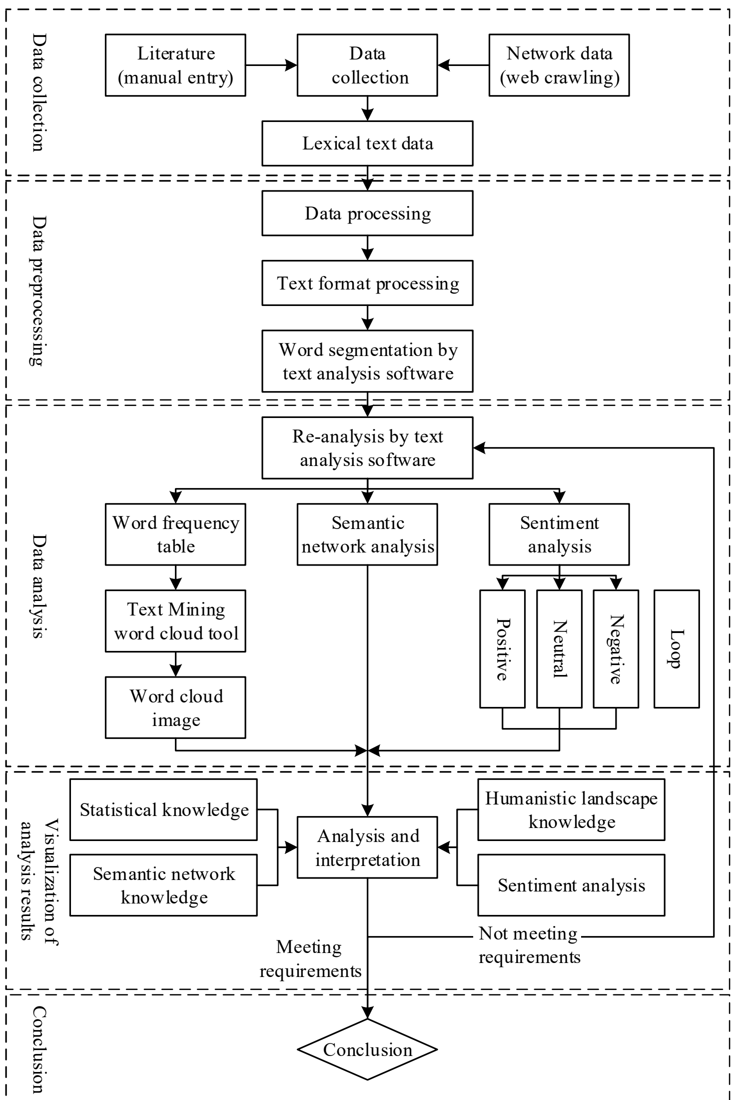

Figure 1: Specific operations of poetry vocabulary-based text data analysis

II. B. 2) Visualization and interpretation of analysis results

(1) Word frequency analysis — word cloud display

Word frequency analysis, also known as word frequency statistical analysis, is a commonly used basic analysis method in the process of analyzing poetic texts. The basic principle involves counting the number of times each word group appears in a fixed text. By analyzing word frequency statistics, one can explore the patterns of vocabulary within the text and uncover hidden information. This form of text analysis based on vocabulary is simple to perform and yields clear results. The final output of word frequency analysis is a word frequency statistics table. Since this table consists solely of text and numbers, it has low visual appeal. Therefore, the word frequency statistics table can be visualized by converting it into a word cloud diagram. The presentation format of word clouds can also be adjusted based on research needs. Common formats include geometric shapes, map shapes, characters, and graphics related to the research topic. When interpreting word clouds, it is important to have a basis for your interpretation. Word frequency refers to the number of times a particular word or phrase appears in a text. Typically, this number is normalized to avoid bias. The same word or phrase may appear more frequently in longer documents than in shorter ones. Therefore, the text data is first divided into words, meaningless words are filtered out, and then the word frequency is calculated. The specific calculation formula is:

$$TI\left(Word\ frequency\right) = TF \times IDF \tag{1}$$

$$TF = \frac{The\ number\ of\ occurrences\ of\ a\ certain\ word}{Total\ number\ of\ words\ in\ the\ article} \tag{2}$$

$$IDF = \log_{10} \frac{Total\ number\ of\ articles}{The\ number\ of\ articles\ containing\ a\ certain\ word} \tag{3}$$

After performing the above formula calculations, the word frequency of a particular term can be determined. By applying word frequency analysis, the core content and perspectives expressed in the text can be identified.

(2) Visualization of Sentiment Analysis

During the visualization of sentiment analysis, based on the analytical capabilities and results of the Rost CM8.0 software, this paper categorizes emotions into three levels: positive emotions, negative emotions, and neutral emotions. These correspond to positive sentiment, negative sentiment, and neutral sentiment, respectively. Here, a higher sentiment score indicates a more pronounced and intense emotional tendency in the poetic text. Conversely, the lower the emotional score, the more subtle and muted the emotional tendency.

(3) Semantic network analysis visualization

Semantic network analysis refers to describing the relationships between keywords and the associations among them, and expressing the keyword associations formed by text analysis results using a network tree diagram. In this paper, we use "centrality degree," "word clusters," and "node association degree" to quantitatively analyze keywords in the text.

Neutral association degree. In semantic network analysis, centrality is typically used to quantify the associations between keywords in a graph. Centrality research is further divided into centrality degree (also known as absolute degree centrality) and relative centrality degree. In this study, we selected relative centrality degree for analysis and calculation. The calculation formula is as follows:

$$\frac{C_{AD}\left(X\right)}{n-1} C_{AD}\left(X\right) \left(C_{AD}\left(X\right) represents\ the\ absolute\ degree\ centrality\ of\ node\ X, and\ n\ is\ the\ number\ of\ nodes\ in\ the\ graph\right) \tag{4}$$

Among them, C_{AD} is the number of other points directly connected to a given keyword. If there are n points in the graph, then the maximum centrality degree of any point in the graph can only be $n-1$ (the point itself has no centrality degree).

Word clusters typically study the centrality of points in a graph, not just the centrality connections of individual points. In the analysis process, the overall centrality of the graph is often studied. Therefore, keywords are grouped into one or several clusters, rather than being limited to the study of a single keyword. Keyword cluster analysis helps to grasp the overall nature of the research.

The association degree of a node refers to the numerical description of the closeness of the connection between keywords. In other words, the closer the connection between a keyword and other keywords, the higher the numerical value, and the more distant the connection, the lower the numerical value.

II. C. Emotional theme mining of Huang Tingjian's poetry based on LDA and NMF

II. C. 1) Topic mining model based on LDA and NMF

The purpose of topic mining is to automatically extract the implicit topic information from large-scale unlabeled text. This paper combines the Latent Dirichlet Allocation (LDA) model with another topic modeling method, Non-negative Matrix Factorization (NMF), to establish the optimal emotional topic model for poetry texts.

LDA is a probabilistic graphical model containing latent variables, where the latent variable is topic $(topic)$. The input of the LDA model is a series of documents $(document)$ composed of terms $(word)$, and the output is the term distribution $P(word \mid topic)$ for a given topic and the topic distribution $P((topic \mid doc)$ for a given document. The LDA model assumes that the word distribution for a given topic and the topic distribution for a given document both follow a multinomial distribution, with parameters denoted as θ and Φ, respectively. Since the parameter estimation method of the LDA model is maximum a posteriori likelihood estimation, the parameters θ and Φ of the multinomial distribution follow their conjugate prior distribution, the Dirichlet distribution, whose parameters are denoted as α and β, respectively.

NMF is a technique that decomposes a non-negative matrix V into two other non-negative matrices W and H, and is widely used in image processing, speech processing, text mining, and other fields. In text mining, H represents the document-term frequency matrix, W represents the document-topic matrix, and V represents the topic-term matrix. The dimensions of the V, W, and H matrices are $n\times m$, $n\times k$, and $k\times m$, respectively, where n denotes the number of documents, m denotes the number of terms, and k denotes the number of topics. The training objective of the NMF model is to find suitable matrices W and H such that WH is closest to matrix V. The loss function used in this paper is based on the KL distance loss function. The KL distance is a concept in information theory used to characterize the similarity between two probability distributions, as shown in Equation (5).

$$J(V,W,H)=\sum_{i=1}^{n}\sum_{j=1}^{m}\left(V_{ij}\log\frac{V_{ij}}{(WH)_{ij}}\right) \tag{5}$$

II. C. 2) Topic consistency measurement based on word vectors

Topic Consistency (TC) is a metric used to evaluate topic models. The higher the topic consistency, the better the performance of the topic model. Thematic Consistency calculates the average semantic similarity of the top K words under all themes. With the rise of word vector technology, methods using word vectors to calculate semantic similarity have achieved better results. Therefore, this paper adopts the word vector-based Thematic Consistency TC-W2V, calculated as shown in Equation (6).

$$TC-W2V=\frac{1}{NC_K^2}\sum_{j=2}^{K}\sum_{i=1}^{j-1}\cos\left(v_j,v_i\right) \tag{6}$$

Here, $\cos(\cdot)$ denotes cosine similarity, v_i and v_j are word vectors, N is the number of topics, and C denotes the number of combinations of word vectors.

III. Practical application of sentiment analysis on Huang Tingjian's poetry texts using Python

III. A. Statistical analysis of high-frequency emotional words based on Python text mining

III. A. 1) Statistics on high-frequency words in poetry texts

After using Python-related software to perform word segmentation and remove irrelevant words from Huang Tingjian's poetry texts, we conducted a statistical analysis of the high-frequency words that appeared, as well as the high-frequency words and their frequencies of occurrence in the three categories of emotional carriers: natural imagery, human imagery, and allusions. We then conducted corresponding analyses.

Table 1 summarizes the 30 most frequently occurring high-frequency words in Huang Tingjian's poetry texts. The top 30 most frequently occurring words in Huang Tingjian's poetry texts include “mountain, person, wind, water, and sun,” among which ‘mountain’ appears most frequently (203 times), followed by “person” (198 times). Among the top 30 high-frequency words, most are imagery of natural landscapes, which is consistent with Huang Tingjian's poetic style of using objects to express his emotions.

Table 1: Top 30 frequently-occurring words in Huang Tingjian's poetic

Serial Number	Words	Word frequency	Serial Number	Words	Word frequency
1	Mountain	203	16	Dream	90
2	Person	198	17	Guest	87
3	Wind	184	18	Return	85
4	Water	175	19	Sadness	81
5	Sun	160	20	Night	74
6	Cloud	152	21	Road	70
7	Old	146	22	Bamboo	67
8	Spring	135	23	Stone	63
9	River	130	24	Word	31
10	Wine	122	25	Tears	58
11	Poem	117	26	Boat	57
12	Book	109	27	Light	54
13	Rain	103	28	Swan	50
14	Flower	98	29	Wilderness	48
15	Moon	94	30	Staff	45

III. A. 2) Statistics on high-frequency words expressing emotions in poetry texts

Further statistical analysis was conducted on the three categories of emotional words that appear most frequently in Huang Tingjian's poetry texts: natural imagery, human figures, and allusions. Table 2 lists the top five keywords in each of the three categories. Among natural imagery, the five most frequently appearing emotional words are pine (150), plum (147), bamboo (136), wild goose (135), and willow (128). Among human figures, the top five emotional keywords are: old man (146), exiled official (140), madman (137), wanderer (130), and old friend (129). The top five emotional keywords among allusions and symbols include phoenix (145), falling leaves (139), high mountains and flowing water (132), Confucius (120), and Qu Yuan (117). Natural imagery primarily features traditional symbols of purity and nobility, while character imagery focuses on figures who are either disillusioned or content with poverty, contrasting sharply with the aristocracy. Allusions primarily employ classical imagery that combines emotional and moral aspirations.

Table 2: Frequent words of the three types of emotional words(Top 5)

Natural objects		
Serial Number	Words	Word frequency
1	Pine	150
2	Plum	147
3	Bamboo	136
4	Swan	135
5	Willow	128
Character images		
Serial Number	Words	Word frequency
1	Old man	146
2	Exiled official	140
3	Crazy person	137
4	Traveler	130
5	Old friend	129
Folklore symbols		
Serial Number	Words	Word frequency
1	Phoenix	145
2	Falling leaves	139
3	Rivers Flowing over High Mountains	132
4	Confucius	120
5	Qu Yuan	117

III. A. 3) Statistics on high-frequency emotional words in the early, middle, and late stages of poetry texts

Huang Tingjian's poetic works span a broad timeframe, with noticeable differences in emotional tendencies across different periods. Therefore, his poems are categorized into early, middle, and late periods based on their creation dates, and the top five high-frequency emotional keywords for each period are statistically analyzed. Table 3 presents the statistical results of the top five high-frequency emotional keywords for the three different periods. In Huang Tingjian's early poems, the top five most frequently occurring emotional keywords are "spring breeze" and "jianghu," which evoke the image of a young man full of vigor and vitality. By the middle period, however, the hardships of work and life led to a shift in emotional keywords toward more ethereal imagery such as 'dream' and "moon." By the late period, the emotions expressed in his poetry became more introspective. In terms of the frequency of emotional keywords, the frequency of emotional keywords in each period exceeded 140 times, with the highest reaching 183 times and the lowest at 142 times.

Table 3: Most frequently used words for emotional tendencies in 3 periods (top 5)

Period	Serial Number	Words	Word frequency
Preliminary-term	1	Spring breeze	183
	2	Jianghu	170
	3	Plum blossoms and peonies	164
	4	Youth	157
	5	Wine	148
Mid-term	1	Old	175
	2	Dream	163
	3	Worry Back	160
	4	Return	155
	5	Moon	150
Later-term	1	Tears	172
	2	Desolate	163
	3	Death	151
	4	Empty	146
	5	Illness	142

III. B. Modeling and classification of emotional themes in poetry based on LDA and NMF

III. B. 1) Comparison of the effects of modeling emotional themes in poetry

After conducting a statistical analysis of high-frequency emotional words in Huang Tingjian's poetry texts, we further utilized LDA and NMF models to calculate, mine, and analyze emotional words and emotional themes. Ultimately, an emotional theme model for Huang Tingjian's poetry was established. To evaluate the effectiveness of the LDA+NMF emotional theme modeling approach, this study selected multiple similar theme models for comparison with the proposed model in terms of theme modeling performance. Figure 2 shows the comparison of emotional theme modeling performance among different models. The LDA+NMF emotional theme model achieved an accuracy rate (P) of 91.67%, a recall rate (R) of 91.29%, and a harmonic mean (F1) of 91.26%, making it the only model among all compared models to exceed 90%. Therefore, it is concluded that the LDA+NMF emotional theme modeling performance is superior, enabling more precise matching and categorization of emotional theme keywords with emotional themes.

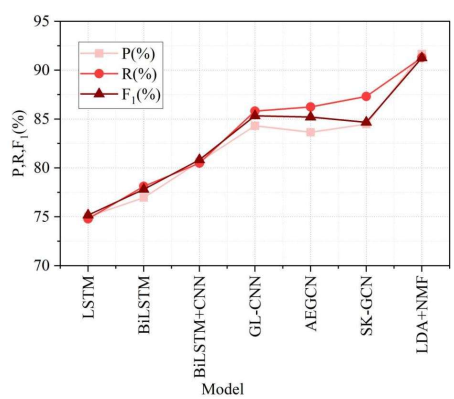

Figure 2: Comparison of Emotional Theme Modeling Effects of Different Models

III. B. 2) Three-class sentiment classification under topic modeling

To further test the performance of the LDA+NMF sentiment theme model, the model was applied to the sentiment classification task of Huang Tingjian's poetry texts, categorizing the overall sentiment and sentence-level sentiment of his poems into three categories: positive sentiment, neutral sentiment, and negative sentiment. Figure 3 visualizes the confusion matrix of the sentiment classification experiment results for Huang Tingjian's poetry. The classification accuracy for positive, neutral, and negative emotions reached 0.925, 0.929, and 0.927, respectively, all exceeding 0.900. It can be seen that the theme model demonstrates excellent classification performance when conducting the three-class sentiment classification experiment on Huang Tingjian's poetic texts.

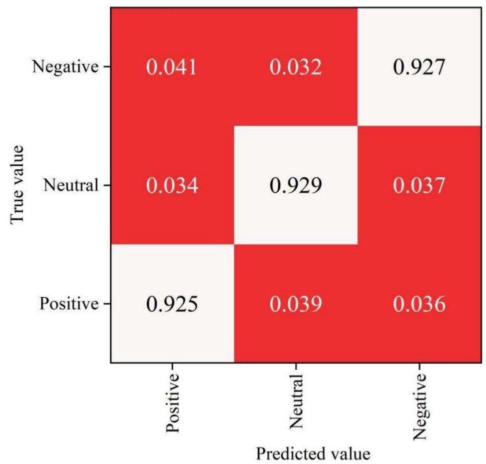

Figure 3: Experimental Results of the Three-Classification of Poetic Emotions

III. C. Analysis of the emotional changes in Huang Tingjian's poetry throughout different periods

Using the constructed emotional theme model, we categorized and analyzed the emotional tendencies of Huang Tingjian's poetry according to the early, middle, and late periods to study the specific changes in the emotions of Huang Tingjian's poetry. Figure 4 shows the emotional changes in Huang Tingjian's poetry during each period. Across the three periods, the proportion of positive emotions in Huang Tingjian's poetry decreased overall, dropping from 0.675 in the early period to 0.409 in the middle period, and further to 0.106 in the late period. The proportions of neutral and negative emotions increased, with neutral emotions rising from 0.302 in the early period to 0.397 in the middle period, and further to 0.433 (late period). Negative emotions increased from 0.023 in the early period to 0.194 in the middle period and then to 0.461 in the late period. The proportions of the three types of emotional tendencies align with the changes in high-frequency emotional words across the three periods, indicating that the constructed emotional theme model effectively links emotional words with emotional themes. The emotional tendencies in Huang Tingjian's poetry shifted from predominantly positive emotions in the early period to predominantly neutral and negative emotions in the middle and late periods, reflecting a reserved style of emotional expression in his poetic creation.

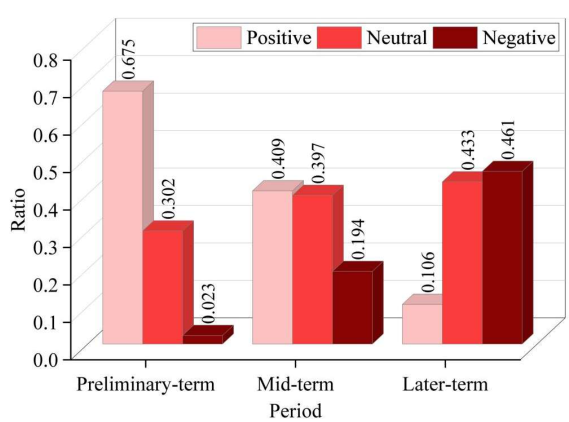

Figure 4: Emotional changes in Huang Tingjian's poetry across different periods

IV. Conclusion

This paper uses Python to mine and statistically analyze high-frequency emotional words in Huang Tingjian's poetry texts and establishes an emotional theme model. The LDA+NMF emotional theme model achieved the highest precision rate (91.67%), recall rate (91.29%), and harmonic mean (91.26%) among seven comparison models, demonstrating the best emotional classification performance. The theme model achieved classification accuracy rates of 0.925, 0.929, and 0.927 for positive, neutral, and negative emotions in Huang Tingjian's poetry texts, respectively. In the early, middle, and late periods, the proportion of positive emotions changed from 0.675 to 0.409 to 0.106. The proportion of neutral emotions changed from 0.302 to 0.397 to 0.433. The proportion of negative emotions changed from 0.023 to 0.194 to 0.461.

Given the efficient coding advantages of Python, future software design and development can further explore the emotional tendencies of Huang Tingjian's poetry texts in greater detail, comprehensively studying the characteristics of emotional changes in his poetry.

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