Functional Design of Personalized Services for Digital Humanities Platforms: A Case Study of Shanghai Library (Postprint)

Authors: Liu Peizhong, Dai Qingyi

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Abstract

[Purpose/Significance] Based on users' individual research interests and information needs, this study explores pathways to achieve precise push of digital humanities information, so as to optimize the functions of China's digital humanities platforms. [Method/Process] Taking the digital humanities platform of Shanghai Library as an example, it explores the application of three service methods—knowledge graph, user profiling, and hot-spot push—in the field of humanities, aiming to enhance the service quality of modern libraries and provide users with more efficient and high-quality services. [Results/Conclusion] The study shows that combining efficient artificial intelligence recommendation algorithms with digital humanities services can provide users with various precise and high-quality recommendation services, pushing high-value information precisely to users.

Full Text

Preamble

Research on Personalized Service Function Design for Digital Humanities Platforms: A Case Study of Shanghai Library

Liu Peizhong, Dai Qingyi

Shanghai Library, Shanghai Institute of Scientific & Technical Information, Shanghai 200031

Abstract: *[Purpose/Significance]* To optimize the functions of digital humanities platforms in China, this study explores pathways for achieving precise push of digital humanities information based on users' personal research interests and needs. *[Method/Process]* Taking the digital humanities platform of Shanghai Library as an example, this article investigates the application of three service approaches—knowledge graphs, user profiling, and hotspot push—in the humanities field to enhance the quality of modern library services and provide users with more efficient and high-quality services. *[Result/Conclusion]* The research demonstrates that combining efficient artificial intelligence recommendation algorithms with digital humanities services can provide users with various accurate and high-quality referral services, precisely pushing high-value information to users.

Keywords: digital humanities; knowledge graph; library services

With the rapid development of modern information technologies such as data science, big data, geographic information systems, text mining, and information visualization, digital humanities (DH), characterized by its interdisciplinary and cross-domain nature, has profoundly influenced fields including historical geography, literature, and computer science, becoming a powerful supplement and driving force for traditional humanities research. Particularly in the big data environment, digital humanities conferences [1-2], research projects [3-4], and centers [5] worldwide are flourishing.

The digital humanities wave has driven the widespread emergence of digital humanities platforms both domestically and internationally. A digital humanities platform refers to a network platform that provides digital humanities scholars with a series of resources, data, tools, and services related to the digital humanities discipline. Such platforms collect and organize relevant information to enable unified access to digital humanities information resources, serving as a bridge for analyzing and disseminating digital humanities information. They satisfy the diversity of humanities scholars' research needs and provide support for using technology to promote interdisciplinary humanities research [6].

Currently, foreign digital humanities platforms include the American Historical Association (AHA) Digital Humanities Platform and the ACO*HUM—Advanced Computing in the Humanities platform, among others. Domestic digital humanities platforms are relatively few, with examples including the "Digital Humanities Research Center" of National Taiwan University and the "Digital Humanities Research Center" of Wuhan University, which have established corresponding digital humanities platforms.

Most existing digital humanities platforms merely use linked data technology to organize and publish knowledge at the metadata level of literature, lacking sufficient mining, extraction, and filtering of massive data. This results in low value density of services provided by digital humanities platforms, preventing users from obtaining valuable information in a timely and efficient manner and causing resource waste. To optimize digital humanities platform services, this article attempts to use the practice of Shanghai Library's digital humanities platform as an example to explore the possibility and potential of implementing personalized digital humanities services through comprehensive application of knowledge graph recommendation [7], user profiling push, and popularity-based recommendation.

2. Research and Development Status of Digital Humanities Platforms

The library community both domestically and internationally has long conducted in-depth research on digital humanities. According to statistics on relevant domestic literature by He Panpan from the School of Information Management at Nanjing University [8], domestic research can be divided into three stages: the early 萌芽 stage (2011-2012), when Chinese literature emerged nearly a decade later than foreign literature. The first relevant document was a speech at the "Third Sino-American International Symposium on Library and Information Science Education in the Digital Age" [9], which proposed that qualified "embedded librarians" should possess knowledge in digital humanities, statistical and computational methods, natural language processing, corpus linguistics, and other areas to provide knowledge consulting services; the initial development stage (2013-2015), when research literature grew slowly, with annual output remaining at 5-15 articles; and the rapid development stage (after 2016). In 2016, Peking University Library launched a series of digital humanities activities, including hosting the first Peking University "Digital Humanities" Forum and inviting domestic and international digital humanities scholars for special lectures, resulting in a "blowout" growth in academic papers in 2016. In terms of recent development trends, relevant research in the digital humanities field in China is already in a stage of rapid development.

A digital humanities platform is an application of digital humanities technology, essentially "a knowledge sharing platform and content open platform that aggregates data resources, data tools, and data services based on digital humanities technology" [10]. However, literature research in this area remains scarce. As of October 17, 2021, using "digital humanities platform" as a keyword to search titles in the CNKI database yielded only 36 results. These documents discuss the comprehensive service functions that digital humanities platforms can achieve, including text mining, visual analysis, scene simulation and restoration, and corpus utilization, but few study the implementation methods and functional design of personalized services from a user perspective.

From the library perspective, personalized service is user-centered, providing information services based on the study of user behavior, interests, hobbies, specialties, and habits [11]. For users with specific research needs, compared to comprehensive and flat information services, they more urgently desire precisely targeted personalized services. Specifically, this means collecting, organizing, and classifying digital humanities information through various channels according to knowledge graph co-occurrence, user profiling, and other technologies, and providing and recommending relevant digital humanities information to users, thereby offering precise information services. Overall, personalized digital humanities services transform the traditional passive service model into a comprehensive active service that fully utilizes various resources of the digital humanities platform to meet users' personalized digital humanities needs. Although this platform construction thinking has been widely used in various commercial platforms, it is rarely applied in digital humanities platforms. According to the author's investigation of National Taiwan University's "Digital Humanities Academic Research Platform" and Wuhan University's "Digital Humanities Research Center Platform," these platforms primarily provide data feedback through user queries without collecting and analyzing user data for personalized services. Therefore, adding personalized service functions to digital humanities platforms can provide more targeted services for users.

3. Functional Design of Personalized Services for Digital Humanities Platforms

To provide readers with high-quality personalized services, Shanghai Library's digital humanities platform planned its functional design from three aspects from the initial stage: using knowledge graphs for data construction, collecting user behavior data for user profiling, and conducting popularity recommendations based on recent browsing data. In this practice, personalized services are specifically reflected in two aspects: improving the matching degree between digital humanities platform information services and user needs, filtering information noise as much as possible, and solving the popularity bias problem; improving the prediction accuracy of digital humanities platform information services for user needs, shifting from passive service to proactive and precisely targeted prediction, and promptly pushing welcome digital humanities information that matches users' personalized interests.

3.1 Co-occurrence Function

"Co-occurrence" refers to the phenomenon where information described by characteristic items of literature appears together. These characteristic items include external features of literature such as title, author, and institution, as well as internal features such as character relationships, institutional evolution, and related events. The co-occurrence requirement for search results means that Shanghai Library's digital humanities platform, based on users' search behavior, not only matches relevant literature by external features of search terms but also pushes literature knowledge associated with internal features to users [12], helping the platform reveal content associations of information and implications hidden in characteristic items.

3.2 Push Function

The push function refers to the platform's proactive push of information, literature, or resources to users. Personalized push is based on users' interest points, delivering different content to different customers according to their personalized needs. The backend mechanism of the personalized push function is to collect data on users' searches, browsing, and comments during platform usage, analyze and process it to form user profile data, and proactively push content related to their interests when users use the platform in the future.

3.3 Recommendation Function

The recommendation function refers to uniformly recommending hotspot resources to all users. Shanghai Library's digital humanities platform needs to collect users' recent search and browsing data, analyze user-platform interaction data to obtain current hotspot content, and display it to all users in the platform's recommendation column. The recommendation algorithm needs to adopt a more aggregated popularity algorithm to solve the popularity bias problem. The platform needs to provide a popularity ranking table to recommend hotspot content to platform users more comprehensively and specifically [13].

4. Implementation of Personalized Services for Digital Humanities Platforms

The personalized functions of Shanghai Library's digital humanities platform can be implemented using different algorithms. This section mainly introduces the sequential recommendation algorithm based on knowledge graph embedding and multi-neural networks [14-15], user profile extraction algorithms, and vocabulary popularity algorithms.

4.1 Implementing Co-occurrence Function Based on Knowledge Graphs

Knowledge graphs store a large amount of digital humanities information. Combining co-occurrence information obtained from knowledge graphs can present more specific and comprehensive recommendations to users of Shanghai Library's digital humanities platform.

4.1.1 Representation of Knowledge Graphs A knowledge graph is a large-scale semantic network that stores human knowledge in graph form. In recent years, knowledge graphs have achieved extensive and successful applications in natural language processing, question-answering systems, recommendation systems, and many other fields. Nodes in a knowledge graph represent entities, and edges represent relationships. In knowledge graphs, facts are represented as triples, generally denoted as <head entity, relation, tail entity>.

[Figure 1: see original paper] shows an example of a classical texts knowledge graph:

[Figure 1: see original paper] Example of Classical Texts Knowledge Graph

The classical texts knowledge graph shown in [Figure 1: see original paper] consists of information on 2.5 million extant Chinese classical texts from 734 libraries and research institutes worldwide, including 649,549 ancient book entities (Work instances), 221,783 responsible persons for classical texts (Person instances), 1,498,383 versions of ancient books (Version instances), and 13,960 place name nodes (Place instances). These four types of nodes and their relationships form a massive classical texts knowledge graph, with nodes, attributes, and edges forming a three-dimensional, multi-dimensional, multi-purpose ancient book knowledge association network. This achieves a relatively comprehensive description of bibliographic information on major extant Chinese classical texts worldwide, providing researchers with a one-stop platform for mining knowledge hidden behind massive ancient book bibliographic data and greatly enhancing ancient book knowledge service functions [16].

4.1.2 Extracting Walk Sequences Using Knowledge Graphs The idea of node2vec [17] is to generate random walks, sample (node, context) combinations from random walks, and then model such combinations using word vector processing methods to obtain representations of network nodes.

This article uses existing knowledge graphs and then uses the node2vec algorithm concept to construct random walk sequences. Taking Shanghai Library's digital humanities platform as an example, a knowledge graph was constructed based on digital humanities resources, combining events, people, places, and institutions, as shown in [Figure 2: see original paper].

[Figure 2: see original paper] Digital Humanities Knowledge Graph

The probability of random walks is:

$$P(c_i = x | c_{i-1} = v) = \begin{cases} \frac{\pi_{vx}}{Z}, & (v, x) \in E \\ 0, & \text{otherwise} \end{cases}$$

where π_{vx} is the unnormalized probability, and Z represents the normalization constant. c_i denotes the i-th node in the random walk, v and x represent nodes in the knowledge graph, and E represents the knowledge graph. For common random walks, the relationship between π_{vx} and entity edge weights is: $\pi_{vx} = \alpha_{pq}(t, x) \cdot \omega_{vx}$, where ω_{vx} is the weight between node v and node x. The coefficient $\alpha_{pq}(t, x)$ is calculated as follows:

$$\alpha_{pq}(t, x) = \begin{cases} \frac{1}{p}, & d_{tx} = 0 \\ 1, & d_{tx} = 1 \\ \frac{1}{q}, & d_{tx} = 2 \end{cases}$$

where t represents the previous node, x represents the next possible node in the random walk, and the values of p and q control deep and broad walks, respectively. d_{tx} represents the shortest distance between nodes t and x. This article uses node2vec's deep walk strategy to obtain item sequences as input for the next step of item2vec, better capturing similarity between items. By using the random walk sampling method in node2vec, random walk paths such as (New Culture Movement, Hu Shi, Peking University) are obtained, from which digital humanities entity sequences are extracted. The breadth-first and depth-first traversals of node2vec can effectively extract homogeneity and isomorphism between entities. The sequence extraction from the knowledge graph yields a sequence collection $H_k = \{I_1, I_2, \dots, I_m\}$, where $I_i = \{x_1, x_2, \dots, x_n\}$ represents a generated random walk.

4.1.3 Extracting Historical Interaction Sequences of User Behavior Assume $U = \{u_1, u_2, \dots, u_n\}$ represents a set of users, and $I = \{i_1, i_2, \dots, i_m\}$ represents a set of items. A user's historical interaction sequence is represented as $B(u) = \{(i_1^u, t_1), (i_2^u, t_2), \dots, (i_{|B(u)|}^u, t_{|B(u)|})\}$, where (i_1^u, t_1) indicates that user u operated item i_1^u at time t_1. The obtained $B(u)$ is the required historical interaction sequence.

4.1.4 Embedding Interaction Sequences into Knowledge Graph Vectors Combining sequences extracted from the knowledge graph with existing user interaction sequences as input for item2vec ultimately yields embedded vectors of items. Knowledge graph sequences can compensate for the shortcoming that item sequence embedding rarely considers item content information. The neural item embedding model is analogous to the word vector model. Items interacted with by users naturally form sequential order over time, and item sequences obtained from knowledge graphs are analogous to natural language sentences. Items with the same author, same publishing institution, and same context information are close to each other in the embedding space. Specifically, given a user interaction sequence collection $H = \{S_1, S_2, \dots, S_N\}$ and a sequence combination obtained from the knowledge graph $H_k = \{I_1, I_2, \dots, I_N\}$, the item2vec technology's Skip-gram model aims to maximize the following objective:

$$\text{argmax target} = \sum_{i=1}^{K} \sum_{j \neq i} \log p(x_1 | x_2)$$

where K is the length of sequences S_i and I_i, x_i represents items in the sequence, and $p(x_1|x_2)$ is defined as a softmax function:

$$p(x_1|x_2) = \frac{\exp(w_i^T v_j)}{\sum_k \exp(w_i^T v_k)}$$

where w_i and v_i are potential vectors representing the target and context of x_i, respectively. For each user u, an interaction sequence with embedded items can be generated, as shown in formula (5):

$$R_u = \{v_1, v_2, \dots, v_n\}$$

where v_j represents the d-dimensional potential vector of item x_1.

In the above algorithmic process, item2vec clusters items, captures item similarity, and generates a unified item representation space, where the generated vectors can interpret item similarity and sequential relationships. Items clustered together have strong associations.

4.1.5 Advantages of node2vec and item2vec Algorithms The node2vec and item2vec algorithms can effectively filter nodes in chaotic graph databases based on users' search behavior, through random walks on knowledge graphs and interaction sequences of embedded items. When unfolding node information of the same dimension, they can obtain node content that best matches users. After Shanghai Library's digital humanities platform adopted node2vec and item2vec algorithms, it not only implemented the platform's co-occurrence function but also enabled more precise push of co-occurrence information to users.

4.2 Implementing Push Function Based on User Profiles

User profiling is a technology for 刻画 ing user information models. By mining real user data, it extracts user interest points and presents a virtual complete picture of user information, providing a basis for offering users precise personalized push services. This article models user profiles through the proposed sequence modeling framework.

4.2.1 User Profile Algorithm This article applies Convolutional Neural Networks (CNN) to users' interest points, fully considering users' historical interaction sequence context information to learn users' interest points and form user profiles.

Learning interests first requires dividing users' interaction sequences based on timestamp information, then using CNN to learn users' interest points. This article divides user sequences into long, medium, and short three periods to dynamically learn user preferences. The convolutional preference modeling model is shown in [Figure 3: see original paper]:

[Figure 3: see original paper] Convolutional Preference Modeling Model

This article uses one-dimensional Convolutional Neural Networks (CNN) to learn users' interest points and interest points in different time periods. CNN has a good ability to balance context information and can effectively model users' interest points in a time period, mining users' interest preferences. Traditional CNN requires a very deep network or very large filters to obtain sufficient context information. This article applies dilated convolution to interest point preference learning. For one-dimensional sequence input $X \in \mathbb{R}^N$ and filter $f : \{0, \ldots, k-1\} \in \mathbb{R}$, where N is the input dimension, the convolution operation F on elements of the sequence is defined as:

$$F(s) = (X *_d f)(s) = \sum_{i=0}^{k-1} f(i) \cdot X_{s-d \cdot i}$$

where d represents item vector dimension, k is the convolution kernel size, and $s - d \cdot i$ indicates the direction of past convolution operations. f represents the filter in the convolution operation, and s represents elements in the sequence. In [Figure 3: see original paper], v_0 represents the item vector, P_{T+1} represents the output result of the $(T+1)$-th time, and b represents the dilation factor of dilated convolution. Therefore, dilated convolution introduces a fixed step between every two adjacent filters. When $b = 1$, dilated convolution becomes regular convolution. Using a large dilation factor can make the top-layer output represent a larger range of inputs, thereby effectively expanding the receptive range of CNN. The residual block in this article contains a branch that, through a series of transformations of F, has its output added to the block's input:

$$o = \text{Activation}(X + F(X))$$

Through CNN learning, the interest point sequence $P_u = \{P_1, P_2, \dots, P_j\}$ for user u is obtained. This sequence is the personal profile data of user u and can effectively 刻画 this user's preferences.

4.2.2 Advantages of CNN Algorithm The CNN algorithm extracts feature values from massive user data through multiple convolution calculations. In Shanghai Library's digital humanities platform, users' search behavior and browsing content are first collected, and then feature values are extracted through the CNN algorithm. These extracted feature values represent users' interest point sequences, which constitute users' personal profile data. Based on these personal profile data, when users search again, the system prioritizes presenting search results that best match the user to them, thereby implementing the user profile push function. After adopting the CNN algorithm, Shanghai Library's digital humanities platform can better prioritize pushing corresponding search results to users based on different users' interest points, greatly improving user experience.

4.3 Implementing Recommendation Function Based on Popularity Algorithm

Recommending hotspot content to users is the current trend, and users also hope to broaden their horizons and obtain popular and noteworthy digital humanities content. Shanghai Library's digital humanities platform adopts a popularity algorithm, collecting recent user-platform interaction data to provide users with hotspot resource recommendations.

4.3.1 Popularity Calculation Model for Humanities Vocabulary Based on Timeline Definition: For each vocabulary w_i, four data points are counted. Within time period d_0, a represents the total number of searches on Shanghai Library's digital humanities platform containing w_i, and b represents the total number of searches not containing w_i. Outside d_0, c represents the total number of searches containing w_i, and d represents the total number of searches not containing w_i. As shown in :

Search Statistics

	$d_t \in d_0$	$d_t \notin d_0$
Containing w_i	a	c
Not containing w_i	b	d

The calculation of vocabulary popularity is shown in formula (8):

$$\text{Popularity} = \frac{(ad - bc)^2}{(a+b)(a+c)(b+c)(b+d)}$$

4.3.2 Vocabulary Popularity Algorithm Based on Multi-user Clusters In Shanghai Library's digital humanities platform, hierarchical clustering algorithms are used to cluster users into multiple clusters based on interest points. The hierarchical clustering algorithm merges the two closest objects based on the distance between each pair of objects. After merging, new objects are generated and merged pairwise, and so on, until all objects are merged into one category. For fairness reasons, vocabulary popularity calculations should be performed for each cluster; otherwise, clusters with many users would dominate the user space and exert strong control over popular vocabulary.

First, the number of searches for each vocabulary by users in each cluster p_i within time period t_0 is counted in parallel, and the top ten most searched vocabularies are taken as popular vocabulary. Taking the first cluster p_1 as an example, the popular vocabulary set is denoted as T_1. Then, for each popular word $w_i \in T_1$, the total number of searches containing w_i in cluster p_1 within time period t_0 is counted as a_1, and the total number of searches not containing w_i is b_1. Outside t_0, the total number of searches containing w_i is c_1, and the total number of searches not containing w_i is d_1, and the vocabulary popularity of popular word w_i is calculated. Next, the popularity statistics of popular vocabulary from each cluster are compiled into a total popular vocabulary table, with popularity values of the same popular vocabulary accumulated. Finally, a Top-N popular search list is formed based on vocabulary popularity ranking.

4.3.3 Advantages of Vocabulary Popularity Algorithm The vocabulary popularity algorithm used on Shanghai Library's digital humanities platform comprehensively employs two branch popularity algorithms: timeline and user clusters. The timeline popularity algorithm ensures that vocabulary popularity must decay over time, preventing vocabulary with historically high popularity values from occupying recommendation positions for long periods. The user cluster popularity algorithm, on the other hand, first classifies user clusters based on user interest points before calculating vocabulary popularity in each cluster and then summing them to form the final popularity value. The cluster popularity algorithm can prevent large clusters from exerting excessive control over popular vocabulary. Through the cluster popularity algorithm, the resulting popular vocabulary is more diverse and not concentrated in certain specific fields. After using the above two popularity algorithms, Shanghai Library's digital humanities platform presents rich and diverse popular recommendation content, meeting the original design expectations.

5. Implementation Effects of Personalized Services for Digital Humanities Platforms

In 2020, Shanghai Library launched the "Historical Humanities Big Data Platform" project, integrating various digital resources of Shanghai Library to form the current Shanghai Library digital humanities platform. This platform reorganizes existing digital resources through knowledge recombination, supporting new digital humanities personalized services such as data-driven quantitative analysis, visual display, text analysis, social network relationship analysis, and geographic space analysis.

Personalized service functions are an important module of Shanghai Library's digital humanities platform. Using knowledge graph technology to implement the co-occurrence function enables the platform to comprehensively and completely present the overall framework of information users query; using user profiling technology helps the digital humanities platform grasp users' interest dynamics and provide users with the most scientifically professional personalized customized push; using hotspot algorithm technology enables the platform to control and analyze overall user data and provide users with hotspot resource recommendations. This section introduces the front-end page presentation effects of Shanghai Library's digital humanities platform's personalized service functions.

5.1 Co-occurrence Function Implementation Effect

In Shanghai Library's digital humanities platform, the implementation of knowledge graph co-occurrence is mainly presented on the page after users search for keywords, as shown in [Figure 4: see original paper]. Taking the search keyword "New Culture Movement" as an example, the left half of Shanghai Library's digital humanities platform page shows literature search results based on external features; the right half sequentially presents co-occurrence information generated based on the search keyword "New Culture Movement" and knowledge graph walk sequences, including characters, institutions, related events, and related literature.

[Figure 4: see original paper] Search Co-occurrence Results Based on Knowledge Graph

5.2 Push Function Implementation Effect

In Shanghai Library's digital humanities platform, combined with user profiling, different users searching with the same keyword will see different search results, as shown in [Figure 5: see original paper]. The left and right sides show different users using the same keyword for search, but the presentation of search results differs. The left side shows a new user's search results, while the right side shows an old user. The platform continuously updates the old user's profile based on their search history, reading content, and literature review methods, forming an interaction sequence with the platform. By analyzing the old user's backend profile data on the right side of [Figure 5: see original paper], it was found that the old user had previously frequently searched for keywords "May Fourth" and "National," and often read literature content related to the "May Fourth Movement." Therefore, this user formed a specific user profile. When the same search term was entered and generated a large number of search results, the system prioritized pushing data matching this user's profile to them, ultimately resulting in different content in the search results.

[Figure 5: see original paper] User Profile Implementation Results

5.3 Recommendation Function Implementation Effect

In Shanghai Library's digital humanities platform, popular searches are presented on the page as a popularity recommendation list, as shown in [Figure 6: see original paper]. Based on popularity values calculated by the popularity algorithm, relevant literature is sorted and displayed. Users can view the popularity list to understand the interests of all users and select literature they are interested in based on the popularity list.

[Figure 6: see original paper] Popular Search Implementation

Libraries have a natural connection with digital humanities. The development of digital humanities brings both opportunities and challenges to libraries. This article analyzes personalized services for digital humanities platforms, proposes combining efficient artificial intelligence algorithms with digital humanities, and embeds personalized functions into Shanghai Library's digital humanities platform to provide readers with various accurate and high-quality referral services. Through platform testing and verification, the results basically meet expectations. The next step will involve continuing research on how to build richer and more intelligent knowledge graphs, improve the efficiency and accuracy of personalized services, and optimize readers' reading experience.

References

[1] Centers. An international network of digital humanities centers [EB/OL]. [2021-04-26]. https://dhcenternet.org/centers.

[2] Zhu Benjun, Nie Hua. Crossover and integration: Digital humanities from a global perspective—A review of the first Peking University "Digital Humanities Forum" [J]. Journal of Academic Libraries, 2016, 34(5): 16-21.

[3] Fitzell S, Lange L, Li-Madeo C. Linked Jazz: Using linked open data to map community relationships in archival documents [EB/OL]. [2021-04-26]. http://mysite.pratt.edu/~infosils/SAAPosterAUG9.pdf.

[4] Sula CA. Digital humanities and libraries: A conceptual model [J]. Journal of library administration, 2013(53): 10-26.

[5] ACRL RESEARCH PLANNING AND REVIEW COMMITTEE. Top trends in academic libraries [EB/OL]. [2021-04-26]. https://crln.acrl.org/index.php/crlnews/article/view/9137/10061.

[6] Cheng Jing. Current status and thoughts on the construction of digital humanities service platforms at home and abroad [J]. Library Science Research, 2020(2): 37-42.

[7] Chen Tao, Liu Wei, Shan Rongrong, et al. Research on the application of knowledge graphs in digital humanities [J]. Journal of Library Science in China, 2019, 45(6): 34-49.

[8] He Panpan, Chen Ya. A review of digital humanities research in Chinese libraries [J]. Library Science Journal, 2018, 40(4): 132-137.

[9] Susan Schreibman, Ray Siemens, et al. A companion to digital humanities [M]. Malden: Blackwell, 2004: 16-27.

[10] Chen Yu. Research on the construction ideas of the Republic of China archives digital humanities service platform [J]. Beijing Archives, 2021(8): 28-31.

[11] Jia Hong. Overview of personalized service technologies for digital libraries [J]. Modern Information, 2006(3): 71-74.

[12] Dong Yan. Research on library knowledge service innovation under the background of artificial intelligence [J]. Library Science Journal, 2019, 41(7): 78-81.

[13] Zhang Lei, Wushour Slamu, Maimaitiyiming Hasimu, et al. Microblog recommendation algorithm under big data [J]. Laser Journal, 2016, 37(6): 1-6.

[14] Donkers T, Loepp B, Ziegler J. Sequential user-based recurrent neural network recommendations [C]. Como: Proc of the 11th ACM conference on recommender systems. 2017: 152-160.

[15] Shen Dongdong, Wang Haitao, Jiang Ying, et al. Sequential recommendation algorithm based on knowledge graph embedding and multi-neural networks

[J]. Computer Engineering & Science, 2020, 42(9): 1661-1669.

[16] Ouyang Jian, Liang Zhufang, Ren Shuhuai. Research on constructing a large-scale knowledge graph of extant Chinese classical texts [J]. Library and Information Service, 2021, 65(5): 126-135.

[17] Grover A, Leskovec J. Node2vec: Scalable feature learning for networks [C]//Proc of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining. San Francisco: 2014: 701-710.

Author Contributions:

Liu Peizhong: Paper framework design, data research, and paper writing;

Dai Qingyi: Program development and testing.

Note: Figure translations are in progress. See original paper for figures.