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CUSTOMIZED PATH PROPOSAL UTILIZING NEURAL NETWORKS-ACCEPTED A* SEARCH METHOD

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Original Article

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Abstract

In this paper, we study a critical problem in spatially based applications: personalised route recommendation, or PRR. Given a road network and users' route queries, the PRR task is to generate user-specific route suggestions. An old-fashioned approach is to tweak search algorithms to yield pathfinding-like results. These methods often focus on narrowing the search space by applying suitable heuristic strategies. Because heuristic strategies for these search algorithms are often built, they are not appropriate for application in scenarios involving complex tasks. Moreover, it is difficult to integrate useful background data into the search procedure. To produce a more principled solution, we propose to apply neural networks to improve search techniques for resolving the PRR issue, which is based on the well-known A* algorithm.

***Keywords**: Customized Path, A* authorised search, Route Planning, Machine Learning*

Introduction

As portable electronics with satellite navigation capability have grown in popularity, a vast amount of user trajectory data has been accessible across several domains. Customized Route Suggestion (PRR) is a fundamental feature of many location-based web services, such as online maps. PRR attempts to provide user-specific route recommendations on-the-spot for path planning from a source to a destination given the road network. Effective pathfinding in a vast and intricate road network is difficult. Rich context information is required for an appropriate route selection, and this includes factors like road network constraints, customized preferences, and spatial-temporal influences [1-3]

The creation of an efficient cost function is the secret of heuristic search algorithms. The cost function was heuristically established in the majority of earlier research, which severely limited their application. Furthermore, it is challenging to use different types of context information throughout the search process. Numerous research have used machine learning techniques to solve the PRR challenge in order to provide more adaptable ways. Using principled models, these techniques can characterize spatial-temporal information or location dependencies [4-11]

They can naturally pick up effective input-to-output mapping strategies or creative representations of characteristics from unprocessed data. This study attempts to integrate the advantages of both types of techniques in a rational way, based on these talks. Our approach gains inspiration from the latest developments in machine learning for games like Atari and Go, where learnable elements are included into heuristic search algorithms. Primarily, we think about tackling three significant challenges for this reason. To begin with, we must specify a form that works well for the cost in the PRR job. Unlike typical graph search problems, our task's objective cannot be readily optimized by a simple heuristic cost.[11-15]

Literature Survey

Fatemeh Hosseinzade(2016) proposed Using a macroscopic fundamental diagram (MFD), the research presents two fairness-centered route guidance (RG) control schemes: anticipatory control and proportional fairness, intended for a diverse urban network. As resource equity is ensured and traveler utilities are maximized, anticipatory control incorporates user routing behavior. When compared to a simple control scenario, sensitivity analysis under different scenarios demonstrates enhanced efficiency and fairness, with anticipatory control offering smoother RG ratios.

Nandita Basu **(**2017**)** proposed cross-sectional methodology of the current study takes into account theory-informed characteristics that affect pedestrian route choices at the individual, physical, and temporal levels. To investigate variations in trade-offs between route choices during the day and at night, two distinct models are created.

Fang Xu(2019) proposed a methodology on Free Node-based Routing method (FNRA), a unique routing method proposed in this research, is intended to tackle the difficulties encountered in the Social Internet of Things (SIoT) environment. A thorough framework for message forwarding that differentiates between in-community and out-of-community circumstances is a key component of the FNRA technique. It divides source, relay, and destination nodes into four different structures outside the community using a graph-theoretic method.

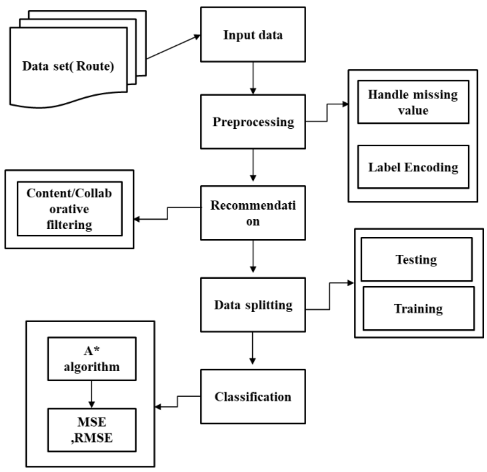
Anranur Uwaisy M **(**2023**)** proposed a scheduling and route-searching system for tourists to address Traveling Salesman Problems (TSP). Utilizing the tabu search method, tourists can find optimal routes considering factors like travel time and attraction operating hours. Multi-Attribute Utility Theory (MAUT) is incorporated to determine optimal tours based on popularity, cost, and attraction count. Comparison with the firefly method shows superior performance of the tabu search method, with a significant increase in accuracy, average running time, and number of tours visited over a 3-day period.

After analysing the previous papers the route recommendation have been proposed on the terms of nodical data which is a little difficult to point so in our customized path proposal we propose the a* algorithm in the way of latitudes and longitudes wich are easy to point on the locations of the map and hence it reduces the time taking and with the longitude and latitude are taken as the indexed values which can be easily determined.

Proposed Methodology

Route recommendation is vital in navigation apps, suggesting optimal paths between locations. Personalized recommendations are crucial to meet individual preferences, considering factors like mode of transport and time constraints. The A* search algorithm plays a key role, efficiently finding optimal routes by intelligently exploring paths based on cost and estimated destination distance. Its integration enables navigation systems to dynamically adapt, delivering personalized routes aligned with user needs.

A. System Architecture:



B. Methodology:

1. Input data sets: Data set is taken from the Kaggle taxi data set in which the data contains 11 attributes and the attributes contains vendor id, pickup time, drop off time, latitudes and longitudes of the pick-up and drop-off and the distance from the latitude and the longitude. And it contains the time taken for the vendor to reach the final destination. The data set contains 11 attributes and each attributes has 90,000+ records. The taken data is already pre-processed and clean data but it has been again pre-processed again to get the better and accurate results

2. Data Pre-processing: Label Encoding: Converts categorical variables into numerical representations, facilitating the model's understanding of the input feature.

Binary Replacement: Involves converting categorical variables to numerical ones, assigning 0s and 1s to represent different categories for machine learning compatibility.

Data Reshaping: Ensures the input data is in a suitable format for the deep learning model, such as reshaping arrays or sequences as needed for the chosen architecture

3. Model Training: Neural Networks: An artificial intelligence technique called a neural network trains computers to process information like that of the human brain.

A* search: It is a useful approach that is frequently applied to map traversal in order to determine the shortest path. A* was created to aid in the development of a self-navigating robot. It is still a very well-liked graph traversal algorithm.

4.Compilation: Optimizer (Adam): The Adam optimizer is commonly used in deep learning for efficient gradient-based optimization.

Loss Function (Binary Cross Entropy): Appropriate for binary classification problems, binary cross-entropy measures dissimilarity between predicted and actual outcomes.

Metrics (Accuracy): Accuracy is chosen as the evaluation metric during training, representing the proportion of correctly predicted outcomes over the total predictions.

RSME: One of the most popular metrics for assessing the accuracy of a forecast is the root mean square error, also known as the root mean square deviation.

5.Evaluation Metrics: The metric that this task should be assessed by is defined as overall accuracy; it evaluates the number of predictions predicted correctly and, thus represents percentage correct classifications.

6. Accuracy (Result Comparison): To evaluate the performance of our suggested deep learning model, its accuracy is compared to baseline models or current techniques. Elevated precision signifies the model's capacity to accurately forecast ideal routes for users to choose. The suggested methodology seeks to improve the model's resilience, generalization, and prediction accuracy by combining data augmentation, pre-processing techniques, and a deep learning architecture using A* search algorithm. The capacity to estimate a precise and correct route recommendation for the user is ensured by the selection of relevant performance measures.

Performance Metrics

The performance metrics aid in assessing the suggested SNM's network settings. The performance metrics used in this work include f1-score, recall, accuracy, and precision.

a) Accuracy:

Measures the overall correctness of recognized signs or gestures compared to the ground truth.

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ Number\ of\ Predictions}$$

b) Precision:

Precision signifies the proportion of correctlyrecognized signs among all recognized signs.

$$Precision = \frac{TP}{TP + FP}$$

Where

TP= True positive

FP= Flase Positive

c) Recall:

It indicates the proportion of the correct identification among all actual signs.

$$Recall = \frac{TP}{TP + FN}$$

Where

TP= True positive
FP= Flase Positive
FN=False Negatives

d) F1-score:

The average precision and recall means, a balanced value of the model performance.

$$F1 - Score = 2\ X \frac{Precision\ X\ Recall}{Precision + \ Recall}$$

e) EDT:

EDT (Empirical distribution test) which is a statistical method for comparing used for comparing algorithms. n real The EDT works by comparing the empirical cumulative distribution functions (ECDFS) for the data sets being studied.

$$F^i(x) = \frac{1}{n_i} \sum_{j=1}^{n_i} I(X_{ij} \leq x)$$

Fi(*x*)- empirical cumulative distribution function (ECDF)

n_i- number of observations in ith-datasets

X_{ij}- j-th observation in ith data set

Implementation

The approach recommends customised routes using the Beijing Trip Data Set and the Spyder IDE. The data is pre-processed and can handle the NLP Preprocessing, the missing data, perform label encoding and drop unwanted columns. In the classification step we implement two different algorithms. We predict that it is based on A* search algorithm. Now, we analyse the above metrics.

Results and Discussion

By considering our task is to maximize the conditional probability Pr(ðp|q; u; DÞ). And by equally minimizing the negative log in the formula -log Pr(ðp|q; u; DÞ). So by the given path it considering the possible paths form the source to destination. Where the nodes are determined by k. the is determined by l_s ->l_1->$l_{2........}$->l_3->l_d

$$-\log \Pr(p|q,u,\mathcal{D}) = -\sum_{i=0}^{m} \log \Pr(l_{i+1}|l_s \rightarrow l_i, q, u),$$

A. DataSet:

Data set is taken from the Kaggle taxi data set in which the data contains 11 attributes and the attributes contains vendor id, pickup time, drop off time, latitudes and longitudes of the pick-up and drop-off and the distance from the latitude and the longitude. And it contains the time taken for the vendor to reach the final destination. The data set contains 11 attributes and each attributes has 90,000+ records. The taken data is already pre-processed and clean data but it has been again pre-processed again to get the better and accurate results

pickup_latitud	dropoff_longit	dropoff_latitud	store_and	trip_durat	dist_metei	wait_sec
0.528947475	-78.5494469	-0.361362603	N	2025	24228	346
0.391949868	-103.3666	20.68697134	N	389	2962	3675
0.563279525	-100.165737	25.61938737	N	168	951	0
0.590416254	-100.491721	25.67629431	N	1659	11082	358
0.580418527	-100.104166	25.64386166	N	272	2021	3614
0.564267624	-100.186171	25.64312939	N	22	2502	517
0.631889111	-100.257612	25.72749166	N	6175	3579	346
0.061642383	-80.7025234	-0.96816754	N	2412	19933	114
0.62679597	-100.495666	25.68718998	N	2698	4770	292
0.390198194	-103.359451	20.66955834	N	401	2733	71
0.579780756	-100.081929	25.643473	N	512	4251	3689

vendor_id	pickup_datetime	dropoff_datetime	pickup_longitude
Quito	17-09-2016 09:32	17-09-2016 10:05	0.632054634
Guadalaja	17-09-2016 09:59	17-09-2016 10:06	0.32780423
Monterrey	17-09-2016 10:06	17-09-2016 10:09	0.140909735
Monterrey	17-09-2016 09:45	17-09-2016 10:13	0.20756473
Monterrey	17-09-2016 10:12	17-09-2016 10:16	0.128881294
Monterrey	17-09-2016 10:18	17-09-2016 10:18	0.141188213
Monterrey	17-09-2016 08:40	17-09-2016 10:23	0.157986709
Manta	17-09-2016 09:52	17-09-2016 10:32	0.797677023
Monterrey	17-09-2016 09:48	17-09-2016 10:33	0.223599657
Guadalaja	17-09-2016 10:28	17-09-2016 10:35	0.327516769
Monterrey	17-09-2016 10:27	17-09-2016 10:36	0.129025024

B. Comparison Table

Table i. Comparison of accuracy performace with different machine learning models

SNo	Model	Accuracy(%)
1	ASR	94.3
2	Collaborative Filtering	90.3
3	Deep Neural Networks	91.2
4	MFD	85.2
5	MNLM	88.5
6	Tabu Search	87.3
7	FreeNode Algorithm	82.2

Where,
ASR=A* search Representative,
MFD= macroscopic fundamental diagram
MNLM=Multi-Nominal Logit model
FNBA=Free Node based Algorithm

The above table compares the accuracies of the different models while recommending the route for the customers the ASR(A* search Representaition) shows the most of the accuracy although the Deep Neural networks show the accuracy nearer to the ASR but the ASR integrates with the deep Neural networks to achieve the highest accuracy.

A. Performance Analyze Graph

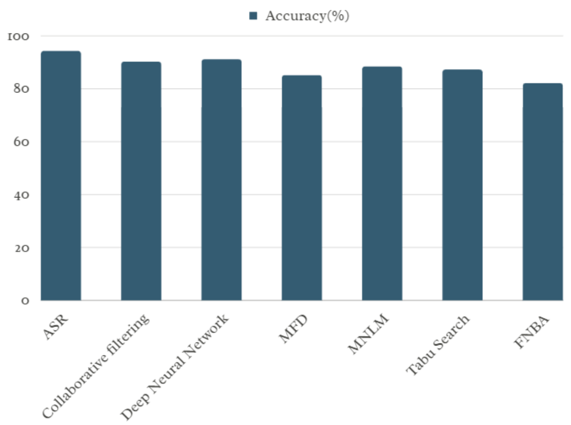


Fig 1: Performance Analyse Graph

The Accuracy of all the models are analysed and compared in the graphical format and By the observations of the graph the ASR model is recommended for the Route recommendation for the personal and daily use for better usage.

B. Model Performance Comparison

As the ASR model has the most accuracy the ASR model is compared in terms of the metrics and EDT.

Table ii: comparison of performace metrics with ASR

S.No	Metric	Accuracy (%)
1.	Accuracy	94.3
2.	Precision	0.82
3.	Recall	0.84
4.	F1-Score	0.64
5.	EDT	5.72

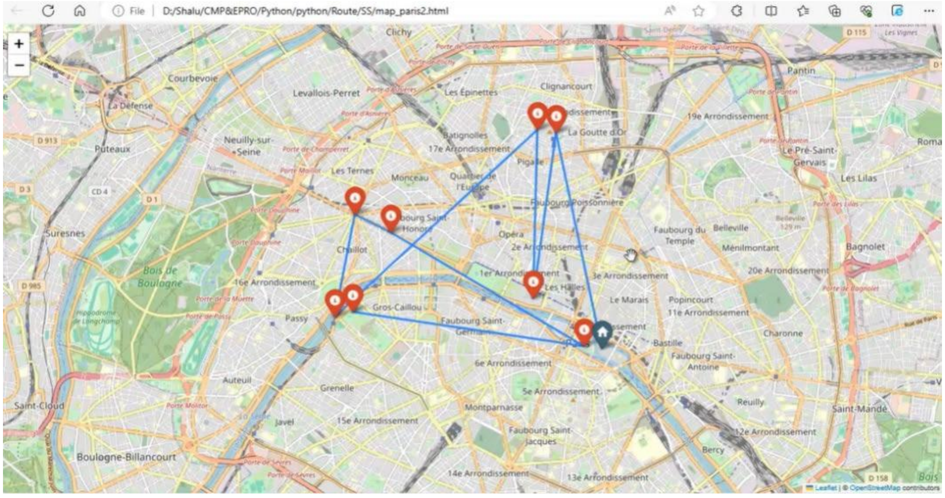
The accuracy of the ASR model is 94,3%, indicating ahigh overall correctness in predictions. Specificity is 94.3%, suggesting a good ability to correctly identify true negatives. Sensitivity (Recall) is 84%,showing model'seffectiveness in identifying true positives. Precision is 82%,indicating that when the model predicts positive cases, it is highly likely to be correct. F1-Score is 0.64, which combinesprecision, recall by providing a well balanced measure of how model performs.

A. Time complexity:

The time complexity of the A* search algorithm when it is used with the latitudes and longitudes as an indexes way for recommending the route and, The A* as compared to the trajectory data has more time complexity and for locating the path by using the trajectory data is an time talking process so we take the longitude and latitude data for recommendation

Result:

Using neural networks, we started by outlining the appropriate form for the search cost and providing a straightforward A∗ approach for resolving the PRR problem. Then, The RNN component for and the estimating network for are the two costs which we set up to learn respectively. The longitudes and latitudes are taken into consideration as an indexed values and hence reducing the time complexity and space complexity to the path proposal .which will be easy to the customer. The introduction of these have also increased the accuracy of the algorithm in an efficient way. To get a more precise cost of a potential search site, the two elements were brought together in a methodical manner.



Position-aware graph attention networks serve as the foundation for the estimate network, a significant innovation in this paradigm. With appropriate anchor set selection, the estimating network may learn distance and road networks' preference structure features. To confirm the efficacy and resilience of the suggested paradigm, we built comprehensive tests. Surprisingly, we have discovered that the suggested model may successfully shrink the search space in addition to improving system performance. Adding previous knowledge is one way that our work may be expanded. Currently, the historical trajectories which may be noisy or sparse are the primary means by which we learn the model and data representations. It will also be helpful to include previous data on traffic conditions, such as a crossroads' peak congestion period, to our model in order to make it better. Furthermore, the choice of each candidate location in our technique is based on the cost function. But it's challenging to comprehend the cost function; for example, why a candidate location is expected to be quite expensive. In further work, we'll think about creating an easier-to-understand estimating network to calculate the cost. Furthermore, our sophisticated model structure adds a little bit more computational complexity. Thus, increasing computing efficiency is another way that our model might be extended.

References

1. Wang, J., Wu, N. and Zhao, W.X., 2021. Personalized route recommendation with neural network enhanced search algorithm. IEEE Transactions on Knowledge and Data Engineering, 34(12), pp.5910-5924.

2. H. Wu, Z. Chen, W. Sun, B. Zheng, and W. Wang, "Modelling trajectories with recurrent neural networks," in ICJAI'17, 2017, pp.3083–3090.
3. S. Zheng, Y. Yue, and P. Lucey, "Generating long-term trajectoriesusing deep hierarchical networks," in NIPS'17, 2017, pp. 1543–1551

4. Parimi, S. K., & Yallavula, R. (2025). Generative AI for Enterprise Trust: A Governance-Aligned Framework for Safe and Transparent Automation at Global Scale. International Journal of Artificial Intelligence, Data Science, and Machine Learning, 6(1), 218-225.

5. Putchakayala, R., & Cherukuri, R. (2022). AI-Enabled Policy-Driven Web Governance: A Full-Stack Java Framework for Privacy-Preserving Digital Ecosystems. International Journal of Artificial Intelligence, Data Science, and Machine Learning, 3(1), 114-123.

6. Yallavula, R., & Putchakayala, R. (2024). AI for Data Governance Analysts: A Practical Framework for Transforming Manual Controls into Automated Governance Pipelines. International Journal of AI, BigData, Computational and Management Studies, 5(1), 167-177.
7. Parimi, S. K., & Yallavula, R. (2023). Enterprise Risk Intelligence: Machine Learning Models for Predicting Compliance, Fraud, and Operational Failures. International Journal of Emerging Trends in Computer Science and Information Technology, 4(2), 173-181.
8. Yallavula, R., & Putchakayala, R. (2022). A Data Governance and Analytics-Enhanced Approach to Mitigating Cyber Threats in NoSQL Database Systems. International Journal of Emerging Trends in Computer Science and Information Technology, 3(3), 90-100.
9. Yarram, V. K., & Cherukuri, R. (2025). User Experience Patterns for Front-End Integration of Retrieval-Augmented Generation in Enterprise Platforms. International Journal of Emerging Trends in Computer Science and Information Technology, 6(2), 87-94.
10. Parimi, S. K., & Cherukuri, R. (2024). Proactive AI Systems: Engineering Intelligent Platforms that Sense, Predict, and Act. International Journal of Emerging Trends in Computer Science and Information Technology, 5(3), 122-130.
11. Cherukuri, R., & Putchakayala, R. (2021). Frontend-Driven Metadata Governance: A Full-Stack Architecture for High-Quality Analytics and Privacy Assurance. International Journal of Emerging Research in Engineering and Technology, 2(3), 95-108.
12. Putchakayala, R., & Yallavula, R. (2025). The Intelligent Governance Core: A Multi-Layer AI Framework for Predictive Compliance and Autonomous Digital Analytics. International Journal of AI, BigData, Computational and Management Studies, 6(1), 171-179.
13. Cherukuri, R., & Yarram, V. K. (2023). AI-Orchestrated Frontend Systems: Neural Rendering and LLM-Augmented Engineering for Adaptive, High-Performance Web Applications. International Journal of Emerging Research in Engineering and Technology, 4(3), 107-114.
14. Putchakayala, R., & Cherukuri, R. (2024). AI-Enhanced Event Tracking: A Collaborative Full-Stack Model for Tag Intelligence and Real-Time Data Validation. International Journal of Artificial Intelligence, Data Science, and Machine Learning, 5(2), 130-143.
15. Cherukuri, R., & Yarram, V. K. (2024). From Intelligent Automation to Agentic AI: Engineering the Next Generation of Enterprise Systems. International Journal of Emerging Research in Engineering and Technology, 5(4), 142-152.