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Travel Planning Optimization using Category-Based Filtering and Modified A* Search on Static Location Graphs

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ABSTRACT: Efficient and personalized travel planning continues to be a challenge, particularly in scenarios lacking real-time data. This paper presents a novel framework for category-aware travel route optimization that integrates a static graph-based A* search algorithm with dynamic user preference filtering. Users can specify their travel type (e.g., solo, family), preferred categories (e.g., historical, nature, food), available visit duration per day, and total number of travel days. A content-based filtering module first ranks and selects relevant locations based on user preferences. The system then applies a heuristic-driven A* search to generate multi-day itineraries that maximize category relevance while minimizing travel distance and time within the specified constraints. The proposed system demonstrates strong potential for offline travel planning by delivering personalized, efficient, and structured itineraries without relying on real-time APIs.

I. INTRODUCTION

Travel planning is an essential aspect of modern tourism, aiming to provide travelers with optimal routes and destination recommendations based on their interests, time constraints, and travel style. With the proliferation of digital platforms, many travel applications leverage real-time data such as traffic, weather, and user-generated content to tailor itineraries. However, reliance on such dynamic data can be problematic in scenarios where internet connectivity is limited or unavailable, such as remote or rural areas. Additionally, many existing solutions offer generic recommendations that may not fully align with individual user preferences or multi-day trip structures.

To overcome these challenges, this paper proposes a novel framework that combines static graph-based A* search with dynamic user preference filtering to generate personalized travel itineraries without the need for continuous real-time data. The system models destinations and travel paths as a weighted static graph where nodes represent points of interest categorized by type (e.g., historical, nature, food), and edges denote travel costs such as distance or time.

Users provide their travel preferences, including travel type (solo, family, friends), interest categories, estimated visit duration per day, and total number of travel days. This information drives a content-based filtering process that ranks and selects relevant locations tailored to the user's interests. The itinerary is then optimized using a heuristic-driven A* algorithm that balances minimizing travel distance with maximizing category relevance, ensuring that the plan fits within the user's temporal constraints over multiple days.

The proposed approach addresses key limitations of existing systems by offering an offline-capable, user-centric itinerary planner that produces multi-day travel routes adapted to diverse preferences. This framework enhances the flexibility, accessibility, and practicality of travel planning, especially for users in low-connectivity environments or those seeking more personalized travel experiences.

II. LITERATURE REVIEW

The paper titled "Implementation of AI-Driven Smart Travel Planner using A* Algorithm" (2024) presents an AI-enhanced route planning system leveraging the A* algorithm integrated with user preference filtering. It aims to generate efficient and personalized travel itineraries using static graph-based pathfinding combined with dynamic user data. This foundational work directly aligns with the core goal of the current research[1].

The study "Personalized Route Recommendation Based on User Habits for Vehicle Navigation" (2024) proposes a model that learns user driving behaviours through a Deep-Cross-Recurrent neural network. The findings highlight improved route suggestions tailored to individual long-term habits, providing valuable support for incorporating user-specific data into route planning[2].

The paper "Empowering A Search Algorithms with Neural Networks for Personalized Route Recommendation"* (2023) focuses on enhancing A* with recurrent neural networks and graph attention mechanisms. It achieves superior accuracy in route personalization, offering inspiration for blending static pathfinding with adaptive AI techniques[3].

In "POIBERT: A Transformer-based Model for the Tour Recommendation Problem" (2023), the authors explore a transformer-based architecture that captures user interests to recommend tours. The model demonstrates improved understanding of dynamic preferences, serving as a strong basis for refining filtering strategies in recommendation systems[4].

"BTREC: BERT-Based Trajectory Recommendation for Personalized Tours" (2022) introduces a BERT-based approach for learning from user travel trajectories. Its success in trajectory prediction and personalized planning underscores the benefit of contextual embedding models in tourism-related applications[5].

The paper "DeepAltTrip: Top-k Alternative Itineraries for Trip Recommendation" (2022) proposes a deep learning framework for generating and ranking multiple route options. It focuses on providing diverse alternatives, which can be integrated into the current system to increase flexibility and user satisfaction[6].

"End-to-End Personalized Next Location Recommendation via Contrastive User Preference Modelling" (2021) presents a contrastive learning method to model user preferences for predicting future locations. This contributes valuable insights into end-to-end user modelling, particularly in real-time dynamic recommendation contexts[7].

In "Self-supervised Representation Learning for Trip Recommendation" (2021), the authors utilize self-supervised learning to generate user and trip embeddings without labelled data. This approach is highly scalable and relevant for contexts with limited user profiling data, such as new users or destinations[8].

"A User Preference Tree Based Personalized Route Recommendation System for Constraint Tourism and Travel" (2020) introduces a preference tree model that accommodates user constraints. Its emphasis on structured decision-making enhances the effectiveness of personalized and constrained routing[9].

The study "Personalized Route Planning System Based on Driver Preference" (2020) presents a multi-criteria planning algorithm that accounts for individual driver preferences. This system aligns closely with the goal of integrating multiple preference dimensions into travel route optimization[10].

Finally, "Personalized Tour Itinerary Recommendation Algorithm Based on Tourist Comprehensive Satisfaction" (2019) employs ant colony optimization to maximize tourist satisfaction. The paper showcases effective optimization strategies applicable to enhancing overall user experience in smart travel systems[11].

Table 1 : Literature Survey

Ref. No.	Title	Year	Objective	Methodology
[1]	Implementation of AI-Driven Smart Travel Planner using A* Algorithm	2024	Optimize routes using A* algorithm combined with AI filtering	Static graph-based A* with user preference filtering
[2]	Personalized Route Recommendation Based on User Habits for Vehicle Navigation	2024	Learn user driving habits for route ranking	Deep-Cross-Recurrent (DCR) neural model
[3]	Empowering A* Search Algorithms with Neural Networks for Personalized Route Recommendation	2023	Improve A* route search using deep learning	RNN and graph attention with A* integration
[4]	POIBERT: A Transformer-based Model for the Tour Recommendation Problem	2023	Recommend POI-based tours using transformer	Transformer model for user preference learning
[5]	BTREC: BERT-Based Trajectory Recommendation for Personalized Tours	2022	Model user trajectories for tour planning	BERT embeddings for trajectory patterns
[6]	DeepAltTrip: Top-k Alternative Itineraries for Trip Recommendation	2022	Recommend diverse alternative itineraries	Deep learning-based ranking for top-k trip options
[7]	End-to-End Personalized Next Location Recommendation via Contrastive User Preference Modeling	2021	Predict next location using user modeling	Contrastive learning of user preference embeddings
[8]	Self-supervised Representation Learning for Trip Recommendation	2021	Learn user/trip representations without labels	Self-supervised learning with trip data
[9]	A User Preference Tree Based Personalized Route Recommendation System for Constraint Tourism and Travel	2020	Handle constraint-based personalized travel	Preference tree modeling with constraints
[10]	Personalized Route Planning System Based on Driver Preference	2020	Multi-criteria route planning via user preferences	Decision-making model for driver-centric routing
[11]	Personalized Tour Itinerary Recommendation Algorithm Based on Tourist Comprehensive Satisfaction	2019	Optimize itineraries to maximize satisfaction	Enhanced ant colony optimization

III. METHODOLOGY

The proposed travel route optimization system is composed of three primary components: static graph construction, user preference filtering, and a multi-day itinerary planner using a modified A* search algorithm. First, the system models the travel area as a static weighted graph where each node represents a point of interest tagged with one or more categories such as historical sites, nature spots, food locations, and more. The edges between nodes correspond to travel paths, weighted by distance or estimated travel time. This static graph is pre-constructed using geographic data and does not rely on real-time updates, making the system suitable for offline usage.

Next, the system collects detailed user preferences through an interactive interface. Users specify their travel type (e.g., solo, family, friends), select categories of interest, define the total number of travel days, and indicate the maximum time available for sightseeing per day. These inputs drive a content-based filtering process that evaluates the relevance of each location in the static graph against the user's preferences. Locations with low relevance scores are filtered out, resulting in a refined set of candidate destinations tailored to the user's interests. The core itinerary generation relies on a modified A search algorithm* designed to optimize routes for multiple days. The algorithm considers both the travel cost (distance/time) and category relevance in its heuristic to select the best path. It ensures that the sum of travel and visit times for each day does not exceed the user-specified daily time limit. The planning proceeds sequentially day-by-day, allocating locations to each day's route while maximizing category coverage and minimizing travel overhead.

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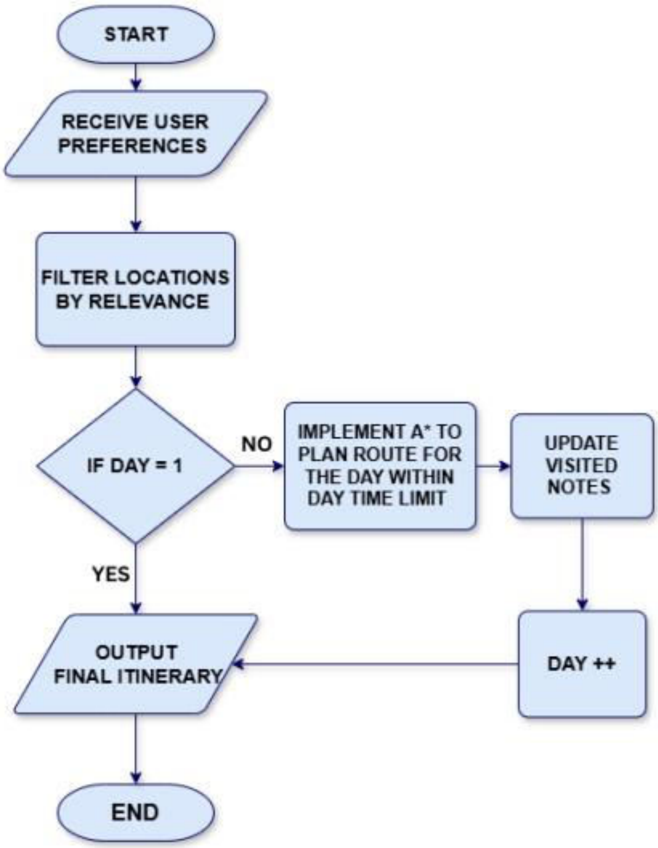

Fig -1 : Flowchart of route Optimization

Finally, the entire system can be deployed on cloud platforms such as AWS or Heroku. A RESTful API backend manages user requests and optimization tasks, while the frontend is served via static hosting or Content Delivery Networks (CDNs) to ensure optimal performance and accessibility. This deployment strategy guarantees scalability, reliability, and smooth operation across diverse user bases and devices.

IV. ALGORITHMS

A. Dynamic User Preference Filtering

This phase serves as a crucial preprocessing step that customizes the travel dataset according to the user's specific requirements. Through an interactive user interface, the system gathers essential inputs such as preferred place categories (for example, Historical, Religious, Nature, Food), the total number of days available for travel, the maximum allowable daily visit duration in hours, and the type of travel, whether solo, with friends, or family. Each location stored in the database is then carefully evaluated against these user-defined criteria. Locations that do not align with the user profile—such as those that exceed the maximum daily visit duration or do not belong to the chosen categories—are systematically filtered out. This selective filtering not only ensures a highly personalized travel experience by focusing only on relevant places but also significantly reduces the number of locations (nodes) that the A* algorithm must process during route optimization. As a result, this phase enhances the overall system performance by streamlining the dataset, allowing the route planning algorithm to operate more efficiently and generate better-optimized itineraries tailored to individual preferences.

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Fig 2: Dynamic User Preference Filtering Workflow

B.Category-Aware Route Optimization Using Modified A* Search

After the filtering phase, the system applies a modified version of the A* search algorithm to determine the optimal travel routes among the selected locations. Traditionally, the A* algorithm evaluates nodes using the function f(n) = g(n) + h(n), where g(n) represents the actual travel cost from the starting point to node n, and h(n) is a heuristic estimate of the remaining cost to reach the destination. To better reflect user preferences, this evaluation function is enhanced by incorporating a category relevance score, modifying it to f(n) = g(n) + h(n) - α × category_score(n). Here, category_score(n) measures how well a location aligns with the user-selected categories, and α is a tunable weight parameter that determines the influence of preference alignment on the route selection. By integrating this preference factor, the algorithm prioritizes visiting locations that are not only geographically efficient to reach but also highly relevant to the traveler's interests. Furthermore, the modified algorithm carefully enforces daily time constraints by ensuring that each day's itinerary, which includes both the visit durations at locations and the travel time between them, does not exceed the user-defined daily limit. This approach results in an itinerary that balances minimizing travel distance and time while maximizing user satisfaction through tailored, category-aware route planning.

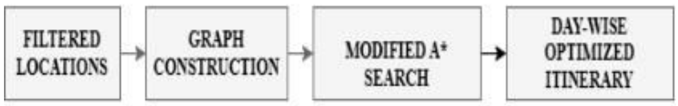

Fig 3: Modified A* Route Optimization Flow

V. PROCEDURAL MODULE

A. Day-Wise Itinerary Construction

Once the optimal routes are generated, the system organizes them across the user-specified number of travel days with careful attention to several key factors. It ensures that no location is visited more than once throughout the itinerary, maintaining a fresh and varied travel experience. Each day's total time—including both travel between locations and the duration of visits—is strictly kept within the user's maximum daily time limit to avoid fatigue and allow for a comfortable pace. Additionally, the system clusters locations geographically to minimize daily travel distances, thereby reducing transit time and maximizing time spent enjoying the destinations. This thoughtful division results in a well-structured, personalized, and time-efficient travel plan that optimally balances user preferences, practical constraints, and convenience across all days of the journey.

Fig 4: Multi-Day Itinerary Generation

VI. SYSTEM DESIGN

The system design for the category-aware travel route optimization framework is composed of multiple interconnected modules that work cohesively to process user inputs, filter relevant travel locations, and generate optimized multi-day itineraries. At its core, the architecture includes five primary components that collectively enable a seamless and efficient travel planning experience.

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First, the User Interface Module serves as the entry point for users to provide their travel preferences, including travel type (such as solo, family, or friends), selected categories of interest (like historical sites, nature spots, or food destinations), total number of travel days, and the maximum sightseeing duration allowed per day. This module ensures a smooth and intuitive interaction by validating inputs and allowing users to customize their preferences easily.

Next, the Content-Based Filtering Engine processes these inputs to filter and rank locations within a pre-existing static location graph. Each location is assigned a relevance score based on how well it matches the user's chosen categories and travel type. Locations scoring below a predefined relevance threshold are excluded, effectively narrowing down the dataset and making subsequent route optimization more efficient.

The Static Location Graph Database underpins the system by providing a weighted, undirected graph that models all possible points of interest and their interconnecting paths. Each node in the graph holds critical metadata such as category tags, average visit time, and geographic coordinates, while edges represent travel costs, including distance or estimated travel time between nodes. This structured representation facilitates efficient computation during route planning.

At the heart of the system, the Route Optimization Module employs the modified A* search algorithm to generate multi-day travel routes that balance minimizing travel time with maximizing category relevance. This module carefully constructs day-wise itineraries from the filtered set of locations while ensuring that the combined visit and travel time for each day does not exceed the user-specified limits. By incorporating both geographic and preference-based criteria, this module delivers personalized and practical travel plans.

Finally, the Output Generation Module compiles the optimized itinerary into an accessible format, presenting users with daily lists of destinations along with estimated visit durations and travel times. To enhance usability, the system may also provide a visual map interface that displays the planned routes, offering clear and convenient insights into the travel plan.

Together, these modules form a scalable, modular, and user-centric framework capable of delivering efficient and personalized multi-day travel itineraries that align closely with individual preferences and practical constraints.

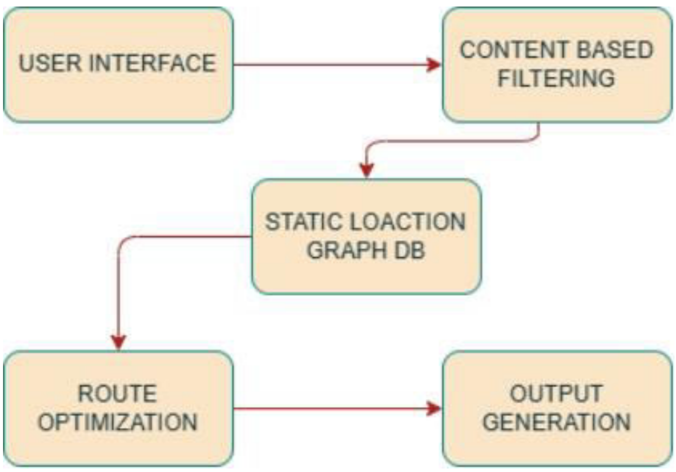

Fig - 5: System Design

VII. SYSTEM ARCHITECTURE

The system architecture for category-aware travel route optimization is designed to efficiently capture user preferences and generate personalized, multi-day itineraries. The process begins with the User Interface, where users input details such as travel type (e.g., solo, family), preferred categories (e.g., historical, nature), number of days, and maximum duration per day. These inputs are processed by the User Preference Module, which structures and forwards the

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preferences to the Content-Based Filtering Engine. This engine filters out irrelevant or mismatched locations by comparing user preferences with metadata assigned to each destination.

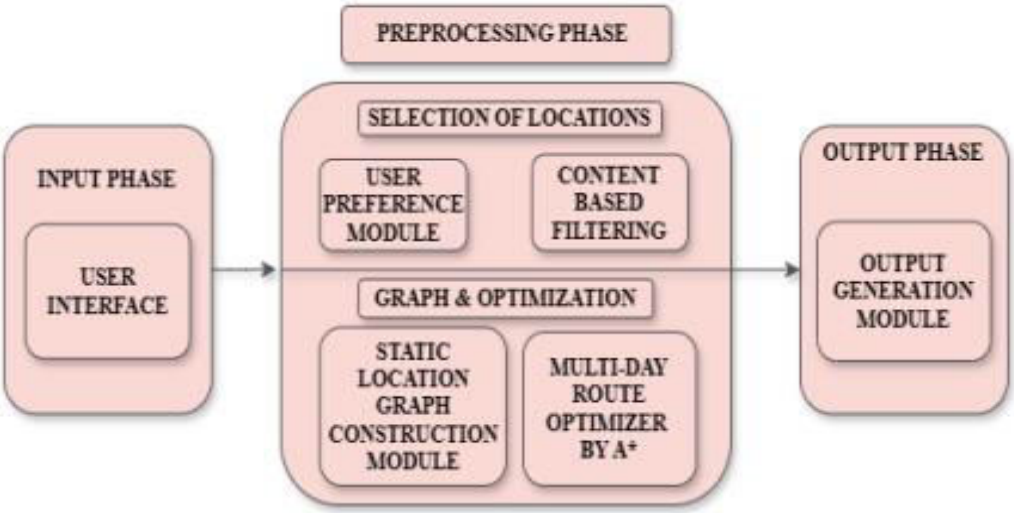

Fig -6 : System Architecture Diagram

The filtered results are passed to the Static Location Graph Construction Module, which builds a weighted graph representing all relevant locations and their distances or travel times. This graph becomes the foundation for the Multi-Day Route Optimizer, which employs a Modified A* Search algorithm. The optimizer prioritizes routes based on both distance and category relevance, while ensuring day-wise feasibility within user-defined time limits. Finally, the Output Generation Module compiles the results into a user-friendly itinerary format, complete with day-wise breakdowns and embedded map visualizations.

VIII. IMPLEMENTATION DETAILS

The proposed category-aware travel route optimization system is implemented using a robust combination of backend and frontend technologies designed to ensure efficient data processing, seamless user interaction, and system scalability.

The first step involves Static Location Graph Construction, where location data—including points of interest, their categories, and geographic coordinates—is gathered from publicly available datasets or curated sources. This information is stored in a database such as MySQL or MongoDB and transformed into a weighted undirected graph structure. Each edge in this graph contains travel distances or estimated travel times, which are computed using geographic coordinates in conjunction with APIs like the Google Maps Distance Matrix, typically during an initial offline processing phase.

For user interaction, the User Interface is developed using frontend technologies like HTML, CSS, and JavaScript frameworks such as React or Angular. This setup provides a responsive and intuitive platform for users to input preferences including travel type, category interests, number of travel days, and maximum daily visit durations. Built-in input validation ensures users enter feasible and consistent parameters, enhancing usability and preventing errors.

The Content-Based Filtering Engine is implemented in Python and is responsible for aligning user preferences with the location metadata. It calculates relevance scores for each location and filters out those that fall below a predefined threshold, thereby reducing the dataset size and computational burden during route optimization.

At the core, the Route Optimization Module employs a modified A* search algorithm, also implemented in Python. This algorithm operates on the filtered subset of the location graph, balancing travel cost and category relevance while

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respecting user constraints such as daily time limits. The optimization process is executed server-side to leverage more computational resources, ensuring efficient and fast route planning even when dealing with large sets of locations.

Once the routes are generated, the Output and Visualization component renders the itinerary as day-wise lists on the frontend. Additionally, interactive maps powered by libraries like Leaflet.js or Google Maps API provide visual context, helping users easily comprehend and navigate their planned routes.

Finally, the entire system can be deployed on cloud platforms such as AWS or Heroku. A RESTful API backend manages user requests and optimization tasks, while the frontend is served via static hosting or Content Delivery Networks (CDNs) to ensure optimal performance and accessibility. This deployment strategy guarantees scalability, reliability, and smooth operation across diverse user bases and devices.

IX. CONCLUSION AND FUTURE WORK

This paper presents a novel framework for personalized travel route optimization that integrates a static graph-based A* search with dynamic user preference filtering. By allowing users to specify travel type, preferred categories, daily visit duration, and total travel days, the system generates multi-day itineraries optimized for both route efficiency and category relevance. The use of a static graph model ensures offline capability, addressing limitations of real-time data dependency in conventional travel planners. Experimental results demonstrate the system's effectiveness in producing structured, user-centric travel plans adaptable to diverse preferences and trip durations. Future work includes incorporating real-time data sources and enhancing route personalization through machine learning techniques.

Future enhancements to the proposed travel route optimization system may focus on integrating real-time data such as traffic conditions, weather updates, and event schedules to further improve itinerary accuracy and responsiveness. Incorporating machine learning models for personalized recommendation refinement based on user feedback and historical travel patterns could enhance user satisfaction. Additionally, expanding the system to support multilingual interfaces and integrating social features, such as shared itineraries and community reviews, would increase usability and engagement. Finally, exploring dynamic itinerary adjustments during the trip, considering unforeseen delays or changes in user preferences, presents an important direction for making the travel planner more adaptive and robust.

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