



## Distance Optimization Minimum Statistical Network Model to Estimate Preferences for Tour Plans

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### ABSTRACT

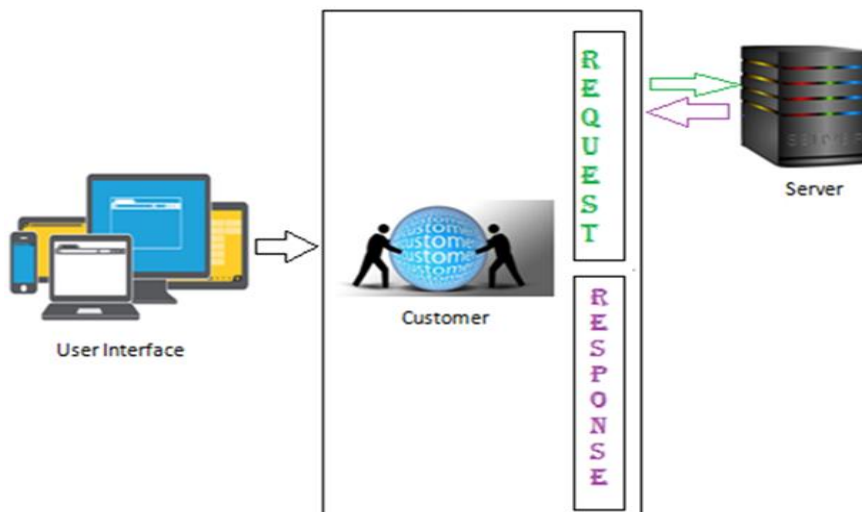
In recent days tourism transportation has become a recent research area and rapid development of internet technology has overloaded information. The proposed a Two-Stage space time network solution algorithm based on the set of alternative transactions known trip origins and destination and traveler preferences. Based on further activation descriptions of individual travel characteristics and enrichment and Improvement of the transportation data set, the travel planning method based on the spatiotemporal networking modeling idea proposed can be used as a reference for personalized tourism travel systems.

**Keywords:**-two-stage; daily travel planning; spatiotemporal network; personalized travel; shortest path algorithm.

### 1. Main text

Nowadays tourism transportation has become a hot topic of research, and the rapid development of Internet technology has overloaded information, which has made it impossible to provide services with different preferences for different users. Therefore, personalized tourism transportation has become the current mainstream trend. According to the different preferences of travelers for money and travel time, based on the analysis of mainstream tourism services, and combined with multi-source traffic data, this paper proposes a mathematical model for personalized travel planning. This paper proposes a two-stage spatiotemporal network solution algorithm. In the first stage, based on the set of travel attractions given by the traveler, the shortest path algorithm is used to plan an approximate optimal path that meets the traveler's preferences and to implement connection of multiple travel modes. The second stage is combined with the spatiotemporal network to achieve daily travel planning between multiple attractions. The two-stage spatiotemporal network algorithm is feasible for solving path planning problems, and can simplify route planning problems with time windows, which provides a useful reference for future personalized travel planning recommendations.

#### 1.1 Structure



## 1.2 Construction of references

Personalized tourism recommendation technology is the key technology to solve the current information redundancy in the tourism industry. When a traveler is planning a travel itinerary, they will find related travel information. However, the large amount of data makes it difficult for travelers to quickly and efficiently obtain valuable information from complex data. At present, some scholars have done some preliminary research on personalized tourism recommendation models, mostly use historical information provided by travelers to recommend travel information suitable for them. In 2017, Haqqani M., Li X., Yu X. proposed a preference estimation method, which combined implicit relevance feedback method into the journey planner and used the user's travel history data to estimate the corresponding preference model; In 2018, Li Xiaoxu, Yu Yaxin, Zhang Wenchao in order to deal with large-scale social network trajectory data efficiently, MapReduce programming model with optimized clustering is used to mine the coterie group pattern; In 2020, Liu Zelin, Cao Jian, Tan Yudong, Xiao Quanwu proposed an effective method of air travel planning, which can find many air travel plans by calling the API provided by the airline.

## 1.3 Proposed Work Modules

To implement this project have designed following modules

- 1) Upload Travel Data set: using this module we will upload data set to application
- 2) Preprocess Data set: using this module we will process data set to replace missing values
- 3) Build Collaborative & Clustering Model: using this module we will build collaborative and clustering model using users favourite places and ratings and then convert entire data set into numeric vector so we train this vector with machine learning algorithm
- 4) Train KNN Algorithm: above vector will be input to machine learning KNN algorithm to train recommendation model. This model can predict close destination places based on user input parameters
- 5) Predict Recommendation: this module will take user parameter as input and then apply KNN model to predict closed destinations

## 1.4 Proposed Algorithm

K-Nearest Neighbors (KNN) Algorithm: The KNN algorithm is a simple and commonly used classification or regression algorithm that's based on finding the "nearest neighbors" to a given data point. In the context of this code, KNN is likely used to find similar user preferences and make recommendations based on the preferences of similar users.

### Step 1: Data Preparation

In your project, you have a Dataset containing user profiles and corresponding categories or travel destinations.

### Step 2: Feature Extraction

Convert each user profile into a numerical representation using TF-IDF vectorization. Let's say you have a user profile "content" for user  $i$ , and this content is represented as a TF-IDF vector  $X_i$ .

### Step 3: Choosing K

Choose a value for  $K$ , which represents the number of nearest neighbors to consider. Let's say  $K = 5$  in your project.

### Step 4: Calculating Distance

Calculate the distance between the TF-IDF vector  $X_i$  of the user for whom you're making a recommendation and the TF-IDF vectors of all other users in the Dataset. The cosine similarity is often used as the distance metric:

$$\text{Cosine Similarity} = \frac{\text{dot}(X_i, X_j)}{(\text{norm}(X_i) * \text{norm}(X_j))}$$

Where:

- $\text{dot}(X_i, X_j)$  is the dot product of vectors  $X_i$  and  $X_j$ .
- $\text{norm}(X_i)$  is the Euclidean norm (magnitude) of vector  $X_i$ .
- Calculate the cosine similarity for each user  $j$  in the Dataset.

### Step 5: Finding K Neighbors

Select the  $K$  users with the highest cosine similarities (nearest neighbors) to user  $i$ . Let's denote this set of users as  $N_i$ .

### Step 6: Voting or Weighted Voting (Classification) / Averaging (Regression)

Since your project involves classification (recommendation of categories), you'll perform a majority vote among the categories of the K nearest neighbors.

For each category c, calculate the weighted vote count:

$$\text{Weighted Vote}(c) = \sum (1 - \text{Cosine Similarity}(j)) \text{ if category of user } j \text{ is } c, \text{ for } j \text{ in } N_i$$

Step 7: Prediction

The category with the highest weighted vote count is the predicted category for user i.

Step 8: Recommendation

Provide travel recommendations based on the predicted category.

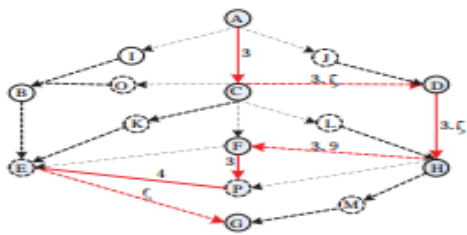
Step 9: Output

The algorithm outputs the recommended travel destinations based on the majority-voted category.

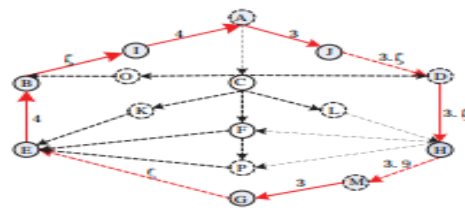
### 1.5 Proposed Algorithm

## 2. Proposed Related work

In the path planning process, in order to better solve the problem of time constraints and the route planning of the loop, the concept of a two-stage space-time network is used here to achieve personalized travel planning for different travelers. Figures 1(a) and (b) show the two route planning schemes that eventually exist in the physical network based on the shortest path algorithm after the traveler has determined the nodes to play and the start and end points.



(b) Network with the same starting and ending points



(a) Network with inconsistent start and end points

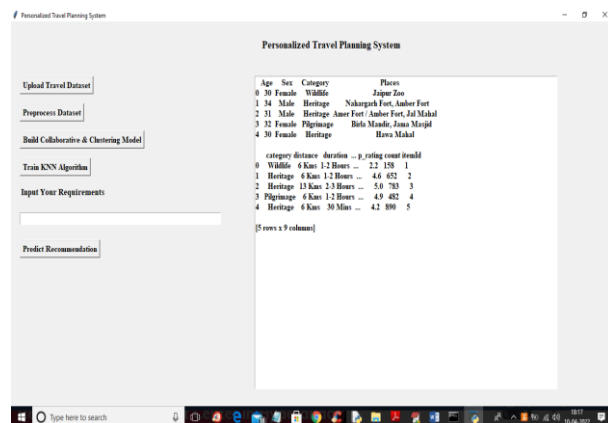
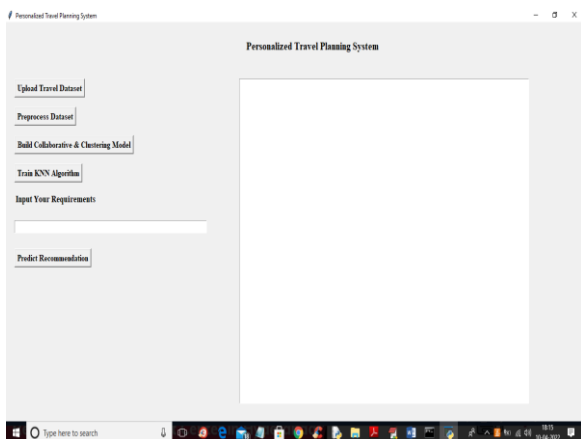
Fig : Two route planning schemes in physical networks

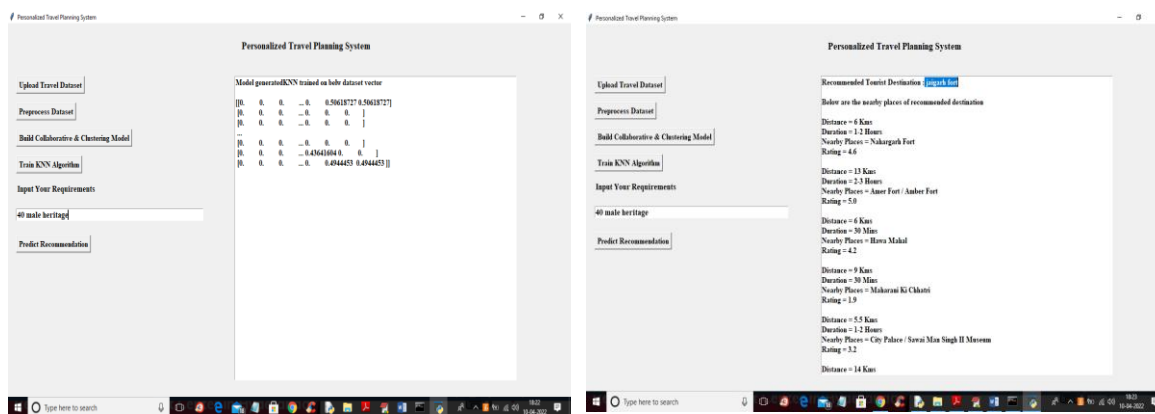
## 3. Equations

**Mathematical Model:** In summary, the travel itinerary planning model with time windows can be expressed as;

$$\min E = y \sum C^a s_{i,t}^u, s_{j,t}^u, x_{i,t}^u, s_{i,t}^u, t_{i,t}, a_{i,j} + y \sum \Delta t^a s_{i,t}^u, s_{j,t}^u, x_{i,t}^u, s_{i,t}^u, t_{i,t}, a_{i,j}$$

## 4. Results and discussion





## 5. Conclusion

A decision tree based tourist recommendation system has been presented in attempt of solving the current challenge of the destination TRS. The data set has been decomposed into two sub data sets using relevant tourism domain knowledge. This was done to increase classification accuracy rate and to reduce the complexity of the decision tree. The optimal decision trees from NMIFS with the highest accuracy rate and simplicity (i.e. less number of leaf and tree size) have been constructed for destination choice.

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