Research on Automatic Generation and Application of Cultural Resource Tags for Tourist Attractions (Postprint)

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Abstract

[目的/意义] To generate high-quality cultural resource tags for tourist attractions, addressing the problems of difficult information retrieval and monotonous recommendation forms in cultural tourism services. [方法/过程] First, a cultural resource tag system comprising both explicit and implicit tag types is designed; then, an explicit tag generation method based on feature word selection and noise word filtering is proposed, and calculation methods for cultural perception intensity and cultural perception similarity in implicit tags are designed, and cultural resource tags for attractions are generated based on the above methods; finally, retrieval and recommendation methods based on cultural resource tags are proposed for different scenarios in tourism information services. [结果/结论] Taking real tourism data from Wuhan City as an example for empirical research, the results show that tags generated based on the proposed method can accurately characterize the cultural resource features of attractions, and the tag-based retrieval and recommendation methods both possess strong interpretability, which can effectively enhance the transparency of information services and users' trust in the results, and have reference value for interpretability research in recommendation systems in other domains.

Full Text

Introduction

Cultural tourism, which relies primarily on cultural resources, is gaining increasing popularity among travelers as it better satisfies their growing spiritual and cultural needs [?]. Scenic spots serve as carriers of culture, containing rich cultural resources. However, the diversity of cultural resources at these spots and the varying cultural preferences of users often require extensive information searching before travelers can find attractions of interest. Investigations reveal that even well-known online travel platforms such as Ctrip, Mafengwo, and TripAdvisor provide only limited information on cultural tourism, mostly generic content. For instance, Ctrip offers personalized recommendations under the theme of "cultural tourism," while TripAdvisor clusters attractions into categories like "historical sites" and "sacred and religious sites." Yet none of these platforms provide specialized search and recommendation services for cultural tourism information, leaving users struggling with information retrieval and inefficient decision-making. Therefore, a critical challenge is how to fully mine and accurately describe the cultural resources of scenic spots to provide precise search and recommendation services for users with different cultural preferences.

Tags, which reflect key characteristics of resources, have received widespread attention from both academia and industry for their ability to enhance resource organization and management efficiency [?]. Representative social platforms in China such as Douban, Zhihu, and Weibo make extensive use of tags for resource classification, information retrieval, and personalized recommendations [?]. Tags are equally suitable for organizing tourism resources due to their ease of understanding and processing. If tags can comprehensively and accurately describe the cultural resources of scenic spots, users can quickly grasp the cultural characteristics of attractions based on tag content, and online travel platforms can provide better search and recommendation services based on these tags. The rapid development of mobile internet and online tourism has generated vast amounts of online travel information, including travel blogs, user visit histories, and user reviews. This information not only reflects authentic user travel experiences but also describes and evaluates the resources and services of attractions from various perspectives. Therefore, this study mines online travel information to generate high-quality cultural resource tags for scenic spots, laying the foundation for cultural tourism information retrieval and recommendation services.

2 Related Research

This study aims to automatically generate scenic spot tags applicable to cultural tourism information services by mining online travel information. The research primarily involves two aspects: automatic tag generation and scenic spot tags. This section reviews and summarizes relevant research in these two areas.

2.1 Automatic Tag Generation Research

Tag generation is a prerequisite for tag application, with three main approaches currently in use: (1) user tagging, (2) expert or administrator tagging, and (3) algorithmic automatic generation [?]. Social platforms have accumulated large quantities of tags thanks to spontaneous user contributions. However, some online platforms, despite having substantial user bases, lack user tagging functionality or introduced it relatively late, resulting in insufficient tags. Moreover, with the advent of the big data era, data volumes across many industries have grown exponentially, and data update speeds have accelerated, making manual tag addition by experts or administrators problematic in terms of operability and timeliness. Consequently, generating high-quality tags automatically with minimal manual intervention has become a research focus.

Scholars have conducted relevant research and proposed domain-specific automatic tag generation methods for videos [?], healthcare [?, ?], social media [?], and knowledge services [?]. Z. Shen et al. [?] proposed an automatic annotation method for outdoor videos based on sensor metadata, which models video scenes as geometric shapes, queries geographic objects corresponding to these shapes from geographic databases, and extracts textual information as video tags. Meng et al. [?] proposed a doctor tag automatic generation algorithm based on online consultation text, incorporating temporal periodic features and textual topic features. Wu et al. [?] proposed a microblog user tag prediction method combining user relationship networks and tag co-occurrence networks, using a random walk model with restart to generate candidate tags and recommending them to target users based on tag chains. Xiong et al. [?] proposed a microblog tag generation method based on the LDA topic model, which generates preliminary tags from user posts and refines them by analyzing posts from users' followers. L. Zeng et al. [?] combined software engineering knowledge with deep learning algorithms to propose a code tag generation method. Zhao et al. [?] studied the intelligence needs of science and technology management departments, using natural language processing algorithms such as keyword extraction and TF-IDF to generate feature tags, and employed collaborative filtering and tag association recommendation algorithms to provide content recommendations for organizations with similar characteristics.

Tag generation quality assessment is also a research focus. Li et al. [?] compared and analyzed various tag quality assessment methods, categorizing existing approaches into eight types including manual assessment, tag statistical property-based methods, and standardized vocabulary-based methods. Zhang et al. conducted series of studies on picture tags [?] and blog tags [?], proposing that tag social attributes can serve as important features for distinguishing tag quality and training higher-performance automatic tag quality assessment models by fusing tag content and social attributes.

2.2 Scenic Spot Tag Research

Although automatic tag generation based on information mining has achieved certain results in the aforementioned fields, related research in tourism remains scarce, with the focus being on tag application rather than tag generation. For instance, Li et al. [?] proposed a personalized travel recommendation method based on feature tags including region, time, theme, and type, but the tags used were manually generated. Shi et al. [?] proposed a collaborative filtering recommendation algorithm based on user social relationships and scenic spot tags, demonstrating higher recommendation accuracy. However, the scenic spot type tags used were also manually generated and only contained high-level summaries such as "lakes, rivers" and "mountains, ridges," providing limited information about the attractions. Additionally, some studies related to tourist profiling and scenic spot entity recognition involve tag generation [?]. For example, Shan et al. [?] constructed user and hotel feature profiles by extracting user attributes, hotel attributes, and review attributes from Ctrip hotel reviews. Liu et al. [?] built tourist user profiles based on basic information tags, behavioral information tags, and contextual information tags, combining ontology methods to propose a tourism contextual recommendation model based on user profiles.

Literature review reveals that existing research on scenic spot tags has certain deficiencies in both tag generation and application. First, in terms of tag generation methods, most studies rely on manual acquisition of scenic spot tags, which is not only labor-intensive but may also result in tags that are limited in quantity, coarse-grained, and homogeneous due to insufficient manpower or time, with high update costs. Second, from the perspective of tag generation, although existing studies have generated scenic spot tags from different dimensions, few tags describe the cultural resource information of attractions, and no relatively complete scenic spot cultural resource tag system has been identified. Third, regarding tag application, existing research primarily focuses on scenic spot recommendation based on tags, with little attention paid to scenic spot retrieval methods. Addressing these issues, this study designs a scenic spot cultural resource tag system from a cultural tourism perspective, proposes an automatic generation method for scenic spot cultural resource tags, and achieves automatic generation of high-quality tags applicable to cultural tourism information retrieval and recommendation with minimal manual participation through mining online travel information.

3 Research Framework and Key Steps

3.1 Research Framework

This study comprises three sub-tasks: (1) designing a scenic spot cultural resource tag system; (2) designing tag generation algorithms to generate tags across various dimensions; and (3) analyzing tag application scenarios and demonstrating specific application examples. To address these tasks, a research framework is constructed as shown in [Figure 1: see original paper], consisting of four steps: tag system design, data collection and preprocessing, tag generation and visualization, and tag application. First, based on cultural hierarchy theory and actual user needs in tourism information services, a scenic spot cultural resource tag system containing both explicit and implicit tag types is designed. Second, scenic cultural theme data and scenic review corpora are collected from online travel service platforms and undergo cleaning, transformation, segmentation, and stop-word removal. Third, tag generation algorithms are designed to generate cultural resource tags for each scenic spot, with tags visualized through word clouds and data tables. Finally, taking scenic spot retrieval and recommendation as examples, the specific application of cultural resource tags in tourism service scenarios is demonstrated.

3.2 Key Steps

3.2.1 Tag System Design The tag system design considers four factors: (1) dimensions of cultural composition, (2) divisions of cultural perception dimensions in existing research [?], (3) characteristics of scenic spot cultural resources themselves, and (4) actual user needs for cultural tourism information services. The specific process and rationale for tag system design are as follows:

First, cultural hierarchy theory posits that culture comprises three dimensions: material culture, institutional culture, and psychological culture [?]. In existing cultural perception research, Yin et al. [?] divided tourist cultural perception into material and intangible cultural perception, while Li et al. [?] divided it into cultural atmosphere perception and cultural product perception based on cultural hierarchy theory, with cultural activity perception being a primary component of cultural product perception. Drawing on these studies, this research designs material culture tags, intangible culture tags, and cultural activity tags. Second, since cultural themes can effectively reflect the type characteristics of scenic spot cultural resources—enabling tourism portals to cluster and display attractions with the same cultural themes and allowing users to quickly find attractions matching their cultural preferences—cultural theme tags are added to the tag system. Third, when making travel decisions, users need to know not only whether an attraction contains cultural resources of interest but also other users' actual perception experiences of these resources. Therefore, cultural perception intensity tags are designed to quantify users' degree of cultural resource perception. Finally, recommending similar attractions requires knowing the cultural similarity between scenic spots, hence the design of cultural perception similarity tags to recommend similar attractions when users show interest in a particular spot.

Based on different generation methods, these tags are divided into explicit and implicit categories. Explicit tags refer to keywords or phrases that can be directly extracted from text using algorithms such as TF-IDF [?] and TextRank [?], such as "blue and white porcelain" and "Sword of Goujian, King of Yue." Implicit tags refer to information obtained only after statistical analysis of explicit data, such as cultural perception intensity and cultural perception similarity. Additionally, since cultural theme tags also cannot be directly extracted from text, they are classified as implicit tags. The specific content of the tag system is shown in .

3.2.2 Tag Generation Methods **(1) Explicit Tag Generation.** The cultural resources of scenic spots can be divided into three categories: material culture, intangible culture, and cultural activities. These resources serve as important bases for travel decision-making and primary objects of user perception during visits. User reviews authentically reflect users' perception of various cultural resources at attractions, with high-frequency elements in reviews indicating cultural attractions of common interest. Therefore, this study generates explicit tags by extracting high-frequency words and phrases of different parts of speech from reviews, with the specific process shown in [Figure 2: see original paper].

The explicit tag generation process includes three main steps:

First, construct feature word and noise word tables. All review corpora from experimental scenic spots are merged into a single document for segmentation, stop-word removal, part-of-speech tagging, and phrase extraction. The Jieba tool [?] is used for segmentation and part-of-speech tagging, the Harbin Institute of Technology stop-word list for stop-word removal, and 2-gram phrase extraction by merging adjacent words. Since material and intangible culture tags are primarily nouns while cultural activity tags are primarily verbs, the top N_n nouns, top N_v verbs, and top N_p phrases by frequency are extracted to form high-frequency word tables. Manual selection from these tables identifies qualified words and phrases as feature words stored in the feature word table, with remaining words classified as noise words stored in the noise word table.

Second, extract target scenic spot tags. The review corpus of the target scenic spot is preprocessed, with extracted high-frequency phrases added to Jieba's custom dictionary to ensure phrases can be extracted as whole units when using TF-IDF and TextRank. The corpus is then reprocessed to extract the top T_n nouns, top T_v verbs, and top T_p phrases to form the target spot's high-frequency word table. The feature word table filters these high-frequency words to obtain candidate tag set D_1 and remaining high-frequency words. Algorithms then extract the top N keywords from the review corpus to obtain keyword tables K_1 and K_2, which sequentially filter the remaining high-frequency words using the noise word table and keyword tables to obtain candidate tag set D_2. Finally, D_1 and D_2 are merged to form the explicit tag collection D for the target scenic spot.

Third, tag classification. Collection D is manually classified into material culture tags, intangible culture tags, and cultural activity tags.

(2) Cultural Theme Tag Generation. The "Wanglüzhe Tourism Network" (whlyw.net) is a tourism information service platform that manually annotates the cultural themes of scenic spots and clusters attractions by cultural theme at the municipal administrative level. Taking Wuhan as an example, the platform collected information on 69 cultural tourism attractions in Wuhan and clustered them into 22 different cultural themes including ecological culture, architectural culture, and celebrity culture. A single attraction can belong to one or multiple themes based on its cultural resource characteristics. This study collects the required cultural theme information from Wanglüzhe Tourism Network and converts the collected "cultural theme—scenic spot" matrix into a "scenic spot—cultural theme" matrix to obtain cultural theme tags for each attraction.

(3) Cultural Perception Intensity Tag Generation (CPI). Cultural perception intensity refers to users' cognitive and experiential degree of scenic spot cultural resources during actual visits—the deeper the cognition and richer the experience, the stronger the cultural perception. This study quantifies cultural perception intensity by designing three metrics: overall cultural perception intensity, cultural perception intensity based on cultural theme tags, and cultural perception intensity based on explicit tags.

- Overall cultural perception intensity: Calculated for each scenic spot, this metric reflects the combined influence of material culture, intangible culture, and cultural activities. The more cultural resource objects mentioned in reviews and the higher the frequency of cultural attribute words, the stronger the perception. Therefore, overall cultural perception intensity is defined as the weighted average of all explicit tag word frequencies, as shown in Formula (1):

$$CPI(S_k) = \frac{\sum_{i=1}^{3} \sum_{j=1}^{m_i} w_i \cdot n_{ij}}{N}$$

where $CPI(S_k)$ represents the overall cultural perception intensity of scenic spot S_k, the number 3 indicates three categories of explicit tags, m_i represents the number of tags in category i, w_i represents the weight of category i, n_{ij} represents the word frequency of the j-th tag in category i, and N represents the total number of reviews for the target scenic spot.

- Cultural perception intensity based on cultural theme tags: Calculated for different themes within cultural theme tags, this metric serves two purposes: (1) comparing users' perception differences of different cultural themes at the same attraction (e.g., for "East Lake," which includes both "ecological culture" and "Chu culture," users' perception of ecological culture is significantly stronger than that of Chu culture), and (2) comparing users' perception differences of the same cultural theme across different attractions (e.g., both "Yellow Crane Tower" and "Former Residence of Comrade Mao Zedong" contain "architectural culture" and "celebrity culture," but users' perception of architectural culture at Yellow Crane Tower is significantly stronger than at Mao's former residence, while the opposite is true for celebrity culture). Considering that the number and frequency of tags included in a theme positively correlate with perception intensity, the calculation method is designed as shown in Formula (2):

$$CPI(T_i) = \frac{\sum_{j=1}^{m} n_j}{N}$$

where $CPI(T_i)$ represents the cultural perception intensity of theme T_i, m represents the number of tags included in theme T_i, n_j represents the word frequency of the j-th tag, and N represents the total number of reviews for the target scenic spot.

- Cultural perception intensity based on explicit tags: Calculated for different categories of explicit tags, this metric compares users' perception differences of the same explicit tag category across different attractions. For example, "Enshi Tujia Daughter's City" features rich folk performances such as hand-swinging dances, daughter's festivals, and crying marriage ceremonies, resulting in significantly stronger user perception of "cultural activities" compared to attractions like "Yellow Crane Tower" or "East Lake." After calculating the cultural perception intensity of each explicit tag category for every scenic spot, recommendations can be provided based on user preferences. For instance, if a user seeks attractions with rich "cultural activities," attractions can be sorted by cultural activity perception intensity to generate a recommendation list. The calculation method is shown in Formula (3):

$$CPI(E_i) = \frac{\sum_{j=1}^{m} n_j}{N}$$

where $CPI(E_i)$ represents the cultural perception intensity of tag category E_i, m represents the number of tags in category E_i, n_j represents the word frequency of the j-th tag, and N represents the total number of reviews for the target scenic spot.

(4) Cultural Perception Similarity Tag Generation (CPS). Cultural perception similarity refers to the degree to which users perceive similar cultural resources across different scenic spots. Since explicit tags are generated based on user perception results to describe scenic spot cultural resources, the more semantically similar the explicit tags of different attractions, the more similar the cultural perception users experience. Therefore, this study designs a cultural perception similarity calculation method based on tag semantic correlation, including three steps:

First, obtain tag word vectors. Word2Vec [?] training generates word vectors that effectively represent semantic relationships between words, with cosine distance between vectors measuring word similarity. This study uses all scenic spot review data as a corpus, trains Word2Vec word vectors using Python's Gensim toolkit with the Skip_{gram} algorithm, and sets the vector dimension to 128 to obtain vector representations for each tag.

Second, calculate cultural perception feature vectors. Explicit tags reflect the specific content of user cultural perception, and cultural perception feature vectors represent this content in vectorized form. Drawing on text vectorization methods, this study performs weighted averaging of all explicit tag word vectors, with tag weights equal to normalized TF values. The feature vector calculation formula is:

$$Vec(S_k) = \sum_{i=1}^{n} tf_i \cdot vec_i$$

where $Vec(S_k)$ represents the cultural perception feature vector of scenic spot

S_k, tf_i represents the TF value of the i-th tag, vec_i represents the word vector of the i-th tag, and n represents the total number of tags.

Third, calculate scenic spot cultural perception similarity. Cosine similarity is commonly used to evaluate vector similarity. Therefore, this study assesses cultural perception similarity between attractions by calculating the cosine value of feature vectors, as shown in Formula (5):

$$CPS(S_i, S_j) = \frac{\sum_{k=1}^{n} Vec(S_i)_k \times Vec(S_j)_k}{\sqrt{\sum_{k=1}^{n} (Vec(S_i)_k)^2} \times \sqrt{\sum_{k=1}^{n} (Vec(S_j)_k)^2}}$$

After constructing the scenic spot cultural perception similarity matrix using the above method, the cultural perception similarity between any two attractions can be obtained by querying the matrix.

4 Experiments and Results Analysis

This section validates the proposed methods using real tourism data, including explicit tag generation and evaluation, implicit tag generation and evaluation, tag visualization, tag-based scenic spot retrieval, and tag-based scenic spot recommendation.

4.1 Data Collection and Preprocessing

Taking Wuhan's cultural tourism attractions as the research object, a Python-based web crawler collected 57,324 review data entries from 34,785 users for 57 attractions with substantial review volumes from Ctrip (ctrip.com). Each data entry includes attraction name, user ID, review content, rating, and review time, with collection completed by March 2021. Data preprocessing includes: (1) removing reviews with empty or non-Chinese content, and (2) removing duplicate reviews with identical attraction names, user IDs, and review content. After processing, 57,122 valid review entries were obtained, with sample data shown in .

4.2 Tag Generation Results

4.2.1 Explicit Tag Generation Results Explicit tags include material culture tags, intangible culture tags, and cultural activity tags. Following the method described in Section 3.2.2(1), experiments were conducted with parameters set as $N_n = 1000$, $N_v = 500$, $N_p = 500$, $T_n = 300$, $T_v = 500$, $T_p = 50$, and $N = 200$. After generating explicit tag collections, six scenic spots were randomly selected and visualized using the WordCloud tool [**?**]. The tag word clouds for each spot are shown in [Figure 3: see original paper].

Observation of the word clouds reveals that the generated explicit tags effectively describe the cultural resource characteristics of the attractions. To further verify the performance of the proposed method in explicit tag generation, keywords were extracted using TF-IDF, TextRank, and the proposed method, with precision, recall, and F1 values calculated for 5-50 extracted keywords [**?**]. The results are shown in [Figure 4: see original paper].

The results demonstrate that the proposed method achieves higher precision, recall, and F1 values than TF-IDF and TextRank. When extracting 50 keywords, TF-IDF and TextRank generally achieve precision, recall, and F1 values below 40%, with significant performance variation across different attractions (all three metrics below 20% for "East Lake Scenic Area"). The proposed method generally achieves precision, recall, and F1 values above 70% with smaller performance variations across attractions, demonstrating better stability. Although the proposed method requires some manual effort to construct feature and noise word tables, the cost is low—approximately 25 minutes to build general feature and noise word tables for 57 attractions in Wuhan. Once constructed, explicit tag collections for scenic spots can be automatically generated by the algorithm.

4.2.2 Implicit Tag Generation Results Implicit tags include cultural theme tags, cultural perception intensity tags, and cultural perception similarity tags. First, following the method in Section 3.2.2(2), cultural theme tags for each scenic spot were obtained, as shown in . Then, following Section 3.2.2(3), cultural perception intensity was calculated for each attraction. Cultural perception intensity includes three metrics: shows the overall cultural perception intensity and explicit tag-based cultural perception intensity, while shows cultural perception intensity based on cultural theme tags. For overall cultural perception intensity calculation, parameters were set as $W_1 = 0.4$, $W_2 = 0.2$, and $W_3 = 0.4$, with intensity values normalized to the 0-1 range.

The overall cultural perception intensity results in indicate that users generally perceive temples and museums more strongly. Among the Top 10, temples include Baotong Temple, Gude Temple, and Changchun Taoist Temple, while museums include Jianghan Customs Museum, Hubei Provincial Museum, and Xinhai Revolution Museum. The reasons are similar to overall cultural perception: compared to other attractions, temples and museums have relatively small spatial areas but rich cultural resources—temples feature ancient building complexes and various Buddha statues, while museums contain numerous cultural relics densely presented to users. Additionally, the continuous Buddhist music and chanting in temples and the lighting and equipment used for auxiliary display in museums immerse users in a strong cultural atmosphere, resulting in stronger cultural perception.

The Top 10 attractions for intangible cultural perception intensity align with their actual cultural resource characteristics. For example, the three attractions with the highest intensity values—Guqin Platform, Xinhai Revolution Museum, and Yuji Palace—indeed contain well-known intangible cultural resources: the historical story of "high mountains and flowing water," the historical event of the "Xinhai Revolution," and the mythological legend of "Yu the Great controlling floods." Attractions with stronger cultural activity perception are primarily natural ecological types, with East Lake, Mulan Tianchi, Jinligou, Jiuzhen Mountain, and others among the Top 10. This is because natural ecological attractions typically feature mountains and rivers, cover large areas, and allow managers to develop various cultural activities such as horse riding, archery, and bonfire parties, enriching user experiences and enhancing cultural perception.

The results in show that perception intensity for different cultural themes at the same attraction typically varies. For example, Baotong Temple shows stronger religious culture perception than architectural culture perception, while Mulan Lake shows stronger ecological culture perception than celebrity culture perception. Perception intensity for the same cultural theme across different attractions also varies, enabling theme-based attraction retrieval and recommendation sorted by intensity values.

Finally, following Section 3.2.2(4), cultural perception similarity between attractions was calculated using cosine similarity of feature vectors, with values ranging from [-1, 1]. shows the most and least similar attractions to target attractions including Hubei Provincial Museum, East Lake Scenic Area, Guiyuan Buddhist Temple, and Wuchang Uprising Memorial Hall. The results show that highly similar attractions typically share 1-2 cultural themes (e.g., East Lake Scenic Area, East Lake Moshan Scenic Area, and Luojia Mountain all include "ecological culture"; Guiyuan Buddhist Temple, Baotong Temple, and Gude Temple all include "architectural culture" and "religious culture"). Less similar attractions typically share no cultural themes and differ significantly in cultural resource content. For example, the attraction least similar to Hubei Provincial Museum is Mulan Tianchi (indoor cultural relics exhibition vs. outdoor ecological tourism), and the least similar to East Lake Scenic Area is Madame Tussauds (outdoor ecological tourism vs. indoor wax museum). These results align with actual conditions.

To further evaluate implicit tag generation quality, expert evaluation using a 5-point scale was conducted on the results in , , and , with 1 representing "very inconsistent" and 5 representing "very consistent." Seven domain experts familiar with Wuhan's attractions participated. The average score for cultural perception intensity tag results was 4.375, and for cultural perception similarity tag results was 4.357, indicating high reliability of the proposed implicit tag generation method.

4.3 Tag Visualization

After generating explicit and implicit tags, each scenic spot can be represented through tag clouds to build cultural resource profiles (as shown in [Figure 3: see original paper]) or detailed tables. uses Hubei Provincial Museum as an example to display generated tags, where the number after each tag category represents cultural perception intensity on a 1-10 scale obtained by multiplying normalized values by 10. Users can judge whether an attraction's cultural resources match their preferences based on tag content and intensity values.

4.4 Tag Application

The generated cultural resource tags enable more precise retrieval and recommendation services based on user needs and preferences. Applications in scenic spot retrieval and recommendation are analyzed below.

4.4.1 Scenic Spot Retrieval When users have clear interest objects, they can retrieve attractions through keywords. For example, a user who has heard about Wuhan's famous cherry blossoms can use the keyword "cherry blossoms" for retrieval. Two scenarios exist: (1) the keyword matches existing tags, and (2) the keyword matches no tags. For these scenarios, this study provides tag content-based retrieval and tag semantics-based retrieval.

(1) Tag Content-Based Retrieval. Applicable when tags matching the retrieval keyword exist. Method: Retrieve all attractions whose tags contain the keyword, sort them by overall cultural perception intensity, and display to users. Result: Using "cherry blossoms" as the keyword, the Top 5 attractions are Luojia Mountain, Wuhan University, East Lake Cherry Blossom Garden, Tanhualin, and East Lake Moshan Scenic Area.

(2) Tag Semantics-Based Retrieval. Applicable when no tags match the retrieval keyword. Method: First, obtain the word vector of the keyword through the trained word vector model, then calculate the average cosine similarity between the keyword and all explicit tags of each attraction, and sort attractions by similarity. Result: If a user interested in classical architecture searches with the keyword "classical architecture," they will find only "ancient architecture" in the tags. Using semantics-based retrieval yields Top 5 attractions: Qingchuan Pavilion, Changchun Taoist Temple, Guiyuan Buddhist Temple, Gude Temple, and Yellow Crane Tower. The method not only provides retrieval results but also explanations, which research shows can significantly enhance user trust in results [?]. lists the Top 5 retrieval results and explanations.

4.4.2 Scenic Spot Recommendation User information typically includes basic personal data (gender, age, etc.) and retrieval/visit histories on tourism websites. After analyzing user interest preferences, personalized recommendations can be made based on cultural resource tags. Three recommendation methods are provided for different service scenarios:

(1) Cultural Theme Tag-Based Recommendation. Applicable when user cultural theme preferences are known from retrieval or visit histories. Method: First, obtain all attractions under the user's interested cultural theme from the "cultural theme—scenic spot" matrix. Then, generate recommendation lists either directly by cultural perception intensity based on theme tags (see) or by integrating multiple factors including intensity, popularity, and ratings through weighted indicators.

(2) Explicit Tag-Based Recommendation. Applicable when user cultural category preferences are known. Method: Using "cultural activities" preference as an example, first obtain the sorted attraction list by cultural activity perception intensity from the "cultural activity—scenic spot" matrix (see), then generate recommendations using the method described in Section 4.4.2(1).

(3) Cultural Perception Similarity Tag-Based Recommendation. Applicable when a user is known to be interested in a particular attraction or has selected one from a recommendation list. Method: Generate recommendation lists either by sorting similarity values (see) or by integrating factors such as popularity and ratings through weighted indicators.

Result: Taking "Gude Temple" as the user's selected attraction, shows the Top 10 recommendation results based on cultural perception similarity + popularity + ratings. Providing explanations for recommendations has been a key challenge in personalized recommendation research. This method can display specific reasons for each recommended attraction, helping improve user acceptance and trust.

Conclusion

This study addresses the problems of difficult information retrieval and monotonous recommendation forms in cultural tourism by proposing an automatic generation method for scenic spot cultural resource tags based on online travel information. For different information service scenarios, it provides two retrieval methods (tag content-based and tag semantics-based) and three recommendation methods (cultural theme tag-based, explicit tag-based, and cultural perception similarity tag-based). Using real datasets from Wuhan's attractions, the feasibility of the proposed methods is verified.

The main contributions include: (1) Proposing to describe, retrieve, and recommend scenic spots from a cultural resource perspective, designing a cultural resource tag system that provides new ideas for scenic spot organization and management; (2) Proposing a cultural resource explicit tag generation method based on feature word screening and noise word filtering, with experiments showing better performance than traditional methods; (3) Designing calculation methods for cultural perception intensity and similarity, demonstrating that these metrics effectively reflect cultural characteristic differences between attractions and actual user perception, serving as important bases for retrieval result ranking and recommendation; (4) Providing two retrieval methods and three recommendation methods based on generated tags, all with strong interpretability that effectively improves service transparency and user trust, offering reference value for interpretable recommendation research in other fields.

Limitations include: (1) Although explicit tag collections can be automatically generated, manual classification is still required; (2) Indicator weights used in generating recommendation lists are empirical values, while dynamic settings based on user preferences would better meet actual needs; (3) The number of experts evaluating implicit tag generation results was small. Future work will focus on: (1) Researching automatic classification of explicit tags; (2) Studying dynamic weight setting methods based on user preferences to make recommendations more aligned with actual needs; (3) Researching effective quantitative evaluation methods for cultural resource-based scenic spot retrieval and recommendation results.

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