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Research article

EmotionLens: Interactive visual exploration of the circumplex emotion space in literary works via affective word clouds

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ABSTRACT

Emotion (e.g., valence and arousal) is an important factor in literature (e.g., poetry and prose), and has rich values for plotting the life and knowledge of historical figures and appreciating the aesthetics of literary works. Currently, digital humanities and computational literature apply data statistics extensively in emotion analysis but lack visual analytics for efficient exploration. To fill the gap, we propose a user-centric approach that integrates advanced machine learning models and intuitive visualization for emotion analysis in literature. We make three main contributions. First, we consolidate a new emotion dataset of literary works in different periods, literary genres, and language contexts, augmented with fine-grained valence and arousal labels. Next, we design an interactive visual analytic system named *EmotionLens*, which allows users to perform multi-granularity (e.g., individual, group, society) and multi-faceted (e.g., distribution, chronology, correlation) analyses of literary emotions, supporting both exploratory and confirmatory approaches in digital humanities. Specifically, we introduce a novel affective word cloud with augmented word weight, position, and color, to facilitate literary text analysis from an emotional perspective. To validate the usability and effectiveness of *EmotionLens*, we provide two consecutive case studies, two user studies, and interviews with experts from different domains. Our results show that *EmotionLens* bridges literary text, emotion, and various other attributes, enables efficient knowledge discovery in massive data, and facilitates raising and validating domain-specific hypotheses in literature.

1. Introduction

Emotion is crucial to understanding and appreciating literature such as poetry and prose. In psychology, the term *emotion* refers to a collection of changes in human thoughts, behaviors, actions, and personality, as a result of complex sensory states (Plutchik, 2001). Nowadays, research in digital humanities focuses more on tapping into people's knowledge structures and emotion patterns (Zhang et al., 2021; Yu et al., 2024). As a result, emotion analysis and visualization are receiving increasing attention (Bradley et al., 2018).

Literary emotion is a common focus of both traditional literary studies and computational textual analysis (Graham, 2017). In literature, emotions are closely related to text and affected by many external attributes (e.g., the generation or social movements to which the author belongs) and internal factors (e.g., the conveyed theme and the poem's structural form). Literary researchers would like to explore the relationship between emotions and these factors, determine the emotional expression of different individuals/groups during particular periods, and compare emotional patterns between them. Visualizing emotions in literature not only offers insights into understanding historical figures but also benefits the appreciation of aesthetics in literary works.

The challenges lie in three aspects (Kucher et al., 2018). First, the study of literary emotion is generally based on historical records and literary works (El-Din and Hussein, 2018). Nowadays, more and more researchers adopt Natural Language Processing (NLP) techniques to conduct emotion analysis and build plenty of emotion datasets in different contexts (e.g., modern European poetry and classical Chinese poetry (Birjali et al., 2021)). However, there is a lack of consistent and effective data representation across different contexts, which hinders collaborative analyses and cross-context dialogues. Meanwhile, these literary datasets commonly lack fine-grained emotion labels, and the emotion annotations are not well integrated with other metadata (e.g., the background of creation and the theme of the text), due to disparate data sources and difficulties in matching.

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Second, in computational literature, experts commonly need to conduct multi-granularity (e.g., individual, group, society) and multi-faceted (e.g., distribution, chronology, correlation) analyses over large amounts of literary texts, which requires iterative trials with traditional data analytics (Jänicke et al., 2017). Previous research summarized experts' workflow into exploratory and confirmatory approaches (Gius and Jacke, 2022). The former features conducting multi-faceted analysis over multi-variant data and highlights pattern identification, while the latter is oriented at specific groups or individuals, featuring side-by-side comparisons. Some systems and methods have been proposed to address similar problems in other fields (Lan et al., 2021; Cohen-Kalaf et al., 2022), but cannot support both functions in literature.

Finally, literary emotion visualization features both emotion representation and textual analysis (Alswaidan and Menai, 2020), which are not well integrated with traditional visualization methods. In emotion representation, one of the most influential models is the circumplex emotion space (Russell, 1980), which arranges different emotion categories on the same plane, with valence (degree of positivity) and arousal (degree of evocation) as two dimensions. However, as literary emotions are constantly connected with personal expressions in the analytic process, the circumplex model alone is not sufficient for professional use. Meanwhile, although textual analysis methods (e.g., word cloud) are widely used in digital humanities, traditional word clouds display words based solely on frequency, failing to reflect the emotional features and relationships of specific words. As a result, the two prevalent methods – textual analysis and emotion visualization – are not well integrated, hindering a comprehensive and detailed understanding of emotions in literary texts.

To address experts' needs, we propose *EmotionLens*, a system supporting visual reasoning of literary emotion in multiple granularities, by texts, emotion metrics (quantifiable measures of emotional content such as valence and arousal), multi-faceted metadata, etc. Integrating psychological models, NLP tools, and an original affective word cloud, we support various functions in emotion-based exploration and validation over literary datasets, providing clues for emotion understanding and interpretation. Informed by existing textual sentiment datasets (Chen et al., 2019), we build a multi-dimensional, fine-grained literary emotion dataset covering Chinese and English poetry and prose in classical and contemporary times as well as multi-faceted information about poem creation and literary contexts. We adopt existing valence-arousal lexicons (Mohammad, 2018) and fine-tune domain-specific BERT models (Sun et al., 2022) for emotion labels. After human evaluation and data screening, we obtained a total of 30,420 poems and 6,465 paragraphs, each with professional labels on two-dimensional emotions and other attributes over creative backgrounds and content features.

In terms of visual design, we propose new methods of data representation and view collaboration based on previous research on sentiment visualization (Kucher et al., 2018). We base our analyses on the circumplex emotion space and bridge different views with the CIE lab (Commission Internationale de l'Eclairage, 1978) color space. To combine the specificity of word clouds and the intuitiveness of emotion representation, we design a technique to generate affective word clouds. This entails augmenting word clouds with emotion by highlighting emotionally significant words and adjusting their positions and colors based on emotion metrics, thereby enhancing comprehension. Finally, we integrate multiple views to analyze literature distribution and chronological and correlational features from an emotional perspective. We also incorporate interactions to facilitate researching the dataset by both exploratory and confirmatory approaches.

Our work mainly addresses the task of performing visual analyses of emotion in specific literary datasets. Proved by both case studies and user studies, *EmotionLens* is highly effective in emotion-based literature dataset exploration and emotion-enhanced textual analysis. Meanwhile, different from domain-specific solutions or data-specific representations, the proposed methods in our system can be generalized to other textual datasets with multiple attributes or spatial encodings, which has many potential applications.

To summarize, our contributions are as follows:

- A multi-dimensional, fine-grained literary emotion dataset with text, valence and arousal labels, and other creative backgrounds and content features.
- An original technique to generate affective word clouds with enhanced word weight, position, and color, to facilitate literary textual analysis from an emotional perspective.
- A visualization system including the circumplex model to perform multi-granularity and multi-faceted emotion analyses.

2. Related work

Our system involves various techniques for constructing an explainable emotion space from text data. In this section, we summarize related work in emotion visualization and word cloud.

2.1. Emotion visualization

Emotion visualization is widely applied in fields such as psychology, human–computer interaction, and affective computing, and is particularly common in text analysis (Kim and Klinger, 2018; Yue et al., 2019). It primarily focuses on the representation of emotions, the selection of emotion models, and the relationship between emotions and other attributes (Kucher et al., 2018).

Currently, the three most prevalent types of emotion models are categorical, dimensional, and appraisal-based ones (Alswaidan and Menai, 2020). Categorical approaches highlight emotion annotation and classification, in which the most commonly used model is Navarasa (Sreeja and Mahalakshmi, 2017). Dimensional approaches focus on extracting different continuous and representable dimensions, such as the positivity of emotion (valence, polarity, and sentiment are used for similar meanings in different works (Bernhard and Fabo, 2022)), and the degree of emotion evocation (arousal). Recent work tends to combine these two approaches, arranging different emotional categories by different dimensions (Wang et al., 2020a). In this work, we represent emotions using valence and arousal, which expand a common emotion plane. We also use color to better represent emotions based on previous psychological studies (Ou et al., 2018; Hanada, 2018) and visualization applications (Geuder et al., 2020; Semeraro et al., 2021).

The choice and application of emotion models are also highly relevant to research domains and questions. For example, public opinion tracking of news events focuses on the positivity of a text (Yue et al., 2019), user feedback analysis concentrates on both emotions and related opinions (Oliveira et al., 2016), and user-oriented design cares more about the degree of emotional evocation of users (Lan et al., 2021). Specifically, researchers on artistic emotion commonly adopt aesthetic emotion models (Kim and Klinger, 2018), which belong to fine-grained models under expert knowledge (Wang et al., 2024b).

2.2. Word cloud and text analysis

Most of the theoretical innovations in word cloud stem from Wordle (Viegas et al., 2009), which provides an aesthetic layout with an algorithm to balance different aesthetic criteria. In subsequent studies, ManiWordle focuses on adding human control over typography, color, and composition (Koh et al., 2010), Edwordle supports consistent editing while preserving the neighborhood of words (Wang et al., 2017), and ShapeWordle refines shape adjustment of word cloud through shape-aware Archimedean spirals (Wang et al., 2019).

Along with the progress of theoretical research, word clouds are also implemented in various visual designs for different text-related research areas, such as text analytics (Heimerl et al., 2014), keyword summaries (Felix et al., 2017), and document reading (Badam et al., 2018). Specifically, word clouds are commonly seen in linguistics-related applications. Researchers from IBM utilized tag cloud to visualize vernaculars in personal speeches (Wattenberg and Viegas, 2008). Other researchers applied spatio-temporal projections to explore morphology in ancient dialects (Benito et al., 2017). Similarly, we aim to study literary words from an individual and temporal perspective.

Semantic word clouds refer to those that retain the semantic relationship between words through certain visual channels. Such design is commonly seen in visualization problems that highlight attributes (such as space and time (Li et al., 2018)) or categories (such as topics (Wang et al., 2020b)) of words, and its closeness to human perception is proven over ordinary designs (Hearst et al., 2019). Visual analytic systems using semantic word cloud typically follow a basic structure of NLP preprocessing, semantic similarity evaluation, word clustering, and layout optimization (Rajan and Ramanujan, 2021), with respective focuses (such as word embedding extraction (Xu et al., 2016)).

Beyond word clouds, other text analysis techniques such as topic modeling and interactive visualization are also widely applied in exploring large text collections. Among them, TexTonic provides platforms for interactive exploration, facilitating topic discovery (Paul et al., 2019), TextFlow enhances understanding of topic evolution by combining visualization with topic mining (Cui et al., 2011), Termite visually assesses topic model quality using a tabular layout (Chuang et al., 2012), while LeadLine identifies and explores events in text data through topic modeling and event detection (Dou et al., 2012). Additionally, speculative execution in visual analytics is advanced through user-steerable topic model optimization (El-Assady et al., 2018). However, these methods typically require abundant exterior knowledge and computational complexity. On the other hand, our affective word clouds facilitate a deeper understanding of textual emotion by utilizing word weight, position, and color as enhanced visual channels.

3. Background and system overview

In this section, we introduce the background and concepts of our literary emotion dataset, summarize the data features and analytical tasks, and provide a system overview to demonstrate the whole pipeline.

3.1. Background and concepts

Based on insights from relevant text visualization methods (Viegas et al., 2009; Felix et al., 2017), we first focus on the content and subjects in literary research. As a written art form, literature can be categorized into different genres by language usage, text organization, and aesthetic focus, in which *poetry* and *prose* are the most renowned. We focus on these two genres for visual analysis of emotion in literary works, where *poem* and *paragraph* are the basic units of emotion, respectively.

Next, we delve into the characteristics of literary emotions. Literary emotions are often conveyed through words rich in emotion (Johnson-Laird and Oatley, 1989). However, authors create believable fictional worlds not solely by directly stating characters' emotions or describing their demeanor as angry, fearful, or sad, but also through indirect methods like figures of speech or catachresis (Mellmann, 2002). For example, *positive/negative* paragraphs or poems are those with clear valence towards happiness or sadness, while *implicit positive/negative* paragraphs or poems have more nuanced or less intense emotional expressions. *Neutral* paragraphs or poems generally show a lack of strong emotional inclination.

Meanwhile, emotion in literature is intricately connected with other elements such as setting, theme, and style. This necessitates a balanced approach that combines distant reading (e.g., a rigorous hermeneutic inquiry into the novel's creative background and context) and close reading (e.g., delving into linguistic features of emotional language) techniques (Jänicke et al., 2017). For example, in poetry, some attributes are directly related to the content of a poem, such as the described season, the conveyed theme, and the poem's structural form, while others serve as background information about the poem's creation, such as generation or social movements to which the poet belongs. In our work, we refer to the former as *internal* attributes and the latter as *external* attributes.

3.2. Requirements and task analysis

To understand the needs of our potential users, we conducted semi-structured interviews with experts in the field of literature. Among them, E_A is a specialist in comparative literature, with a PhD degree in English studies and expertise in cross-linguistic practice. E_B is a Ph.D. student studying Chinese language and literature. They have been working on the historical aspects of literature for years, especially those from the Tang and Song dynasties.

Working with our experts, we aimed to identify different approaches and key steps in literary research and establish connections between them and visualization tasks. We divided the interview into three stages. In the first stage, we asked both experts to propose *cases that are directly related to text sentiment analysis*, as well as summarize *research problems in their current research concerning literary emotions*. We also asked them to establish the traditional approaches for solving these questions. In the second phase, we consulted two experts on the fundamental methodologies of digital humanities, especially concerning literary text analysis. Finally, we discussed with experts to structure discrete operation steps into consistent modules and summarize the requirements behind them.

As commonly acknowledged in the fields of digital humanities and computational literature, methodologies concerning computational literary textual analysis can be typically categorized into *exploratory* and *confirmatory* approaches (Graham, 2017; Gius and Jacke, 2022). The major difference between these two approaches lies in whether the expert comes with specific hypotheses or only general research directions. As suggested by our experts, such categorization stems from and also resembles the workflow of traditional literary textual analysis. In the latter, researchers typically go through the two stages of *textual analysis* and *interpretation*, to build up from a set of hypotheses to elaborate discourses. Based on the provided framework, we formulate the primary tasks as follows:

- **T1 Customized Research Scope Definition.** Since experts have different research interests and perspectives on literary emotions, the primary task is to allow them to select a target dataset by different methods (e.g., manual filtering, selection by attribute, time). Meanwhile, as experts typically have different focuses on different research stages, the system should also support an iterative approach to select and adjust certain subsets intuitively.

Exploratory approach. In the beginning, digital humanity experts propose a general problem or research direction. They first select a dataset and apply a consistent emotion model to extract emotion metrics from literary texts. Experts then apply data analytic tools to determine the characteristics and detect possible patterns. In our case, the primary focuses include understanding the emotional structure and characteristics of works or collections, the development of an author's emotion over time, changes in affective styles across historical epochs, as well as the affective relationships between different authors and groups. Combined with literary priors, they can derive a set of hypotheses and identify corresponding subsets for further validation. Based on the workflow of the exploratory approach, the first design goal is to *support preliminary observation and feature identification of quantitative emotions in literary datasets (G1)*, including:

- **T2 Consistent Emotion Metric Representation.** This task focuses on the emotional analysis of a specific literary dataset. The system should support a consistent affective computing and mapping approach, using established emotion models and metrics to quantify, predict, and visualize emotions from text. This contrasts with traditional literary studies, which might use *"ad-hoc methods that can be fragmented, highly individualized, and sometimes unintentional."* *(E_B)*
- **T3 Multi-Faceted Emotion Pattern Identification.** This task involves preliminary feature extraction. Experts require an explicit method to extract emotion patterns for trends, relationships, etc. with visual analytic tools. The goal is to determine features and propose hypotheses for further validation.

Confirmatory approach. Once literary experts have a clearer definition of the research questions and possible clues, they tend to shift to a hermeneutics methodology, to connect existing clues and develop a consistent interpretation iteratively. In digital humanity research, this commonly manifests as a deeper analysis of selected texts, with specific words and expressions as focal points and creative context in consideration. In our scenario, experts particularly care about the relationship between emotion characteristics and literary text. They need to enhance traditional textual analysis methods with emotion metrics, to better plot the embedded affective state, and finally, to facilitate argument construction with comparative methods (theme, symbol, language, context, etc.). Based on the workflow of the confirmatory approach, the second design goal is to *facilitate focused textual analysis and comparison through emotion-text relationships (G2)*, including:

- **T4 Emotion-Enhanced Text Analysis.** This task aims to facilitate establishing connections between literary emotion and text analysis. The basic requirement is to explore emotion-text relationships and represent emotions in textual analysis methods. The idea is to augment textual visualization techniques (e.g., word cloud) to manifest information from different perspectives, at different levels of the dataset.
- **T5 Portrait Comparison.** This task is derived from experts' need for textual contextualization and interpretation. As indicated by our experts, comparison and contrast serve as a fundamental approach across various analytical frameworks in literary research (e.g., analyzing themes, characters, narrative structures, or linguistic elements). They aim to condense and combine emotional and textual features (creating *literary portraits* of authors, groups, and societies (Wallen, 1995)) for multi-granularity, multi-faceted comparisons.

In summary, we collaborated with our experts to identify key methodologies and task requirements for emotion analysis in literary research. Based on these insights, we developed EmotionLens, a system designed to support multi-faceted emotion analysis and help experts better understand emotional patterns in literary texts.

3.3. System overview

Fig. 1 provides a system overview of *EmotionLens*. It is a web-based application with a data preprocessing module, an attribute analysis module, a data explanation module, and an emotion visualization module. The former two use a backend implementation in Python and MySQL, which is responsible for extracting emotion metrics and other internal attributes from literary works. The emotion visualization module is a frontend application using Vue.js, Flask, and D3.js with multiple coordinated views to support multi-faceted analyses.

4. Data representation

This section describes our data source, format, and analytical methods. We first apply data filtering and attribute prediction to the original dataset. We then specify our emotion model and apply query and learning-based methods to derive emotion metrics in different subsets.

4.1. Data description

Our study uses a variety of data sources to comprehensively analyze literary emotions. Based on the expertise of our domain experts, we first determine English and Chinese as target languages, both with rich literary histories. Then, we discussed with our experts to consult about data authority and common sources. Finally, we selected three different types of data. The first is raw texts of literary works, which are then processed and assigned multiple labels. The second provides background information on literary works such as metadata and author biography. The third is emotion reference, which provides text-emotion correspondence. We use these datasets to obtain text-based emotions.

Literary Work and External Attribute. In choosing raw texts of literary works, we focus on wide coverage of different genres, languages, and times, as well as comprehensive labeling and credible sources. For the form of poetry, we refer to the 20C Poetry dataset (Piper, 2018) which contains 75,297 English-language poems by 454 contemporary authors, and the Complete Tang Poems (Werneror, 2018), which consists of 49,403 Classical Chinese Poetry by 2,339 poets from the Tang Dynasty (A.D. 598–929). The former dataset also comprises comprehensive background information about each author, such as gender, nationality, and movement. For the metadata of Classical Chinese Poetry, we refer to the China Biographical Database (CBDB) (Harvard University, 2019) which contains biographical information on 521,442 historical Chinese figures, 53,850 in the Tang Dynasty. For the form of prose, we choose five novels (Ezis, 2024) covering different periods and genres. In this way, we obtain the content, author, and other external attributes of literary works.

Emotion Reference. Because our datasets mainly include contemporary English and ancient Chinese, we need to establish methods to extract sentiment from the text for each context. We refer to NRC-VAD (Mohammad, 2018), a well-established sentiment lexicon in English, which consists of 20,007 words with three-dimensional labels of valence, arousal, and dominance. Due to a lack of ancient Chinese emotion lexicons, we apply machine learning to predict the emotion of Complete Tang Poems from a

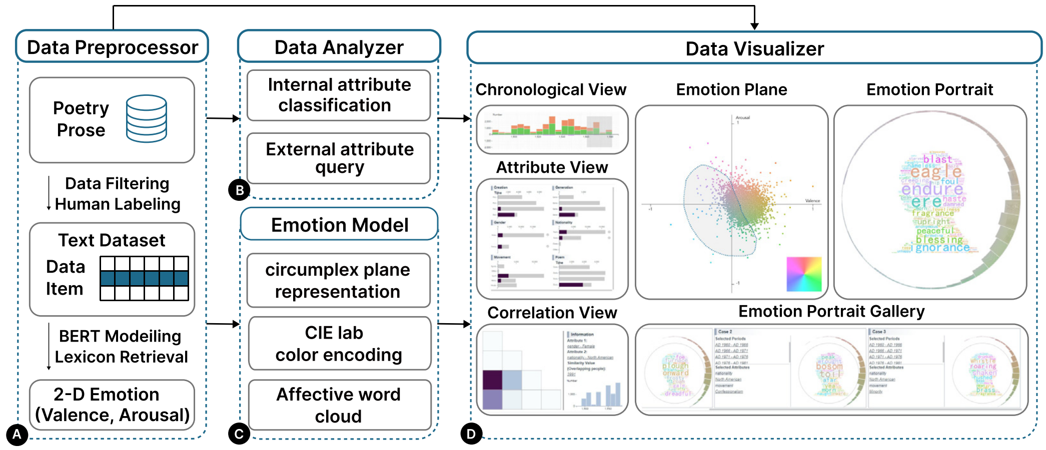

Fig. 1. System overview. *EmotionLens* has four parts: data preprocessor (A), data analyzer (B), emotion model (C), and data visualizer (D).

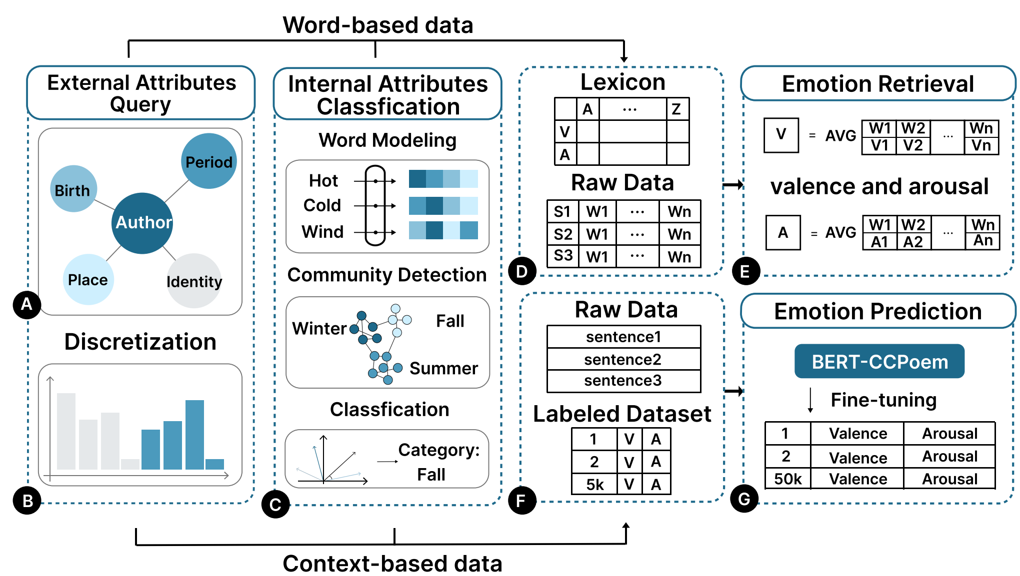

Fig. 2. The pipeline of data analysis. External attributes are obtained from the database (A, B). Internal attributes are extracted from literary texts (C). For different subsets, valence and arousal are derived by lexicon-based retrieval (D, E) or deep learning prediction (F, G).

relatively small set of labels. Specifically, we optimize the Fine-grained Sentimental Poetry Corpus (FSPC) (Chen et al., 2019), adding arousal annotations to the original 5,000 annotations of valence. After expert examination, we obtain a dataset of 5,000 poems with high-quality, two-dimensional emotion annotation. These labels are further applied to finetune a BERT model for emotion prediction.

4.2. Data preprocessing

Fig. 2 shows our data analysis process. The analysis module mainly includes data preprocessing, intrinsic attribute classification, and aesthetic emotion modeling. After constructing datasets of literary works and author metadata, we first establish the correspondence between each work and its creation context via the author. For poetry subsets, we retrieve background information from the database with the author's name and time period as inputs. Due to the large amount of data, we discard results with duplication or missing attributes. Meanwhile, as the original labels in datasets are not consistent, with many similar classes and identical labels in different expressions, we establish a word2vec model (Mikolov et al., 2013) to assist in selecting and aggregating attributes.

4.3. Internal attribute classification

Internal attributes refer to those features that can be directly derived from the content of literary works, such as structural form, content genre, and thematic connotation. For faster classification and better involving expert knowledge, we adopt a lexicon-based graph network to classify literary works under each internal attribute. For example, in the subset of Classical Chinese Poetry, we implement collaborative labeling by the following steps:

- **Word Modeling.** We first use Jiayan (2021), an NLP tool for ancient Chinese, for word tokenization in the Classical Chinese Poetry subset. Then, we train a word2vec model and calculate the similarity between each pair of words.
- **Community Detection.** Based on the previous step, a graph network is established with words as nodes, and similarities as weights of links. We then use the Louvain algorithm (Blondel et al., 2008) to classify and sort the words. Finally, we implement human validation and expand the lexicons.
- **Poem Classification.** The previous steps provide lexicons for different categories. By calculating the similarity between poetry and categorical words in the model, we derive the

confidence that a poem belongs to each category and obtain its label.

This method is applied to all internal attributes except for emotion. We also adopt a similar approach for English texts. Based on the principles and research focus of literary contexts, we assign different external and internal attributes to each subset.

4.4. Emotion prediction

To quantify literary emotions, our experts chose a two-dimensional (2D) scale, specifically *the circumplex model*, for analyzing emotions in literature. This model, based on the work of Russell (1980), arranges different emotion categories according to their relationships in two dimensions: valence and arousal. *Valence* refers to the degree of positivity or negativity of the emotion, while *arousal* indicates the degree of evocation or intensity. This model is particularly effective in representing secondary emotions with major cognitive components, typical in literary works (Stangor, 2012). The model has also been widely applied in various fields including literature and linguistics and has yielded some representative achievements (Russell et al., 1989). Expert E_B commented on "*its ability to capture the complexity and nuance of emotional experiences in a structured manner.*"

To derive emotions from ancient Chinese, we base our work on the FSPC dataset, which includes fine-grained valence labels on 5,000 Classical Chinese Poems. After examining their labels, we observe an uneven distribution that the number of positive/negative poems is much less than implicit positive/negative or neutral ones. As the author claims, the annotation of fine-grained emotions is highly individual (Chen et al., 2019). Through similar experiments, we also observe that people's perception of emotion polarity is much more consistent than their perception of emotion degree. Therefore, we aggregate the labels into three categories (positive, neutral, and negative) in the training process.

To achieve emotion representation on a two-dimensional plane, we add another 5,000 labels to the original dataset. Students from relevant majors in two local universities are asked to label the arousal dimension of poem emotion on both verse and poem levels. After expert examination, we collate results into the FSPC dataset alongside valence labels and finetune a pre-trained model for Classical Chinese Poetry, BERT-CCPoem (Sun et al., 2022). Finally, we change the last layer of the model from classification output to continuous output, obtaining desirable prediction results. For the task of emotion classification in Classical Chinese Poetry, our model achieves accuracies of **0.67** and **0.65** for valence and arousal, respectively, surpassing previous deep models, all of which achieved accuracies below 0.64 (Tang et al., 2020). Finally, we establish a dataset that describes multi-faceted features of literary works. Despite covering different genres, languages, and historical times, each dataset has a similar structure to ensure that the system adapts effectively to different contexts.

5. Emotion visualization

In this section, we demonstrate the process of visualizing literary emotions according to expert needs. We first encode the 2D emotions into unified positions and color channels. As literary emotion is more fine-grained than general sentiment and emphasizes the connection between emotion and text, we apply two original word cloud designs to refine its feature extraction and distinction (**T3**).

5.1. Emotion plane

In the emotion visualization domain, it is commonly acknowledged that leveraging other visual channels can help facilitate its expression and comprehension (Lan et al., 2023). We implemented different designs to better encode and express literary emotions in the Circumplex Model.

We first experimented from the position encoding perspective. We tested various coordinate systems such as rectangular coordinates and polar coordinates, different value ranges including the unit circle and unit square, as well as different mapping methods such as Elliptical Grid Mapping (Heer and Shneiderman, 2012). Through expert evaluations and user trials, we identified continuity and symmetry as crucial for users to effectively comprehend the emotion space. Consequently, we selected a standard Cartesian coordinate system, with valence and arousal as perpendicular axes.

Our experts point out color as a candidate visual channel, for "*intuitive and expressive emotion externalization.*" (E_A) We thus reference previous studies on the relationship between color and emotional understanding (Ou et al., 2018; Hanada, 2018), both of which demonstrate or validate the CIE Lab color space as the most relevant for representing emotions. For alternative designs, we also tested the RGB, HSL, and HSV color spaces, each of which posed specific challenges in accurately capturing emotional nuances. The RGB space, for instance, led to a lack of perceptual uniformity, where similar emotional states were not consistently represented by similar colors. HSL and HSV, despite offering better perceptual linearity, tended to either exaggerate or understate subtle differences in emotional states, leading to potential misinterpretations. More critically, these color spaces occasionally caused perceptual distress due to their high saturation levels, which can be overwhelming in a densely populated emotion space. In contrast, the CIE lab color space emerged as the most suitable choice. Its perceptual uniformity ensures that color differences correspond more consistently to differences in emotional states, providing a richer and more legible representation. As recommended by previous research and the CIE lab guidelines (Commission Internationale de l'Eclairage, 1978), we set $L = 70$ and assign dimensions a and b to represent valence and arousal, respectively. Fig. 3 displays the emotion distribution of four different novels, where emotions are mapped on the Cartesian coordinate and encoded with the CIE Lab color space. Since experiments have demonstrated the impact of individual differences (Ou et al., 2018), we also allow experts to adjust colors according to their preferences.

5.2. Affective word cloud

As indicated by prior research (Gius and Jacke, 2022), literary research relies heavily on textual analysis. Expert E_B also claims that text analysis is *"both the starting point, foothold, and cornerstone of our field."* On the other hand, in the digital humanities community, the most specific tool for textual analysis is word cloud (Graham, 2017). However, traditional word clouds cannot encode and reflect the emotional perspective of literary text. Based on our discussion with experts, we propose two designs to address the problem.

Emotion-Significant Word Weight. In deriving an emotionally representative word cloud, we tried the method of including a stop word list. However, such a word list would require constant adaptation to each dataset or selected region. We may also predict every word's emotion and its emotional closeness to the selected region, but that would require abundant calculations. To enhance versatility and processing speed, we leverage the feature that a point's emotional attributes are intrinsically encoded by

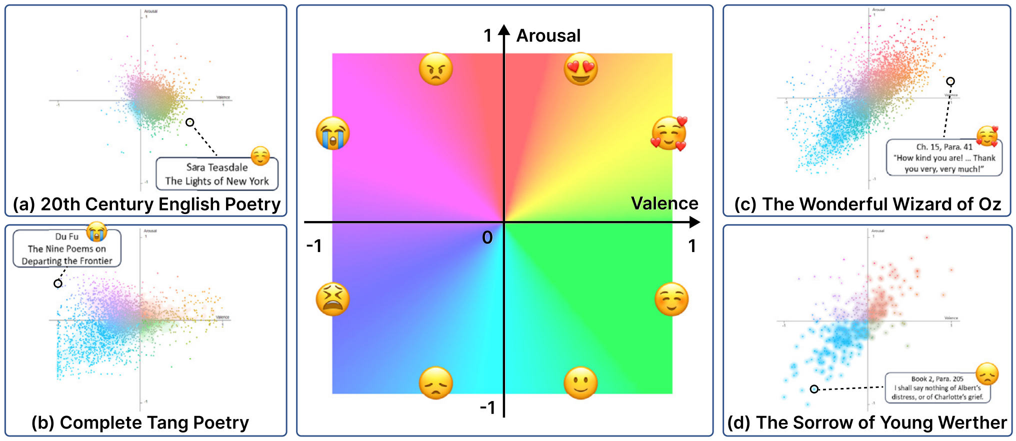

Fig. 3. The circumplex model with position and color encodings. The two dimensions are valence (degree of positivity) and arousal (degree of evocation). We also display the emotion distribution of two poetry datasets and two novels as examples. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

its spatial location within our system (Section 5.1). Based on this correlation, we efficiently extract emotional weight directly from the spatial significance of each point, rather than through more computationally intensive methods.

We first propose a locality-significant weighting method to highlight the most relevant words to the selected emotion. Different from other word clouds that achieve semantic or shape encoding by layout control (Hearst et al., 2019), we modify the weight of each word from simple frequency. The method is based on the TF-IDF algorithm (Ramos et al., 2003) that can assess the importance of a term within a collection of documents. Generally, the original weight of word k in the full set S and selected dataset S_i are:

$$w_k = \frac{f_k}{\sum_{k \in S} f_k}, \quad w_{ik} = \frac{f_{ik}}{\sum_{k \in S_i} f_{ik}}, \tag{1}$$

where f_k and f_{ik} denote the frequency of k in S and S_i, respectively. To better reflect the emotion-specific words, we represent the significance of the word's presence in the selected dataset over the full set with:

$$s_{ik} = p\left(\frac{w_{ik}}{w_k}\right), \tag{2}$$

where $p(x)$ is a normalization function (commonly linear) to derive comparative magnitude and trend. Meanwhile, we calculate the distance between each word and the target word set S_t (e.g., plants, nouns, colors) and normalize the results similarly:

$$d_{kt} = q\left(\frac{\sum_{j \in S_t} \|v_k - v_j\|_2}{|S_t|}\right), \tag{3}$$

where v_k denotes the vector representation of word k in the word2vec model, and $q(x)$ is another normalization function. Our optimized weight is expressed as:

$$w'_{ikt} = \beta s_{ik} + (1 - \beta) w_{ik} + \gamma (1 - d_{kt}), \tag{4}$$

where $\beta \in [0, 1]$ controls the locality of weight encoding of the word cloud, and γ constrains the relevance of each word to the target word set. A large β will reflect words that most significantly contribute to the selected emotion subset, whereas a small one will reduce the weight to word frequency.

We conducted a series of comparative studies over different β values and the choice of different $p(x)$, $q(x)$. The qualitative results are shown in Fig. 4. From our user study (Section 8.4), the optimal β values for different word clouds vary by the dataset, location, and number of points. Therefore, we display a comparatively preferable default value (0.5) on the visual interface. We also provide multiple parameter settings with corresponding explanations, allowing users to easily explore different perspectives of the dataset. For instance, they can select the "frequency only" setting, where both β and γ are set to 0.

Position and Color Enhancement. On the other hand, to better represent and reflect the emotion of each single word in a word cloud, we also improve the Python package by Müller (2023) to constrain the position and color of each word with its two-dimensional emotion.

After mapping the two-dimensional emotions to positions on the integral image, we optimize the proximity of each word to its specified target position, while maintaining the query structure for real-time processing speed. As the three constraints of word size, processing speed, and placement cannot be simultaneously optimally satisfied, we prioritize the former two aspects. Additionally, we use the same color encoding as mentioned in Section 5.1 to encode the valence and arousal of each word. Such design enables experts to recognize the emotional connotations of the words more effectively.

Fig. 4 shows the construction process of an affective word cloud. The comparison demonstrates that our Emotion-Significant Word Weight and Position and Color Enhancement offer distinct advantages. Specifically, experts can capture emotionally important words more easily. From the color and placement of each word in a word cloud, they can intuitively derive its emotional connotations, facilitating the research process. In contrast, the vanilla word cloud often has an emotionally implicit and contextually disconnected presentation of words.

6. Emotionlens system

In this section, we first present an overview of *EmotionLens*, followed by details of our visual components and cross-view interactions.

6.1. Visual components

Fig. 5 illustrates the visual interface of *EmotionLens*, which consists of six interrelated views for literary emotion analyses. Among them, the Chronological View (Fig. 5-A) and the Attribute View (Fig. 5-B) enable customized data selection to define the research scope (**T1**). The Correlation View (Fig. 5-C) displays the concurrence between different selected attributes, facilitating the

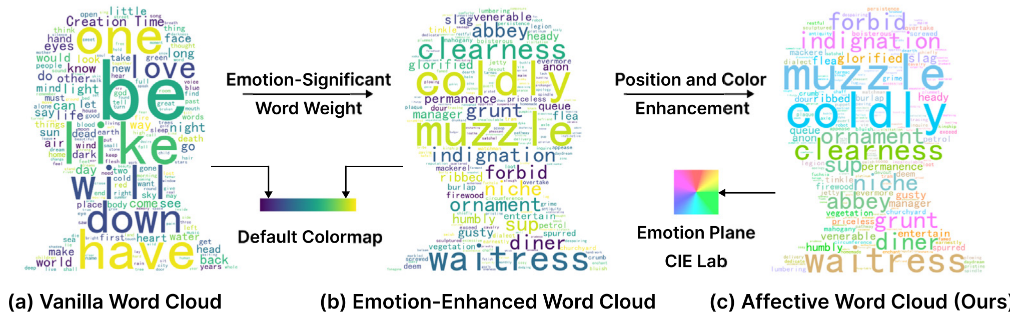

Fig. 4. The construction process of an affective word cloud. (a) Vanilla Word Cloud determines word weights only by the word frequency and applies random position and default colormap. (b) Emotion-Significant Word Weight can manifest words most relevant to the emotions. (c) Position and Color Enhancement (according to Section 5.1) can reflect word emotions and cluster emotionally similar words. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

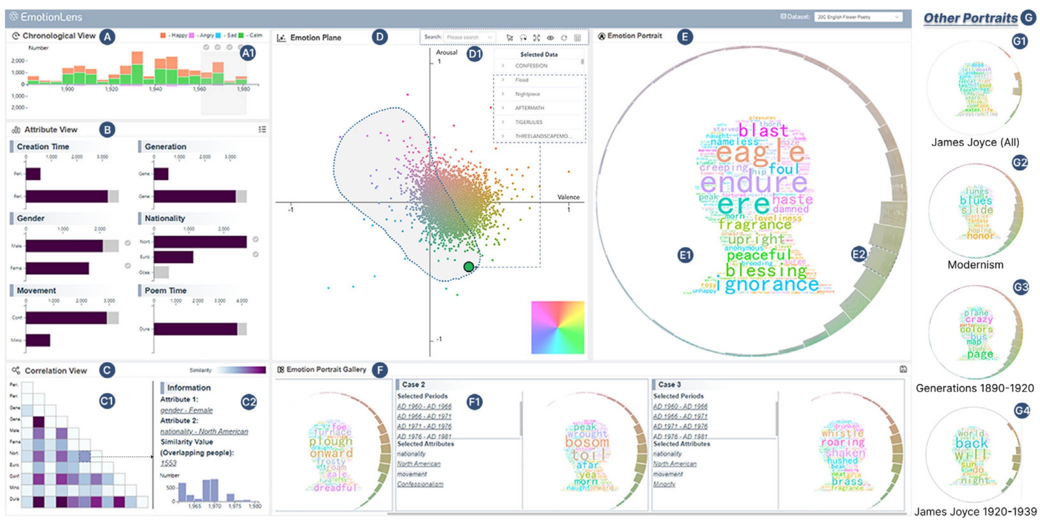

Fig. 5. The visual interface of *EmotionLens*. The Chronological View (A) and Attribute View (B) support customized data selection. The Correlation View (C) shows the number of concurrences between different selected attributes. The Emotion Plane (D) visualizes the emotion of each data point on a circumplex emotion space. The Emotion Portrait (E) includes a rose map to condense the emotion features and an affective word cloud to manifest the emotion-significant words. The Portrait Gallery (F) stores emotion portraits under different filtering conditions for comparison. In the right figure (G), we display four emotion portraits including Joyce's poetry collection, poems from the modernist movement and Generations 1890–1920, as well as Joyce's works published after 1920 (Case 1).

identification of multi-faceted emotion patterns (**T3**). The Emotion Plane (Fig. 5-D) visualizes the emotion metrics of each data point within a consistent circumplex emotion space (**T2**). The Emotion Portrait (Fig. 5-E) includes a rose map and an affective word cloud to distill and display key emotional features (**T4**). Finally, the Portrait Gallery (Fig. 5-F) stores emotion portraits under various filtering conditions for effective comparison (**T5**).

Chronological View. Our chronological view encodes the temporal change of individual and group emotions. In literary research, the chronology or time perspective is commonly related to topics such as emotional journeys, the evolution of themes, and changes in aesthetic styles throughout history. The Temporal View (Fig. 5-A) displays both changes in the number of works and emotion distributions in each time period. The body of this view is a bar chart that displays the number of all literary works by time. Each bar is divided into four parts by color (Fig. 5-A1), representing the number of works in each quadrant of the emotion plane. By referring to this view, experts quickly gain an understanding of the temporal features in the given dataset, including the changing trend of literary emotions throughout history. The view can also be applied to other data forms with chronological information, such as the plot development of a book, which is demonstrated by our third subset of English novels.

Attribute View. As literary interpretation requires a deep understanding of the creative background and context, visualizing the attributes is a quick and common way to capture the structure and characteristics of the selected dataset. The attribute view (Fig. 5-B) comprises a series of bar charts, each representing a specific attribute of the dataset. These charts provide a visual representation of the attribute distribution within a user-selected subset. In each bar chart, the length of a bar indicates the frequency of that attribute. When an expert hovers over a bar, detailed information appears, showing the attribute's label and its count both in the full dataset and within the selected subset. Furthermore, the expert can interact with the emotion plane by clicking on one or several bars within an attribute category. This action filters the points on the emotion plane to display only those associated with the selected attributes. Clicking on multiple attributes enables the display of their intersection, facilitating a more nuanced delineation of the dataset from different perspectives.

Correlation View. The correlation view (Fig. 5-C) is designed to help experts better understand the dataset and discover implicit relationships. We design a heat map that encodes the intersection over union (IoU) of each pair of classes in the selected dataset. Experts can select any number of classes from the Attribute View to update the map and compare in two dimensions to derive relationships between different attributes (Fig. 5-C1). By hovering over a particular cell on the heatmap, experts can view the specific quantity and temporal change within the intersection union (Fig. 5-C2). This view not only supports establishing and determining possible connections but also infuses the classic analytical approach with an emotional perspective.

Emotion Plane. The Emotion Plane (Fig. 5-D) is a primary visual component to display two-dimensional emotion of different works in a given dataset, to facilitate set-level analysis and inspection. According to the circumplex emotion model (Section 4.4), each literary work is represented as a point on the valence-arousal plane according to its two-dimensional emotions. We also apply the position and color encoding methods as mentioned in Section 5.1, and include a series of visual cues and legends for experts to quickly grasp the emotion connotations in different areas. Via function keys in the row above (Fig. 5-D1), experts can zoom in, pan, or enclose an area by lasso selection. When hovering over any point on the Emotion Plane, a tooltip shows the corresponding literary text. The lasso-selected literary texts are displayed in a list beneath the function keys, and hovering over a list item reveals the point's position and detailed content. Finally, as overly dense points may affect the perception of density, we include an additional density map as another layer. Experts can shift between different layers to capture both global and detailed information.

Emotion Portrait. As inspired by the concept of *portrait* in literary research, we work with experts to form an informative and expressive design to summarize the key textual and emotional features in a selected dataset for effective comparison. Similar to a real-world portrait, our emotion portrait (Fig. 5-E) mainly consists of two parts: an inner affective word cloud (Fig. 5-E1) with frequency, color, and position enhancements as described in Section 5.2; and a contour (Fig. 5-E2) to summarize the circumplex emotion distribution in the form of Nightingale Rose Chart. Specifically, we slice the emotion plane into 36 sectors, each with a 10° arc. For each sector, we arrange all points within it into a one-dimensional sequence based on their distance to the origin. Finally, we represent each point as a thin line of equal width inheriting its color and stack them to form an inward radial bar.

Emotion Portrait Gallery. In an iterative selection process, the emotion portrait constantly changes depending on the current dataset and focus area on the emotion plane. Once the expert has determined an ideal dataset or has spotted some interesting findings, they can save the current emotion portrait into the portrait gallery (Fig. 5-F) for further analysis and comparison. As mentioned in Section 3.2, such comparison can be based on different periods, authors, groups, and even individuals versus groups. On the other hand, for each emotion portrait, we record the selection procedures including filtering by time, filtering by attribute, and searching by author (Fig. 5-F1). The goal is to facilitate intuitive understanding and rapid reuse in the literary interpretation process.

6.2. Cross-view interactions

EmotionLens provides various interactions, allowing users to conduct comprehensive analyses based on inter-coordinated views. Fig. 7 illustrates a complete exploration process, including Data Selection (Fig. 7-X), Emotion Pattern Identification (Fig. 7-Y), and Text-Emotion Feature Comparison (Fig. 7-Z).

Switching Context. Experts can explore different types of data by selecting from the dataset switch box (Fig. 7-X1), which will change the attributes and labels in the Attribute View and the Correlation View.

Filter and Query. Experts can choose subsets of interest by temporal filtering, attribute filtering, or name searching (Fig. 7-X2). The selected works will also be updated with attribute proportions in the Attribute View, temporal distribution in the Chronological View, and rose chart in the Emotion Portrait.

Lasso Selection. Experts can draw a contour (Fig. 7-Y2) in the Emotion Plane to turn the selected points into a word cloud, which will display the result in the Emotion Portrait, and also update the Temporal View, the Attribute View. A list can show the details of selected points.

Storage and Restoration. During the use of *EmotionLens*, Experts can save the current dynamic Emotion Portrait as a static image by clicking on the save button and putting it in the Portrait Gallery. Experts can retrieve the corresponding state by clicking on the image.

7. Case study

We evaluate the usability and effectiveness of *EmotionLens* with two case studies. Experts in Section 3.1 are invited to freely explore *EmotionLens*. We summarize their observations and comments and form them into two cases to fully demonstrate the system.

7.1. Case 1: From vibrancy to disillusionment: Navigating Joyce's emotional tapestry

In the first case study, E_A aimed to explore *"the relationship between James Joyce's understanding of his emotional journey and the emotional trajectory depicted in his works."* This topic concerns a critical research topic in literature. As introduced by E_A, in contemporary literary studies, examining an author's creative experience and emotional journey relies on two key indicators: their collection of work and biographical works about them (such as autobiographies, memoirs, etc.). From a postmodernist perspective, the meaning and influence of a historical figure often appear as "invented" or "constructed". Biography studies are crucial in literary research because they shed light on this "construction" process. E_A hoped to approach the "construction" of James Joyce from an emotional perspective, observing the correlation in emotional patterns between his poetry collection and his semi-autobiography *A Portrait of The Artist as a Young Man* (PAYM).

E_A began by confirming some existing academic consensus around James Joyce (J.J.) They first switched to the 20th Century English Poetry Dataset and searched James Joyce by name. They clicked on the Chronological View to split his collection of work according to three literary historical stages (**T1**). As the emotional distributions of the works are relatively scattered, E_A then selected all works for each stage and derived three emotional portraits of J.J., which are saved in the gallery (Due to space limit, we include one example in Fig. 5-G1, the same applies below) (**T4**).

After individual-centered exploration, E_A shifted towards establishing the context. They restarted from the whole dataset and clicked on the Attribute View to examine the emotional characteristics of both the Modernist movement and Generations 1890–1920 (**T1**). E_A applied the same chronological filtering method to depict three emotional portraits for each group (Fig. 5-G2&G3) (**T4**). Based on the 9 emotional portraits, E_A focused on the emotion distribution and affective word cloud to conduct comparative reasoning. From the perspective of emotional changes, arousal in the modernist movement has increased, while valence in the Generations 1890–1920 has decreased. Joyce's works exhibit emotional changes more in line with the latter. However, as indicated by keywords and themes, Joyce's emotion portraits are more consistent with the modernist movement (**T5**). E_A interpreted the phenomenon by Joyce's uniqueness as a founder of modernist poetry. They also believed that *"expanding this method may provide novel evidence for literary classification."*

Fig. 6. Additional results of case studies. In analyzing Joyce's semi-autobiographical novel, E_A creatively extended the time dimension to represent the sequence of paragraphs. This demonstrates the potential of our system to be generalized for broader applications.

Finally, E_A focused on the emotional journey in PAYM. They creatively proposed to treat paragraphs as the fundamental units of emotion and assign their sequence as temporal information (**T2**). They contemplated the Chronological View for the overall emotional trajectory of the entire book (Fig. 6-M1). The Correlation View suggested a close relationship between short sentences, conversation, and the theme of religion (**T3**, Fig. 6-M2). E_A claimed it *"aligns with the intrinsic, direct, and conflicting nature of J.J.'s religious expressions."* By selecting different Chapters on the Attribute View, E_A derived five emotional portraits within PAYM (Fig. 6-M3), which are commonly associated with subsequent life stages of J.J. from childhood to late youth (**T4**). However, they noticed that the third- and fifth-word clouds included some negative emotional keywords that are not commonly seen in Joyce's early poetry. On the contrary, these words echo the emotional themes found in Joyce's works from after 1920 (**T5**, Fig. 5-G4). E_A suggested that this may indicate potential dramatic and prophetic elements beyond the common sentimentality found in autobiographical works, inspiring further research.

7.2. Case 2: Between court and couplet: Exploring Li Bai's emotional spectrum

In the second case study, E_B aimed to identify *"whether Li Bai's emotional patterns align more closely with traditional literati or officials."* They introduced that the intersection and strong connection between literati and officials are characteristic of ancient China. However, the CBDB dataset collects fractured labels for each historical figure, which are adopted as attributes by *EmotionLens*. E_B also provided the academic conduct and motivation. In ancient literary research, a person's identity is often defined by post-structuralist classification methods, which "*derive subordination relationships based on similarity between features of unknowns and representatives.*" Following the common practice, they would like to question and explore Li Bai's identity from a literary emotion perspective.

E_B started by switching to the Complete Tang Poetry dataset (Fig. 7-X1). They explored the emotional patterns of Tang poems from a global perspective, summarizing an overall tendency towards negativity, with an increasing proportion of low-valence negative emotions (**T2**, Fig. 6-N1). E_B clicked on the Attribute View and selected Literati and Official (Fig. 7-X4) to inspect their correlation with different periods, places, and poem themes (**T3**, Fig. 6-N2). They summarized that "*these two groups each held sway over the poetry scene during the High Tang - Before the An Shi Rebellion (Fig. 7-blue) and Middle Tang - After the An Shi Rebellion (Fig. 7-red) periods, corresponding to Li Bai's life trajectory.*"

After that, E_B shifted to a subset level of literary emotion in the High Tang and Middle Tang Period (**T1**). They introduced that the two periods were divided by the An Shi Rebellion (755 A.D.), which marked a sharp decline in people's outlook and confidence in the country's future. E_B focused on the negative emotions and selected all points on the left half plane (Fig. 7-Y2) to depict four emotional portraits of both literati and officials, before and after this event (Fig. 7-Z1-Z4) (**T4**).

Following that, E_B dived into the specific individual. Under our guidance, they searched Li Bai by name (Fig. 7-X2) and filtered by time (Fig. 7-X3) to inspect his lifelong emotional journey. E_B intuitively connected the emotion patterns and works with major historical events such as the Minister of Hanlin (743 A.D.) and the An Shi Rebellion. They commented that the impact of these two historical events is reflected in the two peaks in the quantity of Li Bai's creations and the negative turn in the emotions expressed in his works, which was "*basically in line with my perception.*" They in turn depicted Li Bai's emotional portraits before and after the An Shi Rebellion and saved them in the portrait gallery (Fig. 7-Z5&Z6) (**T4**).

Finally, E_B conducted a multi-level comparison between the six portraits saved in the portrait gallery (Fig. 7-Z1-Z6). They discovered that in terms of overall color and outer ring distribution, there was no significant change in literary emotion for Li Bai before and after the An Shi Rebellion, while the literati and official groups showed a noticeable decrease in arousal. At the same time, observing specific words in the word cloud, E_B identified that the literati group shifted their emotional themes from social environments (e.g., *government*) to natural environments (e.g., *autumn*) after experiencing the Rebellion, while personal feelings (e.g., *alone*) are rivaled by philosophical insights (e.g., *universe*) in the official group, aligning with Li Bai's emotional keyword transition (from *"alone"* to *"separation"*) (**T5**).

E_B concluded that despite the individual distinctiveness typically found in distinguished poets, Li Bai's literary emotions resemble more officials than literati. They claimed that Li Bai spent most of his early life living and contacting extensively with officials in the capital city, which may be a reason. They commented that "*I got some proofs for further validation and many interesting results along the way.*"

7.3. Expert interview

Visualization and Results. Both experts highly appreciated the usability of our system. From their comments, we summarized four aspects that *EmotionLens* facilitates and extends traditional literary text analysis. The first aspect concerns effective text sentiment analysis and emotional theme mining. As E_B commented, *EmotionLens "significantly simplified the process of performing repetitive textual analysis on large datasets."* E_A also thought it *"greatly helped uncover emotion themes and*

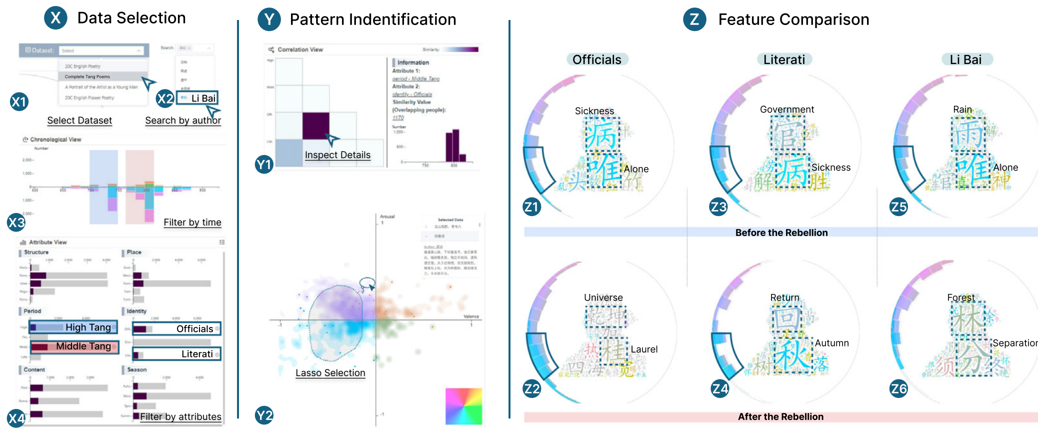

Fig. 7. An example exploration procedure with *EmotionLens*. In exploring Li Bai's identity (Case 2), E_B iteratively depicted the emotion portraits of literati, officials, and Li Bai before and after the An Shi Rebellion. The results demonstrated both independent features of emotional changes in his poetry, as well as more similarity between Li Bai's emotional keywords and his contemporary officials.

trends." This was mainly achieved through visually presenting emotional sentiments distribution and changes within texts. The second aspect is associated with our emotion visualization techniques. E_B highly commented on the emotion model we apply, saying *"I think valence is highly individual-dependent and occasion-variant, and arousal may be an important indicator in certain times."* Meanwhile, *EmotionLens* excels in graphically representing literary emotions and themes through position and color encodings, *"offering intuitive insights into the emotional atmosphere and thematic characteristics." (E_A)* Moreover, *EmotionLens* demonstrated effectiveness in facilitating multilevel emotion analysis and interactive exploration. Experts can *"see from word-level to overall emotional experiences in works." (E_A)* Users can also freely navigate and explore connections between various attributes and emotional dimensions. This *"enhances understanding of the diversity and complexity of emotions in literary works." (E_B)* Finally, experts acknowledged the reliability of the result. As E_B mentioned, "*most results conform to common knowledge, and the system also adapts to multiple effective validation processes.*" E_A also commented that through *EmotionLens*, they "*not only can expand knowledge but also continuously validate existing conclusions in the process.*"

Procedure and Interactions. Both experts are generally satisfied with *EmotionLens*'s support for different workflows. As E_A mentioned, the interactivity of *EmotionLens* is fundamental in *"integrating various independent methods within digital humanities."* We demonstrate the correspondence between literary issues and our interactions as follows: Firstly, *EmotionLens* enabled experts to better approach the research subject. As E_B mentioned, experts can *"efficiently switch their focus and approach different aspects of their target."* E_A also noticed that our system *"enables observation from different angles, such as converting point clouds to word clouds and exploring details through zooming and hovering."* Secondly, *EmotionLens* served as a vital link between exploratory and confirmatory approaches, facilitating iteration between them. In our cases, both experts validated existing conclusions during the exploration process, while the validation process often led to additional inspiration and discoveries. As E_B commented, the system *"enhances collaboration between experts and systems, effectively utilizing expert knowledge in research endeavors."* Finally, *EmotionLens* demonstrated capabilities in both consolidating and broadening analytical methods. E_B thought *"it streamlines the research process by consolidating repetitive forms and aids in exploratory efforts,"* such as determining and generating different signatures. E_A recognized that our system widens the scope of textual analysis methods, *"providing flexibility and possibilities by multiple filtering operations."*

Emotion Portrait. We pay special attention to the efficacy of Emotion Portrait and summarize its two merits from expert interviews. First, as a way to graphically represent literary emotions and themes, the Affective Word Cloud intuitively bridges textual analysis and emotion metrics. As E_B mentioned, *"it was particularly challenging to effectively link them together in traditional research."* However, the two aspects are *"indeed interrelated and complement each other."* In this regard, *EmotionLens* made beneficial attempts by augmenting abstract textual analysis with concrete emotion metrics. Second, condensing complex features into a portrait facilitates the analysis and comparison of emotional styles across different authors and literary genres. As demonstrated by the cases, through comparing different portraits, our system revealed unique author- and group-specific emotional expressions, enriching the understanding of emotional connotations in literary works. Finally, the cases demonstrated different roles of literary emotion as a direct analytical target or a pathway to address corresponding core domain issues. As E_A mentioned, "*literary emotion is more about a view and methodology, which is more important than studying itself.*"

Suggestions. Experts' suggestions mainly focused on facilitating the selection of specific works and providing additional background information. E_B suggested a philological perspective, adding meticulous documentation of source materials emphasized in ancient literary studies such as specific pages from particular editions, to facilitate further scholarly investigation. E_A outlined a conceptual framework integrating literary criticism theories and methodologies, including relevant psychoanalytic theories, to better serve practical literary research. Both experts encourage interdisciplinary dialogues to foster methodological innovations in literary analysis, opening avenues for exploring the intersection of emotion visualization and digital humanities.

8. User study

We conduct two user studies under multiple user scenarios, with different focuses and metrics, to evaluate the performance of *EmotionLens* in different tasks and the emotion-significant word cloud in specific. With reference to similar works (Zhang et al., 2022; Wang et al., 2021), we include a set of *controlled analyses* where users are required to complete certain tasks, as well as a period for *open-ended analyses* where users are asked to freely explore the system in a think-aloud manner. In this way, we aim to validate the system in three aspects:

A1 Effectiveness. *EmotionLens* can help users to identify the suggested information related to literary emotion.

A2 Efficiency. The design and interaction of our system are easy for users to understand and support efficient operation.

A3 Satisfaction. The system can elicit insights into literary emotions from multiple angles, to fulfill user-specific requirements and exploratory needs.

8.1. Participants

We recruited 12 university students/researchers for the two studies. All of them are postgraduate students or postgraduate degree holders, including 8 Ph.D. students (P_A–P_H), and 4 master's students (M_A–M_D). We also invited 2 literary researchers (L_A and L_B) and 4 visualization researchers (V_A–V_D) to evaluate *EmotionLens*. Overall, there were 7 female participants and 11 male participants. Based on their expertise in relevant fields, we divided them into two groups. Group 1 consists of all students from other majors (P_A–P_H, M_A–M_D), including science, art, and design. Group 2 includes the other six users (L_A–L_B, V_A–V_D) with professional literature or visualization competence.

8.2. Procedure

We conducted two sets of experiments on both groups, with different focuses. Users in Group 1 were asked to complete all the tasks in controlled analysis (20 min) and explore the system with the remaining time (10 min). For Group 2 users, we briefly introduced the analytic results with key insights (10 min) and focused more on self-motivated exploration (30 min).

Controlled Analyses. The first user study involves a series of semi-open tasks in the form of customized questions, which aim to verify **A1** and **A2**. We first introduced the functions and interactions of our system in several slides and a video demonstration. Considering their different knowledge backgrounds and literary preferences, users were allowed to choose customized research objects by selecting a literary context and a subset of it, in either data filtering way shown in our interaction (**T1**). We also introduced some concepts and background information in their choosing process. Based on their individual subsets, we asked the participants to answer a list of questions with the assistance of experimenters:

Q_a1 What are the general emotions in X and the proportion of each kind of emotion? (**T2**)

Q_a2 What is the relationship between emotion and other attributes of literary works in X? (**T3**)

Q_a3 How do the number and emotion of literary works change over time? (**T3**)

They mainly comprise the set-level inspection. The users were then asked to shift their attention from a set of mixed works to a certain author. Similarly, we asked them to choose an author of interest by filtering in the inspection view or searching by name (**T1**). We asked a second series of questions based on the specific author:

Q_b1 What is the distribution of emotions in Y's poetry? (**T3**)

Q_b2 What are the words strongly associated with Y's emotions? Among them, what may be the main cause? (**T4**)

Q_b3 What are the difference in emotion distribution and emotional key words between subset X and individual Y? (**T5**)

These questions represent the detailed exploration functions of *EmotionLens*. For each question, we focused on the exploratory process, functions used, and how users derived insights from the results, along with other comments. We are also interested in users' preference for word clouds with different levels of locality focus (β) in different scenarios. Therefore, we added a set of controlled experiments, where users were asked to choose one of six word clouds that best represented the target emotions in ten different scenarios.

Open-ended Analyses. In the second study, users were allowed to freely explore the system and derive insights based on their individual preferences and prior knowledge. For example, by selecting several subsets or authors, users could explore and contrast them in different aspects. Beyond the functions used in controlled analyses, we also provided cross-context, cross-set, and cross-work comparisons between English and Chinese, classical and contemporary times, as well as poetry and prose, in order to stimulate more insights. The second study consists of one trial for ordinary users and five trials for domain experts. During the experiment, we recorded all the operations and results on the screen. We expect users (especially those in Group 2) to assess the advantages and disadvantages of our system and connect its capabilities with solving domain problems. (**A3**) Specifically, we aim to validate whether *EmotionLens* can quantitatively validate certain theories and provide inspiration for cutting-edge research issues. Finally, we asked both groups of users to fill in an anonymous scale and provide overall impressions and detailed feedback for each component (data filtering, set-level inspection, and detailed exploration). We collected these data for further processing and demonstrate the results in the following sections.

8.3. Results and feedback

Questionnaire Results. Based on the System Usability Scale (SUS) (Brooke, 1996), we design a questionnaire to evaluate the overall performance of *EmotionLens* and its usability in data filtering, set-level inspection, and detailed exploration. We collected the scores from all 12 users in Group 1 and display the results in Fig. 8-L. The average scores were 80.2, 84.0, 78.8, and 78.5, significantly exceeding the recommended average of 68, which supports **A1**.

Task Performance. Based on their educational and knowledge background, as well as personal preferences, four of the users chose the Contemporary English Poetry dataset. The explored topics include sad content and imagery (P_A), gender-specific poetry writing (P_E), the generation of poets as a literary concept (M_A, M_D), the relationship between Beckett's emotions and life (M_D), etc. The other eight users chose the Classical Chinese Poetry dataset. Their focuses cover a wide range from emotion differences between poem themes (P_B), author identities (P_C, P_H), and time periods (P_B, P_C, P_G, P_H), to attribute relations such as romantic and southern China (M_C), civilian and winter (P_G). Under professional verification, most of these conclusions are *"supported by in-depth research"* (L_B) or have already become a consensus in the field of literature (L_A, L_B). Such rich and various results derived in a short period of time constitute mighty evidence to **A2** and **A3**.

User Feedback. Users commented that the results from *EmotionLens "are consistent with my prior recognition,"* (P_E, P_F) and *"fit my preconceptions."* (M_A, M_D) Four users (P_B, P_E, P_F, M_B) found it interesting to use the whole system, especially the locality-focused word cloud (P_E, P_F). Three users (P_B, P_G, M_B) claimed they obtained more knowledge after several trials. Specifically, literary researchers thought *EmotionLens "helped us handle large amounts of data,"* (L_A) validated some preliminary guesses and conclusions (L_A, L_B), and might be useful for studying the evolution of literary styles (L_A) and the relationship between genres (L_B).

From the perspective of visualization, *EmotionLens* is evaluated to support coherent (P_G), comprehensive (V_C), and fine-grained (V_A) analyses, and the method can be transferred to other scenarios (P_H). For example, the Reasoning View is very intuitive (P_C, P_G, P_H, M_C), bridging other views with similar color encodings (P_G, V_C); the Parameter View not only displays the emotion distribution (M_C), but also provides functions such as *Group Portrait*

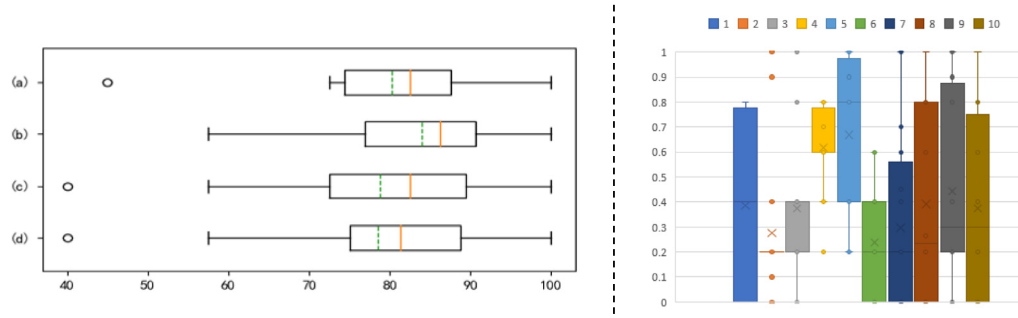

Fig. 8. L: SUS questionnaire result. The four aspects are (a) overall, (b) data filtering, (c) set-level inspection, and (d) detailed exploration. R: User preference of locality focuses in different cases. For Emotion-Significant Word Weight, we include the results of user preference over different β values.

(P_C, M_A, M_D), and inspection of political and economic changes (P_B, P_C); the Temporal View demonstrates changes in emotion distribution (P_B) and thus social climate vicissitudes (P_C, M_B), as well as *"the way a poet was born,"* (P_A) in the context of historical times. Many users think that different word clouds reflect different levels of emotion (P_G) and have certain complementary relationships (M_B).

8.4. Word cloud preference

We recorded 16 users' choices of word clouds that best reflect local emotions from different β values. We controlled the three variables of dataset, position, and number of points, and calculated their correlation with the most preferable βs. The results were −0.44, 0.51, and −0.21, respectively. There was also a high variance between different people's perceptions, which further proves the necessity of including a Word Cloud Gallery for personal choice. Detailed results can be found in Fig. 8-R.

9. Discussion

Significance. Our system and methods for visually exploring literary emotion have proven effective with literary datasets and are expected to have broader applications across various textual formats (such as posts or comments), user scenarios (such as social media and blogs), and different art forms (such as paintings and music) (Wang et al., 2024a; Ye et al., 2024). To understand literary emotions beyond general models, we designed a word cloud that derives emotion specificity from locality significance. Similar weighting methods can be applied to extract local features of textual data using spatial encoding, whether through geographical coordinates or abstract representations like ours. Finally, the literary emotion dataset we built encompasses different periods, languages, and genres, making it valuable for other studies in digital humanities.

Lessons Learned. We observed some cognitive divergences between the fields of computation and literature and incorporated insights from experts to enhance our system. For example, computational scientists focus more on statistics, while literary scholars prioritize texts, shapes, and colors. This distinction guided the design of our Emotion Plane and Emotion Portrait. Additionally, literary research typically values the richness and reliability of data, which we improved by incorporating multiple contexts (e.g., time, attributes, and the origin of literary works) into our system. Finally, we adapted the generalized concept of *time* in literature to propose a consistent analytic form for examining intra-data characteristics (such as the paragraph order within a single work) and inter-data relations (such as the chronological relationship between different works).

Limitations. Although we have demonstrated the effectiveness of *EmotionLens*, there is still room for improvement. For example, some other design choices (e.g., list or column display (Jänicke et al., 2017)) and user factors (e.g., term lookup inefficiencies (Viegas et al., 2009)) have not been statistically compared or evaluated. Additionally, when deriving an emotion-significant word cloud, the optimal beta is influenced by the size of the subset. While this method generally yields good results, it may produce inaccuracies in extreme cases: the largest subset of all points may result in a plain word cloud lacking emotional significance, and the smallest subset with only three points might highlight words that are characteristic but irrelevant to emotion. Other models and algorithms could be explored and tested to optimize the results.

Future Work. From our design process and results, we identify several areas for future work in data analysis, data visualization, and word clouds. Our emotion prediction model and internal attribute classifier can be further improved by incorporating recent techniques (Sun et al., 2020; Lin et al., 2022). When deriving emotion using the lexicon method, we might add relative importance as a weight or use energy models to optimize word choice and layout within a specific subset. We could also apply similar designs to the Temporal View to create a sequential word cloud, mapping a word's continuous distribution over time to a specific location and size. Additionally, some visual channels in our views are not fully utilized. We could encode other textual attributes or metadata using point shapes to convey more information and design glyphs for more intuitive understanding and exploration.

10. Conclusion

This paper proposes *EmotionLens*, a system for visual reasoning of literary emotion. Based on the circumplex emotion model, we calculate the valence and arousal of different literary works and form a dataset together with other attributes. We also propose an affective word cloud to integrate text analytics and emotion visualization. An interface is designed to visualize the distribution, temporal change, and correlation of literary emotion. We validated its effectiveness with different datasets and domain tasks through case studies, user studies, and expert interviews.

EmotionLens can help experts address many domain problems, and we envision several promising directions for future research. We plan to expand our dataset to make it more representative, incorporate more advanced data analytics to improve prediction and classification results, refine the visual design for better accessibility, and improve the robustness of the affective word cloud. They may provide better future solutions to text analysis, emotion visualization, and digital humanities.

CRediT authorship contribution statement

Bingyuan Wang: Writing – original draft, Methodology, Formal analysis, Conceptualization. **Qing Shi:** Visualization, Validation, Software. **Xiaohan Wang:** Writing – review & editing, Data curation. **You Zhou:** Visualization, Resources, Investigation. **Wei Zeng:** Writing – review & editing, Supervision, Conceptualization. **Zeyu Wang:** Writing – review & editing, Project administration, Funding acquisition, Conceptualization.

Ethical Approval

Informed consent was obtained from all participants prior to their involvement in the study. Signed consent forms are on file and available upon request.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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