奨励金No.1538

AI を活用した調整可能なパーソナライズド交通情報推薦システムによる交通の円滑化

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AI enabled coordinated and personalized travel information recommender for smooth traffic

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この研究は、交通流の最適化と渋滞の緩和を目的とした AI 駆動型の個人向け旅行情報推薦システムの開発を目指しています。時空間グラフ畳み込みネットワークと強化逆学習アルゴリズムを活用して、リアルタイムの交通データと個々のユーザーの好みに基づく動的なルート提案を行います。広島東市でのシミュレーション実験を通じて、これらの個人向け推薦への遵守がどの程度交通渋滞を軽減し、道路網の効率を向上させるかを定量的に評価し、持続可能な都市開発を促進し、交通管理戦略を強化するための貴重な洞察を提供します。

This research aims to develop an AI-powered personalized travel information recommender system designed to optimize traffic flow and reduce congestion. By leveraging spatiotemporal graph convolutional networks and reinforcement inverse learning algorithms, the system will provide dynamic route suggestions based on real-time traffic data and individual user preferences. Through simulation experiments in Higashi-Hiroshima, the study will quantify the extent to which adherence to these personalized recommendations can mitigate congestion and improve road network efficiency, thereby offering valuable insights to enhance traffic management strategies and facilitate sustainable urban development.

1. 研究内容

1.1 Research Background

With the rapid urbanization and increase in motor vehicles, urban road infrastructure has struggled to keep pace, leading to severe traffic congestion. Traditional traffic management systems often rely on aggregated predictive models assuming uniform behavior among residents, which fails to address individual differences and dynamic changes. Personalized travel information can significantly improve traffic management by providing customized route recommendations based on real-time traffic conditions and user preferences.

Studies show that users often modify their travel behavior based on recommended travel information, which can effectively reduce traffic congestion. When a sufficient number of drivers follow the personalized route recommendations, it can balance traffic flow across the network, reduce congestion on busy routes, and improve overall road utilization. Conversely, if many drivers ignore the recommendations, it can exacerbate congestion on certain roads. Therefore, studying and understanding the impact of adherence to recommendation information by different travelers is crucial for designing more effective traffic management strategies and intelligent navigation systems.

1.2 Research Objectives

The primary goal of this research is to develop a personalized travel information recommendation system integrating advanced AI technologies to alleviate urban traffic congestion and enhance road network efficiency. The specific objectives include:

(1) Developing a Spatiotemporal Graph Convolutional Network for Predicting Travel Times: Construct a deep learning model to predict future travel times using real-time traffic data.

(2) Designing an Inverse Reinforcement Learning Algorithm for Route Recommendation: Develop an algorithm to track user preferences and update personalized route recommendations based on user feedback.

(3) Implementing ChatGPT for Real-time Event Monitoring: Use ChatGPT to monitor and respond to unforeseen traffic events, providing intelligent and accurate travel options.

(4) Assessing the System's Impact on Traffic Congestion: Evaluate the system's effectiveness in reducing traffic congestion and travel times.

(5) Conducting Simulation Experiments in Higashi-Hiroshima: Validate the proposed strategies through simulation experiments in Higashi-Hiroshima.

1.3 Approach and Proposed Methodology

This study introduces an advanced intelligent navigation system designed to provide personalized route recommendations. The system integrates Inverse Reinforcement Learning (IRL) and Machine Learning (ML) technologies to analyze and predict user-specific travel preferences and route selections. The system architecture is divided into five key modules: Input, State Definition, Strategy Network, Evaluation, and Real-time Monitoring. The specific structure of the system is illustrated in Figure 1.

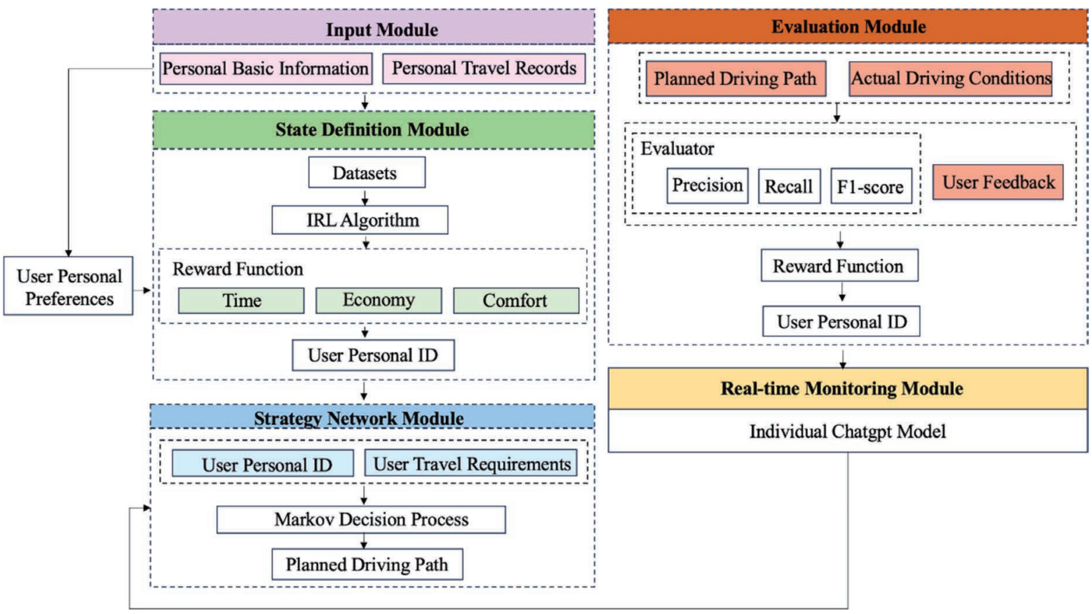

Figure 1. The network structure of the personalized travel information recommendation system

1.3.1 Input Module

The Input Module collects and processes key user information, forming the foundation of the personalized navigation system.

Collection of User Basic Information: Includes demographics such as gender, age, income, occupation, and vehicle model.

$$U = [Gender, Age, Income, Occupation, Vehicle\ Model]$$

Acquisition of Travel History: Compiles recent travel history, providing a contextual backdrop for understanding travel patterns.

$$Trips_{history} = \{Trip_1, Trip_2, \ldots, Trip_5\}$$

Identification of User Preferences: Users score their driving route preferences from 1 to 5, reflecting their inclination towards cost efficiency, comfort, or time optimization.

$$P_{preference} = [p_{economy}, p_{comfort}, p_{time}]$$

These scores are integral to adjusting the weights within the system's reward function, tailoring the navigation to individual preferences.

1.3.2 State Definition Module

The State Definition Module defines the road network and user interactions using a directed graph and Markov Decision Process (MDP).

Definition of Road Network Directed Graph: The urban road network is formalized as a directed graph $G = (V, E)$.

Definition of GPS Trajectory: A GPS trajectory, denoted by τ is conceptualized as a sequence of time-ordered GPS points logged by a vehicle's navigation system.

$$\tau = ((q_1, t_1) \to \ldots \to (q_i, t_i) \to \ldots \to (q_m, t_m)),$$

Where each q_i is a coordinate pair specifying the latitude and longitude of the vehicle's location at a given point in time, and t_i represents the corresponding timestamp of the vehicle's presence at location q_i.

Reward Function Generation: Trains the reward function R. using data from ride-sharing services, considering user preferences for economy, comfort, and time efficiency.

$$MDP = (S, A, P, R)$$

The reward functions are refined into three preference-based functions corresponding to economy, comfort, and time efficiency:

Incorporating Comfort Preference:

$$R_{comfort}(s, a) = -\left(\eta_{grade} \cdot Slope(s, a) + \eta_{signals} \cdot TrafficLights(s, a)\right)$$

Prioritizing Economy Preference:

$$R_{economy}(s, a) = -\left(\eta_{distance} \cdot Length(s, a) + \eta_{toll} \cdot Toll(s, a)\right)$$

Emphasizing Time Efficiency Preference:

$$R_{time}(s, a) = -\left(\eta_{time} \cdot \frac{1}{Speed_{limit}(s, a)} + \eta_{directness} \cdot Deviation(s, a)\right)$$

Composite user preference reward function:

$$R_{user}(s, a) = \theta_{economy} \cdot R_{economy}(s, a) + \theta_{comfort} \cdot R_{comfort}(s, a) + \theta_{time} \cdot R_{time}(s, a)$$

Initial Preference Fine-tuning Based on Personal Information: When a new user registers, personal information, declared preference scores, and recent travel history are encoded into feature vectors influencing the personalization weights.

$$\Theta_{preference} = f_{demographics}(U) + f_{declared}(P_{preference})$$

$$\Theta_{history} = IRL(R_{aggregate}, Trips_{history})$$

The personalized reward function is then formulated by combining the general reward function derived from DiDi data, $R_{user}(s, a)$, with personalization adjustments:

$$R_{personalized}(s, a) = R_{user}(s, a) \cdot (\alpha \cdot \Theta_{preference} + \beta \cdot \Theta_{history})$$

1.3.3 Strategy Network Module

The Strategy Network Module uses the personalized reward function $R_{personalized}(s, a)$ to determine optimal driving paths that align with individual user preferences.

$$a^* = \text{argmax}_a R_{personalized}(s, a)$$

sing the personalized reward function, the system synthesizes a recommended route that maximizes the expected personal utility for the user. This synthesis employs Dijkstra's algorithm, modified to identify not the shortest but the most rewarding path according to $R_{personalized}$.

1.3.4 Evaluation Module

The Evaluation Module assesses the accuracy and efficiency of the route recommendations using metrics such as precision, recall, and F1-score, incorporating user feedback to continuously improve the system's performance.

$$\text{Precision} = \frac{\textit{Distance of correct recommended road segments}}{\textit{Distance of the recommended route}}$$

$$\text{Recall} = \frac{\textit{Distance of correct recommended road segments}}{\textit{Distance of the actual route}}$$

$$\text{F1}-\text{score} = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

In tandem with this quantitative analysis, the user provides a satisfaction rating for the route on a scale of 1 to 5. This rating, a direct measure of user feedback, is incorporated into the update of the reward function. The update is mathematically structured as a targeted adjustment where the user rating influences the magnitude and direction of the gradient step. The reward function $R_{personalized}$ is modified accordingly:

$$\phi \leftarrow \phi + \alpha \nabla_{\phi} L_{\phi} + \beta(Rating_{user} - R_{expected}) \frac{\partial R_{\phi}(s, a)}{\partial \phi}$$

Finally, the obtained reward functions are updated within the user ID records. This ensures that the reward function is fine-tuned not only to the predicted preferences but also to the nuanced, subjective user feedback. The update aims to reconcile the model's predictions with real-world user satisfaction, thereby enhancing the personalization of route recommendations.

1.3.5 Real-time Monitoring Module

The Real-time Monitoring Module ensures the system's recommendations remain aligned with real-time traffic conditions using the ChatGPT model to predict unforeseen events and dynamically adjust routes.

(1) Data Collection and Query Preparation: Continuously gather traffic information from various sources.

(2) GPT Model Consultation: Process the contextual query through the GPT model, analyzing the current traffic scenario.

(3) Route Recommendation and Adjustment: Evaluate the GPT model's output to identify and adjust the optimal route based on live traffic analysis.

By integrating these modules, the system provides personalized and dynamically optimized navigation suggestions, improving traffic flow and user driving experience.

1.4 Traffic Flow Prediction

We utilize the TimesFM model for predicting traffic flow due to its ability to handle long-term

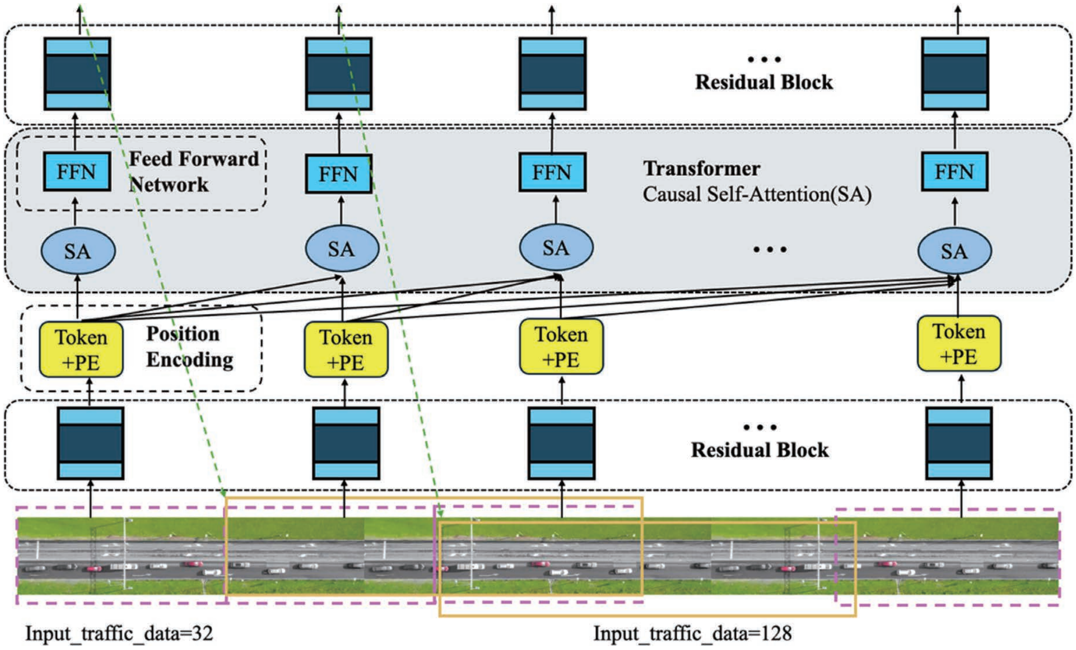

Figure 2. Traffic Flow Prediction Network

dependencies and variable-length sequences, which enhances prediction accuracy. This model excels in processing large-scale pretraining data, reducing error accumulation.

First, we collect and preprocess recommended and actual travel route data, organizing it into a time-ordered series. The data is segmented into fixed-length time windows (e.g., every 10 minutes) and normalized. This time series data is then chunked into blocks for model input. The TimesFM model uses these blocks to predict future traffic flow by analyzing patterns within the data. For a time series of 256 steps, the model predicts the next 128 steps, then combines these predictions with the original data to forecast additional steps. The resulting predictions are converted back into time-series format, providing detailed traffic flow forecasts for each road segment. The TimesFM model architecture is illustrated in Figure 2.

1.5 Future Work

Our project has entered a crucial phase in app development, integrating the Advantage Actor-Critic (A2C) algorithm into a navigation app. The focus is on seamless integration and real-time, personalized route recommendations. The team is currently refining functionalities for an intuitive user experience ahead of alpha testing. This stage is pivotal for subsequent beta testing and data collection, which will refine the algorithm based on user feedback. Successful completion will lead to data analysis and academic documentation for publication.