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RURAL TOURISM ROUTE RECOMMENDATION METHOD INTEGRATING GREEDY ALGORITHM AND ATTENTION MECHANISM

Abstract: To address the challenges associated with the fragmented distribution of scenic attractions, the ever-evolving nature of user preferences, and the suboptimal performance of multi-objective optimisation in rural tourism settings, this research introduces an innovative route recommendation approach that synergistically combines the greedy algorithm with an attention mechanism. The methodology involves the development of a dual-channel attention framework, which dynamically assigns weights to user behaviour patterns and textual semantic features. Additionally, a multi-constraint path-generation architecture, grounded in the greedy algorithm, is engineered to harmonise conflicting objectives, including time expenditure, alignment with attraction preferences, travel distance, and financial limitations. The results show that when recommending 20 scenic spots, the average absolute error decreases to 0.6921, the running time is only 0.1762 seconds, the coverage of scenic spot types increases to 6.5, and the recommended diversity index increases to 0.85. Compared with mainstream recommendation algorithms, this method significantly leads in total route revenue, accuracy of 0.83, and F1 score of 0.80, and has the lowest computation time. Application analysis shows that the recommended route has a high coverage rate, and the time consumption slows down with the increase of the number of scenic spots, taking into account personalised needs and diversity of scenic spot types. The method proposed by the research can effectively balance the real-time and personalised needs of route planning, while reducing path redundancy and enhancing the interpretability of recommendations, providing a new technological path for rural tourism route recommendations.

Keywords: greedy algorithm, attention mechanism, rural tourism, route recommendation, user profile, scenic spot portrait

Introduction

With the deepening of the rural revitalisation strategy and the increasing demand for urban-rural integration development, rural tourism has gradually become an important engine for promoting rural economic transformation. According to statistics, the number of rural tourism visitors in China has exceeded 2.5 billion in 2023, and the demand for personalised and experiential tourism from tourists is becoming increasingly significant. However, facing challenges such as scattered distribution of rural scenic spots, high heterogeneity of tourism resources, and dynamic changes in tourist preferences, there are still many technical bottlenecks in efficiently generating tourism route recommendations that meet user needs [1, 2]. Conventional recommendation systems predominantly rely on

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collaborative filtering techniques or rule-based engines, which often struggle to strike a balance between the real-time demands of route planning, the spatiotemporal dependencies among scenic attractions, and the intricate, nuanced associations inherent in user interests. Consequently, these traditional approaches frequently lead to issues such as redundant pathways, deviations from the intended thematic focus, or suboptimal computational efficiency in the generated recommendations [3, 4]. The method of generating recommendations by mining user historical behaviour data also faces two major limitations in rural scenarios: Firstly, rural tourism data has obvious sparsity and cold start characteristics, and deep models are prone to overfitting due to insufficient training. Secondly, existing models are difficult to effectively balance multi-objective optimisation problems, such as simultaneously considering transportation costs, attraction popularity, user preference intensity, and seasonal factors [5]. In recent years, greedy algorithms have shown high efficiency in combinatorial optimisation problems, but their local optimal characteristics may lead to insufficient recommendation diversity. However, the attention mechanism can capture complex feature associations through dynamic weight allocation, but lacks explicit modelling of global path constraints. How to organically combine the advantages of both and become the key to improving the quality of recommendations.

Aiming at the problem that the traditional route recommendation methods do not fully consider the dynamic popularity of points of interest, Ge et al. [6] proposed an intelligent tourism route recommendation method based on the popularity of points of interest. Based on the tag and association rule algorithm, interest tag data is fused, and combined with the content recommendation mechanism, personalised route generation is achieved. Experiments show that this method significantly improves the accuracy and recall rate of the recommendation results, and can provide tourists with more scientific and reasonable travel route planning. Zhu [7] proposed a tourism route recommendation scheme that integrated particle swarm optimisation and ant colony algorithm. User preferences were obtained through pseudo demand sequences and text mining, and semantic/geographic distance was weighted to update recommendations. The experiment showed that the algorithm had an error of only 0.005-0.089 under four benchmark functions, and the accuracy of topic recommendation exceeded 75 %, taking into account both emotional and temporal dimensions. Pitakaso et al. [8] proposed a safety oriented heterogeneous tourist route design method. By integrating security standards through artificial multi-intelligence systems, in the case of 50 scenic spots/44 teams, the total risk was reduced by 26.1 %, efficiency was improved by 16.16 % - 36.26 %, and preference and fairness were increased by 5.83 % and 25.57 % respectively. Rashid et al. [9] developed a deep learning framework to generate Top-K differentiated itineraries. Combining graph autoencoder and bidirectional LSTM ITRNet to evaluate POI probability, and generating diverse routes through constrained perceptual sampling algorithm. The experiment showed that it was superior to existing methods and achieved alternative recommendation driven by historical travel for the first time. Zheng et al. [10] put forth a multi-objective evolutionary algorithm that was grounded in a two-stage decomposition framework and Pareto stratification. They enhanced the distribution of solutions by implementing an extreme/intermediate population crowding mechanism, which effectively managed the density of solutions in different regions of the solution space. Furthermore, they refined the neighbourhood search by amalgamating cross-mutation weights, thereby improving the algorithm’s ability to explore and exploit the solution space. Experimental evaluations conducted using Beijing scenic spot data demonstrated that their proposed algorithm outperformed the benchmark algorithm across various performance metrics, and it also exhibited superior diversity in the recommended results.

Greedy algorithms have demonstrated strong practical value in many practical problems, such as data compression, path planning, resource scheduling, etc. Wang et al. [11] proposed an advanced iterative greedy algorithm for solving distributed hybrid flow workshop scheduling problems with blocking constraints. A mixed integer linear programming model was established, and an inter-factory neighbourhood search and a local search strategy based on exchange were designed to balance the global/local search capabilities. Tests on 80 instances show that this method is significantly superior to the five comparison algorithms. Medvedev [12] studied the modelling and solution of target alternation in multi-yard vehicle routing problems, with a focus on analysing the constraint conditions without sub loops. Five greedy algorithms and an adaptive algorithm based on variable randomisation were designed. The effectiveness of the adaptive algorithm in dynamic adjustment was verified by comparing the algorithm performance through objective function mean, running time, and parameter tuning experiments, providing a new solution framework for multi-yard collaborative scheduling. Aslan [13] proposed a new greedy algorithm for unmanned aerial vehicle path planning. This algorithm generated two leading paths, starting target and target starting, through bidirectional heuristics, and optimised path safety, length, and operability by combining advantageous line segments. In 3 battlefield scenarios and 12 test cases, the algorithm demonstrated better planning consistency than metaheuristic, and its running speed was 9 times faster than artificial bee colony algorithm. Gupta [14] previously established the efficacy of greedy algorithms in addressing multi-channel online matching problems under general position gap conditions. He proposed an innovative allocation framework that integrated three distinct types of resources: offline resources, as well as online resources that could be either queued or non-queued. This framework unified diverse challenges, such as dynamic matching and network revenue management, into a cohesive approach. The theoretical findings derived from this work significantly broadened the scope of algorithmic guarantees for online resource allocation, thereby enhancing our understanding and capabilities in managing such complex systems. Kong et al. [15] previously proposed a hybrid algorithm combining Thompson sampling and proportion greedy to address uncertainty in edge computing task allocation. They modelled rapid device recognition as a multi-armed bandit problem and derived a lower bound for computation delay by analysing velocity heterogeneity. Simulation results indicated that, in linear regression tasks, this approach reduced latency by over 15 % compared to existing methods, thereby validating its theoretical optimality.

In summary, existing research on rural tourism route recommendation has limitations such as insufficient dynamic adaptability, low efficiency of multi-objective coordination, strong data dependence, and lack of interpretability. Although greedy algorithms are widely used in fields such as combinatorial optimisation, path planning, and resource allocation due to their efficiency and simplicity, their core limitations lie in the tendency to fall into local optima, insufficient diversity, and weak adaptability to complex multi-objective optimisation. To tackle the aforementioned challenges, the research devises a dual-channel attention mechanism that precisely quantifies the contribution weights of users' historical behaviours and review texts, thereby mitigating the local constraints inherent in traditional greedy algorithms. By extracting user interest labels via Latent Dirichlet Allocation (LDA) and integrating them with Bidirectional Encoder Representations from Transformers

(BERT) pre-training techniques to analyse review texts, a multi-source feature fusion user attraction profile is constructed to effectively address the cold-start problem. Finally, a dynamic programming mechanism is incorporated to simultaneously optimise route length, time expenditure, and budget constraints, yielding efficient and cost-effective routes.

Methods and materials

The research designs a scenic spot representation module based on multi-dimensional attention mechanism, integrating user portraits, scenic spot semantic features, and real-time contextual information through adaptive weight calculation. Secondly, a greedy strategy driven path generation framework is constructed, introducing dynamic programming mechanisms to synchronously optimise route length, theme fit, and time cost. Finally, the reinforcement learning paradigm is adopted to achieve end-to-end training of recommendation strategies.

Scenic spot recommendation method based on portrait and attention mechanism

In the process of building a recommendation model, two types of basic data need to be fully collected: One is tourist data that includes population attributes, behaviour patterns, and scene features. The second is scenic spot data that involves basic attributes, tourism resource categories, and classification labels. The study extracts potential features of users and attractions through data mining techniques, and then uses LDA topic models to extract keywords from the information, forming corresponding interest tags, and constructing user portraits and attraction portraits.

The LDA topic model, as a typical representative of unsupervised learning, has significant advantages due to its feature of not requiring manual annotation. This model can achieve automated processing through parameter tuning, demonstrating good scalability and logical modelling capabilities in the fields of natural language processing and data mining. It has been widely used in multi-source heterogeneous data processing [16, 17]. The LDA model can be characterised by the joint probability distribution formula, P as shown in equation:

$$P(\theta, z, w \mid \alpha, \beta) = P(\theta \mid \alpha)\prod_{n=1}^{N} P(z_n \mid \theta) P(w_n \mid z_n, \beta) \tag{1}$$

where the observed variable w corresponds to the document vocabulary, the latent variable z represents the topic attribution, and θ is the document topic distribution. The hyperparameters α and β control the sparsity of these two distributions separately, and N is the total sampling amount. The key to solving the model lies in calculating the posterior probability distribution of the latent variables:

$$P(\theta, z \mid w, \alpha, \beta) = \frac{P(\theta, z, w \mid \alpha, \beta)}{P(w \mid \alpha, \beta)} \tag{2}$$

For this complex optimisation problem, Gibbs sampling algorithm is used for parameter estimation. As a typical representative of Markov chain Monte Carlo method, this algorithm approximates the target distribution through iterative sampling. According to the convergence condition of Markov chain, the distribution of document topics and topic vocabulary can be calculated:

$$\begin{cases} P_{\text{Topic}}(w \mid k) = \dfrac{C_{wk} + \beta}{\sum_{v=1}^{V} C_{vk} + W\beta} \\ P_{\text{word}}(k \mid d) = \dfrac{C_{dk} + \alpha}{\sum_{k=1}^{K} C_{dk} + W\alpha} \end{cases} \tag{3}$$

where C_{wk} represents the number of times the vocabulary w appears in the topic k. V indicates the size of the vocabulary. W indicates the total number of topics. C_{dk} represents the number of words belonging to topic k in document d. k represents the total number of preset themes.

The user profile model, as shown in Figure 1, covers three core levels: identity attributes, behaviour trajectories, and environmental elements. Among them, the identity attribute layer covers stable basic attributes such as user identity, demographic attributes (gender, age), consumption ability level, and tourism interest tendency. This type of static feature constitutes the benchmark identification system for user portraits and is suitable for direct tagging processing. The behaviour trajectory layer focuses on users' dynamic interaction data, including real-time updated behaviour trajectories such as travel mode selection, travel history trajectory, social platform interaction behaviour (likes/favourites), etc. This type of data stream provides temporal feature input for prediction models, which can effectively capture the evolutionary patterns of user preferences. The environmental element layer introduces spatiotemporal situational variable analysis, focusing on external environmental parameters such as seasonal cycles, meteorological conditions, and social group composition. These dynamic variables affect users' decision paths and search behaviour patterns.

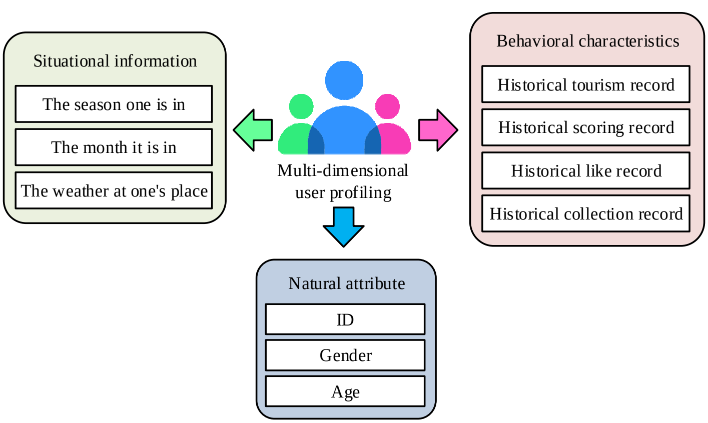

Fig. 1. User portrait model

As shown in Figure 2, the scenic spot portrait is deconstructed using a three-level feature labelling system, which includes three core dimensions: ontology attributes, theme classification, and group evaluation features. The ontology attribute layer covers the basic descriptive data of the scenic area, including inherent attribute parameters such as geographical location, resource scale, and facility support, forming the entity feature framework of the scenic area portrait. The theme classification layer uses fuzzy semantic analysis technology to divide the theme of scenic spots into dual dimensions: On the one hand, it classifies tourism functions based on resource characteristics, and on the other hand, it combines seasonal features to establish the best experience cycle model. The group evaluation feature layer extracts consumption experience correlation features from tourist behaviour data. By establishing a collaborative analysis model of cost-effectiveness index and experience satisfaction index, a classification and identification system for high cost-effectiveness scenic spots and high-quality experiential scenic spots is formed.

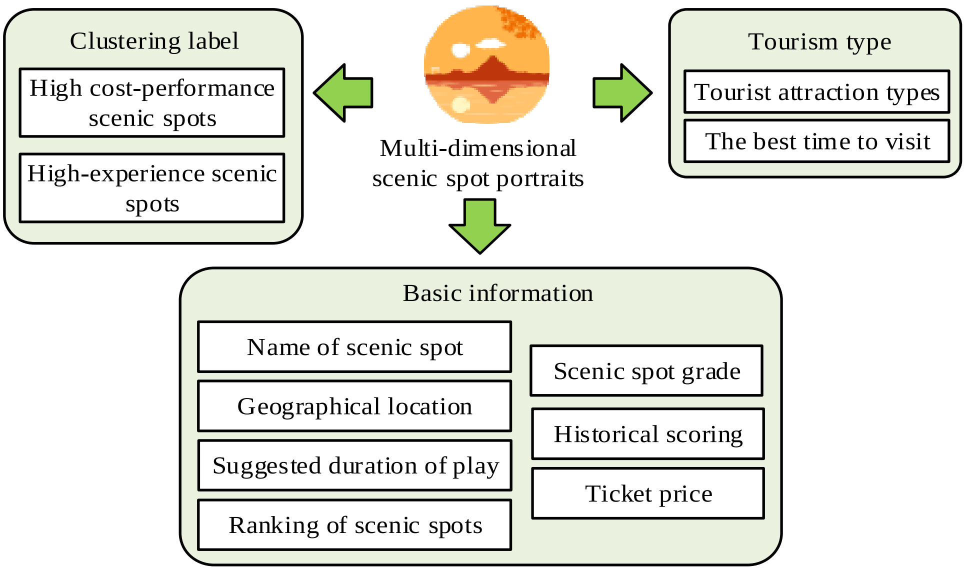

Fig. 2. Portrait of the scenic spot

The Attention Enhanced Multi-Source Feature Tourism Recommendation (AEMFTR) model proposed in this study optimises the recommendation performance through multi-source feature integration and dynamic weight allocation mechanism. As shown in Figure 3, the system architecture consists of four core modules. The interactive feature extraction module adopts Product-based Neural Network (PNN) as the basic architecture, and analyses user attraction interaction behaviour through feature cross modelling to capture explicit behaviour patterns and potential associated features. This module constructs a distributed representation of user behaviour trajectories, forming an initial interest feature space. The text semantic parsing module integrates BERT pre trained language models and text mining techniques to perform deep semantic deconstruction of tourism review texts. Context sensitive feature vectors are extracted through Transformer encoder and a mapping relationship between unstructured text and structured behavioural features is established. The attention weight allocation module addresses the shortcomings of traditional recommendation system feature processing by designing a dual channel attention mechanism: The behavioural attention network evaluates the temporal influence weights of historical interactive behaviours, and the text attention network quantifies the information contribution of different semantic units. The multi-modal prediction module integrates the broad deep dual path learning architecture of the Deep Factorisation Machine (DeepFM), which combines weighted behavioural features and text features through feature cross layer integration. A dynamic factorisation machine is used to optimise high-order feature interactions and personalised recommendation lists are ultimately generated.

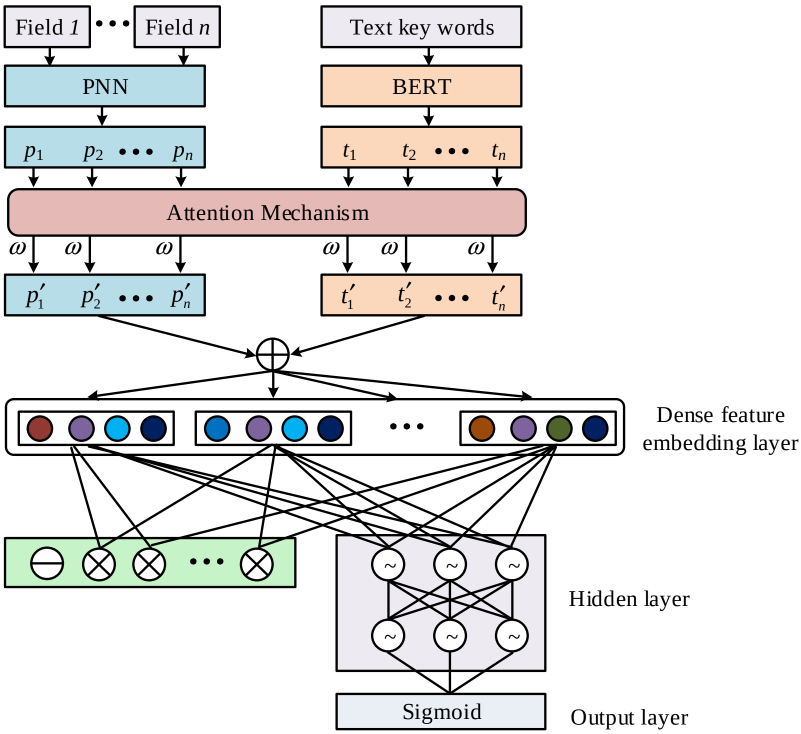

Fig. 3. Framework diagram of the AEMFTR model

When inputting PNN into the Field, the interaction behaviour feature matrix is generated through the collaborative operation of linear and nonlinear components. The BERT model is used to encode the keyword set in context and a text feature matrix is output. The study designs a dual attention network to calibrate the feature weights of the behaviour matrix P and text matrix T, separately:

$$\begin{cases} P' = (\omega_1 p_1, \omega_2 p_2, \dots, \omega_m p_m) \\ T' = (\lambda_1 t_1, \lambda_2 t_2, \dots, \lambda_n t_n) \end{cases} \tag{4}$$

where ω_m and λ_n respectively represent the attention weight coefficients of behavioural features and textual features. The weighted feature matrices P' and T' are vector concatenated and input into the DeepFM framework. Among them, the FM component extracts second-order interaction patterns between features, while the DNN component captures high-order nonlinear relationships through multi-layer perceptrons. Vector connection is performed on the output vectors of the FM layer and DNN layer to achieve feature fusion, and the final recommendation probability score is output through one-dimensional processing via a fully connected network. This model introduces a differentiable attention mechanism to dynamically adjust the contribution of different historical behaviours and text features, effectively alleviating the information loss problem caused by average pooling.

Multi-constraint rural tourism route recommendation based on greedy algorithm

While recommendation approaches rooted in user profiling and attention mechanisms can adeptly uncover user interests and preferences, enabling precise single-attraction recommendations, in real-world rural tourism contexts, tourists frequently require sequential planning of multiple attractions amidst multiple constraints, including time costs, transportation distances, and spending budgets. To this end, the research further proposes a multi-constraint route recommendation method based on greedy algorithm, which dynamically balances resource constraints and user needs to transform discrete scenic spots into executable travel routes that conform to real-world scenarios.

Greedy algorithm is an algorithm strategy that adopts the optimal decision in the current state at every step of the selection process, hoping to accumulate local optimal solutions and ultimately achieve the global optimal solution [18, 19]. Its core idea is to pursue the best option for the current step in a "short-sighted" manner, without considering the long-term impact of the overall problem [20]. If the spatial topology network of a scenic spot consists of a network structure of candidate scenic spots and their spatial correlations, the mathematical representation is $Y = (S,R)$. Among them, $S = \{s_1, s_2, ..., s_n\}$ represents a set of n candidate scenic spot nodes, each corresponding to a specific rural tourist attraction. $R = \{r_1, r_2, ..., r_l\}$ forms an edge set of l travel paths between scenic spots, and the edge weight *Tra* represents the actual distance between the two scenic areas. As shown in Figure 4, the global tour path starting from A constitutes the network, and the edge weight numbers visually display the driving time between adjacent attractions.

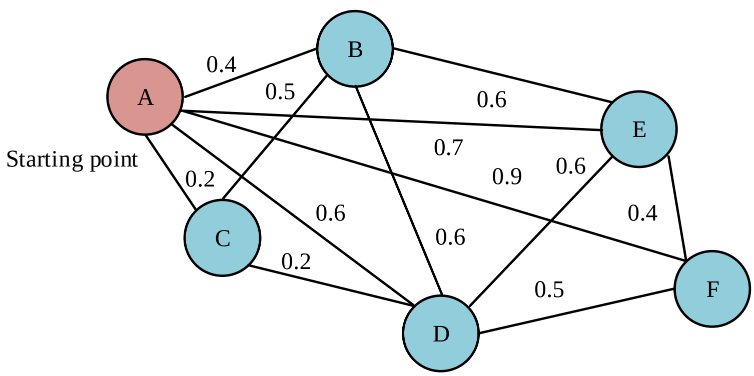

Fig. 4. Schematic diagram of the transfer relationship of scenic spots

The personalised constraint set Con_u = (Con_{dur}, Con_{cost}) proposed by tourist u includes two core dimensions: Con_{dur} is the maximum daily travel time limit to ensure the rationality of travel time; Con_{cost} is the upper limit of the tourism budget to control economic costs. Each scenic spot *s* is comprehensively characterised by an octet as shown in equation (5)

$$s = (Pri, His, Typ, Btp, Lng, Lat, Dur, Pre) \tag{5}$$

In equation (5), *Pri* represents the ticket price, which directly affects the economic cost. *His* is the score for historical evaluation, reflecting the popularity of the scenic spot. *Typ* is the resource type label, used for interest matching. *Btp* is the best travel season, it affects the suitability of the itinerary. *Lng* and *Lat* are geographic coordinates used for spatial distance calculation. *Dur* is the recommend travel duration which guides time allocation. *Pre* is the preference score generated by the AEMFTR model.

Ordered access path $r = \{s_1, s_2, ..., s_i\}$ represents the complete tourism route, s_i is the *i*-th tourist node, and the order reflects the actual access sequence. The spatial distance calculation is accurately calculated using the Haversine spherical distance formula:

$$Tra_{A,B} = 2\arcsin\sqrt{\sin^2\frac{\Delta Lat}{2} + \cos(Lat_A)\cos(Lat_B)\sin^2\frac{\Delta Lng}{2}} \times 6378.137 \tag{6}$$

where ΔLat represents the latitude difference between attractions and ΔLat represents the longitude difference between attractions. Traffic congestion assessment can be represented through $D_{max} = \max\{\bar{d}_1, ..., \bar{d}_m\}$. Among them, $\bar{d}_m$ represents the delay of vehicles on the *m*-th entrance lane. The speed parameters of the road section are calculated:

$$\bar{v} = \frac{nL}{\sum t_i} \tag{7}$$

where *L* is the length of the road section, t_i is the passage time of vehicles, and *n* is the number of vehicles passing during the observation period. The unified congestion coefficient is calculated:

$$CFRS = e^{-\gamma(Dmax + QTImax)} \tag{8}$$

where γ is the adjustment coefficient and *QTImax* is the maximum queuing time index. The travel time calculation model is shown:

$$\begin{cases} TDA_{A,B} = \dfrac{Tra_{A,B}}{\bar{v}} \\ TTT(r) = \sum_{i=1}^{n-1} TDA_{s_i, s_{i+1}} \\ TTR(r) = \sum_{i=1}^{n} Dur_i + \sum_{i=1}^{n-1} TDA_{s_i, s_{i+1}} \end{cases} \tag{9}$$

where $TDA_{A,B}$ reflects the time required for passage between two scenic areas, which is influenced by both the actual distance and the average vehicle speed. *TTT*(*r*) is the total transfer time between all nodes of the entire line. The total travel time *TTR*(*r*) includes both sightseeing and transportation factors, where Dur_i is the recommended length of stay for the *i*-th attraction.

To quantify the theme consistency between routes and user preferences, the study introduces a theme fit index, which is calculated based on the semantic matching between user interest tags and scenic spot theme tags. Specifically, user interest tags are extracted from historical behaviour data through the LDA model to construct an interest vector T_u with dimension D. The theme type tag of scenic spot i is transformed into a unique heat vector T_{v_i}. The degree of fit $\mathrm{TopicFit}(u,v_i)$ between scenic spot i and the user's theme is defined as the cosine similarity of their vectors, and the calculation formula is shown in equation:

$$\mathrm{TopicFit}(u,v_i)=\cos(\mathrm{T}_u,\mathrm{T}_{v_i})=\frac{\mathrm{T}_u\cdot\mathrm{T}_{v_i}}{\|\mathrm{T}_u\|\|\mathrm{T}_{v_i}\|} \tag{10}$$

The closer $\mathrm{TopicFit}(u,v_i)$ is to 1, the higher the matching degree between the theme of the scenic spot and the user's interest. Finally, the comprehensive evaluation *TRS* of rural tourism routes under the condition of meeting the constraints is obtained:

$$TRS=\lambda_1\sum_{i=1}^{n}Pre_i+\lambda_2\cdot N_{\mathrm{type}}+\lambda_3\cdot TTR+\lambda_4\cdot\frac{1}{n}\sum_{i=1}^{n}\mathrm{TopicFit}(u,v_i) \tag{11}$$

where λ_1, λ_2, λ_3 and λ_4 are all weight adjustment coefficients, and the relative importance is determined through grid search (the experimental values are 0.5, 0.2, 0.2 and 0.15 respectively). N_{type} represents the total number of types of scenic spots covered by the route.

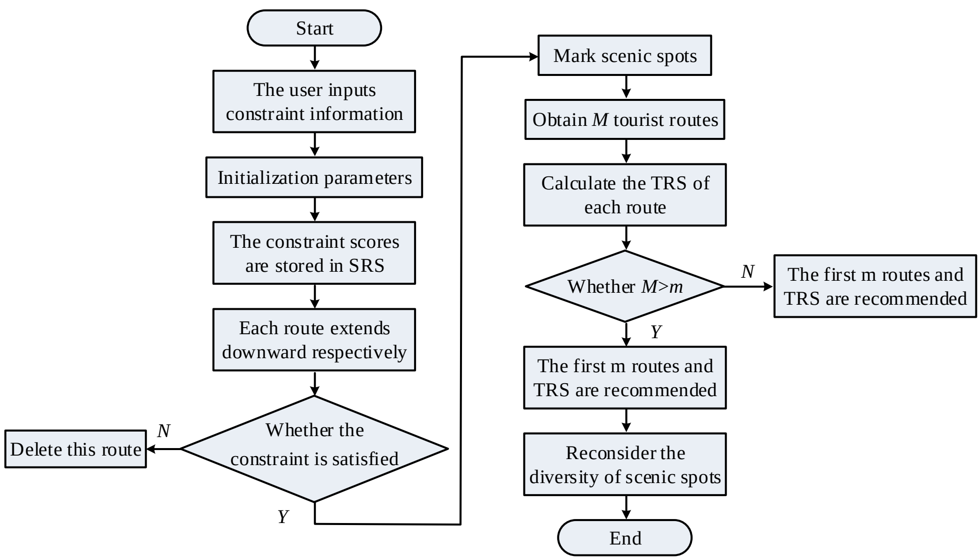

Fig. 5. Flowchart of the greedy algorithm

The greedy algorithm generates optimised routes through a multi-stage filtering mechanism, and the complete process logic is shown in the flowchart in Figure 5. The core execution process includes five key stages: To begin with, the visited scenic spot record array and the route score *TRS* (initialised to 0) are set up. Subsequently, a dynamic expansion strategy is employed, whereby dual constraint verification is conducted based on the top n high-scoring candidate points of the current node each time the next attraction is selected. If incorporating a new attraction leads to exceeding the time or cost limits, it is excluded from consideration. The current path generation process is terminated when there are no more viable candidate points. The visit flags for each valid attraction are updated to avoid duplicate visits. Finally, the generated *M* feasible routes undergo intelligent screening. In cases where *M* surpasses the required quantity *m*, the top *m* routes with the highest *TRS* scores are chosen. Otherwise, all routes are outputted, and the candidate routes are subjected to a two-stage ranking based on the diversity of scenic spot types.

Results

The study conducted experiments using real datasets, with the objective function of maximising the total path score and the number of scenic spot types. The proposed rural tourism route recommendation method was validated by simulating tourists' sightseeing behaviour.

Algorithm performance validation

The research was based on the tourism vertical platforms "Lvping. Com" and "Qunar. Com" to collect multidimensional attribute data of hotels and attractions. The spatial coordinate information was extracted using geographic information service interfaces, and user comments, price ranges, and service tags were integrated to form a structured dataset that included geographic location mapping, tourism resource classification, and user behaviour characteristics. This dataset integrated multidimensional data from rural tourism scenarios, including portrait information of 5000 users (gender, age, purchasing power, preferred seasons, and historical tourist areas), attribute data of 200 attractions (geographic location, ticket prices, resource types, ratings, and popularity), and 50000 user attraction interaction records (ratings, comment texts, weather, and timestamps). It also covered 10000 spatiotemporal path data between attractions (traffic distance, benchmark travel time, real-time congestion coefficient). The experimental environment and parameters are shown in Table 1.

Table 1

Experimental environment and parameters

Parameters/Configuration	Description/Value
Hardware configuration	CPU: Intel Xeon E5-2680v4, GPU: NVIDIA Tesla V100 32GB
Software framework	TensorFlow 2.8, PyTorch 1.12
Number of iterations	1000 piece
The neighbourhood threshold q of the greedy algorithm	$q = 5$
The attention mechanism hides the dimension of the layer	256
Reinforcement learning rate	0.001

To find the optimal number of recommended scenic spots, a series of comparative experiments were designed. By calculating various evaluation indicators under different numbers, the results were plotted as a line graph, as shown in Figure 6. Analysis of Figure 6 revealed that when the recommended number of attractions was 20, the Mean Absolute Error (MAE) reached its lowest value, which was 0.6921. This indicated that the prediction error of the recommendation model was the smallest and the recommendation effect was the best at this time. As the number of recommended attractions increased, the accuracy gradually improved, but after exceeding 20, the accuracy began to decline, indicating that the recommendation effect started to deteriorate. Meanwhile, as the number of recommended attractions increased, the recall rate and F1 score also correspondingly increased. Taking into account these experimental results, the study ultimately determined that the optimal recommended number of scenic spots was 20.

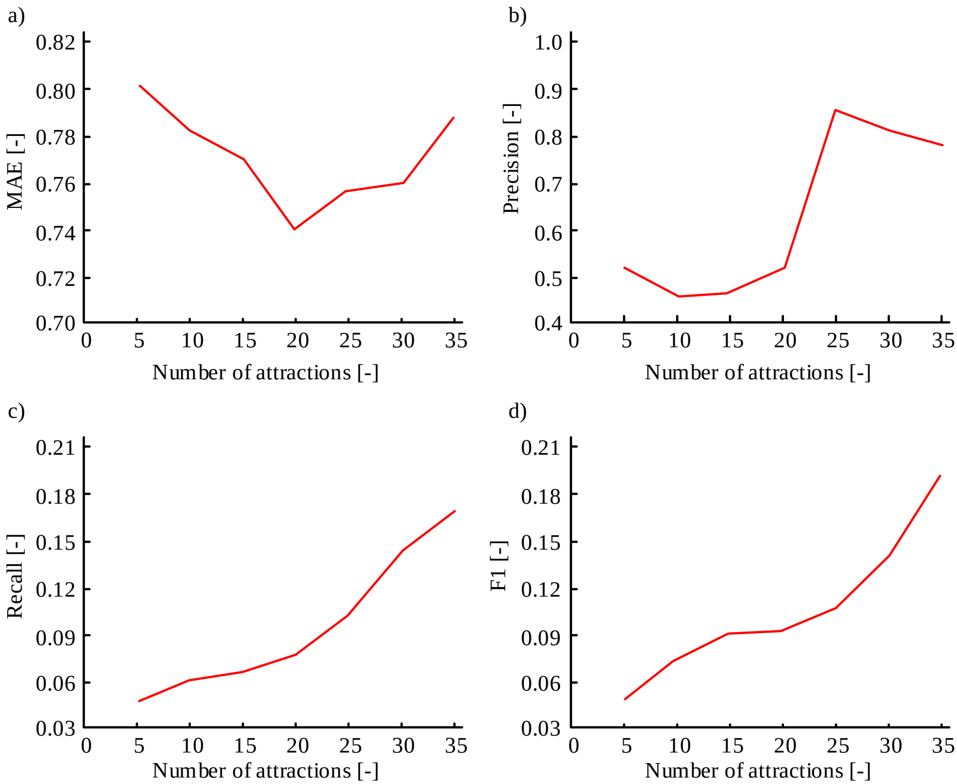

Fig. 6. Algorithm performance under different numbers of recommended scenic spots: a) MAE, b) precision, c) recall, d) F1

In order to further verify the effectiveness of the proposed multi constraint based tourism route planning method, comparative experiments were designed to compare four algorithms: Collaborative Filtering based POI Recommendation Algorithm (CF-PRA), Multi-objective Preference Traveling Salesman Problem (MO-PTSP), Deep Learning based Sequence Generation Model (DL-SGM), and Multi-objective Optimisation Hybrid Recommendation System (MOO-HRS). The experimental results are shown in Figure 7. It can be seen from Figure 7a that the benefit value of this method is significantly ahead of models such as MO-PTSP and DL-SGM, with an improvement of approximately 35 % compared to MO-PTSP. It breaks through the single-objective limitation of traditional methods and achieves precise coupling of multiple constraints. It can be seen from Figure 7b that although this method is slightly higher than the lightweight model DL-SGM, it is 42 % and 30 % faster than MO-PTSP and MOO-HRS, which also belong to multi-objective optimisation, respectively. In Figure 7c, the LOSS value of this method is the lowest, 10 % lower than that of MO-PTSP. This is because this method adaptively adjusts the priority according to the scenario (such as peak season priority time and off-season reinforcement preference), and combines the global exploration ability of dynamic programming to avoid the local convergence trap of heuristic algorithms (such as MOO-HRS).

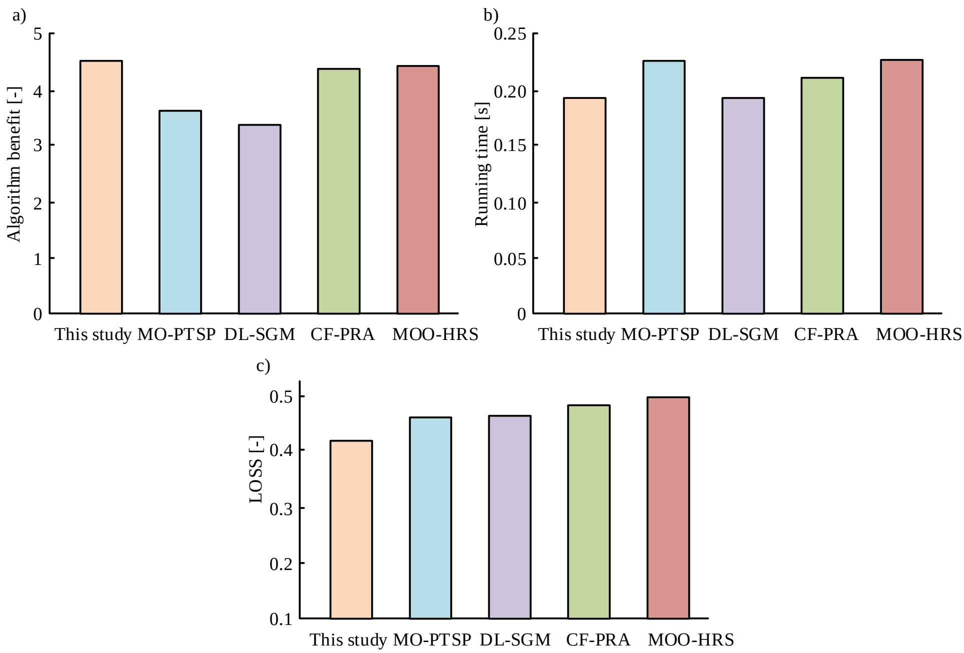

Fig. 7. Comparison of algorithm performance: a) comparison of algorithm benefits, b) comparison of algorithm running time, c) comparison of the final convergent LOSS

Table 2

Multi-dimensional performance comparison of the attention mechanism

Model configuration	**No-attention mechanism**	**Single-channel attention (behavioural characteristics)**	**Dual-channel attention (behaviour + text)**
MAE	0.8321	0.7456	0.6921
Precision	0.74	0.79	0.83
Recall	0.69	0.73	0.78
F1	0.71	0.76	0.80
Path score	8.21	9.05	9.87
Time cost [s]	0.32	0.29	0.26
Attractions cover several types	4.20	5.10	6.50

To comprehensively evaluate the contribution of attention mechanism to recommendation performance, the study compared four dimensions of model accuracy, diversity, computational efficiency, and multi-objective optimisation ability. The comparison results are shown in Table 2. As shown in the table, the dual channel attention mechanism exhibited comprehensive advantages in multi-dimensional performance comparison. Compared to the baseline model without attention mechanism, the dual channel model reduced the average absolute error by 16.8 %, improved accuracy and F1 score to 0.83 and 0.80, respectively, and achieved recommendation diversity of 0.85, significantly optimising the balance of scenic spot types. Meanwhile, the dual channel model covered 6.5 scenic spot categories, indicating that it could effectively coordinate the multi-objective conflict between time cost and user preferences.

Application effect analysis

To verify the effectiveness of rural tourism route recommendations, this study compared the performance differences between the research method and the CF-PRA method using three indicators: coverage rate (reflecting the proportion of tourists adopting recommended routes), popularity index (representing the strength of route preferences), and recommendation time (measuring algorithm real-time performance), as shown in Figure 8. From Figures 8a and b, as the number of recommended routes increased, both coverage and popularity index showed a decreasing trend, but the research method had the smallest decrease and always outperformed the comparison algorithm. From Figure 8c, in terms of recommendation time, the research method showed an efficiency advantage in the first attraction, and as the number of attractions increased, the CF-PRA's time consumption rapidly increased, while the growth of the research method was flat.

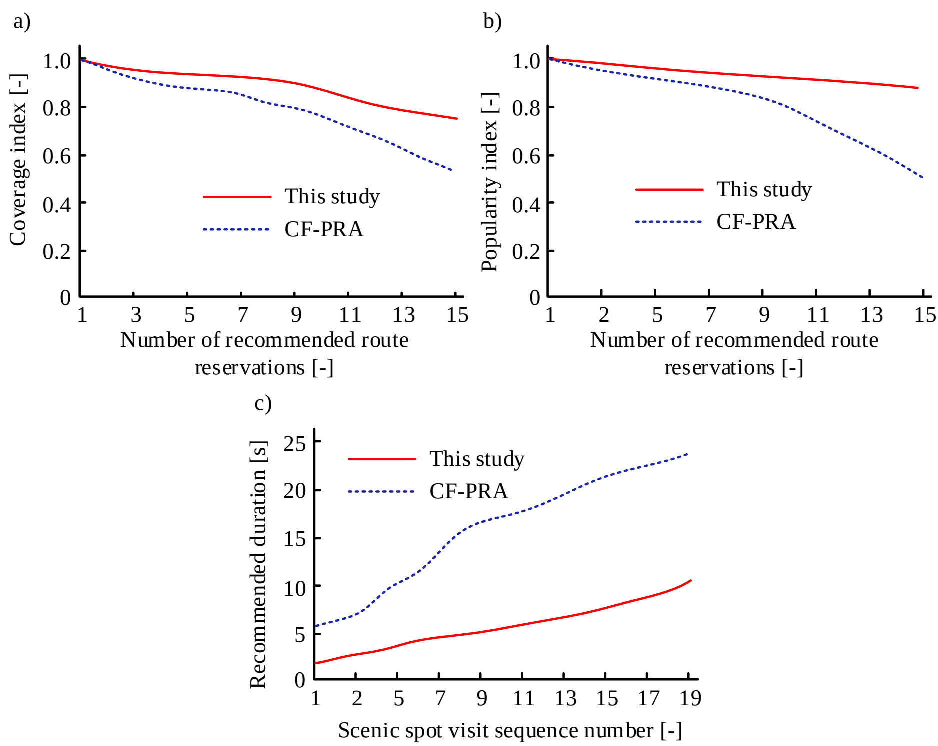

Fig. 8. Evaluation of the recommended route: a) coverage index, b) popularity index, c) recommended duration

Figure 9 shows the recommendation scores of different users under different models. As the number of attractions increased, the total path scores of both models decreased, but the research model always outperformed the CF-PRA model, especially when there were many attractions. The difference in scores between user A and user B was not significant when the number of attractions was 1, but the decrease in User B score was more significant as the number increased. Therefore, the research model performed better in recommending more attractions and could provide higher quality recommendation results.

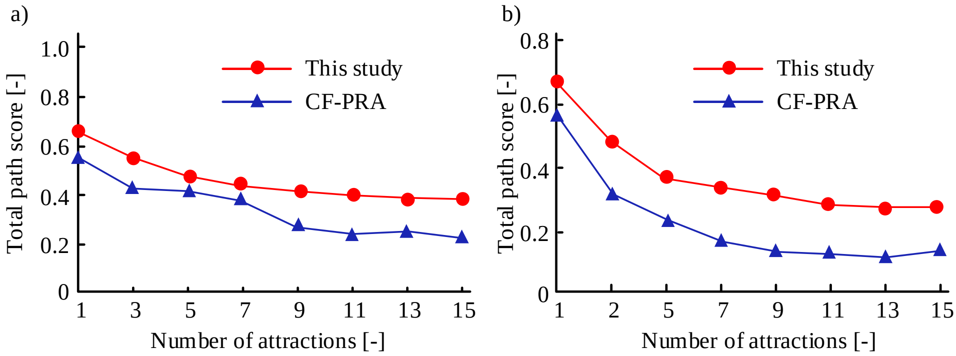

Fig. 9. Recommendation result scores of different users: a) user A's recommendation scores for different models, b) user B's recommendation scores for different models

Table 3

Details of each route

Route name	**Route A**	**Route B**	**Route C**
The number of scenic spots	5	4	4
Total number of tourism types	7	5	4
Total cost [yuan]	40	90	128
Total playtime [h]	8	7.8	8
Per capita expenditure	8	22.5	32
Scenic spot efficiency [h/piece]	1.60	1.95	2.00
Time cost ratio [yuan/h]	5.00	11.54	16.00
Congestion coefficient	0.182	0.201	0.235
Congestion duration [h]	1.46	1.57	1.88
Comfort index	1.31	1.56	1.53

Table 3 reveals the core trade-offs of different rural tourism routes in terms of efficiency, cost and experience. In terms of cost, the total cost of Route A is only 40 yuan, which is much lower than the 90 yuan of Route B and the 128 yuan of Route C. Its time cost ratio is 5.00 yuan per hour, which is only 43 % of Route B's 11.54 yuan per hour and 31 % of Route C's 16.00 yuan per hour. The economic efficiency is the most prominent. In terms of congestion, the congestion coefficient of Route A is 0.182 and the congestion duration is 1.46 hours, both of which are superior to the 0.201 coefficient and 1.57 hours duration of Route B, as well as the 0.235 coefficient and 1.88 hours duration of Route C, offering the highest level of travel smoothness. In terms of scenic spot efficiency, Route A takes 1.60 hours per scenic spot, which is shorter than Route B's 1.95 hours per scenic spot and Route C's 2.00 hours per scenic spot. Although the comfort index of Route A is 1.31, slightly lower than that of Route B at 1.56 and Route C at 1.53, the improvement in comfort of the latter two comes at the cost of significantly higher costs and congestion. From the perspective of algorithmic logic, the greedy algorithm can give priority to choosing local optimal routes like Route A, which perform outstandingly in terms of cost and congestion, and quickly lock in high cost-performance options. The attention mechanism can capture the advantageous features of Route B and Route C in dimensions such as comfort, and respond to the segmented demands of tourists.

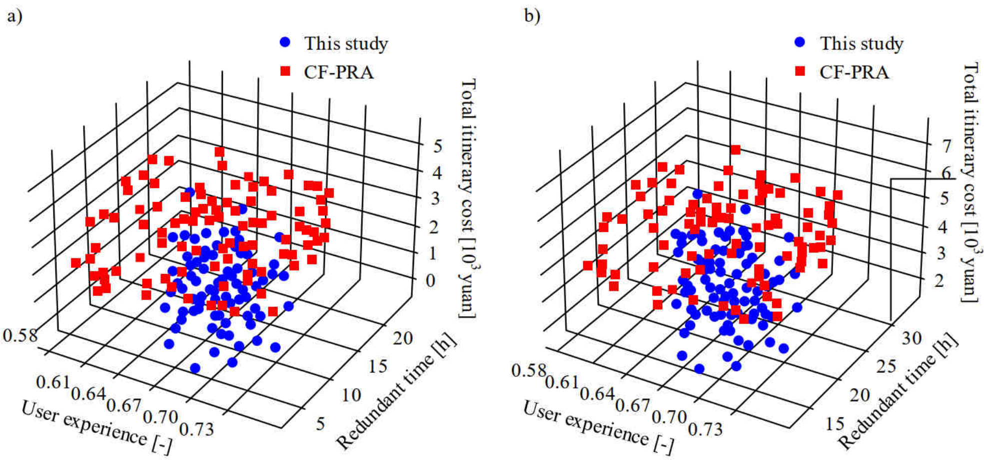

Fig. 10. Distribution map of the Pareto Frontier under different numbers of scenic spots: a) four scenic spots, b) seven scenic spots

The core of the model proposed by the research institute is to provide users with a travel route solution set that comprehensively considers three major goals: user experience, total cost of the trip, and redundant travel time. To verify the effect of the model, route planning was carried out based on the number of different scenic spots. The Pareto frontier distribution map in Figure 10 presents the performance of two different route planning models in various indicators. It can be clearly observed from the figure that the model proposed by the research institute has achieved relatively outstanding results in the planning of tourism routes. Specifically, the routes planned by the model proposed by the research institute mainly focus on the user experience ranging from 0.64 to 0.73, and both the redundant travel time and the total travel cost are lower than those of the CF-PRA model. This fully demonstrates that the model proposed by the research institute has excellent performance in balancing and optimising the three key goals. After further in-depth analysis of the data in the figure, it was found that although the CF-PRA model performed well in the metric of travel redundancy time, there was a certain degree of instability in terms of travel cost and user experience, showing a certain degree of fluctuation.

Conclusion

The study proposed a rural tourism route recommendation method that integrated greedy algorithm and an attention mechanism. By integrating user portraits, multi-modal features of scenic spots, and real-time contextual information, combined with the local optimisation ability of greedy algorithm and dynamic weight allocation of the attention mechanism, it effectively solved the problem of multi-constraint route planning in rural tourism scenarios. The results showed that when the recommended number of scenic spots was 20, the MAE of the proposed model was the lowest, reaching 0.6921, with an accuracy and F1 score of 0.83 and 0.80, respectively, which was 16.8 % lower than the baseline model without an attention mechanism. Meanwhile, the recommended diversity index was increased to 0.85, and the coverage of scenic spot types reached 6.5, verifying the effectiveness of multi-source feature integration. Compared with algorithms such as CF-PRA and MO-PTSP, the proposed model had the highest total route revenue and the shortest running time (0.1762 s), with significant efficiency advantages. Practical application analysis showed that both recommendation coverage and popularity index were superior to traditional methods. For example, route B integrated three types of attractions: food, nature, and culture, while meeting the conditions of a total travel time of 8 hours and zero budget constraints. The preference score reached 0.6116, fully reflecting the balance between personalisation and diversity. This study did not fully incorporate the impact of real-time traffic dynamics on path planning. In the future, the research can focus on the fusion modelling of multi-source heterogeneous data (such as real-time road conditions and social public opinion), and explore multi-agent collaborative optimisation frameworks to further enhance recommendation robustness and diversity in complex scenarios.

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