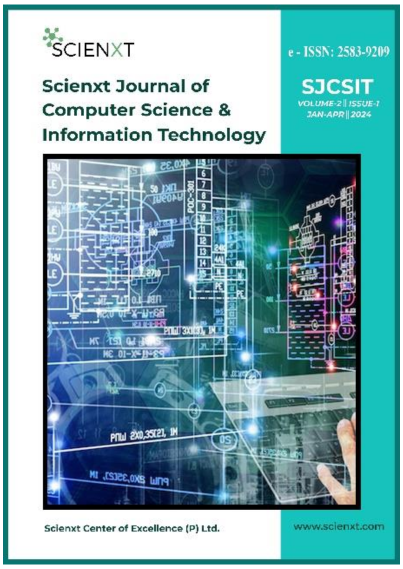

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Explore era: make your tour better

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Abstract:

A tour itinerary recommendation system is a technology that suggests personalized travel plans based on a user's preferences, budget, travel dates, and other factors. In this project we propose a novel approach for generating a tour itinerary using a combination of Genetic Algorithm (GA) and Reinforcement Learning (RL). The proposed approach employs GA to generate the list of POI’s by filtering out the user preferences, while RL is used to create an itinerary from the list of filtered POI’s which maximizes the reward function.

1. Introduction:

In an era defined by wanderlust and the desire to explore the far reaches of our world, This Project emerges as a solution to simplify and elevate the travel experience. Whether embarking on a solo adventure, a family vacation, or a group expedition, planning the perfect itinerary can be a daunting task. This Project aims to streamline this process, catering to the needs of travelers seeking unforgettable journeys. With an ever-expanding array of destinations and a plethora of choices for accommodations, activities, and transportation, the need for a comprehensive and user-friendly tool is paramount. The Tour Planner Project offers a solution that combines state-of-the-art technology, extensive data resources, and a user-centric design to empower travelers in crafting their ideal tripsThis introduction sets the stage for a closer exploration of this Project, highlighting its mission to revolutionize travel planning, enhance the traveler's experience, and make the world more accessible and enjoyable for everyone, from the seasoned globetrotter to the novice explorer. As we delve deeper into this project, we will uncover the features, methodologies, and benefits that make it a pivotal tool in the world of travel.

2. Proposed system:

Design approach for a tour itinerary recommender system using a combination of genetic algorithms and reinforcement learning. List out objects and constraints of a system for generation of the itineraries on the basis of user satisfaction and minimization of travel time. Include constraints like budget and time.

Data Collection and Preprocessing: The next step would be to collect and preprocess the data required for the system. This could include information about the available destinations, activities, accommodations, and user preferences and constraints. The fitness function is a key component of the genetic algorithm and defines the quality of a candidate itinerary based on the user's preferences and constraints. Genetic algorithms are used to generate diverse itineraries that meet user constraints and preferences, using techniques such as crossover, mutation, and selection. Reinforcement Learning Algorithm will be implemented to learn from user interactions and adjust fitness function based on user feedback, training on historical data and updating fitness function based on user feedback. System integration of genetic and reinforcement learning algorithms to generate personalized itineraries. System evaluation to compare generated itineraries to benchmarks and user feedback.

3. Methodology:

First the system takes in the user input for travel details and user preferences

3.1. Preference filtering:

It is done by reducing the items that can be selected among the first generation chromosomes. The user selects a place category, which we limit to the offered items choice.

3.2. Genetic-based search:

We then use genetic algorithm (GA) as a search heuristic. It matches these preferences and constraints with the best possible destinations.

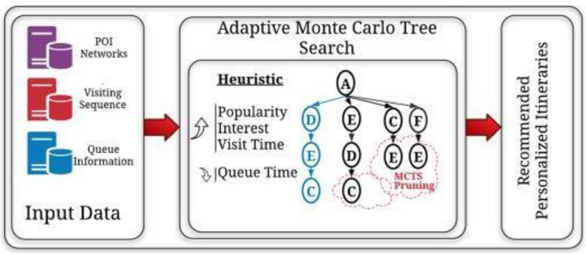
3.3. Fitness function:

$$\text{Fitness function} = \frac{1}{\text{cost score} + \text{duration score}}$$

3.4. MCTS search:

It starts with starting POI as root node and select the next potential POI as the next node based on the visiting time, distance,popularity,user interest etc.. It continues until it finds the destination POI. Then it backtracks to the root node by evaluating the reward function for the generated Itinerary It returns the itinerary with the highest reward as output

3.5. Reward function:



$$Reward = \sum_{p_j \in IH_{temp}} \frac{PoP(p_j) * IoP(c_{p_j}) * VDoP(p_j)}{Queue^t_{p_j}}$$

Figure. 1:

3.6. Benefits:

Providing users with optimal recommendations improves their experiences of the system which can generate personalized tour itinerary based on user preferences and constraints.

This means that in itinerary optimization, more efficient itineraries can be developed by taking into account objectives in line with user satisfaction and travel time.

Such a system can be able to learn from user feedback and adjust the fitness functions so that they can fit more closely to users’ preferences.

The genetic algorithm has a variety of choices that can accommodate users’ preference and constraints.

Besides, the system is scalable to incorporate many users and destinations, thus suiting well for travel agencies.

3.7. Genetic algorithm:

Algorithm 1 Genetic-based recommender search

INPUT: no. of person, budget, duration, POIs database, iteration rate, user tags
OUTPUT: the list of recommended POIs

1: Initialize first population from the POIs database
2: Filter out the population based on the user tags
3: Convert the duration unit from days to hours
- Assuming that in one day, the best effective total visit duration is 7 hours (not including the travel duration, from 9 am to 9 pm).
- The conversion number is given by multiplying the days with a 7 (seven).

4: Create the chromosome and generate the first population based on the user constraints as the following:
- Use the limitation of 75% budget
- Use 100% of the duration constraint in hours
- Generate the population with size = 40 chromosomes

5: Perform the evaluation
- Assign score for each chromosome in the population
- The evaluation function is given in Algorithm 2

6: Improve the fitness score in the new generation
- Start the Genetic-based search with the stopping parameter given below:
  - Iteration rate = 8
  - Acceptable fitness score = 1.2
- For each iteration, the Genetic-based search will run with the below rates:
  - Cross over rate = 10
  - Mutation rate = 0
- Return the best chromosome with the highest fitness score

Figure. 2:

3.8. MCTS search:

Algorithm 1: EffiTourRec-Overview of Algorithm

Data: $P = \{p_1, p_2, \cdots, p_n\}$: POI information; $Queue^t_p$: Queuing time of POI at different times; $p_1 \in P$: Staring POI; $p_n \in P$: Ending POI; t_s: Staring time of itinerary, T: Total time budget; maxLoop: Number of Iterations

Result: $I = \{p_1, \cdots, p_n\}$: Recommended Personalized Itinerary

$T_{visits} \leftarrow emptyTree$; $T_{reward} \leftarrow emptyTree$; /* Initialize visit count and reward tree */
$T_{prune} \leftarrow emptyTree$; /* Initialize MCTS pruning tree */
$I_{list} \leftarrow NULL$; /* Initialize list of itineraries */
for *Iterations* $\leftarrow$ *1 to maxLoop* **do**
  $I_{temp} \leftarrow p_1$;
  $p_i \leftarrow p_1$; $p_j \leftarrow \emptyset$; $totalTime \leftarrow 0$; $tempReward \leftarrow 0$;
  while $totalTime \leq T$ **do**
    $p_j \leftarrow SelectNextPOI(p_i, T_{visits}, T_{reward}, I_{temp})$;
    $I_{temp} \leftarrow I_{temp} \bigcup p_j$; /* Append p_j to temporary itinerary */
    $totalTime \leftarrow totalTime + TDoP(p_i, p_j) + Queue^t_{p_j} + VDoP(p_j)$;
    $tempReward \leftarrow tempReward + Reward(p_j)$
    if $T_{prune}[j, p_j] \neq null$ *and* $T_{prune}[j, p_j] \geq \frac{tempReward}{totalTime}$ **then**
      Break Loop ; /* Prune low rewarded and duplicate itineraries */
    if $p_j == p_n$ **then**
      Break Loop;
    $p_i \leftarrow p_j$;
  $BackPropagationC(I_{temp}, T_{visits})$;
  if $p_j == p_n$ **then**
    $Reward \leftarrow Simulate(I_{temp})$;
    $BackPropagationR(I_{temp}, T_{visits}, T_{reward})$;
    for $\forall p_j \in I_{temp}$ **do**
      $T_{prune}[j, p_j] = \frac{CumulativeReward(I_{temp}, p_j)}{CumulativeTime(I_{temp}, p_j)}$; /* Update Pruning Tree */
    $I_{list} \leftarrow I_{list} \bigcup I_{temp}$;
$I \leftarrow maxReward(I_{list})$;
Return I; /* Return best itinerary */

Figure. 3:

3.9. Flow chart:

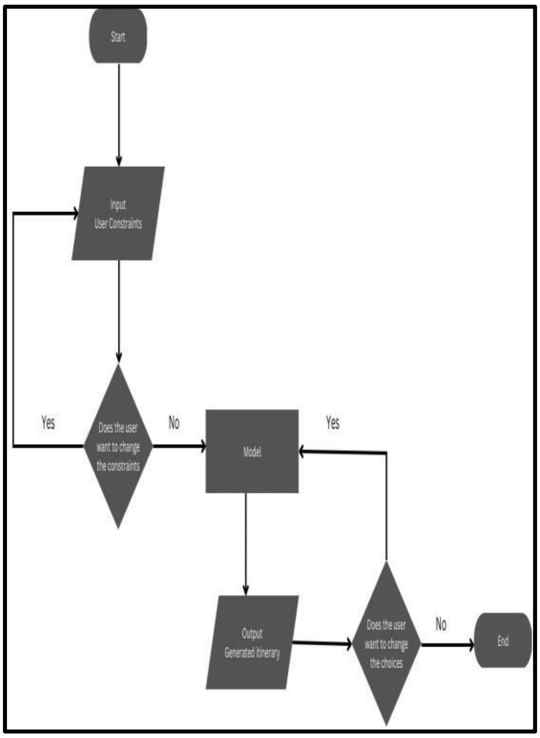


Figure. 4:

4. System architecture:

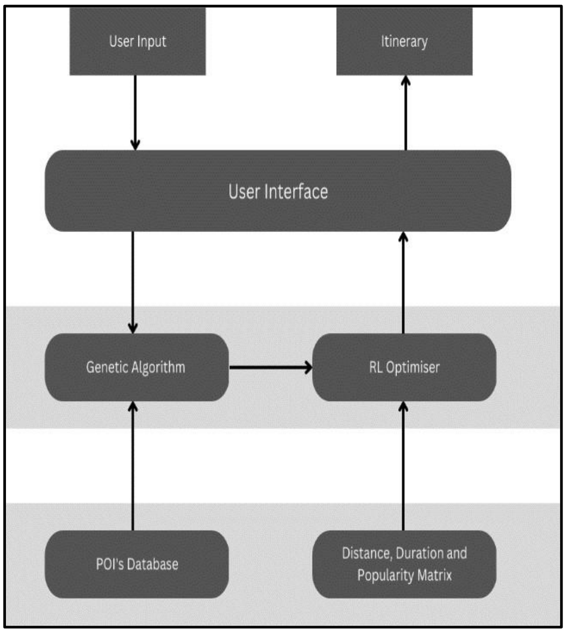


Figure. 5:

Through the user interface of the presentation layer, the user will feed in the constraint and preference that lead to the generation of the output which is a list of POIs recommendations for tourists. The application layer comprises three parts: pairwise preference filtering, genetic-based search, and route optimiser. The system has three databases which are preference, POIs and distance matrix in the data layer.

4.1. Dataset:

We collected geotagged photos from Flickr and landmark categories from Wikipedia for our experiments.

Flickr (www.flickr.com), where locations (geotags) are attached to a significant number of photos uploaded by their users. For groups of users that regularly share not only photos, but also their locations, it is possible to provide additional location-based services by mining their personal location data

5. Recommendation method:

Method Framework. The travel route recommendation algorithm proposed in this paper is divided into data preprocessing, POI mode, association graph construction, and tourist interest preference learning and route recommendation. The POI transfer graph is constructed offline and learns interest preferences of tourists. The POI and the interest preferences of tourists are obtained by analyzing the cooccurrence information of attractions and photo data in the travelogue.

The route recommendation is conducted online. Based on the personal information entered by tourists, the number of expected attractions and the designated tour points, the PTRIP algorithm is used to recommend the routes with the highest benefits to tourists, considering the POI popularity and tourists' preferences. The detailed framework is shown in Figure.

The basis for tourist itinerary recommendations mainly comes from visitor information, design tour sites, budget number of attractions, and profit of route. The first three bases mainly refer to the subjective will of the referee; the last basis is the problem to be solved by the algorithm proposed in this paper. Route profit is calculated by popularity of POI and visitor preference, and the two indicators have their weights. Moreover, the POI mode is the most important part in the travel itinerary recommendation model.

Construct the POI Transfer Graph. The POI transfer graph is constructed offline. Treating all POIs as nodes on the way, the travel routes can be generated by visiting the directed edges in the graph consecutively. (1) Map the photo the web travelogues shared by tourists contain textual description information such as travel routes, travel feelings, and their photos taken at each attraction. The travelogue number and tourist number can be extracted from them. The structure of the photo data shared by the user conclude Photo ID, User ID, Time, Longitude, Latitude, and Category.

Based on the longitude and latitude of each photo, the distance of each POI can be calculated by using Formula Haversine. If the result is less than 200 meters, it is assumed that the photo is taken at this POI. And the list of POI is St = ðp1, p2, ⋯, pnÞ.

6. Problem formulation:

The four decision-making modes are trained in this paper which are: The aggressive incentive (AGGI), aggressive punishment (AGGP), conservative incentive (CONI), and conservative punishment (CONP). The colour of vehicle indicates its type and intention. A white body with a colored roof represents an HV, and an all-blue vehicle represents a CAV; The HV with the red roof (HV1) appears in three lanes randomly and can only go out from "Highway 2" The HV with the orange roof (HV2) is set to emerge from the second lane and can go out from "Exit 1" when it is in the first lane and go out from "Highway 2" when it is in the other lanes; The HV with the green roof (HV3) is set to only appear from the first lane and can only go out from “Exit 0”; It is difficult for CAVs to explore “Exit 1” safely, and the collision risk of leaving the highway from “Exit 1” is higher than it is for other exits.

6.1. Experiment settings:

Simulation environment: They have used open-source simulator SUMO with a Python API for reinforcement learning flow.

6.2. Weights:

To assign explicit weights to the dynamic inputs, they have defined their model as linear weighted. The weights for each human-driven vehicle (HDVs), the feature embedding are inversely proportional to its relative distance to the CAV. A quadratic weight was also defined.

6.3. Action space:

The action space is discrete for each time step indicating the possible actions that the CAV can perform. A = {change to left, keep lane, change to right}. The simulator restricts only the decision of agent from change out of the corridor. Reward function: Reward function consists of 2 types of rewards and 2 types of penalties: Speed reward, destination reward, collision penalty and lane changing penalty Scenario: For all the training and evaluation, they used a 500- meter, 4-lane loop scenario with 1 CAV and 50 HDVs. Initially, the HDVs are spawned uniformly on the road with random perturbation in their initial locations. To add heterogeneity, the HDVs are introduced with a random initial speed ranging from 0 to 15m/s and a random maximum speed from 15 to 30m/s. The road segment speed limit is 50m/s which can be reached only by the CAV

7. Results:

The model was compared with four baseline models including: unweighted and quadratic weighted Deep Set Q learning model, rule-based lane-change model and nolane-change model. The mean and median performance are compared. In most of the scenarios, it can be observed that the linear weighted model outperforms the quadratic.

8. Conclusion:

In conclusion, the AI Tour Planner Project represents a significant advancement in the realm of travel and tourism. This innovative solution has harnessed the power of artificial intelligence to transform the way individuals plan and experience their journeys. By seamlessly merging cutting-edge technology with a deep understanding of user preferences and global travel resources, the project has redefined travel planning. Through the AI Tour Planner, travelers now have access to personalized itineraries that cater to their unique interests, budget, and time constraints.

This project's algorithms provide recommendations that are both informed and intuitive, ensuring that each adventure is as memorable as it is convenient. The AI Tour Planner has not only simplified the process of crafting travel plans but has also opened new doors to exploration. It has broadened horizons, encouraged the discovery of hidden gems, and facilitated cultural immersion, all while maintaining a commitment to sustainability and responsible tourism. As we reflect on this project, it is evident that the integration of artificial intelligence into the world of travel has ushered in an era of unprecedented convenience and enriched experiences. It serves as a testament to the potential of technology to enhance our lives and our understanding of the world.

9. Future work:

The Tour Planner Project has laid a solid foundation for revolutionizing travel planning, but its evolution is an ongoing journey. Here are some avenues for future work:

Implement advanced machine learning techniques to further understand user preferences and deliver even more personalized recommendations.

Explore incorporating real-time data to adapt to changing travel trends and preferences dynamically.

Extend the project's reach to include a broader range of international destinations.

Integrate multilingual support to cater to a diverse global audienc

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