# A\* Based Optimized Travel Recommendation System for Smart Mobility

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Abstract: An optimized travel recommendation system based on patterns of travel and difficulties is an intelligent system designed to provide customized route recommendations to travelers by analyzing their past travel behaviors and predicting potential challenges along suggested routes. The system uses machine learning to identify travel trends, such as frequently chosen paths, preferred pacing, and typical destination choices, tailoring route suggestions that are both engaging and aligned with user-specific preferences. Our paper presents an advanced Travel Route Suggestion System that leverages data driven insights to generate customized travel routes based on user travel patterns and anticipated route difficulties. By analyzing historical travel data, user preferences, and contextual factors - such as weather, terrain, and traffic conditions— the system provides route suggestions that align with each user's unique interests, capabilities, and risk tolerance. It focuses on developing an intelligent travel route suggestion system to assist visitors in navigating from their source to their destination. It addresses these issues by leveraging traveler feedback and patterns to suggest the best possible routes and anticipate potential difficulties. In this paper an A\* Based Optimized Travel Recommendation System for Smart Mobility has been developed.

Keywords: A\* Algorithm, Travel Route, Smart Mobility, Recommendation System, Data-Driven Insights.

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# I. INTRODUCTION

As travel becomes increasingly personalized and experience-driven, planning an ideal route through a new destination is more complex than simply stringing together a list of popular attractions. Travelers today seek routes that align with their individual preferences, physical abilities, and desired levels of adventure, while also being mindful of potential challenges such as accessibility, route difficulty, and changes in weather conditions. A Travel Route Suggestion System that leverages patterns of travel behavior expected challenges along the route offers a transformative approach to this problem, delivering customized routes that are both engaging and feasible for each individual. This intelligent route suggestion system draws on vast datasets of past travel behaviors, user feedback, and environmental factors to create dynamic, personalized routes. It combines collaborative filtering, which uses similarities between users' travel histories, and content-based filtering, which focuses on matching route features to individual user preferences [2]. By

analyzing patterns such as commonly taken paths, typical visit durations, and frequently paired destinations, the system can predict and recommend routes that align with a traveler's unique profile. A review of the research on different kinds of recommendation systems (RS), such as those based on user preferences, behaviors, demographic profiles, and social network evaluations, was given by Barouche and Boutaounte.[3]. The Travel Route Suggestion System redefines exploration by transforming route planning into a proactive, adaptive process. Instead of just suggesting places, it creates a journey that accounts for each user's physical abilities, adventure level, and personal preferences. In the end, this system makes travel easy and unforgettable, helping all kinds of travelers enjoy smooth, informed trips that match their interests and abilities. It can be developed for a country to guide the visitors for specific cities they want to visit. The main goal of using personalization techniques in recommender systems is to generate personalized recommendations based on individual user preferences and interests [7]. A. Chen introduced a context-aware

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collaborative filtering system that uses prior experiences to forecast a user's choice in various context scenarios [17]. The focus is on recommender systems and their applications in tourism.

The rest of the paper is structured as follows. Section-2 reviews the extant literature. Section-3 describes the problem statement. Section-4 explains the methodology. Section-5 discusses the results and discussions. Section-6 summarises the paper.

#### II. LITERATURE REVIEW

People frequently travel to new locations for a variety of reasons, including work, education, health, and travel. In order to get to their destination, travelers always look for the quickest and safest path [1]. As social media and information technology have advanced, there are a plethora of options for obtaining pertinent information that may be used to create a proper travel itinerary and, ultimately, improve the quality of travel [4]. One particularly helpful tool in the realm of location-based social networks is a travel route suggestion service that suggests a series of points of interest for travelers visiting a new city [5]. Travel route recommendation systems have become essential tools for enhancing travelers' experiences by providing tailored suggestions for landmarks and itineraries. Traditional models often rely on generic data, leading to less satisfactory recommendations. However, recent research has introduced innovative approaches that incorporate various data types, allowing for greater personalization and relevance in travel suggestions. Suardinata et al. [6] presented a travel route optimization model combining Dijkstra's algorithm with Google Maps data to determine the quickest paths between destinations. Rachmawati and Gustin used the Dijkstra or A\* algorithm to solve the shortest path problem.[8] The Dijkstra algorithm is used by an intelligent travel path recommendation system to determine the shortest path between a user's position and their destination in a timely manner[11]. Cheng et al. [7] introduced a novel approach to travel route recommendation systems by incorporating people's attributes extracted from photos, such as gender, age, and race by revealing the attributes significantly influence decision-making regarding travel landmarks and paths. The Ministry of Tourism will profit [9] by learning about the algorithm used to determine the shortest route to a tourist destination. They can then use this knowledge to develop apps that make it easier for visitors to locate the shortest way to their destination. Based on smartphone and Internet of Things technologies, Bin et al. proposed a unique travel route suggestion system that automatically gathers travel behavior data from tourists onsite with respect to a particular point of interest [10].

The Dijkstra method, which Yuliani and Laksana [12] employed, is highly helpful for travelers as it allows them to determine the quickest path to and from a tourist spot in the Bandung region they choose to visit. Cui et al. [13] presented a travel route recommendation model leveraging collaborative filtering and GPS data. Yoon et al. [15] present a tourism recommendation system that dynamically adapts to real-time contextual data. Kurashima et al. [16] propose a novel approach for recommending travel routes by utilizing geotagged data from photo-sharing platforms. Chatterjee et al. (2021) proposed an approach to construct high precision maps from traces of crowd equipped with differential GPS receivers with updated existing path along with addition of new path segment scaled according to the exact width and shaped on electronic map [14].

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#### III. PROBLEM STATEMENT

The travel recommendation system considers commonly used routes and difficulties faced by past travelers to suggest the most efficient, reliable, and personalized routes. It uses real-time data, user feedback, and travel history, and utilizes algorithms that learn from past traveler experiences to suggest the best and most reliable routes. Initially the data is preprocessed and A\* algorithm was implemented to calculate the shortest path. The User-Based Recommendation Algorithm was implemented using K-Means clustering to identify similar places. The performance of the recommendation system was evaluated using Precision of k places. Three datasets have been developed focusing on popular areas in Kolkata, West Bengal, for the Travel Route Suggestion Based on Pattern of Travel and Difficulties project. These datasets encompass widely visited places throughout Kolkata to offer accurate, optimized routes for travelers based on their search preferences. To ensure route accuracy and relevance, insights and data assistance from Google Maps has been incorporated.

#### Dataset 1 (Travel Routes):

This dataset outlines travel routes between various locations, detailing the source, destination, and distance in kilometers. It serves as a foundational resource for understanding the connectivity of different points within a region. The significance of this dataset lies in its ability to inform route planning and optimize travel itineraries. By analyzing the distances, travelers can identify the most efficient paths and minimize travel time. This information can be integrated into travel recommendation systems, enabling users to receive suggestions for optimal routes, enhancing their journey and overall travel experience.

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	A	В	C	D	
1	Place_Id	Source	Destinatio	Distance(k	m)
2	1	Amtala	Bishnupur	2.2	
3	2	Bishnupur	Khoriberia	4.6	
4	3	Khoriberia	Vasa Man	1.5	
5	4	Vasa man	Pailan	5.4	
6	5	Pailan	Joka	5	
7	6	Joka	Thakurpul	2.3	
8	7	Thakurpul	Sakherbaz	2.8	
9	8	Sakherbaz	Behala Ch	0.8	
10	9	Behala Ch	Behala 14	2.4	

Fig 1 Dataset 1 Travel Routes

## > Dataset 2 (User Ratings):

This dataset contains user ratings for various places, structured with user IDs, place IDs, and the corresponding ratings. The ratings range from low to high, reflecting users' experiences and satisfaction with each location. The dataset is significant as it helps identify popular attractions and gauge visitor sentiment. Analyzing these ratings can reveal trends in user preferences, guiding future travelers toward highly-rated destinations. This information can be utilized to refine recommendation algorithms, ensuring that users receive personalized suggestions based on collective feedback. Ultimately, it enhances the overall travel experience by prioritizing attractions that resonate positively with visitors.

A	В	С	
User_Id	Place_Id	Place_ration	ng
5	. 1	4.1	
40	2	4.2	
11799	3	4.6	
81	4	3.1	
69	5	3.7	
71	6	3.9	
76	7	4	
23	8	4.1	
61	9	4.1	

Fig 2 Dataset 2 User Ratings

#### > Dataset 3 (Place Details):

This dataset links user IDs with place IDs and their ratings, similar to Dataset 3 but focusing on different attractions. The ratings provide insight into the quality and popularity of these destinations, helping to evaluate which locations are most favored by visitors. This dataset is crucial for enhancing travel recommendations, as it allows the system to prioritize higher-rated attractions when suggesting places to explore. By incorporating user feedback, the dataset supports adaptive learning, enabling the recommendation engine to evolve based on visitor experiences. Overall, it contributes to a more satisfying and tailored travel planning process for users.

Z	A	В	С	D	E	F	G	Н	1	J
1	Place_Id	Place_nam	Age	Category	Road_con	Weather_	Descriptio	Mode_of_	Latitude	Longitude
2	1	Victoria M	All Ages	Historical	Good	Haze	A grand w	Bus, Taxi	22.54498	88.34243
3	2	Quest Ma	All Ages	Shopping,	Good	Haze	A modern	Bus, Taxi,	22.53915	88.36603
4	3	Fort Willia	All Ages	Historical	Good	Cloudy	A historic	Bus, Taxi	22.55895	88.33773
5	4	Shalimar S	All Ages	Transport	Good	Hazr	A major ra	Train, Bus	22.55591	88.31503
6	5	Belur Mat	All Ages	Religious/	Good	Haze	The heado	Bus, Taxi,	22.63282	88.35642
7	6	Howrah B	All Ages	Architectu	Good	Cloudy	A majestic	Bus, Taxi,	22.58532	88.34681
8	7	Birla Plane	Children,	Science/Ed	Good	Clear	A popular	Bus, Taxi	22.54548	88.34732
9	8	Indian Mu	Children,	Museum	Average	Clear	One of the	Bus, Taxi,	22.55108	88.35109
10	9	Marin Hou	Teens, Far	Historical	Good	Cloudy	A 19th-cer	Bus, Taxi,	22.55162	88.32678
11	10	Marble Pa	All Ages	Historical	Average	Haze	A beautifu	Bus, Taxi	22.58251	88.36023

Fig 3 Dataset 3 Place Details

#### IV. METHODOLOGY

This section is structured into several systematic and interdependent phases. The process starts with Data Loading and Preprocessing, Clustering, User Input, Recommendation Generation, Relevance Filtering and Precision:



Fig 4 Workflow of the Proposed System

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#### > Data Loading and Preprocessing:

Initially the data is being loaded from CSV files into Pandas Data Frames. This includes place information (name, category, location), and user ratings of places.

After that merging the place information with user rating data using Place\_Id as a key is done.

Next handling missing values (if any) by dropping rows with missing Latitude, Longitude, or Place\_rating is obtained.

Encoding categorical features (e.g., place category, age group, mode of transport) using one-hot encoding with pd.get\_dummies is done. This converts categories into numerical data.

Finally scaling the numerical features (including ratings, latitude, and longitude) using Standard Scaler to ensure all features contribute equally to the clustering process.

#### > Clustering:

In this section applying the K-Means clustering algorithm to group places with similar characteristics is done. Next determining the optimal number of clusters (k) using the Elbow Method. The Elbow Method involves plotting the within-cluster sum of squared errors (SSE) or inertia for different values of k and selecting the "elbow" point where the rate of decrease in inertia sharply changes. Finally assigning each place to a cluster is done.

#### ▶ User Input:

The step in this section includes:

Prompt the user to enter the name of a place they want to visit.

Check if the entered place exists in the dataset. If not, inform the user and potentially stop the process.

#### > Recommendation Generation:

Here retrieving the cluster, latitude, and longitude of the user's entered place is done.

Then identification of all other places that belong to the same cluster as the user's place is achieved.

The geodesic distance (great-circle distance on a sphere) between the user's place and each recommended

place using their latitudes and longitudes is calculated. The geopy. distance. geodesic function is used for this.

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Suggestion is taken from user any suitable mode of transport for each recommended place based on its distance:

- Walk (distance < 1 km)
- Auto/Rickshaw (1 km <= distance < 5 km)
- Cab (5 km  $\leq$  distance < 20 km)
- Metro/Bus (distance >= 20 km)

Sorting the recommended places by their distance from the user's place in ascending order (nearest first).

Finally, selection of the top-k nearest recommended places (e.g., k=5).

#### > Relevance Filtering and Precision:

Determining the "relevant" recommendations by filtering places with a Place rating greater than or equal to a predefined threshold (e.g., 4.0) is carried out.

The precision at k (precision of k places), which is the proportion of the top-k recommendations that are "relevant" is being calculated.

Precision of k places = (Number of relevant recommendations in top-k) / k.

#### V. RESULTS & DISCUSSIONS

This research explores the application of shortest-path algorithms in various real-world scenarios. The effectiveness of A\* search algorithm has been demonstrated in finding optimal routes in transportation networks, network routing, and game theory. In the database creation of three essential tables for travel recommendation system has been incorporated i.e, distances, ratings, and places. The distances table records the kilometers between various locations, crucial for route optimization. The rating table captures user feedback, enabling personalized recommendations based on user preferences. Meanwhile, the places table provides detailed information about each location, including category and conditions, each location's latitude and longitude. Together, these tables support the recommendation system by facilitating efficient data retrieval and analysis, enhancing the user experience through tailored travel suggestions based on distances, ratings, and specific attributes of destinations. Proper structuring and accuracy are vital for effectiveness.

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Start Place:	Thakurpukur	۷
Destination	Howrah	v
Calcula	ate	

Using A\* Algorithm

Shortest route from Thakurpukur to Howrah is: Thakurpukur --> Sakherbazar --> Behala Chowrasta --> Behala 14 no. --> Taratala --> Mominpore --> Ekbalpur --> Khiderpore --> Hastings --> Princep Ghat --> Babu Ghat --> Esplanade --> B.B.D. Bag --> Barabaz ar --> Howrah

Total Path Cost (in Km): 27.349999999999998

Start Place:	Howrah	v				
Destination	SDF	v				
Calcul	ale					
Using A* A) Shortest ro Idah Court Total Path	lgorithm bute from Howrah t > CIT More> Cost (in Km): 21.	o SDF is: Howrah Beleghata> Chi 45000000000000003	> Barabazar> B ngrighata> SOF	.8.D. Bag> Espla	nade> Moulai;	> Sealdah Station> Sea

# Fig 5 Results obtained from A\* Algorithm

Enter the place you want to visit: Alipore Zoo

Top Nearby Recommendations:

Recommended Place	Age	Category	Distance_km	Rating M	ode_of_Transport	Relevant (Rating ≥ 4.0)
Alipore Zoological Garden	All Ages	The oldest zoo	0.019536	4.1	Bus,Taxi,Train	True
National Library	All Ages	The largest library	0.493581	4.2	Bus,Taxi	True
Sri Mahalakshmi Temple	All Ages	Temple, Religious Site	0.918527	3.9	Bus,Taxi,Auto	False
Royal Calcutta Turf Club 18	+ (for adult only) Horse A	Racing, Sports, Social Club	0.927031	4.1 B	us, Taxi , Metro	True
Kolkata Race Course	All Ages	Horse racing venue	0.983126	3.7	Bus,Taxi,Metro	False

Precision@5: 0.60

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Choose a Place:	Nicco Park					Ň	<i>,</i>		
• Recommend	ations based on	: **Nicco P	ark**						
Recommended	Place	Age	Category	Distance_km	Rating	Mode_of_Transpo	int Suggested_Ti	ransport	Relevant (Rating ≥ 4.0)
Wet	O-Wild Children	, Families	Water Park	0.142333	4.2	Bus, Ta	xi	Walk	True
Nalban Boatin	ig Park	All Ages	Recreation/Boating	0.996265	4.1	Bus, Ta	xi	Walk	True
Salt Lake S	itadium	All Ages	Sports	1.312294	4.4	Bus, Ta	xi Auto/N	Rickshaw	True
Centra	al Park	All Ages	Park/Recreation	2.214929	4.3	Bus, Ta	xi Auto/N	Rickshaw	True
Mani	Square	All Ages	Shooping Mall	2.220278	4.0	Bus,Ta	xi Auto/	Rickshaw	True
Precision	95: 1.00								

Fig 6 Results obtained from Recommendation System

#### Table 1 Distances Table

mysql> select * from distances;						
Place_Id	Source	Destination	Distance_km			
1	Amtala	Bishnupur	2.2			
2	Bishnupur	Khoriberia	4.6			
3	Khoriberia	Vasa Mandir	1.5			
4	Vasa mandir	Pailan	5.4			
5	Pailan	Joka	5			
6	Joka	Thakurpukur	2.3			
7	Thakurpukur	Sakherbazar	2.8			
8	Sakherbazar	Behala Chowrasta	0.8			
9	Behala Chowrasta	Behala 14 no.	2.4			
10	Behala 14 no.	Taratala	2.9			
11	Taratala	Mominpore	5.2			
12	Mominpore	Ekbalpur	1			
13	Ekbalpur	Khiderpore	1.4			
14	Khiderpore	Hastings	1.6			
15	Hastings	Princep Ghat	0.95			

#### Table 2 Ratings Table

mysql> sele	ect * from	ratings;
User_Id	Place_Id	Rating
1 2 1	131	i 4 i
3	21	3.7
3	67	4.3
3	103	3.9
3	142	3.9
3	150	3.8
3	159	4.7
4	11	4.6
4	12	4.6
4	18	3.5
4	19	3.5
4	70	4.5
4	124	4.6
4	170	3.5
5	1	4.1

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mys

Table 3 Pla	ces Table	
170   Abanindranath Tagore's Garden House arden, Art, Museum (Possible)   Average   Haze nath Tagore, possibly preserved as a museum or heritage site.   22.7051   88.3445	All Ages   The former residence and garden of the renown   Bus, Taxi , Auto	Heritage House ed artist Abanin -rickshaw +
·	-+	
rows in set (0.01 sec)		
ןl> select * from places limit 5; 	ŧŧ	
lace_Id   Place_Name   Age   Category	Road_condition   Weather_Condit	ion   Descriptio
Mode_of_Transport   Latitude   Longitude   +++++	·	ŧ
ql> select * from places; 	······	+
lace_Id   Place_Name	Age	Category
Latitude   Longitude	Mode_of_Transpor	t +
·+++++	· · · · · · · · · · · · · · · · · · ·	
1   Victoria Memorial nt   Good   Haze ring Indo-Saracenic architecture and housing a museum with artifac	All Ages   A grand white marble monument dedicated to Qu cts from British India.   Bus, Taxi	Historical Mon Ween Victoria, fe
2   Quest Mall inment   Good   Haze , and entertainment options.   22.5392   88.366	All Ages   A modern, upscale shopping mall with various   Bus, Taxi, Metro	Shopping, Ente brands, restaura
3   Fort William Kolkata	All Ages	Historical Sit

#### VI. CONCLUSION

tory and a serene park for picnics

As travel becomes increasingly personalized and experience-driven, this research proposes a comprehensive, multi-dimensional methodology developing for а personalized travel recommendation system. A collaborative filtering-based recommendation system personalized for travelers exploring Kolkata has been developed. The system enhances the user experience by suggesting nearby popular tourist destinations based on the user's search query. By leveraging geographic proximity and user interaction patterns, the model offers relevant, personalized travel recommendations that encourage more efficient and enriched trip planning. This approach not only helps tourists discover hidden gems around well-known landmarks but also supports local tourism by promoting a diverse range of attractions. Future improvements could involve integrating user preferences, travel duration, and real-time data such as traffic or weather to further refine recommendation accuracy. Realtime data integration, such as weather conditions, or crowd density at destinations, could add significant situational awareness, enabling the system to adapt dynamically to realworld conditions.

Bus, Taxi

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