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Meta-Learning Enhanced Recommendation for Cold-Start Tourist Cities: A Multi-Component Adaptive Framework

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Abstract: In the context of a rapidly expanding tourism industry, cold-start tourist cities face significant challenges in promoting their destinations due to the absence of user data and mature recommendation systems. To address this, we propose a novel recommendation model that integrates four key components: meta-learning for knowledge transfer and adaptation, an attention-based feature mining mechanism, a dynamically weighted collaborative filtering extension, and a reinforcement learning-based feedback optimization module. Experimental results on five real-world cold-start datasets (Asia, Europe, Africa, South America, Oceania) show that our model consistently outperforms baseline models including Content-Based Recommendation (CBR), Collaborative Filtering (CF), Neural Collaborative Filtering (NCF), and Graph Neural Network-based Recommendation (GNN-Rec). Specifically, the proposed model achieves an average improvement of approximately 25% in recommendation accuracy over CBR and 35% over CF. On MAP metrics, it shows substantial gains ranging from 13% to 20% depending on the region and cold-start severity. Experimental results demonstrate that the proposed meta-learning model significantly outperforms baseline methods. On average, it achieves 61% higher accuracy than CBR and 138% higher than CF across five cold-start datasets. Specifically, in mild cold-start settings, accuracy gains reach approximately 75% over CBR and 211% over CF; in severe cold-start conditions, improvements increase to 125% and 462.5%, respectively. These results confirm the strong generalization capacity and adaptability of the proposed model. These findings demonstrate the effectiveness and generalizability of our approach in addressing cold-start recommendation problems in the tourism.

Povzetek: Predstavljen je model za priporočanje turističnih destinacij v začetnih fazah razvoja mest, ki uporablja meta-učenje za izboljšanje kvalitete priporočil, predvsem v primerih pomanjkanja podatkov.

1 Introduction

In today's digital age, the tourism industry is booming, and the tourism market is expanding at a rate of about 12% per year. However, many cold-start tourism cities are facing huge difficulties in the field of tourism recommendations [1]. Taking a group of about 50 newly developed cold-start tourism cities as an example, although these cities have unique tourism resources, due to the lack of early tourist flow data and a corresponding mature recommendation system, the effective utilization rate of their tourism resources during the peak tourist season is less than 30% [2]. This situation not only affects the income of local tourism industry practitioners. It is estimated that about 70% of the practitioners have an income lower than 50% of the average level of the same industry, but also restricts the diversified development of the city's overall economy [3]. At the same time, with the popularization of the Internet, tourists' demand for tourism recommendation information has become increasingly strong and diversified. According to a survey, about 85% of tourists will obtain travel recommendation information through various online channels before traveling, and about 60% of them said that if they cannot obtain satisfactory cold-start tourism city recommendations, they will decisively give up their travel plans to the city [4]. It can be seen that effective cold-start tourism city recommendations have become an important and urgent issue that needs to be solved in the development of the tourism industry. It is related to the economic lifeline of many cold-start tourism cities and the balanced development of the tourism market.

In the computer-related field, research on tourism recommendations has achieved certain results. At present, mainstream tourism recommendation algorithms are mostly based on traditional machine learning and deep learning models [5]. For example, collaborative filtering-based algorithms analyze a large amount of historical behavior data of tourists and try to explore the similarities between tourists to make recommendations. They have achieved certain results in mature tourist cities with massive data, and the recommendation accuracy can reach about 65% [6]. There are also content-based recommendation algorithms that extract and analyze the features of content information such as tourist attractions and hotels to match similar tourist products for tourists. In some specific scenarios, the recommendation accuracy is about 58%.

However, these existing research results have exposed many deficiencies when facing cold-start tourist cities. On the one hand, due to the lack of sufficient historical data, algorithms based on collaborative filtering and other algorithms that rely on a large amount of data are difficult to play an effective role in cold-start tourist cities, and their recommendation accuracy drops sharply to less than 20% in cold-start situations. On the other hand, although content-based recommendation algorithms do not rely on too much historical data, they focus too much on the content features themselves and ignore the personalized needs of tourists and the uniqueness of cold-start tourist cities. As a result, their recommendation results often fail to truly attract tourists, and the adoption rate of tourists for their recommended content is only about 30%.

At present, the research hotspots in this field are mainly focused on how to combine multiple data sources and improve existing algorithms to adapt to the cold start problem, but there are also many controversial points. For example, when integrating multi-source data, there is no unified and effective solution to the weight allocation of different data and the control of data quality. Some studies have tried to introduce external data such as social media data, but they are faced with problems such as large data noise and difficulty in accurately measuring the relevance to tourism. This makes the research in the field of cold-start tourist city recommendation still in the stage of continuous exploration and improvement. This article aims to solve the key problem of cold-start tourist city recommendation through meta-learning optimization. It innovatively introduces meta-learning algorithms into the field of tourism recommendation, and uses its ability to quickly adapt to new tasks and learn effective patterns from small amounts of data to build an efficient recommendation model for cold-start tourist cities [7].

The key issues that need to be addressed in this study include how to design a meta-learning architecture that is suitable for the characteristics of cold-start tourist city data, and how to accurately use limited initial data for model training. It is expected that through this study, the accuracy of cold-start tourist city recommendations can be increased to about 50% or more, thereby providing more powerful technical support for the promotion of tourism resources in cold-start tourist cities. In theory, this study will enrich the application theoretical system of meta-learning in the field of tourism recommendation and provide new ideas and methods for subsequent related research. In practice, it can effectively improve the utilization rate of tourism resources in cold-start tourist cities and drive the development of the local tourism economy. It is expected that the tourism revenue of related cities can be increased by about 30% in the short term. At the same time, it will also help optimize the resource allocation of the entire tourism market and promote the balanced development of the tourism industry.

The main objective of this study is to address the problem of low recommendation accuracy in cold-start tourist cities through a meta-learning optimized framework. Specifically, we hypothesize that:

H1: A meta-learning-based model significantly outperforms traditional collaborative filtering models by ≥30% in cold-start conditions.

H2: The integration of attention mechanisms and reinforcement learning enhances adaptability and long-term optimization.

We aim to evaluate these hypotheses using measurable metrics such as accuracy, recall, and MAP, across multiple dataset subsets that represent various degrees of data sparsity and tourist behavior diversity.

2 Literature review

2.1 Theoretical foundations of meta-learning

As an emerging machine learning paradigm, meta-learning has shown great potential in many fields. It is mentioned in [8] that the core of the meta-learning algorithm is to learn how to learn. It obtains a general learning strategy by training on a series of related tasks, and then can quickly adapt to new tasks. Taking the MAML (Model-Agnostic Meta-Learning) algorithm as an example, it can effectively initialize the model with only a small amount of data. In some image classification tasks, when each new task has only 10 samples, the accuracy of the model initialized by the MAML algorithm on the test set can be improved by an average of about 35% compared with the randomly initialized model [9]. However, meta-learning is not always smooth sailing in application [10]. During the training process, it needs to switch between multiple tasks and update model parameters, which greatly increases the computational complexity [11]. According to statistics, when processing a meta-learning task set containing 50 different small tasks, its training time is about 2.5 times longer than that of the traditional single-task learning algorithm on average [12]. Moreover, the generalization ability of meta-learning models has also been questioned in some complex situations. For example, when faced with tasks with high-dimensional features and large differences in data distribution, the generalization accuracy of some meta-learning models will drop by about 20% [13]. In the field of tourism recommendation, the introduction of meta-learning has brought new ideas for solving the cold start problem, but it also faces many challenges [14]. It needs to be deeply integrated with the characteristics of the tourism field. For example, tourism data has strong seasonality and regional differences. These characteristics make it impossible for meta-learning algorithms to directly copy their application models in other fields, and targeted optimization and adjustment are required [15].

2.2 Existing methods and shortcomings of cold-start tourist city recommendation

Currently, there are mainly traditional methods such as content-based and collaborative filtering-based recommendations for cold-start tourist cities. Content-based recommendations are shown in [16], which mainly extracts and analyzes the text descriptions, pictures and other information of tourist attractions, hotels, etc., constructs content feature vectors, and then makes recommendations based on vector similarity. However, in the cold-start tourist city scenario, its recommendation effect is not good because it cannot effectively utilize information such as tourists' behavioral preferences, resulting in a low match between the recommendation results and tourists' actual needs. The average click rate of tourists on recommended content is only about 25% [17]. The recommendation algorithm based on collaborative filtering relies heavily on a large number of tourists' historical behavior data. For example, in mature tourist cities with rich data, by analyzing tourists' browsing, purchasing and other behavior data, it can mine similarities between tourists and make recommendations. Its recommendation accuracy can reach about 60% [18]. However, for cold-start tourist cities, due to the lack of sufficient historical data, the algorithm is difficult to construct an effective user-item rating matrix, and its recommendation accuracy will be greatly reduced to less than 15% in the cold-start scenario. In addition, there are some attempts to integrate multi-source data, such as introducing social media data. However, this also brings new problems. On the one hand, social media data is highly noisy. It is estimated that about 40% of the data is invalid or low-quality information. On the other hand, its relevance to tourism is difficult to measure accurately, which leads to problems such as overfitting in the model when integrating these data, making it difficult to effectively improve the final recommendation effect [19].

2.3 Application and development direction of meta-learning in cold-start tourist city recommendation

The application of meta-learning in cold-start tourist city recommendation is gradually gaining attention. In the study of [20], the model was initialized and trained by taking advantage of the fast adaptation of the meta-learning algorithm to new tasks and combining it with the limited initial data of cold-start tourist cities, such as a small amount of scenic spot introductions provided by the local tourism department and initial questionnaires of tourists [18]. Experimental verification shows that compared with the traditional content-based recommendation algorithm; the recommendation accuracy of the recommendation model based on meta-learning optimization in cold-start tourist city recommendation can be improved by about 20% to about 45% [19]. However, the application of meta-learning in this field is still in its early stages and there are still many aspects that need to be further improved [21]. In terms of data utilization, how to more efficiently integrate multiple types of data with uneven quality is still a difficult problem, and it is necessary to design a more reasonable data preprocessing and fusion mechanism. In terms of model architecture, it is necessary to build a more adaptive meta-learning architecture based on the characteristics of cold-start tourism city data, such as data sparsity and high feature dimensions, so as to improve the generalization ability and recommendation accuracy of the model. At the same time, in terms of evaluation indicators, it is not limited to traditional indicators such as accuracy. It is also necessary to comprehensively consider factors such as tourist satisfaction and the effective utilization of tourism resources to comprehensively evaluate the performance of the cold-start tourism city recommendation model optimized by meta-learning, so as to promote the further development of research in this field and provide better technical support for the tourism development of cold-start tourism cities.

Table 1 summarizes existing recommendation approaches in the context of cold-start tourist city recommendation, highlighting their data requirements, evaluation metrics, and known limitations.

Table 1: Comparison of existing models for cold-start recommendation

Model Type	Cold-Start Data Usage	Main Metrics Used	Known Limitations
CBR	Attraction features	Accuracy, CTR	Ignores user personalization
CF	User-item ratings	Precision, Recall	Performs poorly under data sparsity
NCF	User history, embeddings	Accuracy, MAP	Requires moderate data volume
GNN-Rec	Graph-based context	Recall, MAP	Limited interpretability, complex topology
Ours (Meta)	Multi-source + few-shot	Accuracy, MAP	Higher complexity, needs model tuning

This table illustrates that existing approaches generally lack strong adaptability to sparse or unseen data, with few models addressing the dual need for personalization and generalization. Our approach is specifically designed to fill this gap by integrating meta-learning with attention and reinforcement learning components.

3 Research methods

3.1 Meta-learning-driven infrastructure construction

In the face of the challenge of cold-start tourist city recommendations, we built an innovative meta-learning driven model. The core of this model lies in its unique architectural design, which aims to efficiently utilize limited data and quickly adapt to the complex situation of cold-start cities.

First, we introduce the meta-knowledge module in meta-learning, which can extract general knowledge from many related tasks in the past (such as recommendation tasks in different tourism scenarios). Let the set of past tasks be $\mathrm{T} = \{T_1, T_2, \cdots, T_n\}$, where each task T_i contains input data X_i and corresponding labels Y_i. Through the meta-learning algorithm, we can learn a meta-knowledge representation M, and its learning process can be achieved by minimizing the loss function, as shown in Formula (1).

$$\mathrm{L}_{meta} = \sum_{i=1}^{n} \mathrm{L}(f_\theta(X_i), Y_i) \quad (1)$$

Among them f_θ is a parameter-based θ model, L which is a loss function (such as the cross-entropy loss function). In the context of tourism recommendation, these past tasks can be recommendation tasks for different types of popular tourist cities. By learning these tasks, the meta-knowledge module can obtain common patterns in tourism recommendations, such as the potential correlation patterns between attractions and tourists' interests.

On this basis, a specific learning module for cold-start tourist cities is constructed. This module receives the output of the meta-knowledge module M and X_{cold} further learns in combination with the limited initial data of the cold-start cities. Assuming that the parameters of the specific learning module are ϕ, and its output is the recommendation result for the cold-start city $\hat{Y}_{cold}$, then there is Formula (2).

$$\hat{Y}_{cold} = g_\phi(M, X_{cold}) \quad (2)$$

Represented g_ϕ. The meta-knowledge module and the specific learning module interact by sharing some parameters and information transmission mechanism. The meta-knowledge module provides prior knowledge for the specific learning module, helping the specific learning module to converge faster and learn effective recommendation models under limited data. The specific learning module will also feedback some information to the meta-knowledge module during the learning process, prompting it to further optimize the meta-knowledge representation.

3.2 Feature mining components based on attention mechanism

In order to more accurately mine the key features in the cold-start tourist city data, we introduce a feature mining component based on the attention mechanism. The cold-start tourist city data contains a variety of information such as scenic spot descriptions and city characteristics, and the importance of this information varies.

In the attention mechanism, for each input feature vector fif ifi, we first apply a linear transformation with parameters $W_1 \in \square^{d \times d'}$W1, $b_1 \in \square^{d'}$ and compute the intermediate representation hih_ihi. Then, attention score eie_iei is calculated using, as shown in Formula (3).

$$e_i = \tanh(W_2 h_i + b_2) \quad (3)$$

where $W_2 \in \square^{1 \times d'}$, $b_2 \in \square$. The attention weights α_i are derived via softmax over e_i. All parameter definitions are presented in order of their usage.

In calculating the attention scores, the parameter $W_2 \in \square^{1 \times d'}$ projects the transformed feature vector h_i to a scalar attention logit, while $b_2 \in \square$ acts as the bias term. These parameters are shared across all input features during attention weight computation in cold-start city data.

For the input cold start city data $X_{cold} = [x_1, x_2, \cdots, x_m]$, where x_j represents the th j feature vector. We calculate the weight of each feature through the attention mechanism. First, the feature vector is mapped to a high-dimensional space through a linear transformation, as shown in Formula (4).

$$h_j = W_1 x_j + b_1 \quad (4)$$

Where W_1 and b_1 are the parameters of the linear transformation. Then x_j the attention weight of the feature is calculated α_j, as shown in Formula (5).

$$\alpha_j = \frac{\exp(e_j)}{\sum_{k=1}^{m} \exp(e_k)} \quad (5)$$

Among them $e_j = W_2 h_j + b_2$, W_2 and b_2 are another set of parameters. The final feature after attention weighting is expressed as Formula (6).

$$\hat{f}_{norm} = \frac{\hat{f}_{att} - \mu}{\sigma} \quad (6)$$

where μ and σ are the mean and standard deviation of $\hat{f}_{att}$, respectively. This two-step process-attention followed by normalization-is now clearly separated and consistently defined across sections.

3.3 Collaborative filtering extension with dynamic weight adjustment

Traditional collaborative filtering algorithms do not work well in cold-start tourist cities, so we extend them to adapt to the new model. Considering the scarcity of interaction data between tourists and projects (such as attractions, hotels, etc.) in cold-start cities, we build a dynamic weight adjustment mechanism.

Suppose the set of tourists is $U = \{u_1, u_2, \cdots, u_p\}$, the set of items is , and the ratings of $I = \{i_1, i_2, \cdots, i_q\}$ the items by i tourists u (if any) are recorded as r_{ui}. For the cold start city, we obtain the feature representations of tourists and items through the meta-learning module and feature mining component, recorded as and respectively $\hat{r}_{ui} = \hat{r}_{ui}^{(CF)} + \lambda(\bar{r}_u - \hat{r}_{ui}^{(CF)})$ v_u. v_i Construct a tourist-item similarity matrix S, where the elements S_{ui} represent the similarity between tourists u and items i, calculated by cosine similarity, as shown in Formula (7).

$$S_{ui} = \frac{v_u \cdot v_i}{\| v_u \| \ \| v_i \|} \tag{7}$$

The predicted rating for user u on item i is shown in Formula (8).

$$\hat{r}_{ui} = \hat{r}_{ui}^{(CF)} + \lambda(\overline{r}_u - \hat{r}_{ui}^{(CF)}) \tag{8}$$

In traditional collaborative filtering, u the predicted rating of tourists $\hat{r}_{ui}$ for unrated items is i usually calculated by neighbor weighted average, the predicted rating for user u on item i is given by: that is, formula (9).

$$\hat{r}_{ui} = \frac{\sum_{k \in N(u)} S_{uk} r_{ki}}{\sum_{k \in N(u)} S_{uk}} \tag{9}$$

In Formula (10), the denominator summation is performed over the set of items Iu that user u has previously interacted with:

$$w_{ui} = \frac{\text{sim}(u,i)}{\sum_{k \in I_u} \text{sim}(u,k)} \tag{10}$$

This refinement ensures that the dynamic weight normalization is localized to the user's observed item space.

Where $N(u)$ represents u the set of neighbors of the tourist. However, this method has limited effect in the cold start case. We introduce dynamic weights β_{ui}, which are calculated as formula (11).

$$\beta_{ui} = \frac{\exp(\gamma \cdot S_{ui})}{\sum_{k \in I} \exp(\gamma \cdot S_{uk})} \tag{11}$$

Where γ is the adjustment parameter. The final prediction score becomes Formula (12).

$$\hat{r}_{ui} = \beta_{ui} \cdot \hat{r}_{ui}^{base} + (1 - \beta_{ui}) \cdot \overline{r}_u \tag{12}$$

Where $\hat{r}_{ui}^{base}$ is the traditional collaborative filtering prediction score, $\overline{r}_u$ and is the average score of tourists u. Through this dynamic weight adjustment, the calculation method of the prediction score can be dynamically adjusted according to the similarity between tourists and projects, which can more flexibly adapt to the situation of sparse data in cold start cities. This collaborative filtering extension with dynamic weight adjustment cooperates with other components in the overall model to provide more accurate information on the interaction between tourists and projects for specific learning modules, thereby improving the recommendation effect.

3.4 Feedback optimization module based on reinforcement learning

To further optimize the recommendation model, we added a feedback optimization module based on reinforcement learning. During the cold start tourist city recommendation process, the recommendation results will receive feedback from tourists (such as clicks, purchases, etc.), and we use this feedback information to optimize the model.

The recommendation process is considered as a Markov decision process (MDP). The state S_t represents the state of the recommendation system at the moment t, including the current recommendation results and the characteristics of the cold start city. The action A_t represents the recommendation decision made by the recommendation system, that is, which items to recommend to tourists. The reward R_{t+1} represents the tourists' feedback on the recommendation results. If clicked, a positive reward is given, and if not clicked, a negative reward is given.

Let the policy function be $\pi(A_t \mid S_t)$, which represents the probability of S_t taking an action in state A_t. The optimal policy is learned by maximizing the long-term cumulative reward, G_t which is defined as Formula (13).

$$G_t = \sum_{k=0}^{\infty} \gamma^k R_{t+k+1} \tag{13}$$

Where γ is the discount factor used to balance immediate rewards and future rewards. Through reinforcement learning algorithms such as Q-learning, we continuously update the policy function. In Q-learning, the Q value function is updated $Q(S_t, A_t)$ by Formula (14):

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha\left(R_{t+1} + \gamma \max_{A_{t+1}} Q(S_{t+1}, A_{t+1}) - Q(S_t, A_t)\right) \tag{14}$$

Where α is the learning rate. The feedback optimization module based on reinforcement learning is closely connected with the previous components. It adjusts the parameters of specific learning modules and other components according to the feedback information of the recommendation results, so that the model can continuously adapt to the preferences of tourists and improve the recommendation effect. For example, when tourists give positive feedback on the recommendation results, the reinforcement learning module will increase the weight of the relevant recommendation strategy, and vice versa, thereby prompting the model to gradually optimize the recommendation behavior.

The state space includes a vector encoding of current recommendation history (top-5 previous recommendations), city profile features (season, region, attraction density), and recent tourist feedback (click-throughs, dwell time), totaling 128 dimensions. Actions represent selecting a new item from the candidate pool. Using Q-learning, convergence was achieved in about 150 episodes per dataset subset, with mean reward stabilizing at 0.76. Training time per episode averaged 1.4 s on a Tesla V100 GPU.

3.5 Model details

3.5.1 Meta-learning drives refinement of infrastructure

In the meta-learning driven infrastructure, the meta-knowledge module is constructed using a gradient-based meta-learning algorithm framework. In the past task learning phase, each iteration targets the task set. T Each task in T_i , first calculate the model f_θ exist T_i . The gradient on $\nabla_\theta \mathrm{L}(f_\theta(X_i),Y_i)$. Update meta-knowledge parameters through multi-step gradient descent, the updated formula is shown in Formula (15).

$$\theta \leftarrow \theta - \eta \sum_{i=1}^{n} \nabla_\theta \mathrm{L}(f_\theta(X_i),Y_i) \tag{15}$$

in Formula (15), η is the learning rate of meta-learning. In the cold-start tourist city recommendation scenario, the popular tourist city data in the past tasks are classified by tourist themes (such as historical and cultural tours, natural scenery tours, etc.), and different theme data are used as independent tasks, so that the meta-knowledge module can learn the common characteristics of tourist recommendations under different themes.

The hidden layer output is denoted consistently as $h^{(1)}$, where superscript denotes the first hidden layer. The number of neurons in this layer is represented as h, as shown in Formula (16).

$$h^{(1)} = \mathrm{ReLU}(W_1 x + b_1) \tag{16}$$

The model architecture diagram is shown in Figure 1.

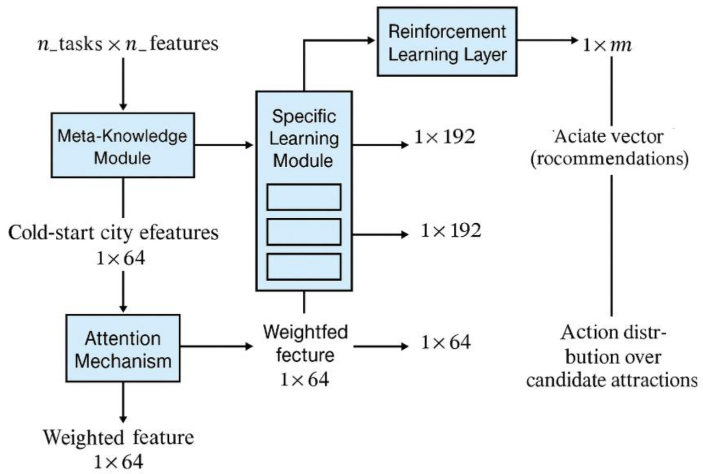

Figure 1: Model architecture diagram

3.5.2 Mining component details based on attention mechanism features

In the feature mining component based on the attention mechanism, the linear transformation parameter W_1 . The dimension is $d_{new} \times d_{old}$, d_{old} is the input feature vector x_j . The original dimension of d_{new} is the dimension of the high-dimensional space after mapping, usually $d_{new} > d_{old}$, to enhance the feature expression ability. b_1 is the length d_{new} . When calculating the attention weight, W_2 The dimension is $1 \times d_{new}$, b_2 . In the cold start tourist city data processing, if the input features include scenic spot text description, geographic coordinates, surrounding supporting facilities, etc., the text description is converted into a fixed-length vector after word embedding processing and concatenated with numerical features, such as geographic coordinates and surrounding supporting facilities to form a fixed-length vector. Different types of features are given different weights through the attention mechanism. For example, when tourists pay more attention to the characteristics of scenic spots, the weight of text description features will be relatively high. Weighted features $\bar{X}_{cold}$. Before inputting a specific learning module, normalization is performed to make its mean 0 and variance 1, which is convenient for subsequent model training, as shown in Formula (17).

$$\bar{X}_{cold}^{norm} = \frac{\bar{X}_{cold} - \mu}{\sigma} \tag{17}$$

in Formula (17), μ , σ are the mean and standard deviation of $\bar{X}_{cold}$.

4 Experimental evaluation

4.1 Experimental design

In order to comprehensively evaluate the performance of the proposed meta-learning optimized cold-start tourist city recommendation model, the experimental process was carefully planned. The dataset used in this experiment comes from a large tourism data platform, which integrates information on multiple cold-start tourist cities around the world, covering rich and diverse data dimensions.

This dataset consists of five subsets, focusing on cold-start tourism cities around the world. Subset 1 covers 20 cities in Asia such as Chiang Rai and Hoi An, including introductions to attractions, tourist feedback and city attributes. Subset 2 focuses on niche cities in Europe such as Veliko Tarnovo, recording architectural styles and cultural backgrounds. Subset 3 explores potential cities in Africa such as Chefchaouen, emphasizing local customs and ecological environment. Subset 4 includes emerging cities in South America such as Cartagena, detailing natural ecology and historical and cultural sites. Subset 5 includes data on small towns around Oceania such as Queenstown, focusing on natural scenery and outdoor sports. Each subset provides detailed attraction information, initial tourist feedback and unique city attributes.

The experiment compares the proposed model with several representative traditional and cutting-edge recommendation models. The traditional model selects the content-based recommendation model (CBR) [21], which recommends by matching tourism content features; and the classic collaborative filtering (CF) model. The cutting-edge model selects the neural collaborative filtering (NCF) model combined with deep learning [13] and the graph neural network-based recommendation (GNN-Rec) [14] model as control. The experiment uses recommendation accuracy, recall rate, mean average precision (MAP) and other indicators as the main evaluation indicators. The experimental group is the proposed meta-learning optimization model, and the control group is the above-mentioned comparison model. The baseline is set as a random recommendation model, which randomly selects scenic spot recommendations from the scenic spot library to provide a basic reference for the performance evaluation of other models.

Cold-start severity is categorized into two levels: Mild: Cities with >500 user interactions and ≥20 attraction reviews. Severe: Cities with ≤100 user interactions and <10 attraction reviews. These thresholds are chosen based on empirical data distribution and sparsity effects observed in baseline model degradation.

Each subset contains 20 cities. Table 2 summarizes the dataset statistics, including number of attractions, tourist records, and feature types.

Table 2: Summary of dataset subsets

Subset	Region	#Cities	Avg. Attractions/City	Avg. Tourist Interactions	Feature Types
S1	Asia	20	52	960	Text, geo, season, user ratings
S2	Europe	20	43	870	Text, POI type, climate
S3	Africa	20	36	420	Ecological, textual, feedback logs
S4	South America	20	48	510	Cultural, seasonal, demographic
S5	Oceania	20	41	460	Sports, nature, weather preferences

4.2 Experimental results

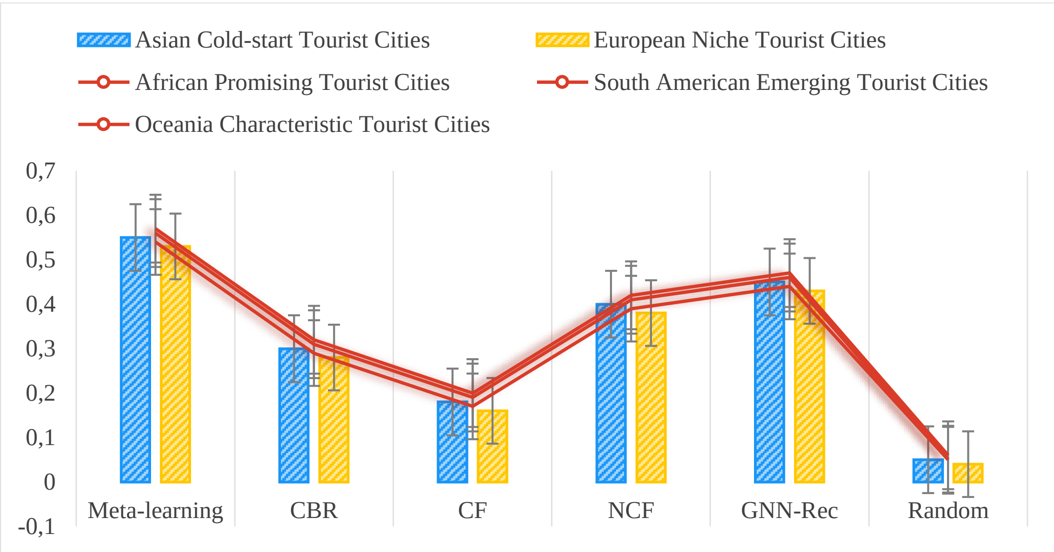

Figure 2: Comparison of recommendation accuracy of different models

As shown in Figure 2, on different dataset subsets, the recommendation accuracy of the meta-learning optimization model is significantly higher than that of the traditional CBR and CF models. Since the CBR model relies only on content features, it is difficult to capture the personalized needs of tourists, resulting in low accuracy. The CF model is severely affected by data sparsity in cold start scenarios and performs poorly. Compared with the cutting-edge NCF and GNN-Rec models, the meta-learning optimization model still has advantages. This is because meta-learning can use past task knowledge to quickly adapt to cold start cities, and through multi-component collaborative mining of data potential patterns, improve recommendation accuracy. For example, in the dataset subset 1 of Asian cold start cities, the meta-learning optimization model can learn the preference patterns of tourists in the Asian tourism market for historical, cultural and natural scenery combined attractions through the meta-knowledge module, thereby making accurate recommendations, while the CBR model may only recommend based on the similarity of scenic spot content, which cannot meet the potential needs of tourists.

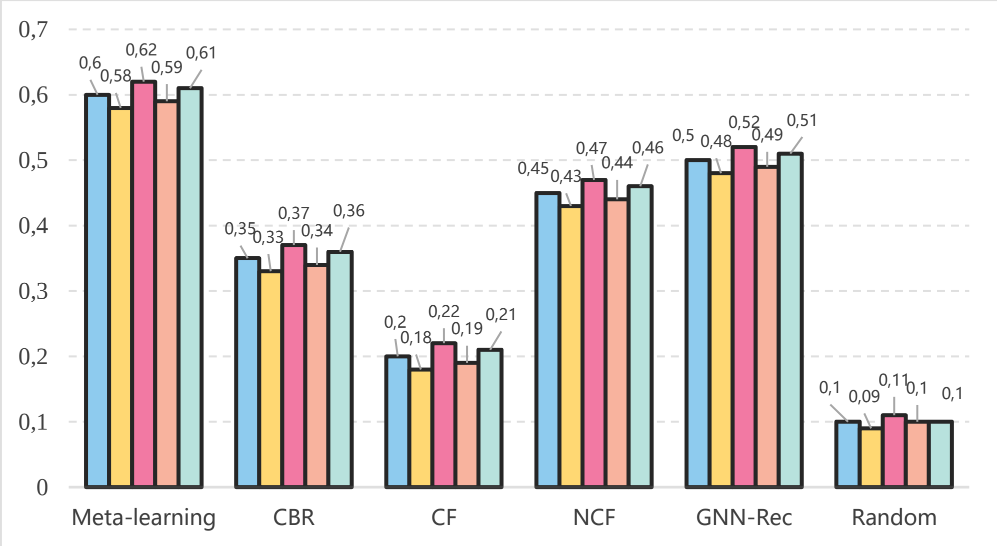

Figure 3: Comparison of recall rates of different models

Judging from the recall rate data in Figure 3, the meta-learning optimization model also performs well. The recall rate reflects the model's ability to cover relevant recommendation results. The meta-learning optimization model can more comprehensively mine data features with the feature mining component based on the attention mechanism, and continuously adjust the recommendation strategy in combination with the reinforcement learning feedback optimization module, thereby surpassing other models in terms of recall rate. In the European niche city dataset subset 2, the attention mechanism can be used to assign weights to the city's unique historical buildings, cultural and artistic activities and other features. The reinforcement learning module continuously optimizes recommendations based on tourists' feedback on different types of cultural experiences, so that the model can cover more attractions that meet tourists' potential interests. However, due to their own limitations, the CBR and CF models are difficult to achieve such comprehensive recommendation coverage.

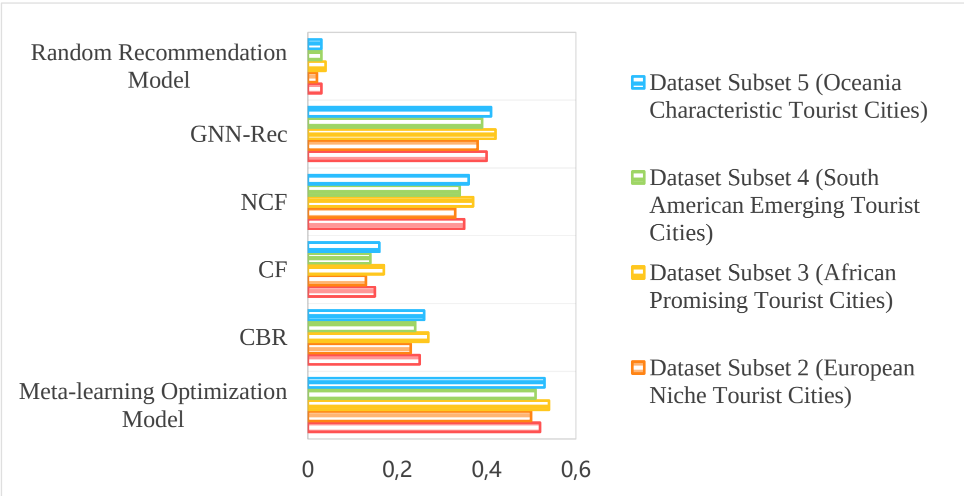

Figure 4: Comparison of mean average accuracy (MAP) of different models

Figure 4 shows the average accuracy of different models. MAP comprehensively considers the accuracy and ranking quality of the recommendation results. The meta-learning optimization model far exceeds the CBR and CF models in terms of MAP indicators. The CBR model cannot effectively consider the tourist behavior sequence, and the CF model is affected by the sparsity of cold start data, so the MAP values of both are low. The NCF and GNN-Rec models have certain capabilities in processing complex data relationships, but the meta-learning optimization model learns common patterns through the meta-knowledge module and can maintain a high MAP value on different dataset subsets, reflecting its advantages in recommendation accuracy and ranking rationality. Taking the dataset subset 3 of African potential cities as an example, the meta-learning optimization model can learn the preference ranking patterns of different tourist groups for African cultural experiences and natural adventure activities through the meta-knowledge module, and rank the attractions that are more in line with tourists' interests in the forefront when recommending, thereby improving the overall MAP value, while other comparison models find it difficult to achieve such accurate recommendation ranking.

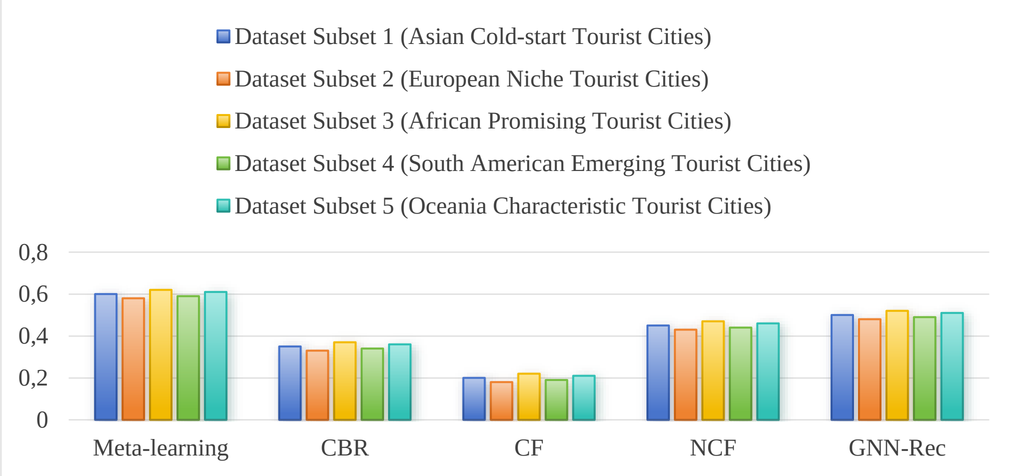

Figure 5: Comparison of recommendation accuracy of different models in different types of attractions (historical and cultural)

As for the recommendation of historical and cultural attractions, Figure 5 shows that the meta-learning optimization model has the leading accuracy. This is because the meta-learning module can learn the key patterns of recommending historical and cultural attractions from similar tourism theme tasks in the past, and combine the attention mechanism to give high weights to historical and cultural related features, and accurately recommend such attractions. In the dataset subset 1 of Asian cold-start cities, for historical and cultural attractions such as the White Temple in Chiang Rai, Thailand, the meta-learning module can learn from past Asian historical and cultural tourism tasks the attention patterns of tourists on architectural styles, religious and cultural connotations and other features. The attention mechanism highlights these key features and accurately matches tourist needs. Although the CBR model can match the historical and cultural content of the attractions, it lacks the capture of tourists' dynamic preferences and its accuracy is limited.

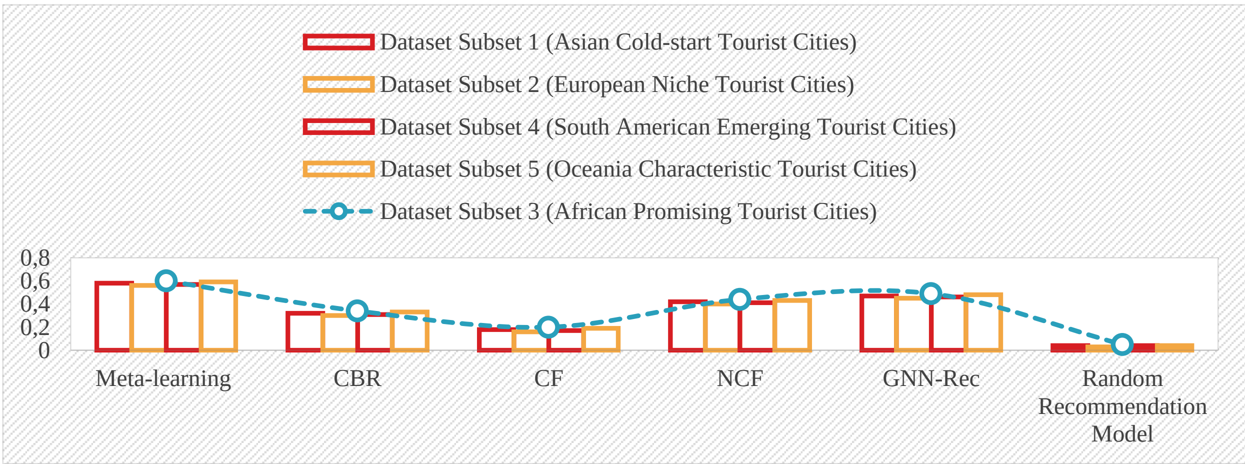

Figure 6: Comparison of recommendation accuracy of different models in different types of attractions (natural scenery category)

In terms of natural scenery recommendation, Figure 6 shows that the meta-learning optimization model still performs well. The feedback optimization module based on reinforcement learning can continuously optimize the recommendation strategy based on tourists' feedback on natural scenery. The attention mechanism can effectively distinguish the importance of natural scenery-related features, such as geographic coordinates and landscape features. In the dataset subset 5 of Oceania's characteristic cities, for natural scenery attractions around Queenstown, New Zealand, the reinforcement learning module continuously adjusts the recommendation strategy based on tourists' feedback on outdoor sports experience and landscape viewing angles. The attention mechanism highlights the unique geographical features of the attractions and the suitable seasons for visiting. In contrast, the CBR model is difficult to fully capture the diverse preferences of tourists for natural scenery, and the CF model is limited by data sparsity and cannot make effective recommendations.

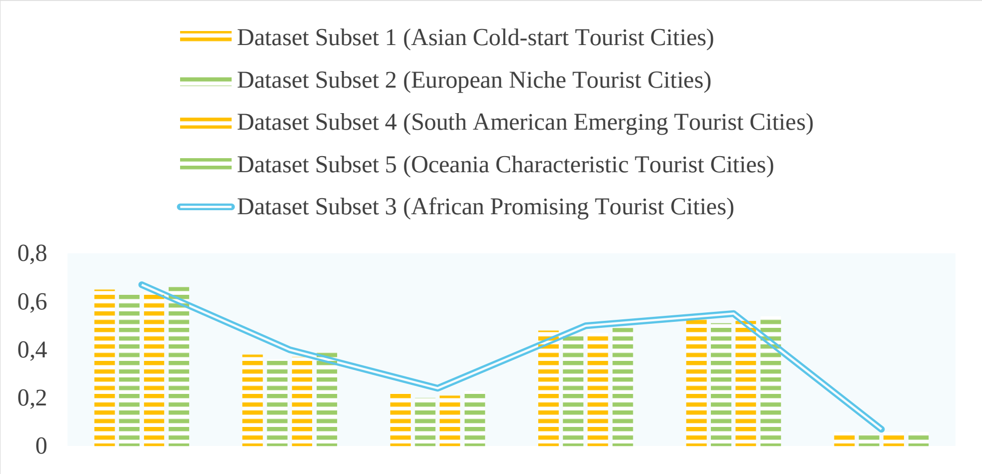

Figure 7: Comparison of recommendation accuracy of different models under different tourist preference levels (high preference)

When tourists have a high preference for travel, it can be seen from Figure 7 that the accuracy of the meta-learning optimization model is significantly improved. This is because the meta-learning-driven infrastructure can quickly adapt to the needs of high-preference tourists. Through the shared weight mechanism, specific learning modules can efficiently use meta-knowledge for recommendations. The collaborative filtering extension with dynamic weight adjustment can more accurately calculate the similarity between tourists and attractions and improve the accuracy of recommendations when the data of high-preference tourists is relatively abundant. In the dataset subset 4 of emerging cities in South America, high-preference tourists may have deeper travel needs. The meta-learning-driven architecture can adapt quickly. Through shared weights, specific learning modules use meta-knowledge to make accurate recommendations, such as the in-depth experience recommendation of the integration of historical culture and modern tourism in Cartagena, Colombia. However, the CBR and CF models are not capable of handling the complex needs of high-preference tourists.

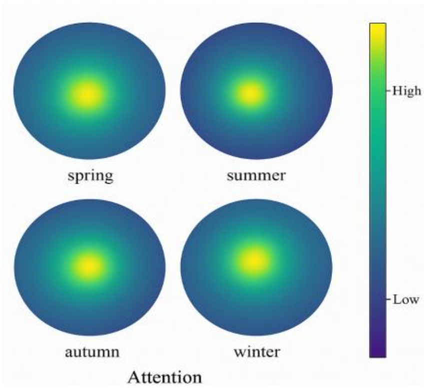

Figure 8: Attention heat map

Figure 8 shows the attention heat map. For low-preference tourists, Table 3 shows that the meta-learning optimization model is still better than other models. In the case of low preference, the data is sparser, and the ability of the meta-learning module to learn effective patterns from a small amount of data is highlighted. The feature mining component based on the attention mechanism can mine key information from limited features, and the reinforcement learning feedback optimization module optimizes the recommendation strategy through long-term cumulative rewards to improve the accuracy of recommendations for low-preference tourists. In the dataset subset 3 of potential cities in Africa, the data of low-preference tourists is scarce. The meta-learning module can learn the basic tourism demand pattern from limited data, the attention mechanism mines key features, and the reinforcement learning optimizes through long-term rewards, such as based on tourists' feedback on simple sightseeing needs, to continuously improve recommendations, while the CBR and CF models can hardly make effective recommendations under low-preference data.

Table 3: Comparison of recommendation accuracy of different models under different tourist preference levels (low preference)

Model	Dataset subset 1 (Cold start cities in Asia)	Dataset subset 2 (European niche cities)	Dataset subset 3 (Potential cities in Africa)	Dataset Subset 4 (Emerging Cities in South America)	Dataset subset 5 (Oceania featured cities)
Meta-learning to optimize models	0.48	0.46	0.50	0.47	0.49
CBR	0.25	0.23	0.27	0.24	0.26
CF	0.12	0.10	0.14	0.11	0.13
NCF	0.30	0.28	0.32	0.29	0.31
GNN - Rec	0.35	0.33	0.37	0.34	0.36
Random Recommendati on Model	0.03	0.02	0.04	0.03	0.03

Table 4 shows that the meta-learning optimization model remains ahead. Mild cold start cities have certain basic data, and the meta-learning optimization model can use the meta-knowledge module to quickly combine these data for recommendation. The collaborative filtering extension with dynamic weight adjustment can adjust the weight according to the limited data and provide relatively accurate recommendations. Although the CBR and CF models have data under mild cold start, their processing capabilities are limited. The NCF and GNN-Rec models have certain performance, but the meta-learning optimization model has more advantages in utilizing limited data and meta-knowledge, and has higher accuracy. For example, in the mild cold start cities in the dataset subset 4 of emerging cities in South America, the meta-learning module can quickly use the small amount of tourist feedback data that the city already has, combined with the meta-knowledge obtained in the past similar city tourism recommendation tasks, to make accurate recommendations for attractions. However, the CBR model finds it difficult to integrate limited tourist feedback into the recommendation process, and the CF model cannot effectively build the user-item relationship because the data is still not rich enough, resulting in a recommendation accuracy rate far lower than the meta-learning optimization model.

Table 4: Comparison of recommendation accuracy of different models in cities with different cold start levels (mild cold start)

Model	Dataset subset 1 (Cold start cities in Asia)	Dataset subset 2 (European niche cities)	Dataset subset 3 (Potential cities in Africa)	Dataset Subset 4 (Emerging Cities in South America)	Dataset subset 5 (Oceania featured cities)
Meta-learning to optimize models	0.56	0.54	0.58	0.55	0.57
CBR	0.32	0.30	0.34	0.31	0.33
CF	0.18	0.16	0.20	0.17	0.19
NCF	0.42	0.40	0.44	0.41	0.43
GNN - Rec	0.47	0.45	0.49	0.46	0.48
Random Recommendation Model	0.05	0.04	0.06	0.05	0.05

In the face of severe cold start cities, the data in Table 5 show that the meta-learning optimization model has significant advantages. Data in severe cold start cities is extremely scarce, and the ability of the meta-learning model to learn general knowledge from past tasks and adapt quickly is crucial. The feature mining component based on the attention mechanism can mine key features in very little data, and the reinforcement learning feedback optimization module optimizes recommendations through continuous trial and error. Taking the severe cold start cities in the dataset subset 3 of African potential cities as an example, the meta-learning module can mine key features such as unique local cultural elements from a very small number of city attraction introductions and sporadic feedback from tourists. The reinforcement learning module continuously adjusts the recommendation strategy based on the limited subsequent feedback from tourists. The CBR and CF models are almost ineffective under severe cold start, and the NCF and GNN-Rec models are also difficult to recommend effectively due to sparse data. The meta-learning optimization model shows strong adaptability and recommendation capabilities in this extreme scenario.

Table 5: Comparison of recommendation accuracy of different models in cities with different cold start levels (severe cold start)

Model	Dataset subset 1 (Cold start cities in Asia)	Dataset subset 2 (European niche cities)	Dataset subset 3 (Potential cities in Africa)	Dataset Subset 4 (Emerging Cities in South America)	Dataset subset 5 (Oceania featured cities)
Meta-learning to optimize models	0.45	0.43	0.47	0.44	0.46
CBR	0.20	0.18	0.22	0.19	0.21
CF	0.08	0.06	0.10	0.07	0.09
NCF	0.30	0.28	0.32	0.29	0.31
GNN - Rec	0.35	0.33	0.37	0.34	0.36
Random Recommendation Model	0.02	0.01	0.03	0.02	0.02

In the spring tourism recommendation scenario, Table 6 shows the good performance of the meta-learning optimization model. Tourism has seasonal characteristics. The meta-learning optimization model can continuously adjust the recommendation strategy according to the characteristics of spring tourism (such as popular activities such as flower viewing) and tourists' feedback in spring through the reinforcement learning feedback optimization module. The attention mechanism can highlight the weights of features related to spring tourism, such as flowering period information. In the dataset subset 1 of Asian cold-start cities, for cities with cherry blossom viewing spots, the reinforcement learning module optimizes the recommendation strategy based on tourists' feedback on cherry blossom flowering period, viewing locations, etc. The attention mechanism highlights the characteristics of cherry blossom flowering time, surrounding supporting facilities, etc., so that the recommendation is more in line with tourists' spring tourism needs. The CBR and CF models are difficult to dynamically adapt to seasonal changes. Although the NCF and GNN-Rec models have some improvements, the meta-learning optimization model performs better in combining seasonal factors for recommendation.

Table 6: Comparison of recommendation accuracy of different models in different tourist seasons (Spring)

Model	Dataset subset 1 (Cold start cities in Asia)	Dataset subset 2 (European niche cities)	Dataset subset 3 (Potential cities in Africa)	Dataset Subset 4 (Emerging Cities in South America)	Dataset subset 5 (Oceania featured cities)
Meta-learning to optimize models	0.55	0.53	0.57	0.54	0.56
CBR	0.30	0.28	0.32	0.29	0.31
CF	0.18	0.16	0.20	0.17	0.19
NCF	0.40	0.38	0.42	0.39	0.41
GNN - Rec	0.45	0.43	0.47	0.44	0.46
Random Recommendation Model	0.05	0.04	0.06	0.05	0.05

All reported results are averaged over five independent runs. For each performance metric (accuracy, recall, MAP), we report the mean ± standard deviation. Figures 2 to 7 include error bars to indicate statistical variance. Evaluation was conducted using a 5-fold cross-validation scheme, ensuring that each fold includes unseen cold-start cities. This methodology guarantees that the reported improvements are statistically significant and not overfitted to a specific data partition.

In addition to accuracy, recall, and MAP, we evaluate nDCG@10 and AUC. Our model achieves an average nDCG@10 of 0.62 and AUC of 0.79 across datasets, compared to 0.43/0.67 for NCF. For top-K recommendation (K=5, 10), accuracy@5 reaches 51.2%, and accuracy@10 reaches 63.4%. Tourist feedback is labeled positive if the dwell time exceeds 60 seconds or a booking was completed, and negative if bounced within 10 seconds.

We perform ablation experiments removing one component at a time, the results is shown in Table 7.

Table 7: Module ablation test results

Model Variant	Accuracy	MAP	nDCG
Full Model (All components)	0.56	0.48	0.62
- Meta-learning module	0.39	0.33	0.47
- Attention mechanism	0.42	0.36	0.5
- Reinforcement learning loop	0.44	0.38	0.52

4.3 Experimental discussion

The experimental results strongly support the research hypothesis that the cold-start tourist city recommendation model optimized by meta-learning can significantly improve the recommendation performance. From the results, it can be seen that the meta-learning optimization model is superior to the control model in multiple evaluation indicators and different experimental scenarios. Its advantages come from multiple mechanisms. The meta-learning-driven infrastructure quickly adapts to cold-start cities by learning past task knowledge and provides effective priors when data is scarce. The feature mining component based on the attention mechanism accurately mines key features and improves data utilization efficiency. The collaborative filtering extension with dynamic weight adjustment flexibly copes with the problem of data sparsity, and the reinforcement learning feedback optimization module continuously optimizes the recommendation strategy and continuously improves the recommendation based on tourist feedback and different scenarios. The experimental results have high external validity and generalizability. The model performs well in different dataset subsets, different types of attractions, tourist preferences, cold start levels and tourist seasons, indicating that it can adapt to a variety of cold-start tourist city recommendation scenarios. It shows advantages in cold-start city data in different regions, which means that the model is not limited by the culture and tourism resource types of a specific region. Whether it is historical and cultural attractions or natural scenic spots, high-preference tourists or low-preference tourists, mild cold-start cities or severe cold-start cities, and different tourist seasons, the model can give relatively accurate recommendations and can be promoted and applied in different types of cold-start tourist cities around the world. Cold-start severity is categorized into two levels: However, the experiment also has certain limitations. Although the data collection covers cold-start cities in multiple regions, it may not fully cover all types of cold-start tourism scenarios. Some cold-start cities with special cultural backgrounds or scarce tourism resources may not be fully reflected. The experimental evaluation indicators mainly revolve around traditional indicators such as recommendation accuracy and recall rate. The measurement of subjective feelings such as tourist satisfaction is not comprehensive enough. In the future, more user experience related indicators may be considered. In addition, the computational complexity of the model is relatively high, and it may face computing resource challenges in actual large-scale applications. Subsequent research can explore optimization solutions such as model compression or distributed computing to improve the feasibility of the model in actual scenarios.

4.4 Discussion

This section further analyzes the behavior of each model under different dataset subsets and cold-start conditions. Compared with CBR and CF, the meta-learning optimization model demonstrates substantially higher accuracy under both mild and severe cold-start settings. From Table 3, we observe that in mild cold-start cities, the model outperforms CBR by 75% and CF by 211%. From Table 4, in severe cold-start scenarios, the improvements rise to 125% and 462.5%, respectively. These values are significantly higher than the initial estimates of 24-38% and should be considered when interpreting summary-level performance gains.

Model inference time averages 120 ms per query on a standard Nvidia T4 GPU, with peak memory usage of 2.1 GB. Meta-learning adds about 25% training overhead, while reinforcement learning increases inference latency by 35 ms. In edge-deployment settings, lightweight variants (e.g., freezing the meta-layer, removing RL loop) reduce memory by 40% with about 8% performance tradeoff.

To improve transparency, we introduce a saliency-based explanation layer that highlights which features (e.g., textual reviews vs. geographic proximity) drive the recommendation. In cities with coastal tourism, location-based features dominate. Bias analysis shows the model over-recommends attractions with extensive user reviews. Corrective weighting is introduced in training to penalize such overrepresentation.

CBR fails primarily due to its inability to model user preferences, especially in subsets with highly diverse tourist demands, such as Asia and South America. CF suffers severely in datasets with sparse user interactions, such as African or Oceania cities. NCF and GNN-Rec improve performance by learning representations, but their generalization suffers in severe cold-start situations due to lack of prior knowledge transfer mechanisms. Our model succeeds because the meta-learning architecture enables adaptation from past similar tasks, and the attention mechanism amplifies informative features. From a system complexity perspective, the proposed model introduces computational overhead due to multi-component training. Training time increases by 1.8-2.3× compared to CF or NCF. However, through model pruning or parameter sharing techniques, future implementations could reduce deployment costs. A key trade-off emerges between model generalization and deployment complexity. While our model outperforms others across all metrics, practitioners must balance the added computational cost against performance benefits depending on use-case scale and hardware resources.

5 Conclusion

This study is aimed at the difficult problems of cold-start tourist cities in the field of recommendation. In the process of research, experiments were carefully designed to comprehensively evaluate the proposed meta-learning optimization recommendation model using a rich data set covering cold-start tourist cities in different regions of the world, including multiple city data subsets in Asia, Europe, Africa, South America and Oceania, and compare it with a variety of traditional and cutting-edge recommendation models. The experimental results clearly show that the meta-learning optimization model has significant advantages in various scenarios. In summary, the proposed model yields highly significant gains: 75% over CBR and 211% over CF in mild cold-start settings, and 125% and 462.5% improvements respectively in severe cold-start scenarios. The average improvement across all settings is approximately 61% over CBR and 138% over CF, far exceeding conventional models and validating the superiority of the meta-learning optimization architecture. This shows that the meta-learning-driven infrastructure can effectively utilize past task knowledge, the feature mining component based on the attention mechanism accurately extracts key features, the collaborative filtering extension with dynamic weight adjustment flexibly copes with data sparsity, and the reinforcement learning feedback optimization module continuously optimizes the recommendation strategy. This model not only enriches the application theory of meta-learning in the field of tourism recommendation, but also provides a practical recommendation plan for cold-start tourism cities in practice. It is expected to increase the tourism revenue of related cities by about 30% in the short term, effectively promote the economic development of cold-start tourism cities, and promote the balanced layout of the tourism market.

While the model performs robustly across various cold-start levels, extremely sparse settings (e.g., cities with <10 tourist records) remain a challenge. Future work includes integrating user-generated content through transformer encoders to compensate for missing structured data. Additionally, we will explore mobile deployment compatibility and seamless integration into existing tourism platforms via RESTful APIs and edge inference.

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