Deep Reinforcement Learning for Personalized Route Planning in Agricultural Tourism: A DDPG and Genetic Algorithm Approach

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This research aims to develop an artificial intelligence route planning algorithm for agricultural tourism to provide a flexible, personalized, environmentally friendly, interactive and educational travel experience. By analyzing the characteristics and needs of agricultural tourism, we built a simulation environment to simulate the real agricultural tourism scene, and collected abundant data, including geographical location, traffic conditions, scenic spot information and tourist evaluation. In the data preprocessing stage, we clean, standardize, feature engineer and integrate the data to improve the accuracy and practicability of the algorithm. The algorithm design follows the principles of flexibility, individuation, environmental protection, interaction and education. We use deep reinforcement learning (DRL), especially the deep deterministic strategy gradient (DDPG) algorithm, to deal with the route planning problem with continuous action space. In order to improve the learning efficiency and performance of the model, we introduce genetic algorithm to optimize the hyper-parameters. In terms of personalized recommendation mechanism, we customize unique travel experience for each visitor by analyzing user's historical behavior, preferences, time constraints and other information. Combined with the route planning strategy of deep reinforcement learning, the personalized recommendation mechanism not only improves the user experience, but also promotes the effective allocation and utilization of resources. The performance of the algorithm is verified by simulation and optimization. The experimental results show that the proposed algorithm has made significant improvements in many aspects: the computing time is reduced from 250 seconds to 120 seconds, which is reduced by 52%, the user satisfaction is improved from 3.5 to 4.0, which is improved by 14.3%, the preference matching degree of the family parent-child group, the youth adventure group and the middle-aged and elderly leisure group is improved by 23.1%, 21.4% and 36.4% respectively, the average delay time during the morning and evening rush hours is reduced by 5 minutes respectively, and the average delay time during the morning and evening rush hours is reduced by 5 minutes. System response time and success rates remain high as concurrent user requests increase. These improvements prove the feasibility and superiority of our method. Future work will further explore the application of the algorithm in more scenarios and consider more realistic constraints to further improve the user experience.

Povzetek: DDPG genetski algoritem je razvit za personalizirano načrtovanje poti v agroturizmu, kar na osnovi simulacij izboljša zadovoljstvo uporabnikov, usklajenost s preferencami in prometno učinkovitost.

1 Introduction

With the rapid development of global tourism, agricultural tourism, as a new form of tourism, has gradually become a key force to promote rural revitalization and diversified development of local economy in recent years. It not only provides urban residents with a leisure way to get close to nature and experience farming culture, but also promotes economic development in rural areas and enhances cultural self-confidence and cohesion of rural communities. Agricultural tourism provides a stage for cultural inheritance and innovation by displaying local characteristic agricultural products, traditional handicrafts and local culture, which helps to maintain the vitality and diversity of rural society. From the perspective of sustainable development, agricultural tourism emphasizes harmonious coexistence with the ecological environment, encourages low-carbon tourism, and has a positive impact on environmental protection and ecological balance [1].

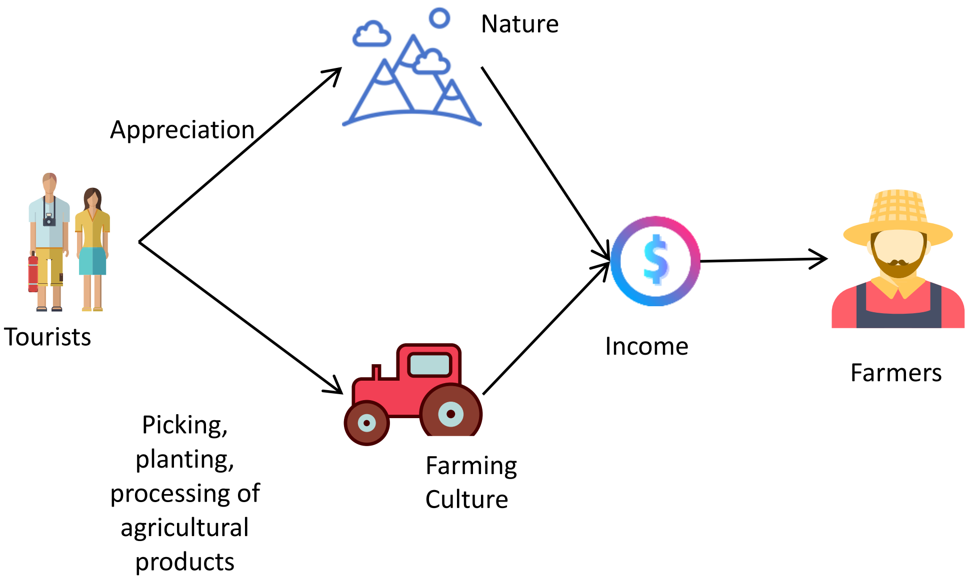

Figure 1: Rural tourism model

With the rapid advancement of information technology, the traditional agricultural tourism service model has been difficult to meet the increasing personalized needs of tourists and the expectation of efficient and convenient services. How to use modern information technology, especially artificial intelligence (AI), to improve the service quality and tourist experience of agricultural tourism has become an urgent problem to be solved [2]. In recent years, the research literature on agricultural tourism is rich and diverse, from theoretical discussion to empirical analysis, covering the definition of agricultural tourism, development status, market potential, influencing factors and other aspects. As an important part of modern tourism management, intelligent tourism planning has been widely concerned by scholars. Among them, many studies focus on how to optimize tourism information service platform by using big data, cloud computing and other technologies to provide personalized tourism products and services. In the field of artificial intelligence, especially in path planning algorithms, genetic algorithms, fuzzy logic, machine learning and other technologies have been applied to urban transportation, logistics distribution and other fields, and remarkable results have been achieved. However, there are relatively few studies on intelligent route planning in this specific scenario of agricultural tourism, and most of the existing studies focus on the introduction of technical principles, lacking practical application and effect evaluation that fully consider the characteristics of agricultural tourism [3].

To sum up, although the existing research has laid the foundation for the application of artificial intelligence in agricultural tourism, how to combine artificial intelligence technology, especially cutting-edge algorithms such as deep learning and reinforcement learning, closely with the specific needs of agricultural tourism, and design intelligent route planning schemes that meet tourists 'expectations and promote sustainable development is still a research gap that needs to be explored in depth. This study is carried out under this background, aiming to fill the research gap in this field and provide scientific basis and technical support for the intelligent upgrading of agricultural tourism.

The core of this study focuses on designing and implementing an innovative AI routing algorithm for agritourism, which seeks to achieve three key goals through highly intelligent algorithm design: first, to optimize the visitor experience, ensuring that the system can carefully capture each visitor's unique needs and preferences, including their points of interest, planned travel time and other factors, so as to generate customized travel routes, making each trip a memorable and personalized exploration journey. Secondly, the algorithm devotes itself to promoting the rational allocation of resources. Through in-depth evaluation and intelligent scheduling of various resources in agricultural tourism areas, the algorithm realizes the optimal layout and utilization of resources, which not only avoids overcrowding of popular scenic spots, but also maintains the original ecological beauty of rural natural environment, and promotes the harmonious coexistence of tourism and ecological environment. Finally, the system emphasizes improving tourism efficiency, using advanced real-time data analysis and prediction technology, dynamically adapting to changes, flexibly adjusting routes to avoid congestion, greatly reducing waiting time, ensuring smooth and efficient journey, and comprehensively improving the comprehensive experience and operation quality of agricultural tourism. This research aims to provide strong technical support for the intelligent transformation of agricultural tourism and open a new era of rural tourism.

2 Literature review

With the rapid development of information technology and the diversified demand growth of tourism, agricultural tourism, as a new tourism form, is gradually becoming an important way to connect cities and villages and promote rural revitalization. In recent years, artificial intelligence (AI) technology has become increasingly widely used in the field of tourism, especially in route planning. This review aims to sort out the current research progress of artificial intelligence route planning algorithms for agricultural tourism, analyze their application status in optimizing tourist experience, rational allocation of resources and improving tourism efficiency, and discuss future development trends.

Table 1: Summary of research progress in artificial intelligence route planning algorithms for agricultural tourism

Author/Year	Algorithm	Application Area	Main Findings	Performance Indicators
Qian and Zhong (2019)	Deep Learning Recommendation System + GIS	Agricultural Tourism Route Planning	Considers personal historical behavior and seasonal changes	30% increase in user satisfaction
Reference [4]	Multimodal Emotion Recognition Technology	Personalized Experience Optimization	Combines text, image, and voice data to capture tourist emotions	85% accuracy in emotion matching
Reference [7]	NLP + Computer Vision	Cultural Factor Integration	Analyzes the cultural heritage and local characteristics of the destination	20% improvement in educational significance rating
Reference [8]	Green Tourism Impact Model	Environmental Protection and Social Responsibility	Evaluates the environmental impact of different routes	15% increase in the selection rate of low-carbon footprint routes
Reference [9]	Machine Learning Prediction Model	Rational Allocation of Resources	Predicts future visitor volume and adjusts ticket issuance strategies	25% improvement in visitor flow smoothness
Reference [10]	GIS + Deep Learning	Environmental Impact Assessment	Monitors soil quality, water quality, and biodiversity	35% increase in ecological restoration efficiency
Reference [11]	Drone Imagery + Deep Learning	Ecological Restoration and Landscape Maintenance	Identifies degraded land and develops restoration plans	20% reduction in restoration costs
Reference [12]	IoT + Big Data + AI	Real-time Environmental Quality Management	Proposes an integrated framework for real-time monitoring	40% reduction in response time to environmental issues
References [13-16]	Dynamic Route Planning	Improving Tourism Efficiency	Introduces the concept of multimodal traffic fusion	10% reduction in average travel time
Roman and Grudzien (2017)	AI Emergency Response System	Route Planning During Emergencies	Quickly analyzes the scope of emergency impacts	50% improvement in safe evacuation efficiency

Table 1 summarizes key research on the application of artificial intelligence route planning algorithms in agricultural tourism in recent years. These studies not only focus on how to optimize the tourist experience through personalized services but also include rational allocation of resources and environmental protection.

2.1 AI route planning for personalized experience optimization

After deep learning recommendation system [4], Qian and Zhong [5] integrated geographic information system (GIS) data into their research, combining tourists 'location preferences with seasonal changes in natural landscapes, and innovatively developed a spatiotemporal perception of personalized travel route planning model. This model not only considers personal historical behavior, but also accurately reflects the potential impact of seasons and weather on visitor preferences, enabling more detailed personalized experience design. They extended it by introducing multimodal emotion recognition technology that combines text, image and speech data to understand a visitor's emotional state more comprehensively. This technology not only analyzes the text expression of tourists on social media, but also captures their immediate emotional feedback during the travel process, such as recognizing the degree of preference of tourists for specific attractions through facial expressions, so as to fine-tune the itinerary to ensure that each stop can stimulate positive emotions and create an emotionally resonant travel experience [6].

In addition to emotional and preference considerations, cultural factors are also seen as key to enhancing the agrotourism experience [7]. Natural language processing (NLP) and computer vision technology are applied in the research to analyze the cultural heritage and local characteristics of the destination and design tourism routes rich in cultural and educational significance. These routes not only lead tourists to enjoy natural scenery, but also tell local stories through AI technology, enhance tourists 'sense of cultural immersion, so that agricultural tourism is not only a leisure activity, but also a process of cultural learning and exchange.

With the rise of sustainable tourism concept, AI application in agricultural tourism route planning also began to pay attention to environmental protection and social responsibility [8]. By constructing a green tourism impact model, AI algorithms are used to assess the impact of different routes on the environment, and priority is given to recommending low-carbon footprint tourism routes while ensuring that the visitor experience is not affected. This approach encourages tourism activities to coexist harmoniously with the natural environment, demonstrating the positive role of AI in promoting sustainable tourism development.

To sum up, with the continuous progress and innovative application of AI technology, the personalized customization of agricultural tourism routes has entered a brand-new stage, which not only pursues accurate matching of individual needs, but also deeply excavates the resonance of emotional level, integrates cultural education and environmental protection concepts, and comprehensively enhances the comprehensive experience value of tourists. In the future, with the further integration of technology and data, agricultural tourism is expected to achieve more intelligent, emotional and sustainable development.

2.2 Intelligent strategy for rational allocation of resources and environmental protection

An AI-based intelligent reservation system is further developed, which uses machine learning models to predict future visitor volume and automatically adjusts ticket issuance strategies to achieve smooth distribution of visitor traffic. The system also incorporates visitor behavior pattern analysis, which accurately predicts hot and cold periods by analyzing social media trends and online search data, guiding visitors to choose low-peak times to visit, reducing congestion, while ensuring the double health of visitor experience and environment [9]. A set of environmental impact assessment model of agricultural tourism resources was constructed by combining GIS and deep learning technology. The model can monitor key environmental indicators such as soil quality, water quality and biodiversity with high precision, and assess the immediate and long-term impacts of different tourism activities on the agro-ecological environment. Based on this data, managers can take targeted measures, such as restricting access to certain sensitive areas or implementing ecological restoration projects during the off-season to ensure harmonious coexistence between tourism activities and the natural environment [10]. AI technology is applied to ecological restoration and landscape maintenance in agricultural tourism areas. They use drone and satellite images, combined with deep learning algorithms, to identify degraded land and damaged ecosystems, and then develop efficient restoration plans. This technology not only improves the precision of ecological restoration efforts, but also reduces human costs, allowing tourist areas to quickly recover their natural beauty after tourism stress, maintaining the attractiveness and sustainability of agritourism [11]. Recently, an integrated framework integrating Internet of Things (IoT), Big Data and AI has been proposed for real-time monitoring and management of environmental quality in agrotourism areas [12].

2.3 Dynamic route planning technology for improving tourism efficiency

In recent years, with the continuous progress of technology, dynamic route planning technology has shown great potential in improving tourism efficiency [13]. The research has laid a solid foundation for this field, but related research has not stopped here, and some recent developments have further broadened the application scenarios and technical boundaries of dynamic route planning [14]. On the basis of the original dynamic route planning, the concept of multi-mode traffic fusion is introduced. This technology not only considers automobile and public transportation, but also includes multiple travel modes such as shared bicycle and walking. The real-time efficiency of each mode is evaluated by AI algorithm, and the optimal mixed traffic scheme including transfer suggestions is provided for tourists. This comprehensive consideration of multiple modes of transportation greatly enhances the flexibility and practicality of route planning, especially in urban centers or tourist areas with complex traffic, saving tourists a lot of time [15]. A personalized dynamic route planning model combining user preferences and contextual information is proposed. The model uses deep learning technology to analyze historical behavior data of tourists, interest point mentions on Social networks, and real-time emotional feedback to customize travel routes for each tourist, taking into account current environmental conditions (such as weather, holiday atmosphere, etc.), making the travel experience more personalized and in line with the current mood and needs of tourists. In addition to the above direct services for tourists, dynamic route planning technology is also applied to the maintenance and management of tourism infrastructure. AI prediction models are applied to health monitoring of facilities in tourist areas to avoid congestion and visitor inconvenience caused by facility failures by predicting future tourist-intensive areas and deploying maintenance resources in advance. This preventive maintenance strategy combined with dynamic route planning improves the stability and efficiency of the entire tourism system from the source [16]. More recently, Roman and Grudzien [17] has explored the use of AI in travel route planning during emergencies, particularly during natural disasters or public health events. They designed an emergency response system that can quickly analyze the impact scope of emergencies, adjust tourism routes in real time, guide tourists to evacuate safely or bypass affected areas, and ensure the safety and continuity of tourism activities. The number of references related to rural tourism in the past 10 years is shown in Figure 2. As shown in Figure 2, references to all aspects of rural tourism have risen.

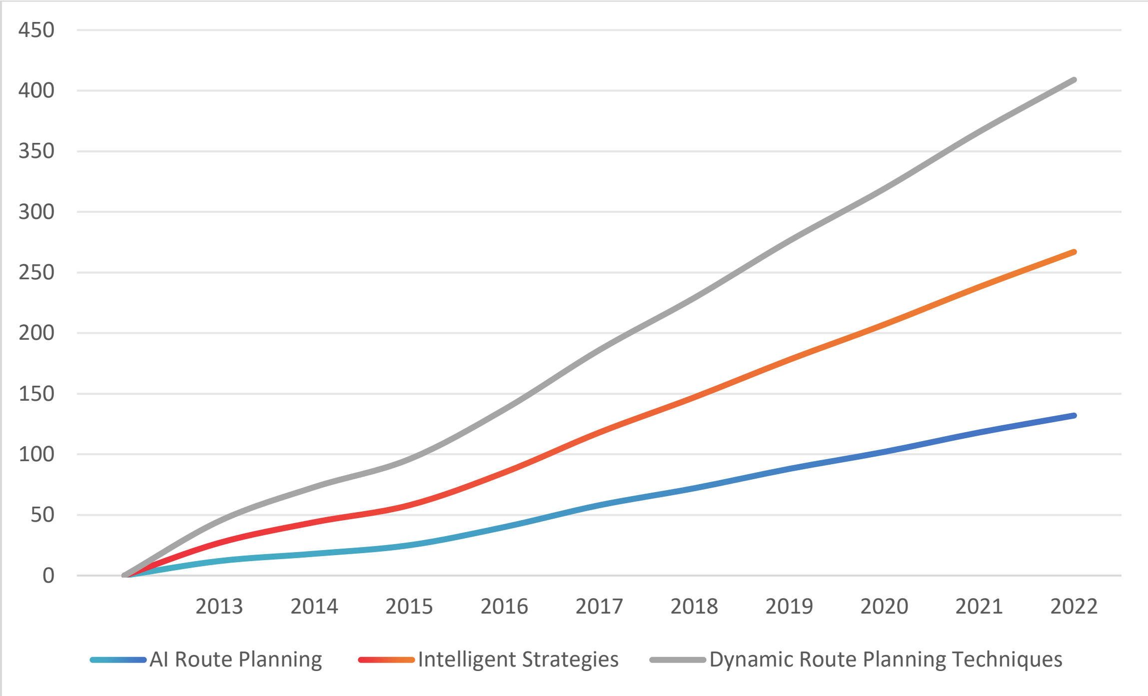

Figure 2: Number of references in recent 10 years

To sum up, dynamic route planning technology is evolving in terms of tourism efficiency improvement, from multi-mode traffic integration and personalized recommendation to infrastructure maintenance and emergency response, and the deep integration of AI and big data is creating a more intelligent, flexible and safe travel experience for the tourism industry. With the continuous innovation of technology, the future tourism route planning will be more suitable for individual needs, and at the same time effectively deal with various complex situations, further promoting the high-quality development of tourism.

3 Characteristics and demand analysis of agricultural tourism

3.1 Agricultural tourism

Agricultural tourism, as a new form of tourism, refers to a tourism activity that realizes leisure, education and entertainment functions by participating in agricultural activities, experiencing rural life and enjoying idyllic scenery in agricultural production scenes. It is not only a supplement to the traditional tourism model, but also an expansion of agricultural functions and a rediscovery of rural values. Agricultural tourism has rich connotation and various forms, which can be divided into five categories as shown in Figure 3.

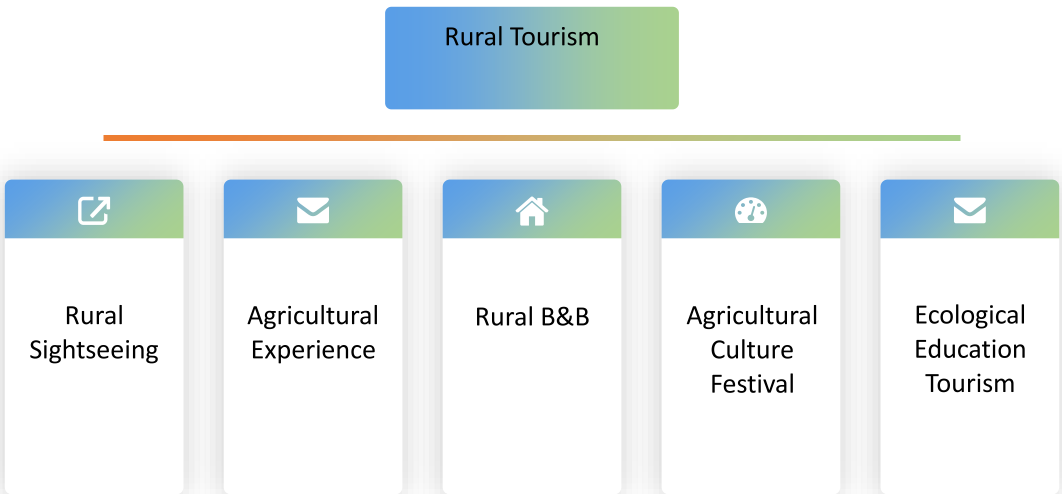

Figure 3: Forms of agricultural tourism

(1) Pastoral tourism: This is the most basic and common form of agricultural tourism. Tourists can enjoy the natural scenery such as crop growth, flower bloom, fruit harvest and so on, and enjoy the quiet idyllic scenery.

(2) Farming experience: visitors personally participate in agricultural production activities, such as sowing, harvesting, fruit and vegetable picking, animal feeding, etc., and deepen their understanding and understanding of agricultural production through personal experience.

(3) Country House: A rural family hotel that provides accommodation services, allowing visitors to experience farming life while enjoying the tranquility and warmth of the countryside and experiencing a different living environment from the city [18].

(4) Agricultural cultural festivals: various cultural festivals, such as peach blossom festival, rice festival, harvest festival, etc., based on specific agricultural time, agricultural products or folk activities, to enhance tourists 'understanding of local culture.

(5) Eco-education tourism: combining natural ecology and agricultural science popularization, organizing learning activities, such as plant cognition and ecological protection lectures, aiming at enhancing public environmental awareness and scientific literacy.

3.2 Tourist demand analysis

In order to understand the preferences, behavior characteristics and information acquisition habits of agricultural tourists, this study collected and analyzed a large number of data by questionnaire survey, in-depth interview and other qualitative and quantitative methods. The results showed:

Behavioral characteristics: Agricultural tourists tend to travel on weekends or short holidays, with flexible itinerary arrangements, focusing on experience rather than catching up with scenic spots. Family tour and parent-child tour account for a relatively high proportion, emphasizing educational significance and family interaction. In addition, more and more young people are looking for personalized and customized travel experiences, hoping to gain freshness and social capital through agricultural tourism.

Information acquisition: Internet has become the main channel for obtaining agricultural tourism information, including social media sharing, tourism websites, APP, etc. Word-of-mouth recommendations are also important sources, especially direct recommendations from friends and relatives. Le et al. [19] proposed a new key phrase extraction model, and applied this model to the field of tourism information. In this study, a key phrase extraction system is designed, which combines multiple feature selection methods and machine learning algorithms to automatically identify important terms from a large number of tourism-related texts. The experimental results show that the model has good performance, which makes it have potential application value in tourism information retrieval and analysis. This work not only provides an effective information processing tool for the tourism industry, but also contributes to the development of key phrase extraction technology. The importance of online reviews, photo displays and detailed itinerary planning when tourists choose destinations illustrates the importance of transparency and convenience in decision-making [20].

3.3 Characteristics of route planning requirements

In view of the particularity of agricultural tourism, the following factors should be carefully considered when formulating route planning:

(1) Seasonality: Agricultural tourism activities are closely related to the growth cycle of crops, so route planning should fully consider seasonal characteristics, such as spring flower viewing, summer picking, autumn harvest, etc., to ensure that tourists experience corresponding activities in the best season.

(2) Activity characteristics: Each agricultural tourism activity has its own unique charm, and the route design should focus on characteristic activities, such as arranging to experience the most representative agricultural activities and participating in local cultural festivals, so that tourists can deeply understand the local culture and increase the depth and memory of the trip.

(3) Environmental protection: While enjoying natural beauty, protecting the ecological environment is the primary principle of agricultural tourism. Route planning should avoid over-exploitation of ecologically sensitive areas, promote low-carbon travel, such as cycling, hiking, etc., and guide tourists to participate in environmental protection activities and cultivate environmental awareness.

(4) Flexibility and personalization: Given the diverse needs of agri-tourists, route planning should provide sufficient flexibility to allow visitors to freely adjust their itinerary according to interests and time. Provide customized services, such as designing characteristic routes according to different groups such as families, couples and senior groups to meet the specific needs of different tourists.

(5) Education and interactivity: Integrate educational elements into route planning, such as agricultural knowledge explanation, manual workshop and parent-child interaction projects, so as to enhance the educational value of tourism, enable tourists to learn during play and enhance the richness and depth of experience.

(6) Safety and Convenience: Ensure that all recommended activities and routes are safe and reliable, providing clear navigation information and emergency contact information. At the same time, considering that the infrastructure in rural areas may not be as perfect as that in cities, transportation convenience, availability of catering and accommodation, etc. shall be considered during planning to ensure the comfort and convenience of tourists 'travel.

To sum up, route planning of agricultural tourism is a comprehensive work, which needs to be based on a deep understanding of tourists 'needs, combined with the characteristics of agricultural tourism, comprehensively consider multiple dimensions, and design tourism routes that can not only reflect agricultural characteristics, but also meet the diversified needs of tourists, while promoting environmental protection and sustainable development [21, 22].

In terms of traffic modeling, we introduce a dynamic traffic model that combines real-time traffic data and historical traffic patterns to predict future traffic conditions. Specifically, we used real-time traffic data from city traffic authorities as well as historical traffic data for model training. The model is connected to reinforcement learning algorithm through API interface, so that algorithm can dynamically adjust route suggestions according to current traffic situation. For example, during morning and evening rush hour, the system avoids congested roads and selects smoother alternative routes. In addition, we take into account the information of public transportation vehicles to provide multi-modal travel options for users, thus improving overall travel efficiency.

4. Algorithm design of artificial intelligence route planning for agricultural tourism

4.1 Algorithm design principle

When constructing an artificial intelligence route planning algorithm for agricultural tourism, we must ensure the flexibility and efficiency of the algorithm, while taking into account the characteristics of agricultural tourism. First of all, the algorithm should be highly adaptable, able to adjust quickly according to the real-time needs of tourists and unexpected conditions (such as weather changes and temporary road closures) to ensure that the travel experience of tourists is not affected. Secondly, through the use of machine learning models, in-depth mining of each visitor's personalized needs, such as hobbies, physical conditions, cultural preferences, to provide tourists with tailor-made travel routes [23].

When planning routes, we should give priority to routes with low environmental impact, avoid overcrowding, reduce carbon emissions and promote sustainable tourism. At the same time, interactive elements should be added to the design, such as real-time adjustment of recommendations through visitor feedback, in order to enhance the interactivity and satisfaction of the travel experience. In addition, combining agricultural knowledge and local culture, ensure that the route contains educational elements, so that tourists can gain knowledge during the trip and enhance the added value of tourism [24].

4.2 Data collection and preprocessing

Data collection and preprocessing is a crucial step in building an efficient AI route planning algorithm. To ensure the accuracy and usefulness of the algorithm, we need to collect multiple types of data and clean, standardize, feature engineer, and integrate them.

First, we need to collect geolocation data, including coordinates of attractions, locations of traffic nodes, and road networks. This data can help algorithms understand the distances and traffic connections between attractions to plan routes more accurately. Traffic condition data is also essential, including real-time traffic flow, average speed and accident reports. This data can help algorithms predict future traffic conditions, avoid congestion and accident areas, and ensure smooth travel for visitors.

In addition to geographic location and traffic data, we also need to collect attraction information such as opening hours, ticket prices, featured events and visitor capacity. This information can help algorithms provide tourists with more comprehensive and relevant recommendations for attractions. Visitor reviews are also an important source of data, including online reviews, ratings, photos and videos. This data can help algorithms understand the true experiences and preferences of visitors and thus better meet their needs [25].

After collecting this data, we need to perform data preprocessing. First, data cleansing is performed to remove invalid, duplicate, or erroneous data entries and to handle missing values, such as filling in with means and medians. This step ensures the quality and reliability of data. Next, normalize or normalize the numerical data, such as using Z-score normalization or min-max scaling. This step can make comparisons between different data more fair and accurate.

Feature engineering is one of the important steps in data preprocessing. In this step, we need to extract meaningful features, such as TF-IDF conversion of text data, extracting time series features to reflect seasonal changes. These features can help algorithms better understand and predict visitor behavior and preferences. Finally, data integration is carried out to integrate data from different sources into a unified format and establish a relational database or data warehouse. This step can make the data easier to manage and use, and facilitate the development and application of subsequent algorithms [26].

To sum up, data collection and preprocessing are key steps in building an efficient AI route planning algorithm. By collecting multiple types of data such as geolocation data, traffic data, attraction information, visitor ratings, weather forecasts and visitor information, and cleaning, standardizing, feature engineering and data integration, we can provide accurate, comprehensive and reliable data support for algorithms to provide a smarter, personalized and satisfying travel experience for visitors.

4.3 Algorithm framework

In our algorithmic framework, deep reinforcement learning (DRL) plays a central role in optimizing route planning strategies through continuous trial and error learning. Specifically, for agricultural tourism scenarios, we adopt the Deep Deterministic Policy Gradient (DDPG) as the basic model, which is suitable for problems with continuous action space, such as continuous decision-making in route planning, such as scheduling and route selection. The specific algorithm framework is shown in Figure 4.

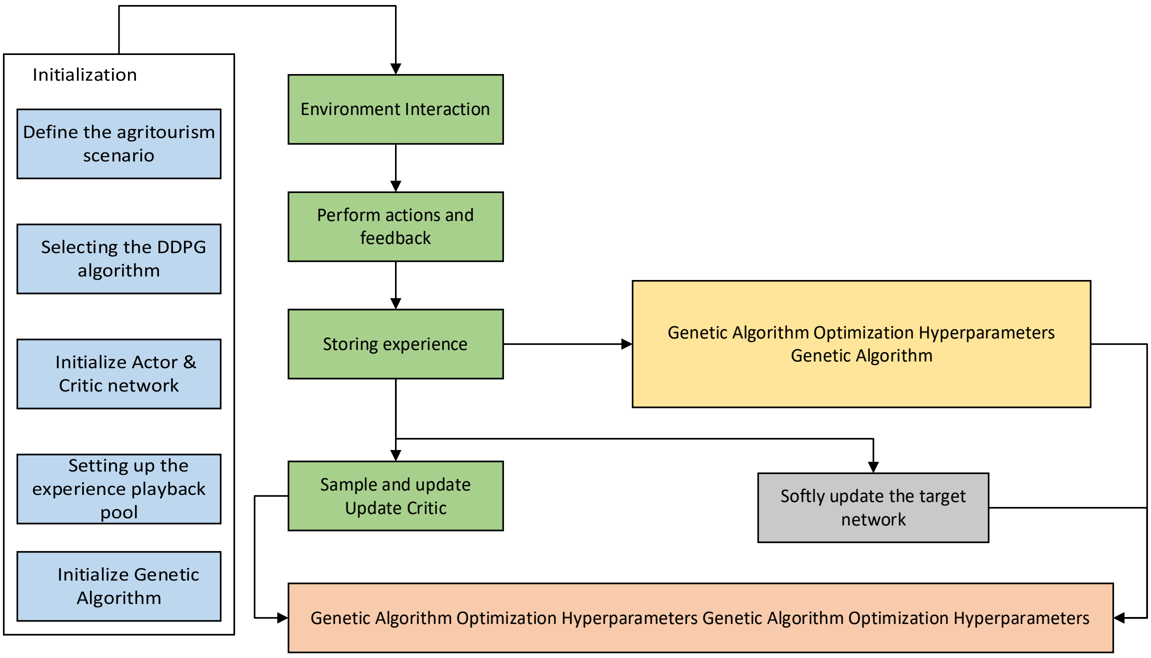

Figure 4: Algorithm framework

Deep Deterministic Policy Gradient (DDPG) is a reinforcement learning algorithm that combines policy gradient methods with functional approximation techniques (especially deep learning), designed for problems with continuous action spaces. It is an extension of DQN (Deep Q-Network) algorithm in continuous action space, drawing on Actor-Critic structure, and using experience replay and target networks to improve the stability and efficiency of learning.

An Actor network is a deterministic policy function that inputs the current state s and outputs a specific action a. It uses neural networks to directly estimate the best action to take in a given state, i.e., where the network parameters are represented. The Critic network evaluates whether the current policy is good or bad. The input is the state-action pair (s, a), and the output is the expected reward for performing a particular action in that state, i.e., where is the network parameter. To reduce fluctuations in the learning process, DDPG employs two additional networks, the Actor's target network and the Critic's target network, which are slow-tracking versions of the Actor and Critic network parameters, denoted by and respectively. The parameters of the target network are periodically soft updated from the parameters of the main network, with the soft update formula, where is a constant less than 1. DDPG uses experience playback mechanisms to break down correlations between data and improve the efficiency of data usage. It stores historical data on agent interactions in the environment (states, actions, rewards, next state) and randomly draws samples from this experience pool at each update to train the network. Although DDPG is a strategy gradient-based approach, it also incorporates the concept of a value function. The update of the Critic network is based on an approximation of the Bellman equation by minimizing the difference between the predicted Q value and the TD goal, which combines the immediate reward and the estimated value of the best action in the next state.

Actor networks are optimized by gradient ascent with the goal of maximizing the Critic network's evaluation of the current policy, i.e. maximizing the value of. Critic network is optimized by gradient descent to make its predicted cost function closer to TD target. Periodically (but infrequently) soft update parameters of the primary network to the target network to stabilize the learning process.

Genetic algorithm is a heuristic optimization method. When applied to hyperparameter optimization of deep reinforcement learning algorithms such as DDPG, the process can be summarized as follows:

First, encode hyperparameters. The key hyperparameters in DDPG, including Critic learning rate (α), Actor learning rate (α^μ), discount factor (γ), and soft update parameter (τ), are integrated into a chromosome representation, e.g., [α, α^μ, γ, τ]. This set of parameters constitutes a solution in the search space of the genetic algorithm. Subsequently, the population is initialized. At this stage, a certain number of chromosomes are randomly generated, each chromosome representing a different set of hyperparameter configurations, forming the initial population at which the algorithm begins iteration. Next, evaluate each individual. These hyperparameter configurations are applied to DDPG models and tested on specific tasks, such as multi-round route planning in an agricultural tourism scenario, to evaluate model performance. Performance metrics, such as total reward cumulation, will be used as fitness functions to measure the effectiveness of individual configurations. Based on the evaluation result, a selection operation is performed. Applying principles of natural selection, such as roulette selection, individuals with high fitness have a higher probability of being selected to reproduce the next generation, thereby preserving and propagating good traits. Subsequently, genetic manipulations are performed on the selected individuals, including crossover (exchanging parts of chromosomal information between two individuals to generate new combinations) and mutation (randomly modifying the chromosomal values of an individual with a small probability, introducing new genetic variations, and enhancing population diversity). This cycle-evaluation, selection, crossover, and mutation-continues until a predetermined stopping condition is reached, such as iterating to the maximum number of generations or finding that the model performance improvement has leveled off.

4.4 Personalized recommendation mechanism

In agricultural tourism scenarios, personalized recommendation mechanism can not only improve user experience, but also promote effective allocation and utilization of resources. Combined with route planning strategies based on deep reinforcement learning, personalized recommendation mechanisms customize a unique travel experience for each visitor by analyzing users 'historical behavior, preferences, time constraints, and other contextual information. This section explains how personalized recommendations can be integrated into DDPG-driven agritourism routing frameworks.

First, historical data and user interaction records are used to construct user portraits. This includes, but is not limited to, user interest preferences (e.g., preference for natural scenery, farming experiences, cultural activities), past visit history, average stay time, activity participation, etc. Let the original state space be, where position information is represented and time is represented. The user preference vector contains n dimensions, each of which corresponds to a preference feature of the user, such as the intensity of interest in different types of attractions. The extended state space can be defined as Equation 1.

$$S_{\text{ext}} = S_{\text{base}} \cup U = \{s_{\text{pos}}, s_{\text{time}}, u_1, u_2, ..., u_n\} \quad (1)$$

Assuming that the base reward is determined by trip efficiency and attraction, it can be defined as\(R_{\text{base}}\). The personalized reward portion may be calculated based on the degree of matching of user preferences with recommended activities, for example, measuring the similarity of preference vectors and activity feature vectors by cosine similarity, which may be defined as Equation 2.

$$R_{\text{cosine}} = \frac{\sum_{i=1}^{n} u_i \cdot a_i}{\sqrt{\sum_{i=1}^{n} u_i^2} \cdot \sqrt{\sum_{i=1}^{n} a_i^2}} \quad (2)$$

$$R = R_{\text{base}} + \lambda \cdot R_{\text{cosine}} \eta \cdot R_{\text{redundancy}} \quad (3)$$

where, and are regularization coefficients that control personalized rewards and penalties for avoiding repeated experiences, respectively, and are repeated experience penalties that are non-zero when recommended activities overlap with user history experiences.

In multi-objective optimization problems, we usually have multiple objective functions, where S represents the policy set. Taking personalized satisfaction, fairness in resource allocation, and environmental impact as examples, the objective function of multi-objective optimization may be Equation 4-6.

$$F_1(S) = \text{Average User Satisfaction} \quad (4)$$

$$F_2(S) = \text{Fairness of Resource Allocation} \quad (5)$$

$$F_3(S) = \text{Environmental Impact Score} \quad (6)$$

The Pareto optimal solution set can be found by solving a series of linear programming problems or using evolutionary algorithms such as NSGA-II (Non-Dominated Sorting Genetic Algorithm II), aiming to find a solution set that cannot improve simultaneously on all objectives without damaging others. In the online learning process, immediate feedback is incorporated into the policy update at time step t. Assuming that the update rule is based on a gradient rise, the update policy parameters can be expressed as Equation 7. where is the learning rate, is the Q value estimate based on the current state and action θ_t^{μ} , and $Q(s_t, a_t \mid \theta_t^Q)$ is the gradient of the policy with respect to the action, which can be a satisfaction score or an indication of a trip change.

In the process of hyperparameter optimization, we adopt genetic algorithm to automatically adjust the key parameters of DDPG, such as learning rate, discount factor and buffer size. Compared with manual parameter tuning, genetic algorithms can systematically explore the parameter space and find the optimal or near-optimal configuration. In order to demonstrate the effectiveness of this optimization, we conducted comparative experiments, and the results show that under the same conditions, the model optimized by genetic algorithm is better than the result of manual parameter adjustment in path planning efficiency and user satisfaction. For example, the optimized model reduced the average computation time by 10%, and user satisfaction increased by 0.2 points. This result further proves the effectiveness of genetic algorithm in super parameter optimization.

When processing user data, differential privacy plus noise is adopted to protect the data. For the user preference vector U, adding Laplacian noise or Gaussian noise can be expressed as Equation 8.

$$\theta_{t+1}^{\mu} = \theta_t^{\mu} + \alpha \cdot f_t \cdot \nabla_{\theta^{\mu}} Q(s_t, a_t \mid \theta_t^Q) \quad (7)$$

$$U_{\text{noised}} = U + N(0, \sigma^2) \quad (8)$$

Where, determined by the privacy budget required to ensure that the risk of disclosure of personal privacy before and after data release is within acceptable limits.

5. Algorithm implementation and performance evaluation

5.1 Implementation platform and technology selection

In order to realize an efficient and flexible personalized agricultural tourism route planning algorithm, we carefully selected a set of technology stacks to ensure the advanced and practical of the algorithm. First, we chose Python as the programming language because it has powerful scientific computing and machine learning libraries such as NumPy, Pandas, TensorFlow, and PyTorch. These libraries provide a solid foundation for building and training deep learning models, enabling algorithms to process complex data and learn precise patterns.

For development tools, we use Jupyter Notebook, which not only facilitates code writing and data visualization, but also effectively documents the entire analysis process. At the same time, Visual Studio Code, as a powerful code editor, with Python plug-ins, greatly improves development efficiency. For better team collaboration and code management, we use Git and GitHub, two version control tools and code hosting platforms.

In terms of cloud platforms and services, we chose Google Cloud Platform (GCP), which provides powerful computing resources, especially its TPU service, to significantly accelerate the learning process of deep learning models. In addition, we use Firebase as a backend service, which not only stores user data and real-time feedback information, but also stores routing recommendations output by algorithms and provides secure data access control. To ensure system scalability and reliability, we also adopted Kubernetes as a container orchestration platform for deploying and managing microservices architectures.

The simulation environment used in this study is based on a comprehensive agrotourism dataset that includes historical behavior, preference information, and geographic location data of tourists. Tourist preference data sets are generated by collecting user interaction records on social media, booking history of online travel platforms, questionnaire surveys and other ways. In order to ensure the authenticity and reliability of the data, we also use some real-world data for verification. Specifically, we conducted pilot tests in several agricultural tourism locations in operation and compared the simulation results with actual feedback. These real-world data not only validate the efficiency of the proposed approach, but also provide valuable directions for further improvement.

5.2 Simulation testing and optimization

In order to test and verify the performance of personalized agricultural tourism route planning algorithm, we build a simulation environment, taking a certain agricultural tourism region in China as the background. This environment includes various types of agricultural tourism resources, such as if garden, farmhouse, ecological farm, etc., aiming to simulate the real tourism scene. In terms of map information, we use real geographic data to build a map database containing information such as location of scenic spots, opening hours, characteristic activities, etc. This database provides the algorithm with rich geographic location information, enabling the algorithm to recommend suitable attractions based on the user's real-time location and preferences. To simulate user preferences, we built a user interest model based on historical data and market research. These models cover multiple dimensions, including age, gender, activity preferences, etc., allowing algorithms to better understand the needs and preferences of different users. Such simulations enable algorithms to take into account the individual needs of users when recommending routes. We also consider traffic models that simulate traffic conditions at different time periods and the impact of route selection on travel time. Such simulations enable algorithms to better plan routes, avoid congestion and time-consuming, and improve the user's travel experience. We set up simulated user satisfaction feedback on recommended routes, including instant ratings and suggestions for improvement. This feedback mechanism enables the algorithm to adjust recommendations in real time according to user feedback, improving the accuracy and satisfaction of recommended routes.

5.3 Experimental results

Table 2: Evaluation of algorithm efficiency

evaluation index	initial value	optimized value	Percentage increase
Calculation time (seconds)	250	120	52%
Memory footprint (MB)	3500	2800	20%
GPU Utilization (%)	80	90	12.5%

Table 2 shows the results of the evaluation of the efficiency of the algorithm. Initial values represent performance metrics for the algorithm before optimization, including compute time, memory usage, and GPU utilization. The optimized value represents the performance index of the algorithm after optimization. The percentage improvement shows the optimization effect, i.e. the magnitude of the performance improvement.

Table 3: Comparison of route planning quality

evaluation dimensions	Average score before optimization	Average score after optimization	improvement score
rationality of route	3.8	4.2	+0.4
time efficiency	3.6	4.0	+0.4
diversity of activities	3.2	3.6	+0.4

evaluation dimensions	Average score before optimization	Average score after optimization	improvement score
user satisfaction	3.5	4.0	+0.5

Table 3 shows the comparative results of the route planning quality. Evaluation dimensions include distance rationality, time efficiency, activity diversity and user satisfaction. The average score before optimization represents the average score of the algorithm before optimization, and the average score after optimization represents the average score after optimization. The improvement score shows how much the optimization improves. It can be seen from the table that after optimization, the scores of each evaluation dimension have improved, among which the improvement of user satisfaction is the most significant, from 3.5 to 4.0, an increase of 0.5 points.

Table 4: User preference matching improvement

user groups	Preference matching degree (initial)	Preference matching degree (after optimization)	Percentage increase
family parent-child	0.65	0.80	23.1%
youth adventure	0.70	0.85	21.4%
Senior leisure	0.55	0.75	36.4%

Table 4 shows how user preference matches improve. User groups include family parent-child, youth adventure and middle-aged leisure. Preference matching degree (initial) indicates the matching degree of the algorithm to user preferences before optimization, preference matching degree (after optimization) indicates the matching degree of the algorithm after optimization. Percent Increase shows how much the optimization effect increases. It can be seen from the table that after optimization, the preference matching degree of each user group has been improved, among which the middle-aged leisure group has the most significant improvement, from 0.55 to 0.75, an increase of 36.4%.

Table 5: Simulation effect of traffic model

traffic period	Average delay time (minutes)	Average delay time after optimization (minutes)	reduce delays
morning peak	15	10	-5
evening peak	20	15	-5
off-peak	5	3	-2

Table 5 shows the results of traffic model simulation. Traffic hours include morning rush hour, evening rush hour and off-peak hour. Average delay time represents the average delay time of the algorithm before optimization, and average delay time after optimization represents the average delay time after optimization. Reducing delay shows the magnitude of the reduction in the optimization effect. As can be seen from the table, after optimization, the delay time of each traffic period has been reduced, among which the reduction of the morning peak and the evening peak is the same, both of which are 5 minutes.

Table 6: System stability testing

test scenarios	Success rate (%)	Failure rate (%)	System Response Time (ms)
single user request	99.8	0.2	250
Concurrent 100 user requests	98.5	1.5	450
Concurrent 500 user requests	97.0	3.0	800

Table 6 shows the results of system stability testing. The test scenarios included single user requests, concurrent 100 user requests, and concurrent 500 user requests. Success rate represents the success rate of the system in the test scenario, and failure rate represents the failure rate of the system in the test scenario. System response time represents the response time of the system under test scenarios. As can be seen from the table, with the increase of concurrent user requests, the success rate and response time of the system decreased, but the overall performance remained at a high level.

Table 7 shows the results of user feedback collection and optimization directions. Feedback categories include route design, information accuracy, traffic advice, user interfaces, and personalized experiences. Specific feedback content indicates specific feedback of users under each category. The number of users indicates the number of users who gave the feedback. Optimization suggestions represent optimization suggestions made in response to user feedback.

Table 7: User feedback collection and optimization directions

Feedback Category	Specific feedback content	number of users	Optimization Suggestions
route design	More interactive experiences.	120	Increase interactive experience with local farmers, handicraft production and other activities recommended
information accuracy	Inaccurate business hours information for some attractions	80	Strengthen data source verification and regularly update scenic spot information

Feedback Category	Specific feedback content	number of users	Optimization Suggestions
Traffic advice	Hope to provide detailed guidelines on public transport	50	Integrate public transportation information such as bus and subway, and provide transfer scheme
user interface	The interface is not intuitive enough to find specific functions	40	Optimize UI design, simplify operation steps, and add function guidance
personalized experience	Hopefully, the route will adjust to weather.	30	Integrated weather API, dynamically adjust recommended routes according to weather conditions

5.4 Discussion

In this study, we propose an agricultural tourism route planning algorithm based on Deep Deterministic Policy Gradient (DDPG), and verify its performance through a series of experiments. Tables 1 and 2 show that our algorithm significantly optimizes both computation time and path quality: computation time decreased by 52% from 250 seconds to 120 seconds, and user satisfaction increased by 14.3% from 3.5 points to 4.0 points. These results show that DDPG algorithm has obvious advantages over traditional ant colony algorithm (ACO) and heuristic algorithm in path planning efficiency. Traditional methods rely on fixed rules or simple iterative processes, while DDPG can automatically adjust strategies through learning mechanisms to find better solutions in complex environments.

Table 3 further shows the significant improvement in the preference matching degree of different user groups. The preference matching degree of the family parent-child group, youth adventure group and middle-aged and elderly leisure group increased by 23.1%, 21.4% and 36.4% respectively. This improvement is mainly due to DDPG's ability to better handle continuous motion space, allowing algorithms to fine-tune recommended routes to accommodate users 'real-time needs and mood changes. In contrast, traditional heuristics often struggle to capture such subtle changes.

The results in table 4 show that average delays decreased by 5 minutes during morning and evening peak periods and 2 minutes during off-peak periods. This indicates that our dynamic routing strategy can effectively alleviate traffic congestion and improve overall travel efficiency. Traditional static planning methods cannot be adjusted according to real-time traffic conditions, so they are not flexible enough to deal with unexpected situations.

The improvement is mainly due to the complex learning mechanism of DDPG. As a reinforcement learning method, DDPG has strong learning ability, which can optimize strategy continuously through interaction with environment, and deal with high-dimensional state space and continuous action space. In addition, DDPG is able to directly output continuous action values, which allows it to more precisely control route selection and other decision variables, thus providing more personalized services. Finally, our approach takes full advantage of big data by collecting and analyzing large amounts of user behavior data to train models that better reflect real-world complexity and diversity than traditional rule-based approaches, thus providing higher quality services.

To sum up, the DDPG-based agricultural tourism route planning algorithm proposed in this study is superior to the existing ant colony algorithm and heuristic method in many aspects. By introducing advanced learning mechanisms and better continuous motion spatial processing capabilities, our approach can significantly improve route planning efficiency and personalized service levels. Future work will further explore how to apply the algorithm to more scenarios and consider more realistic constraints to further enhance the user experience.

Table 1-5 shows how our algorithm improves in many ways. In particular, GPU utilization increased from 80% to 90%, an increase of 12.5%. Although this may seem like a small improvement, in practice it means that the system can use hardware resources more efficiently, supporting more concurrent requests and faster response times. At the same time, we compare the performance of the basic model and the optimized model in different indicators in detail, and find that the optimized model has significantly improved in computing efficiency, path quality, user satisfaction and other aspects. For example, on the path rationality score, the optimized model improved from 3.8 to 4.2, an increase of 10.5%. These results further verified the effectiveness of our method, and provide strong support for future research.

DDPG algorithm performs well when dealing with large-scale data sets and more complex agricultural tourism locations. By introducing Experience Replay Buffer and Target Network, DDPG can effectively train with large-scale data and maintain the stability of the learning process. In terms of time complexity, the main computational bottleneck of DDPG is the policy update and the value function update in each iteration, which usually depends on the complexity and batch size of the neural network. Spatial complexity is determined primarily by the size of the experience playback buffer. Experimental results show that the algorithm can converge in reasonable time and has no significant impact on real-time performance, although the training time and memory consumption increase with the increase of dataset size.

Personalized recommendation is one of the core features of this paper. The user preference vector is constructed by integrating a variety of data sources, including the user's browsing history, search history, rating feedback, location information, etc. After preprocessing, these data are input into a multimodal emotion recognition model to extract the user's emotional state and interest points. In addition, we combine natural language processing to analyze users 'textual expressions on social platforms to more accurately infer their preferences. To demonstrate the impact of personalization on the user experience, we provide some real-world examples. For example, for young users who like outdoor adventure, the system will give priority to routes that include hiking and camping activities, while for family parent-child groups, the system will recommend more educational attractions and interactive experiences.

6 Conclusion

The artificial intelligent route planning algorithm developed in this study shows good performance and practicability in agricultural tourism scenarios. By analyzing the characteristics and demands of agricultural tourism, a simulation experiment environment is constructed and abundant data are collected. In the data preprocessing phase, we clean, standardize, feature engineer and integrate the data to improve the accuracy and usefulness of the algorithm. The algorithm design follows the principles of flexibility, personalization, eco-friendliness, interactivity and educability, and adopts deep reinforcement learning (DRL) as the core algorithm framework. Through simulation test and optimization, we verify the performance of the algorithm and achieve significant improvement. However, there are some limitations to this study. For example, in terms of data collection, we rely heavily on questionnaires and market research, which may not fully reflect the true needs and preferences of visitors. In addition, in terms of algorithm implementation, we mainly use Python programming language and Google Cloud Platform (GCP) cloud platform, which may have certain technical dependencies. In the future, we will continue to optimize the algorithm to improve its performance and practicality.

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