Visual Reasoning for Uncertainty in Spatio-temporal Events of Historical Figures

Wei Zhang, Siwei Tan, Siming Chen, Linghao Meng, Tianye Zhang, Rongchen Zhu, and Wei Chen

Abstract—The development of digitized humanity information provides a new perspective on data-oriented studies of history. Many previous studies have ignored uncertainty in the exploration of historical figures and events, which has limited the capability of researchers to capture complex processes associated with historical phenomena. We propose a visual reasoning system to support visual reasoning of uncertainty associated with spatio-temporal events of historical figures based on data from the China Biographical Database Project. We build a knowledge graph of entities extracted from a historical database to capture uncertainty generated by missing data and error. The proposed system uses an overview of chronology, a map view, and an interpersonal relation matrix to describe and analyse heterogeneous information of events. The system also includes uncertainty visualization to identify uncertain events with missing or imprecise spatio-temporal information. Results from case studies and expert evaluations suggest that the visual reasoning system is able to quantify and reduce uncertainty generated by the data.

Index Terms—History, Uncertainty, Spatio-temporal Events, Visual Reasoning.

1 Introduction

Chronology is the study of arranging the events of historical figures according to their time of occurrence [1]. It presents the life story of historical figures with formatted records such as *[time, location, person, event]*. By investigating such records, historians identify historical figures' visited places, social relationships, and lifestyles in different historical periods. Such identification improves the understanding of living habits and social development in the past, and facilitates comparative studies between historical periods.

Traditional chronology studies rely essentially on literature reviews [2] which may be extremely time consuming. They often require reading and analyzing in details a large amount of original historical documents and books. Recently, the development of digitized humanity projects (e.g., the China Biographical Database) has offered a new perspective for chronology studies. With a structured representation of events extracted from historical literature, the database significantly boosts the efficiency of querying processes carried out by historians to retrieve relevant information on historical figures. Despite the benefits of information retrieval, two major challenges hinder the chronology construction process and in-depth exploration of life cycles based on chronology.

First, the construction of a chronology directly gathered from large collections of event records is a nontrivial task. Reading and analyzing enormous records with highly complex and irrelevant information is computationally demanding to the organization of events.

Second, most chronology sources are affected by a large ratio of missing or erroneous data records on time, locations, and social relationships. The resulting uncertainty associated with chronology data prevent historians from obtaining reliable and accurate information from the analysis of chronology data [3].

Hence, historians are required to use their domain knowledge to cross-validate multiple data sources at different scales and evaluate the large proportion of uncertainties in the extraction results of automatic methods. Tedious validation and evaluation processes have limited historians' research scopes in analyzing the digitized humanity information. To identify relationships and discover patterns in the data, we propose a novel network-based visual reasoning framework for identifying and analyzing uncertain events in chronology data. We also propose a novel visual design inspired by traditional Chinese paintings to summarize the life experience of historical figures, from which uncertain events can be identified and investigated further. This study makes the following contributions:

- A network-based modeling and visualizing scheme for spatio-temporal events that facilitates visual reasoning on the uncertainty in chronology data.
- A novel visual metaphor of traditional Chinese painting that shows the lives of historical figures.
- A visual analytics system that supports comparative analysis of historical figures and uncertainty reasoning on historical events.

2 Data and Tasks

2.1 Data Abstraction

This paper uses two datasets: the China Biographical Database (CBDB) [4] and the Buddhist Studies Authority

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Database (BSADB) [5]. The CBDB records major historical events from the Han Dynasty (7th century) to the Qing Dynasty (19th century) and serves as the primary dataset in this study. We extract 1,400,000 historical events from the dataset. Each event has several properties, including *time*, *location*, *person*, and *descriptions* (Table 1). However, a large number of recorded events lack information on at least one property, such as *time*. Other issues in the data include inaccuracies in the measurement of the properties, such as conflicting *time* or wrong *location*. Missing data and errors result in *uncertainty* in chronology. Events in the dataset exhibit variation in variables associated with political events, literary achievements, social activities, and military affairs. The BSADB provides supplementary information for historical records in the CBDB. More specifically, it includes information, such as spatial coordinates, time duration of dynasties, and background knowledge of each dynasty (governor information and bureaucratic hierarchy).

TABLE 1. Data details.

Event(1,400,000)		
Dimension	Property	Size
Time (T)	Occurrence time of Event Birth/Death year of P Start/End time of L	618 A.D. to 2,000 A.D.
Location (L)	Occurrence place of Event Hierarchical relationship between L	21,060
Person (P)	P that involved in Event Relationship between P	422,402
Description	Label of Event Background knowledge	836 85,034

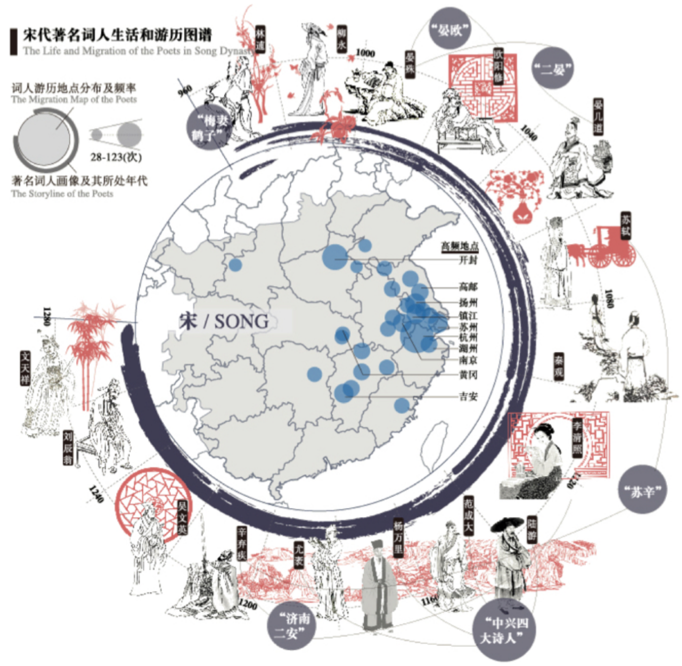


Fig. 1: Example of diagrams we made before working with historians. It shows the spatio-temporal distribution of historical figures [1].

2.2 Working with Historians

We collaborated with five historians during one year, including three researchers on ancient Chinese literature and two experts who built and managed the CBDB. We held regular meetings with them and asked them to characterize the problem domains, discuss the system design, and evaluate the final system.

2.2.1 Prototype Demonstration

In the first phase, the historians showed great interest in visualizing historical data. After several rounds of discussions, we developed a prototype (Figure 1) to demonstrate the visualization capability of depicting the spatial, temporal, and textual information of the poets in the Song Dynasty [6].

The historians recognized the potential and effectiveness of a visual analytics approach to assist their studies. Our early prototype supported visual storytelling for public audiences but lacked in-depth analysis ability. Therefore, we improved our method by focusing on the analysis of uncertainty associated with historical figures to assist historians in exploring data, identifying evidence, and reasoning facts (Figure 1). This storytelling project can be openly accessed [2].

2.2.2 Tasks

Missing data and inconsistencies are often present in the process of collecting information and concatenating pieces of evidence. For example, in the CBDB dataset, nearly 60% of the recorded *events* have neither *time* nor *location* information, and around 15% of the recorded *events* lack *personal* or *bureaucratic* information. Another source of uncertainty stems from vague descriptions of the spatial or temporal information in the data. For example, the name of a region is given instead of the exact city. Time can be also inaccurately reported, with e.g. *a twenty-year period* instead of providing the day, month, and year of the event. We define the uncertainty in the context of events as missing data and error of spatial, temporal, and human relational information. Accordingly, we identified three analysis tasks:

T1. Exploring a chronology from multiple aspects. Historians are interested in the ups and downs in the lifetime of each person. The life story of a historical figure generally comprises multiple aspects, such as political events and social activities.

T2. Identifying and reducing the spatio-temporal uncertainty of events. The system should provide historians with visual analysis of spatio-temporal uncertainty, and enables them to perform cross-validations across multiple views using domain knowledge. Reducing uncertainty allows historians to obtain accurate information, so as to improve the analysis efficiency.

T3. Reasoning the collective behavior of historical figures based on refined results. The final goal of information refinement is to discover group behaviors, such as inter- and intra-party relationships.

1. This image used with permission from the XINHUANET: https://english.news.cn/home.htm
2. http://fms.news.cn/swf/2018_sjxw/quansongci/index.html#/

3 RELATED WORK

This section provides a brief overview of works that are most relevant to the contributions of this paper: digital humanities analysis, chronology (event) visualization, and analysis of uncertainty.

3.1 Digital Humanities Analysis

The use of computational approaches for quantitative history analysis, also called digital humanities, has led to important changes in historical research [7], [8]. CBDB [4], CGED-Q [9] used a semiautomatic text extraction method to collect millions of historical records for data mining. Florian et al. [10] summarized a series of novel visualization techniques and designs for digital humanities. They conducted a survey with experts as the primary target audience, for whom the ability to analyze multisource and heterogeneous data was necessary.

Digital humanities studies have used visualization and visual analysis tools to perform content analysis and distant reading [11]. Bradley et al. summarized the main visual text analysis tasks of close reading and distant reading [12]. Close reading focused on individual work while distant reading provided an overview perspective to analyze text data. Cho et al. proposed VAiRoma [13], which integrated textual and spatio-temporal visualization techniques for effective depiction and analysis of historical figures in Rome, Italy. However, VAiRoma's data was taken from from Wikipedia, which was unlikely to provide sufficient reliability and accuracy for historians. VAiRoma focused on event analysis rather than uncertainty reasoning. CareerLens [14] proposed three levels of tasks to study historical career mobility and understand social mobility and inequality. Other studies [13], [15], [16] used distant reading to analyze social structural changes and explore group behaviors. In this paper, we collaborated with historians to specifically address the uncertainty issue in historical studies with visual analytics, which has not been fully exploited yet.

3.2 Visual Chronology Analysis

Chronology analysis is an important research activity for historians. Before studying a social phenomenon, historians typically investigate a large number of historical figures to summarize common features and seek events of interest. However, each historical figure is characterized by multiple events, making analysis time-consuming.

Storytelling [17] is a general approach to present chronologies, involving personal lives [18] and group variations [19]. Similarly, sequential visualization techniques, such as LifeFlow [20] described lifetime events along a timeline. IdeaFlow [19] visualized information communications among multiple user groups on social media.

BiographyNet [21] proposed a set of natural language processing tools to automatically identify and structure the valuable information from biographical texts in the Resource Description Framework (RDF). BiographyNet built a visualization model with structured metadata, and has provided historians with a user-friendly interface to answer historical questions. BiographySampo [22] built a pipeline to automatically extract a knowledge graph from textual biographical data, enhancing the reading experience of biographies. An interactive variant [16] of Priestley's Chart [23] was proposed to derive new relationships among musicians and discover time-dependent changes in musical institutions over time. Our approach provides historians with an overview of figures' various life stages to quickly discover interesting points.

3.3 Uncertainty Visualization

As Windhager et al. [24] pointed out, uncertainty is present in various aspects of the digital humanities. Identifying and reducing uncertainty are two major components to improve visual reasoning, which is the focus of our study. Historians deal with two types of uncertainty in data: missing data and erroneous data. Note that uncertainty varies with the data modalities and types (e.g., the uncertain time) [25]. Chen et al. [3] performed a comprehensive survey on sources of uncertainty in analyzing user behaviors. Franke et al. [26] suggested using confidence intervals to measure the validity of historical data and findings. Their approach quantified biases associated with the creation and interpretation of historical data.

Various algorithms were proposed to reduce the uncertainty. Clark [27] proposed deductive reasoning, where functional relations were used as clues in uncertainty reasoning. Lao et al. [28] adjusted the weights in the random walk to infer different target relations. AMIE [29] was a rule mining model explicitly tailored to facilitate the open world assumption (OWA) scenarios.

Uncertainty visualization is composed of three components during analysis: identifying [25], [30], and quantifying, and when possible reducing uncertainty [31], [32]. Recently, visual analysis of uncertainty has gained much attention [31], [32]. Providing a detailed review of uncertainty presentation, Hullman [33] emphasized the role of uncertainty in visualization. Kale et al. [34] summarized several novel visualization designs on uncertainty. Quantile dot plots were used by Kay et al. [35] to present uncertainty in real-time transit predictions. A general framework for visual uncertainty analysis was proposed by Correa et al. [31], including bias estimation and visual uncertainty mapping. Gschwandtner et al. conducted a comparative study to evaluate the suitability of different visual encodings for temporal uncertainties [36]. Windhager et al. [37] proposed a more systematic, synoptic, and self-conscious approach to visualize the uncertainty for historical objects or cultural collections. From a theoretical perspective, Roberto et al. [38] addressed the issue of uncertainty representation in the context of the digital humanities. They also suggested progressive visual analysis [39] as a suitable method to mitigate issues stemming from uncertainty in the data in the context of digital humanities.

Cross-verification may be suitable to reduce uncertainty and increase the amount of key information on which decisions are made [40], [41]. Spatio-temporal information is frequently used and valued by historians. Thus, we reviewed related studies of visual analysis in spatio-temporal events. VAUD was a visual analysis system that provided a framework to carry out visual reasoning of urban events [42].

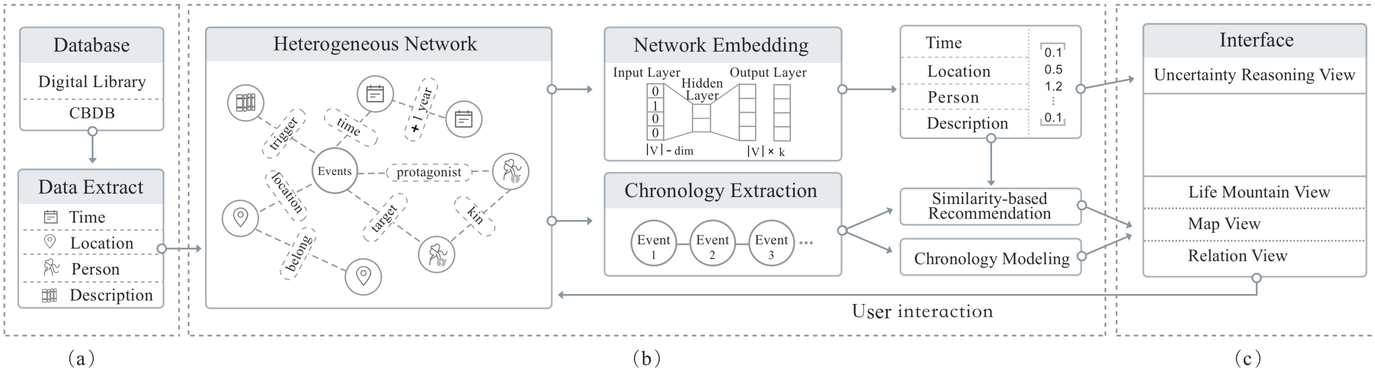


Fig. 2: Overview of our approach. (a) Spatio-temporal events are extracted from the input data. (b) Entities and relationships are extracted to construct a heterogeneous network. Similar events can be identified and compared with the network embedding technique, enabling reasoning with the presence of uncertainty associated with the data. (c) The visual interface identifies uncertainty in events and provides an interactive framework to facilitate reasoning in the presence of uncertainty.

Concurrent patterns of events can be interactively identified and compared [43]. Semantics can also be integrated to analyzing spatio-temporal patterns [44]. Efforts have been made to analyzing social media events derived from Facebook or Twitter. Whisper identified the spatio-temporal opinion-diffusion of catastrophic events such as earthquakes [45]. Detecting the causality of events can also benefit from visualization [46]. Focusing on spatial event detection, Scatterblogs allowed to explore social media events based on topic analysis [47]. Rather than focusing on the evolution of events and their detection, our proposed method targets on uncertainty reasoning, and put emphasis on the cross-verification of events.

4 Data Integration and Analysis Model

Figure 2 shows the pipeline of the proposed approach. Data are preprocessed to integrate information from the CBDB [4] and BSADB [5]. Then, two models are adopted (a chronology model and a representation-learning-based uncertainty reasoning model) to explore chronologies (**T1**) and perform uncertainty reasoning (**T2, T3**). The visual interface (Figure 2 (c)) contains different views to show the lifetime of historical figures and facilitate reasoning in the analysis of events in the presence of uncertainty.

4.1 Heterogeneous Network Construction

As mentioned in Section 2.1, the two data sources adopted in this study are composed of historical data gathered from various records of entities. We construct a heterogeneous network to store the data from CBDB and BSADB. For the sake of simplicity, we only store historical events and related records that support spatio-temporal information reasoning (**T2**). Two types of records are treated as events, including status (e.g., friendship, adversary relationship, etc.) and actions (e.g., criticizing, writing articles, becoming friends, etc.). As shown in Figure 2 (b), concerning an *event* entity, related records include one or multiple involved historical figures (who) who take some actions (what) in specific locations (where) at specific time (when). They are represented as *figure* entities, *event type* entities, *location* entities, and *time* entities, respectively. Different types of edges connect those entities. For example, the edge type between *event* entities and *location* entities is *location is*. In addition, some background knowledge of these records is provided, including the name of the dynasties associated with each year, hierarchical administrative information of locations, office departments, and official ranks of figures' official positions. They are represented by entities and relations.

4.2 Chronology Modeling

Evidence from interviews of historians suggest that a simplified overview is needed to help them understand the variation of a historical figure's life **(T1)**. Thus, we set a scoring rule to evaluate the situation of a historical figure during a specific period. A higher $score$ indicates that the corresponding historical figures are more likely to have a better reputation.

To evaluate the $score$ of an event e, five key factors are considered:

K1. Importance of the involved figures. For example, criticisms from the emperor have more impacts than that from anybody else.

K2. Figure's role in the event. For example, if the person received an award or was promoted, the effect on the historical figure is positive. In contrast, critics have a negative effect.

K3. Event occurrence time. The influence of an event diminishes over time.

K4. Frequency of the events' types. Sparse events such as major successes and weddings should be highlighted.

K5. Interests of historians. Event types that historians are interested in are more important.

Lexicon-based sentiment analysis [48] takes the sum of emotional scores of each word in the text to measure the text's positive or negative sentiment. We refine this approach by computing the $scores$ over time for each historical figure p in year t. The definition of a $score$ can be expressed as follows:

$$score(t) = \frac{\sum_{e \in E_t} (\overline{PageRank}(P_e) \times Grade(e, r_e) \times I(e))}{\sum_{e \in E_t} I(e)} \quad (1)$$

where E_t denotes all events that involve figure p and occur in year t, and e is a single event in E_t. P_e indicates figures involved in e except p, and r_e is the role that the target person plays in e. We calculate the average weight of the involved figures based on their relationship with PageRank [49], which measures the importance of these figures (K1). The PageRank value of each figure is calculated with the directed graph of a heterogeneous network, where we treat figures as nodes and relationships in events as directed edges. We set the maximal iterations as 1,000 to reduce the computational burden.

$Grade(e, r_e)$ is a user-labeled value that considers the target figures' role r_e (e.g. victim or inflicter) in the event (K2). According to the needs of historians, a range of discrete values of about [-10,10] provides sufficient precision for historians to express their negative or positive cognition toward the event type (K5). Five historians are invited to grade 836 event types. We gather their grades and average them.

In addition, $I(e)$ measures the importance of event e:

$$I(e) = e^{-tf(e)} \times idf(e) \times w(type_e) \tag{2}$$

To reduce the bias induced by repeating with a high frequency normal events (K4), the component $e^{-tf(e)} \times idf(e)$ is used from the TF-IDF method in text mining [50]. For example, records of promotion can be easily gathered through historical official documents, which may be oversampled compared to other event types. Last, $w(type_e)$ is the weight of a specific event type, which can be controlled by historians (K5).

For each year t, we apply the weighted-accumulated scores of events before year t within N years. Because historical figures have a short lifespan on average, their situations may change relatively quickly. Historians typically consider the influence of events within five years, and earlier events may be ignored (K3). So we set N as 5, and use the exponential decay function to represent the attenuation value of influence before year t:

$$f(\Delta t) = e^{-\Delta t},\ \Delta t \in \{0, 1, ..., N-1\} \tag{3}$$

Thus, the averaged $score$ in year t should be given as:

$$\overline{score}(t) = \sum_{\Delta t=0}^{N-1} f(\Delta t) \times score(t - \Delta t) \tag{4}$$

Based on the proposed model, we calculate the $score$ for each historical figure and for each year, and visualize the variance of their life time with line charts, as shown in Figure 3 (b). It provides an an overview of the chronology of historical figures.

4.3 Representation-Learning-Based Uncertainty Modeling

We provide the historians with an automatic method to identify possible locations or time of uncertain events, as well as the related events that can be used in reasoning (**T2, T3**). It is equivalent to finding the most reasonable time or location entities linked to the reasoned event with relations *"time is"* or *"location is"* in the heterogeneous network.

The reasoning method of this study is based on the hypothesis that related historical events tend to share the same entities (e.g., figures, locations, and time), and vice versa. The plausibility of this hypothesis is confirmed by interviews with historians. The locations and time of related events are more likely to encounter missing or erroneous information. We apply a representation learning method to find related events and recommend possible reasons of the observed uncertainties.

The representation learning method learns semantic information of the heterogeneous network, embeds entities into low-dimensional vectors, and measures the similarity between two events. In addition, redundant information is filtered by means of the dimension reduction. Thus the inference process is faster than deductive reasoning [27], graph structure-based reasoning [28] and association rule mining [29], which consider redundant information in each prediction. However, since the representation is learned in a vector space, it is difficult to explain the reasons behind similarity observed between two entities. To address the issue, visual methods are used to help explore the potential causes of similarity. More details are provided in Section 5.4.

The system aims at learning both the semantic information of events' properties and the background knowledge, such as the hierarchical relation of the locations. Hence, we apply the random walk technique [28] to generate sequences of entities, which describe more detailed information about events. The sequences are taken as input of the bag-of-words model [51]. Its output is the vector representation of each entity. Each path of the random walk process denotes $P = V_1 \longrightarrow V_2 \longrightarrow \cdots\ V_t \cdots \longrightarrow V_l$ on all entities. V_t is the type of the entity v_t chosen in t^{th} step of the random walk. During the process of random work, the transition probability function f from entity v_t to its successor v_{t+1} on P is as follows:

$$f(v_{t+1}|v_t, P) = \begin{cases} \frac{1}{|N_{t+1}(v_t)|} & (v_t, v_{t+1}) \in E, \phi(v_{t+1}) = V^*_{t+1} \\ 0 & (v_t, v_{t+1}) \in E, \phi(v_{t+1}) \neq V^*_{t+1} \\ 0 & (v_t, v_{t+1}) \notin E \end{cases} \tag{5}$$

where E is the edge set in the heterogeneous network. $N(v_t)$ is the number of entities surrounding v_t, and $\phi(v_t)$ is a mapping function used to obtain the type of v_t. Thus, v_{t+1} must match the specified type V^*_{t+1}. For example, given a meta-path $Person \longrightarrow Event \longrightarrow Location \longrightarrow Location$, the consecutive entity of the $Person$ entities should be an $Event$ entity.

We define 9 types of meta-paths with domain experts and assign each of them a label, consisting of $family$, $politics$, $official\ career$, $religion$, $academics$, $social\ relation$, $migration$, $gender$, and $ethnicity$. We use the random walk to generate two million sequences of entities. They are taken to train the Bag-of-words model, a three-layer fully connected neural network model for vectorization. The cross-Entropy loss, with the SGD optimizer and the learning rate of 0.01, is applied to minimize the error rate of predicting the word in sentences. The outputs of the hidden layer represent the entities as vectors. The dimension of each vector is set to be 300, which is chosen by means of the cross-test technique. The cosine similarity between the vectors measures the probability of co-occurrence of entities.

Based on this result, we can identify the nearest *k* similar events of the event. Those events are more likely to have

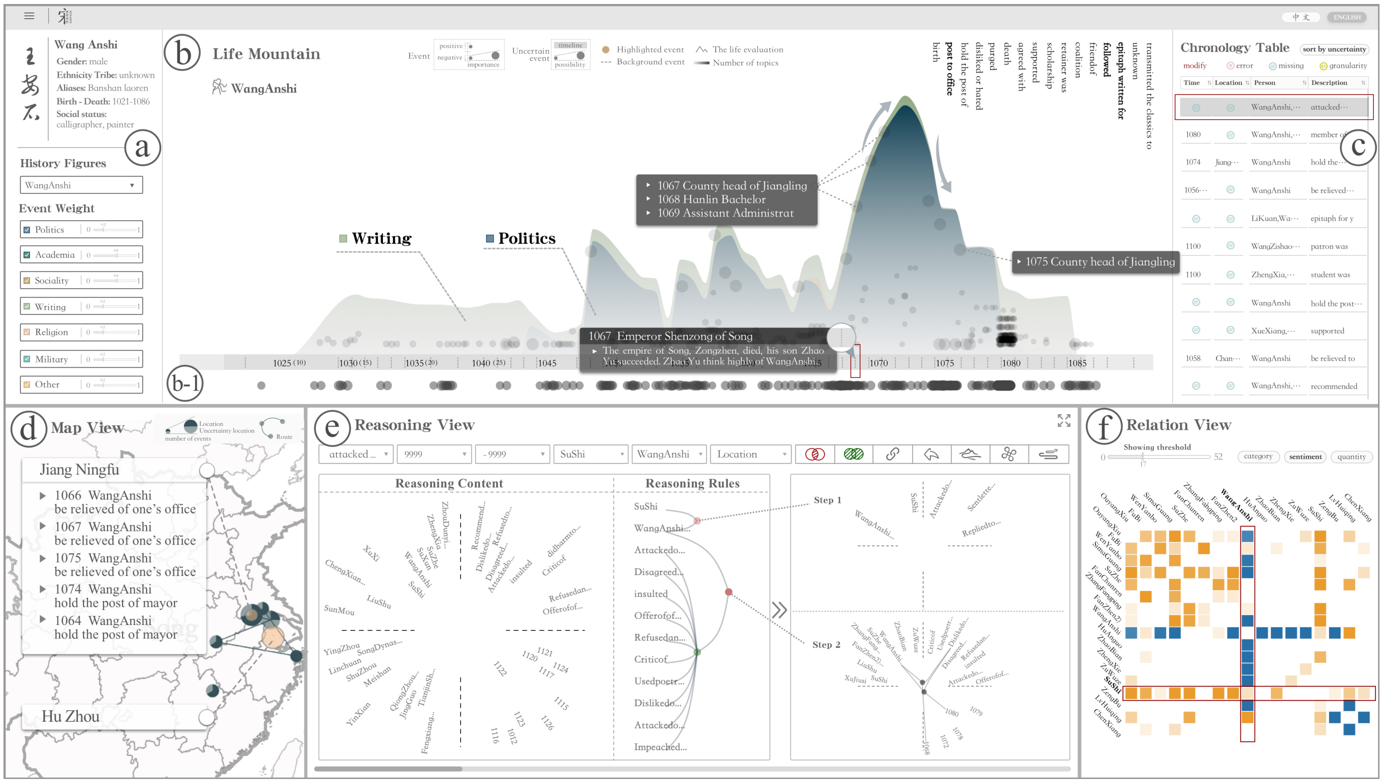


Fig. 3: The interface of proposed system consists of six components: (a) a control panel; (b) a Life Mountain view that shows the overview of historical figures' rise and fall in his (her) lifetime; (c) a chronology table showing the events with different types of uncertainty; (d) a map view showing the moving patterns; (e) a reasoning view that supports the inference of uncertain information in (b-1); and (f) a relation view presenting the social relationship between historical figures.

correlations, causal relationships, and sequential relationships with the target event. We further evaluate the hit ratio (the probability that the nearest k similar events contain the correct answer) of the proposed algorithm with the test data. We collect 1,000 completed *events* from CBDB, where some *entities* (e.g., *location* or *time* of the *events*) are manually hidden to simulate the uncertainty. The hidden parts are viewed as labels. We divide the data into training and testing sets and apply a 10-fold cross-validation method on the testing sets. We run the algorithm to identify the k most similar *events* for each target *event*. In the k similar *events*, if any similar *event* has the hidden *entity* of the target *event* (e.g., a given *location*), the target *event* is considered to be hit and a hit ratio is computed. The top-5 hit ratio of the 10-fold cross-validation is 48.1%, and the top-15 is 70.7%. Meanwhile, this process markedly reduces the search space for finding similar entities. With the visualization of suggested candidates, historians can better investigate uncertainty with domain knowledge.

5 Visual Analytics System

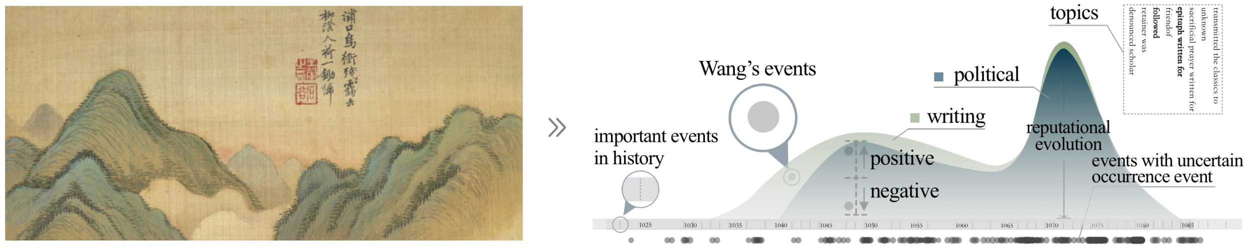
We develop a visual analytics system (Figure 3) to explore the chronology of historical figures and uncertain information. In the general pipeline of uncertainty reasoning in the system, analysts need to select a historical figure and identify uncertain events from the corresponding chronology timeline (Figure 3 (b-1)) to trigger the visualization (**T1**). Inference of the selected event is then enabled in the uncertainty reasoning view based on the entity recommendation (Figure 3 (e)) (**T2**). Additional information for the inference, such as the spatial, temporal, and social relationships among the entities, can be found in the Life Mountain, map and relation views (Figure 3 (b,d,f)) (**T1-T3**). Analysts can gain a deeper understanding of the selected historical figure and reduce uncertainty in the given information through iterative repetition of this process.

In this section, we take the life story of a famous Chinese poet and politician, Wang Anshi, to illustrate the proposed visual interface.

5.1 Chronology Table and Control Panel

The control panel (Figure 3 (a)) shows the selected figure's brief biography and provides a set of adjustment operations. The weight of each event type, $w(type_e)$ (Section 4.2), can also be interactively defined in the control panel.

The chronology table (Figure 3 (c)) enables historians to browse chronology in the tabular form with which they are familiar. The chronology table shows the raw data of certain and uncertain events where Wang is involved. Three icons are designed to distinguish different types of uncertainty: entities with missing information ( ), entities with erroneous or conflicting information (marked by historians,), and entities with coarse granularity ( ). Historians can revise and complete the table according to the recommended results on uncertain information obtained from reasoning views. Entities after the revision will be marked red. Historians can sort the table numerically or alphabetically when necessary. The quantified uncertainty of each event (i.e., the similarity to the most related event) produced by the



（a） Traditional Chinese Painting

（b） Streamgraph based timeline

Fig. 4: (a) A painting called The Return in the Dusk Mist, painted by Wanghui during the Qing Dynasty. (b) An overview of Wang's experience. The visual design of (b) is inspired by the traditional Chinese painting (a).

representation-learning-based model (Section 4.3) can also be adopted to sort the table for explorations.

5.2 Life Mountain View

The Life Mountain view (Figure 3 (b)) is the entrance for historical exploration and uncertainty reasoning, which provides an overview of Wang's life experience. Inspired by the metaphor of typical Chinese landscape painting (Figure 4 (a)), a streamgraph-based visual design is proposed to intuitively depict the ups and downs in Wang's lifetime.

A horizontal timeline (Figure 4 (b)) is adopted, where the important events in history are marked at their time of occurrence and visualized as short vertical lines. Hence, historians can associate Wang's life experience with the historic environment. Wang's life duration is also highlighted to help historians identify events that occurred before his birth or after his death. The height of the stream graph at time t encodes $\overline{score}(t)$ (Section 4.2), indicating the evolution of Wang's lifetime. Different streams show Wang's evolution from different perspectives according to the event categories (e.g., political, academic, military, etc.). These streams are stacked together to depict Wang's overall rise and fall. The events in which Wang is involved are encoded in dots and superimposed on the stream graph as an analogy of the brushwork in a Chinese landscape painting. Along the timeline, an event is positive if the dot is above the center of the mountain, and is otherwise negative. The closer the dot is near the top or the bottom of the mountain, the more positive or negative the event is, respectively.

The types of all presented events are vertically arranged in the top-right corner according to when they first appear, like an analogy of the inscription in a Chinese painting snapshot. The grayscale of each topic indicates its number of occurrences. A darker color indicates a larger number of events and vice versa.

Events with uncertain occurrence times are also encoded as dots below the timeline. Each uncertain event is located at the recommended time extracted from the most similar event (Section 4.3). The size of the dot indicates the event's importance, while the transparency represents the probability of the recommended occurrence time. Historians can therefore select uncertain events with relatively higher credibility to support further reasoning. This view also supports the comparison of multiple historical figures. When historians choose two figures, for example, in the control panel, their lifelines are simultaneously shown in the Life Mountain view. If they are related to an event, a dotted line is shown to indicate the event-based connection between them (Figure 5).

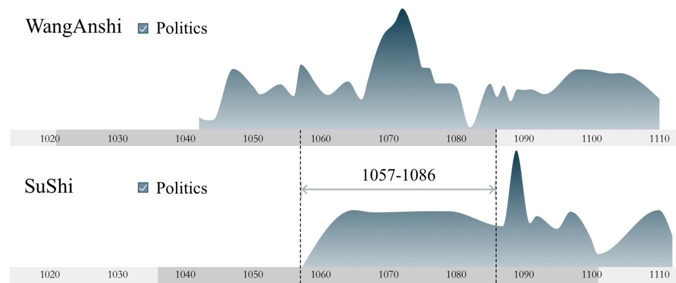


Fig. 5: Su Shi and Wang Anshi's political careers from 1057 to 1086. This timeline comparison narrows down the event occurrence time range effectively.

Interactions. Zooming and panning tools are provided for navigation and exploration. Historians can select an event (either certain or uncertain), and the details of this event are then displayed in a tooltip. Historians can also select interested event categories in the control panel to study the corresponding aspects of the historical figure.

5.3 Map View

We design the map view to visualize uncertain spatio-temporal information (Figure 3 (d)). The example shows Wang's moving pattern by displaying the event locations on the map. For each location, we obtain a set of events that involved Wang and occurred at this location. Events with missing location information are recommended to occur at the location extracted from the most similar event (Section 4.3).

A set of pie charts shown in Figure 3 (d) represent the proportion of certain and uncertain events in event sets at different locations. The size of the pie chart encodes the number of all events in this set. Events with certain time and location information are connected in chronological order to show Wang's moving pattern. Zooming and panning tools are also provided. Once historians select a pie chart, the detailed information on the events in this set will be listed in a tooltip. The listed events are sorted by probability, with certain events on the top followed by uncertain events.

5.4 Reasoning View

The process of uncertain reasoning makes use of the context (events with similar time, place, person, and event type) in the heterogeneous network. In traditional information search designs, two points affect the user experience when they browse the relevant events. First, too many similar events may be displayed and clustered during exploration, and the intensive arrangement makes it difficult for users to exactly select an interested event. Hence, the representation learning method (Section 4.3) is applied to reduce the search space and then decrease the number of results. In the meantime, it simultaneously learns the patterns and measures the similarity between events. Co-occurrence implies possible causality, accompaniment, and other relationships. Based on the machine-recommended data, the system shows relevant events, which can be further judged by historians combined with their domain knowledge. Second, the presented events require cross-verification. Thus, we design a method to categorize and organize the recommended events, which is not well supported by common systems that display search results, such as Google. Typically, each search result of Google is a single answer to the question, while the correlations between the recommended results are not shown. It requires historians to reiterate browsing a large number of search results for further comparison.

We thus design the proposed reasoning view (Figure 3 (e)). Once an uncertain event is selected in the chronology/map view, it will appear at the center of the reasoning view, with other similar events surrounded for uncertainty inference and cross-verification. As shown in Figure 6, the reasoning view consists of two major components: reasoning content and reasoning rules.

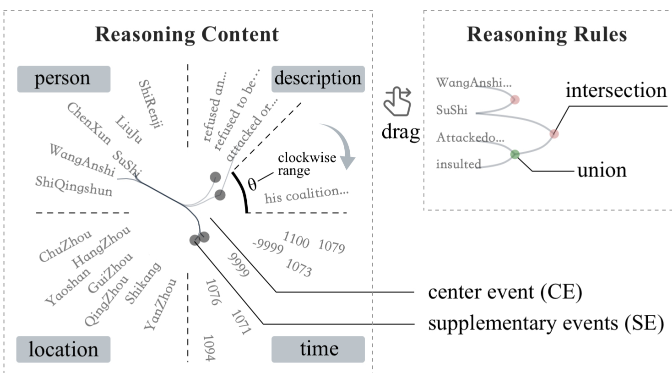


Fig. 6: The reasoning view contains two primary parts: the reasoning content and the reasoning rules.

Reasoning content includes a central event (the selected uncertain event to be reasoned, **CE**) and other supplementary events (**SE**) that provide important reasoning cues. We use the top-50 recommended SEs that are most similar to the CE (Section 4.3) as default. This threshold can be adjusted in the control panel. The selection of SEs is based on the aforementioned hypothesis that events sharing the same entities might be related. Therefore, we further extract the entities *([description, time, location, person])* from SEs.

Figure 6 shows the visual design of the reasoning content. CE and SEs are located in the central circular area as gray dots, with CE in the center surrounded by SEs. The extracted entities are organized in a radial layout outside the central area. Entities of four types *([description, time, location, person])* are arranged clockwise in four quadrants, where entities of *description* occupy the first (top-right) quadrant. The distance between each entity and the CE represents the similarity between the corresponding SE to which this entity belongs and the CE. A smaller distance indicates that this SE and CE pair are more similar to each other. By means of one-dimensional t-SNE [52] that projects SEs to a $[0°, 90°]$ clockwise range, a unique angle is obtained for each corresponding entity to reduce visual occlusion. We took a trial-and-error approach for choosing the perplexity by a divide-and-conquer method. We tested a group of candidates, and finally chose the perplexity as 5. The location of each SE in the central area is determined by averaging the coordinates of the entities extracted from this SE.

The radical layout of words is chosen in that other designs, like node-link based or matrix-based visualizations, are difficult to identify the unique relations among particular nodes and neighborhoods. We also employ the interaction mode in the monadic graph [53], making it more flexible to exploit the reasoning view.

Reasoning rules refer to the user-defined rules for filtering the displayed SEs and entities in the reasoning content (Figure 6), in order to obtain more supportive evidence. Two rules are supported: 1) intersection that preserves SEs containing all selected entities and 2) union that preserves SEs containing at least one of the entities. Historians can interactively drag one or a set of entities from the reasoning content and add rules. Figure 6 shows the visual design of the reasoning rules. Entities are organized according to the drag operation, and rules are represented by circular nodes. Pink nodes indicate the intersection operations, and green nodes indicate the union. In particular, historians can add new rules to previous rules, ultimately formulating a rule tree.

The reasoning process is iterative. A pair of reasoning content and reasoning rules forms a single reasoning step, and a complete reasoning process usually consists of multiple steps. Historians can step by step define new rules based on the filtered content to obtain the most related SEs. As a result, uncertain entity of the CE can be reasonably assumed according to the related SEs. The filtered content produced for the CE will be reorganized and updated on the right at the interface. It thereby allows historians to cross-verify the rationality of the reasoning result from different aspects. Details of the entities from the CE are listed on the top of the reasoning view to help historians find related entities in SEs.

Interactions. Hovering on a SE in the reasoning content will highlight and connect the corresponding entities extracted from this SE. Zooming and panning tools are offered. When it is necessary to clearly show the top-200 recommended SEs, historians can enlarge the reasoning view to full screen size by clicking the enlarging button on the top-right corner. A toolbar is also provided at the top of the view for rule definition, operation recall, and information update. After the reasoning step, historians can update the time, location, involved historical figures, and reasoned event types. The reasoned uncertainty will improve the model by incremental learning. Starting from the CE, a meta-path based random walk is used to generate paths containing corrected information (Section 4.3). Then, these paths are adopted to incrementally train the existing skip-gram model. In addition, a higher leaning rate (0.05) is adopted. Thus, new information is considered in the future reasoning process.

5.5 Relation View

We design the relation view to enable historians to study historical figures' group behaviors in more details (Figure 3 (f)). With the assistance of PageRank (Section 4.2), we extract the top-20 historical figures most related to Wang by default. The threshold is adjustable. The grid (i, j) in the relation view represents a set of events that involve person i and person j. Historians can switch among three modes to display different types of information of these grids. The first mode displays the size of the event set in grayscale, where the darker color indicates more events. The second mode shows the positiveness and negativeness of the event set. A yellow color indicates that the average grade of events is positive, and blue indicates negative. These grades are manually labeled by historians, as described in Section 4.2. The third mode uses a consistent color mapping, as in the Life Mountain view, to depict the leading category (e.g. politics or literature) of the event set. The leading category represents the one shared by the events that occupy the largest proportion in the set. In the relation view, the grids are sorted by the Girvan Newman algorithm [54] so that historical figures with closer relations are gathered.

6 Case Studies

We demonstrate the effectiveness and usability of the proposed system with in-depth case studies. The first case explains a simple visual reasoning process for uncertain information. The second case involves a complex life story of a famous Chinese poet and politician, Wang Anshi. We describe in further detail uncertainty reasoning and party identification.

6.1 Case 1: Uncertainty Reasoning

In this case, we take the event that *Su Shi wrote an epitaph for Fan Zhen* as a central event (CE_{ep}) used to explain the reasoning process. In this event, the *time* information is missing, and the goal of this process is to infer the time of occurrence of CE_{ep}. Figure 7 shows the entities extracted from the related events (SEs) in four quadrants, as described in Section 5.4. In the first (top-right) quadrant, we discover that the entity *"died"* is close to CE_{ep}, indicating a close relationship between CE_{ep} and *"died"*. Historians suggest that people tend to write an epitaph for friends soon after their death. Based on this knowledge, we assume that the time of occurrence of CE_{ep} is likely to be the year when Zhen died. Thus, we add a filter in the reasoning view to identify the intersection set of entities E_{Zhen} and E_{died}. Only one event is preserved after filtering, indicating that Zhen died in 1088. Now, we can reasonably assume that Su wrote an epitaph for Zhen in 1088.

Other common knowledge can also be used for the reasoning process. For example, the event that a person served as a local officer occurred after the retirement/resignation of the former officer.

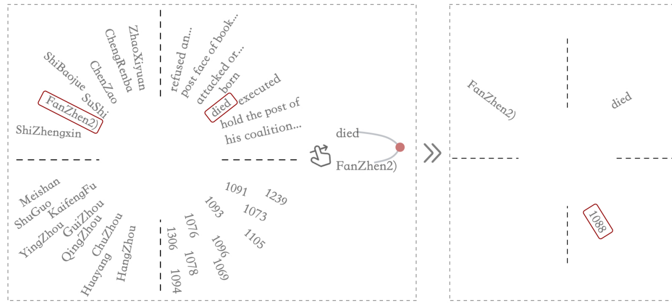


Fig. 7: Uncertainty reasoning of the event that Su Shi wrote an epitaph for Fan Zhen.

6.2 Case 2: Exploring a Historical Figure's Life Story

Consistent with the example described in Section 5, we show a comprehensive case exploring the life of Wang Anshi.

6.2.1 *The Life Story of Wang*

We explore the life story of Wang Anshi in the chronology view (**T1**). Figure 3 (b) shows that the middle- and late-stages in his lifetime has encountered frequent rises and falls. A visual inspection helped us to identify that he primarily focused on political affairs in his middle age and literary writing in his early and late life. A considerable increase on the mountain height occurs around 1067. By browsing the events occurring in a comparable period, we find that Wang held many important government posts after 1067. According to the historical background in 1067, Shengzong, who appreciated Wang, became the new emperor. This hypothesis is supported by evidence of an increase of Wang's $scores$ after 1067. However, after 1074, we observe a reverse trend, which may be associated with the fall of his political life when he lost the appreciation and was sent to Jangling Province. Despite the decline of his political career, Wang's literary life arose suggested by darker green elements in Figure 3 (b).

6.2.2 *Reasoning Uncertainty*

Many uncertain events in Wang's lifetime also occurred, as shown in the chronology table (Figure 3 (c)), resulting in difficulties for historians to get an accurate representation of Wang's lifetime and events associated with historical figures related to Wang. In the control panel, we sort these events according to their levels of uncertainty, as described in Section 5.1. Then we select an event with relatively lower uncertainty to infer. This event indicates that Su Shi disapproved Wang's policy; however the event lacks information about time and location. The goal of this process is to make a reasonable assumption of the missing time and location entities (**T2**). We selected this event as the central event in the reasoning view, denoted as CE_{pol}. Then we added a rule to find the intersection set of entities E_{Wang} and E_{Su}. Three events are preserved after filtering. However, none of them indicate the time or location information (Figure 3 (e)), which hinders the proposed reasoning process.

Reasoning about the time entity (T2). Since CE_{pol} is a political event, it should occur during the intersection of Wang and Su's political careers, which lasted from 1057 to

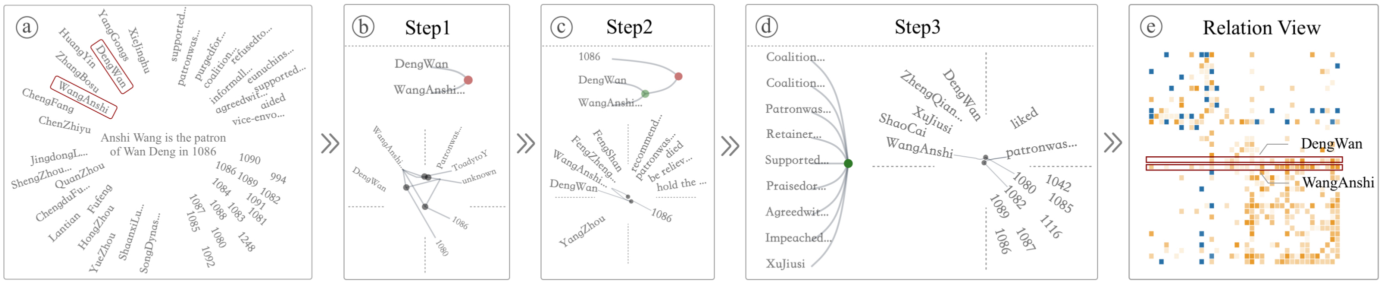


Fig. 8: Process of identifying a political party on Wang Anshi and Deng Wan under different filtering rules. (a) shows related SEs of the CE that Wang helped Deng. (b) shows the entities from the their intersection (colored in red). (c) shows the results generated by additional explorations. (d) shows the union of all entities with positive intentions (e.g., support). (e) indicates Wang and Deng were in a closely connected group, shown in the relation view.

1086 (Figure 5). Typically, political attacks were collective behaviors, making them more effective. Entities with a similar meaning of *disapproval* are displayed in the reasoning view, such as *insult* and *criticism*. It suggests that Wang was politically attacked in 1080 by a group of people. By selecting these people in the relation view, we discover that Su was also in this group (Figure 3 (f)). Thus, we assume that Su might have attacked Wang together with people from the same party in 1080.

Reasoning about the location entity (T2). The next step is to infer the missing location information. By searching for events that occurred approximately in 1080, we discover that Wang served as an officer in Jiang Ningfu in 1077, and Su served as an officer in Huzhou from 1079 to 1080. We confirm that Wang stayed in Jiang Ningfu approximately in 1080 by cross-validation on the map (Figure 3 (d)). The pie charts in green color show all the places of Wang's event occurrence. The circles in yellow indicate the places Wang visited most frequently from 1057 to 1086. Therefore, we assume that CE_{pol} has two possible locations: Jiang Ningfu and Huzhou.

This case highlights a process used to infer missing information of an uncertain and complex event. This method can also be applied mitigate and reduce uncertainty associated with data inaccuracies. We can remove the error location or time of the event, and regard it as a event missing corresponding information.

6.2.3 Identifying a Political Party

We are also interested in Wang's group behaviors (**T3**). Thus a specific event is selected in the chronology view of Wang, stating that Wang Anshi helped Deng Wan in 1086. To find events that involve both Wang and Deng, we add a rule in the reasoning view to find the intersection set of entities E_{Wang} and E_{Deng}. The filtered result shows two events, both of which say that Wang helped Deng (Figure 8 (b)). However, how Wang helped Deng remains unknown. Therefore, we add another rule to find the set $(E_{Wang} \bigcap E_{1086}) \bigcup (E_{Deng} \bigcap E_{1086})$ to obtain all the events of Wang and Deng in 1086. Among these events, we discover one event stating that Deng was promoted to a higher official rank (Figure 8 (c)). The chronology view of Deng confirms this promotion and shows a rapid rise in the streamgraph in the year 1086. Based on these discoveries, we propose that Wang contributed to the promotion of Deng because Deng was a member of a political party led by Wang in 1086.

To confirm this, we must find clues that indicate the existence of a political party. With the union operation for entities such as *support* and *recommendation* in the reasoning view (Figure 8 (d)), events that may indicate the group behavior are filtered. People involved in these events are shown in the relation view (Figure 8 (e)), in which we discover a closely connected group. Wang and Deng are both members of this group, which confirms the proposed conjecture.

7 User Study

To evaluate the usability and functionality of the proposed system, we conducted two user studies under two usage scenarios. The first conducted a **targeted analysis**, where the participants were required to infer the manually hidden location or time of certain events. The second involved an **exploratory analysis**, during which experts freely explored the system to discover insights. We intended to verify three hypotheses through these two user studies:

- **H1** Experts can understand the design and interaction of the proposed system.
- **H2** Experts can use the system to identify the suggested information for uncertain data.
- **H3** Experts can gain insights when exploring historical figures using the system.

7.1 Participants

We recruited fifteen university students/researchers (female: eight) for the two studies. All were postgraduate students or postgraduate degree holders, including three professors (P1-P3), two postdoctoral fellows (F1-F2), eight Ph.D. students (D1-D8), and two master students (M1-M2). Nine were between ages 20-29, five were between ages 30-39, and one was above 40. P1-P3 had experience in the construction and research of historical data in the CBDB for more than seven years. While D2-D4 and D8 had used the CBDB for approximately one year to study historical data annotation and other digital humanity-related issues. Twelve of the participants had a solid academic background in Chinese history, and the remaining three (D5-6, M2) were history enthusiasts. We divided the participants into two groups based on their expertise and project involvement to perform either study. Ten participants (P3, D2-D8, M1-M2), who have never used the system, participated in the first user study. The other five (P1-P2, F1-F2, D1), who had been involved in the iterative design process, took part in the second user study. None of the fifteen participants were a coauthor of this manuscript. Because several participants were located in a different region/country, we deployed the proposed system as a web application and conducted user studies via remote video conferencing.

7.2 Targeted Analysis

The first user study involved targeted analysis and aimed to verify **H1** and **H2**.

7.2.1 Procedure and Tasks

After the participants completed the demographic questionnaires, the experimenter introduced the visual design of the system. Its interactive functions were demonstrated with an example (as in Section 6.1) for approximately 20 minutes. The participants were asked to repeat the operations of the example to go through the system functionalities. This practice ensured that the participants attained adequate familiarity with the system to complete the following tasks.

For the real experiment, we designed a set of tasks related to participants' research problems. We selected four complete historical events in the CBDB, which were regarded as the ground truth. Then, we manually hide their location, time, or both to perform the targeted analysis tasks by figuring out the following questions:

Q1 Wang Anshi wrote a memorial for the death of Cheng Lin in ***1041 or 1080***.
Q2 Qin Hui had ostracized Wang Shang during ***1142-1155***.
Q3 In 1174, Lv Zuqian and Qi Rugui traveled to ***Jinhua or Quzhou*** together.
Q4 During ***1070-1080***, Su Shi criticized Wang Anshi's reforms at ***Huzhou or Jiang Ningfu***.

Using the system, the participants were asked to recover the hidden information (shown in bold and italics), i.e., the exact time in a duration or the correct location of the candidates. These tasks required participants to use different core functions of the system. The participants had no time limits on the tasks, and they could quit the tasks if they were not able to find the answer.

After the tasks, the participants filled out the System Usability Scale (SUS) questionnaire [55] and answered four interview questions. The entire process took approximately one hour.

7.2.2 Data Collection

To verify **H1**, we analyzed the questionnaire results. To verify **H2**, we measured the participants' performance by assessing their answers to the tasks and the time they spent on each task. The experimenter noted participants' interview answers, and recorded their feedback on the various views of the system.

7.2.3 Results

SUS Questionnaire Result. The average System Usability Scale score of the proposed system was 71 (Figure 9), marginally exceeding the recommended average of 68 [55], which supports **H1**.

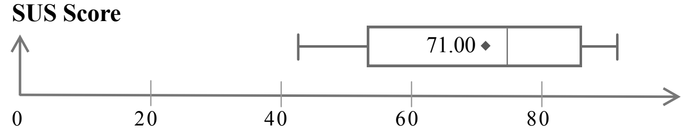


Fig. 9: SUS Questionnaire Result.

Task performance. As shown in Figure 10, most participants found the correct answers with the help of the system except for Q4, which had the lowest accuracy. Q4 was challenging because both the time and location information were hidden, and it had fewer related data in the CBDB. Four participants got either the time or the location corrected. In particular, P3 and D8, who were rigorous about answering the question, argued that the inference result was still uncertain and chose "Song Dynasty" as their answer. It is a convention in the CBDB, albeit they had come across the correct answer during their analysis. P3 commented, *"the system is useful in recommending clues to make reasonable inference when there are no certain answers... but keep in mind that there is no way to make unknown historical events known"*.

On average, participants spent 6.9 minutes completing a task with a standard deviation of 5 minutes. We observed a relatively large variance because participants showed various levels of rigor in the way they select information and how much information they need to draw a conclusion. P3 also mentioned that they typically spent more than an hour on solving a similar problem in their daily work without the proposed system. This system can therefore significantly increase their work efficiency and reduce mundane, tedious tasks. Therefore, the results **bring evidence to support H2**, which states that the system could help solve experts' research problems.

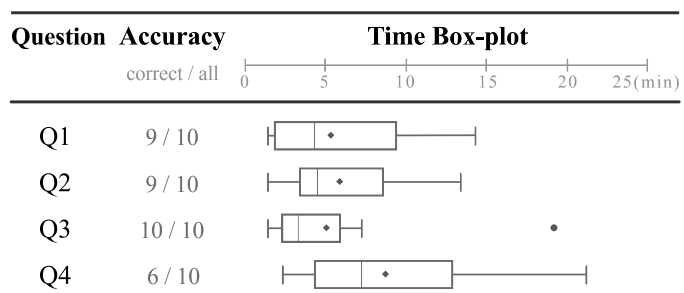


Fig. 10: Quantitative performance of the targeted analysis.

7.3 Exploratory Analysis

In the second study, the participants were tasked with free-form explorations to verify **H3**.

7.3.1 Procedure and Task

Since the five participants were familiar with the system, the experimenter spent only 10 minutes introducing the system. After the demonstration, experts explored the system using the think-aloud protocol for approximately 30 minutes. Following the instructions, they freely explored the system following their research interests to discover insights, and spoke their thoughts during the analysis. After the task, the participants answered the same interview questions as in the first study to evaluate the system functionalities. During the experiment, we recorded participants' screens and voices for analysis. The entire experiment took approximately 1 hour on average.

7.3.2 Results

During the free-form exploration, all participants were able to find interested insights. For example, F1, who studied the writers from the Song Dynasty, was interested in the writers' life events. In her exploration, she first selected Huang Tingjian, a famous poet in the Song Dynasty, and found a series of outing activities in 1097. This discovery inspired her to further investigate Huang's poems. However, she observed that the location information of these outing activities was missing. She explored the related events and figures, and found a group of people going outing with Huang at that year. She became more curious and selected one of them, called "Song Ban", in the reasoning view (Figure 11). She set the union operation of Song Ban and Huang Tingjian in 1097 and found that Song Ban originated from Sichuan Province. Other people in the group were all from or related to Sichuan. Then, she accidentally found an unknown "traveling group" in Sichuan at 1097 with a close relationship to Huang Tingjian. With this discovery, she reduced the uncertainty and concluded that Huang was in Sichuan. She also connected these outings with the event that Huang was demoted to Fuzhou, Sichuan Province. She designated Fuzhou city as a probable location for these outings. She was very satisfied with this exploration and expressed her interest in further exploring unknown traveling groups using the proposed system.

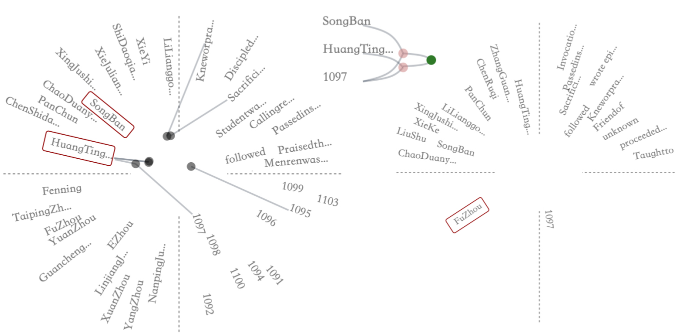


Fig. 11: Exploring the event of "Huang Tingjian went on an outing with Song Ban" to infer the possible location of "Fuzhou" in Sichuan Province. Key findings are highlighted in red.

P1 explored several events and commented, *"although the recommendation cannot provide direct confirmation of uncertainty, it helped me reduce the search space of the related information considerably, which is beneficial for my research"*. Thus, the results of this experiment brings some evidence that **H3** is true.

7.4 User Feedback

From the two studies, we analyzed user feedback collected through the interview questions.

The Life Mountain View: All participants confirmed that the mountain structure was a very intuitive visual form of expression. D4 said, *"the mountain structure reasonably shows the political, academic, and other multiple aspects of life"*. D1 and D4 appreciated the adjustment function of the proportion of each aspect. F1 mentioned, *"the system extracts the multivariate information on the timeline of the life of historical figures. The scoring mechanism and the chronology view indicate the important status of their lives"*.

The Reasoning View: Once we introduced and demonstrated the function of the reasoning view with an example, all participants gradually knew how to interact with it. Five participants indicated that the reasoning view was easy to understand (D1-4, D7). While five stated that it required a lot of background knowledge and logical thinking (M1, D5-D6, D8, P3). P3 said: *"This function is helpful, but not easy to understand, and I think this module is the most difficult but worth it for users to understand in the entire system. I do not think it is a poor thing. In the process of system promotion, it is necessary to explain this module fully"*. Without exception, participants stated that they did not know any tools with a similar function. They also agreed that it was a powerful function for scholars to extract relevant events from massive data quickly, and conduct further reasoning and textual researches.

The Uncertainty Recommendation Algorithm: Participants thought that the method could significantly help people reduce information uncertainty with very detailed and valuable clues (P3, M4-6). This algorithm can be used as an additional reference tool in historical textual research and help improve the work efficiency (M3, M5-7).

Usability and Learning Difficulty: Regarding learning difficulties, they all agreed that most parts of the tool were easy to understand, except for the reasoning view and the interactions between each view. They agreed that the 20-minute introduction allowed them to understand the core functions of the system. F3 stated, *"The timeline, relation view, and maps are familiar to me; thus, there are no problems for me to learn them. The reasoning view looks somewhat complex, but after trying the dragging function, I already know how to use it"*.

Overall Evaluation: F1 commented, *"with the data-driven approach, we can observe the grouping patterns of the writers in my research, to understand their common behaviors in that period. Such results provide good hints in this study"*. F2 particularly appreciated the visual design of the proposed system, stating, *"the interface has both technical elements and classical beauty. Each panel is clearly stated with fluent interaction. To improve usability, I suggest providing an operating manual"*.

Suggestions for Improvement: Participants provided many valuable suggestions and expressed the needs for such a system in their research. One precious suggestion from F2 is focusing on the minority in the analysis: *"Famous figures have been well studied. However, historical figures in a specific area have not gained much attention. I suggest investigating such figures more closely, possibly to gain new insights"*.

8 Discussion

This section summarizes the learned lessons and the limitations of this study, and envisions possible future research paths.

8.1 Lessons Learned in Collaboration with Historians

Researchers from computer science and humanities have different views on data. As computer science researchers, we focus more on patterns, trends, and correlations. This study has helped us to understand the important role of the spatio-temporal locations of events in analyzing historical figures. Historians prefer the human-in-the-loop perspective of visual analytics, which fits with their working styles. We believe that their view is sensible and constrained us to improve our approach to analyze and present data.

Integrating the domain knowledge of historians into a visual analytics system is a challenging but rewarding task. In the iterative design for uncertainty reasoning, we conducted a trial by inviting historians to label the data of event type, which was integrated into the proposed model. The evaluation feedback brings some evidence of the effectiveness of collecting these manual labels. However, since the concept of data analysis has not yet been fully applied in history research, some misunderstandings remain. For example, we have a different understanding of data scales. Historians tend to conduct small but in-depth research, while computer scientists tend to collect big data for pattern identification. In the system design phase, historians also refer more to the text materials instead of numerical data as evidence.

8.2 Limitations and Future Works

The proposed approach emphasizes reasoning about the causes of uncertainty but encounters difficulty to capture it. In the case study, we focus more on reducing uncertainty with missing data and vague granularity. For data errors or conflicts, we rely on the historians' pre-labeling. Future works might integrate the full workflow of identifying, reasoning, and refining uncertainty.

As suggested by historians in the evaluation phase, the advantage of the proposed uncertainty reasoning is to narrow down the search space but not to provide seemingly correct answers without accounting for uncertainty. Since the proposed approach is based on inference and recommendations from possible hidden relations, the results may not be perfectly correct. These issues motivated us to develop the visual interface to involve historians' judgment via interactive exploration. In the proposed system, when historians try to find the missing data of an *event* (e.g., *location*), we currently recommend the most possible answer according to similar events. However, it should be beneficial and flexible to explore more possibilities if other possible answers are provided.

Analyzing historical remain complex since the interpretations from different historians may not necessarily converge. Furthermore, various reasoning results may introduce additional sources of uncertainty. Hence, we currently allow historians to explore the data recorded in the CBDB, and save the reasoning results to their personal computers, but we do not update the results to the online digitized database.

The proposed uncertainty reasoning method is shown in a case-by-case manner, which fits with the common approach of historical study. However, our approach is not scalable enough to deal with all possible sources of uncertainty and historical contexts. In the future, we envision combining active learning methods to possibly extend historians' judgment on more cases to improve the efficiency of uncertainty reduction.

During the uncertainty reasoning process, we envision to further recording historians' operations, which would be more convenient for historians to review the previous steps to examine. These features might allow us to set up a collaborative environment for historians to work on uncertainty reasoning and group behavior analysis.

9 Conclusion

In this study, we propose a visual reasoning method for reducing uncertainty associated with records of historical figures. Powered by the heterogeneous network-based embedding method, the reasoning process is able to generate uncertainty recommendations and conduct interactive visual explorations. In this process, we integrate the domain knowledge of historians using labeled data as the input of the proposed model. Then suggestions are provided for historians to make judgements. Our results suggest that historians can considerably reduce the search space for specific uncertain events to improve efficiency. The related features and explorations can also help historians to get new research insights into group behaviors. Strong collaboration with historians can contribute to visual analytics communities with in-depth requirement analysis and evaluation feedback, paving the way for future research in these directions.

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