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INTELLIGENT ALGORITHMS FOR PERSONALIZED TRAVEL ROUTE PLANNING A GRAPH NEURAL NETWORK AND HYBRID MOVNS-A* APPROACH

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ABSTRACT

Personalized travel route planning is a combinatorial optimization problem that must simultaneously satisfy diverse user preferences, budget constraints, time limitations, and geographic factors. Existing approaches either rely on rigid rule-based systems or single-objective optimization methods that fail to capture the complexity of real-world tourism scenarios. This paper proposes an intelligent framework comprising three tightly integrated algorithms: (1) a Graph Neural Network (GNN)-based personalized tourist attraction recommendation algorithm that models user–object interaction graphs to capture latent preference patterns; (2) a hybrid Multi-Objective Variable Neighborhood Search combined with A* pathfinding (MOVNS-A*) algorithm for multi-constraint route optimization, balancing travel time, cost, and user satisfaction simultaneously; and (3) a Stacking Regression ensemble model for predicting post-visit user satisfaction scores. Experimental evaluation on a real-world dataset of 15,420 tourist trajectories from Uzbekistan demonstrates that the proposed framework achieves a Precision@10 of 0.847, an NDCG@10 of 0.831, and a mean route satisfaction prediction error (RMSE) of 0.312 — outperforming baseline methods including collaborative filtering, Dijkstra-based routing, and standalone deep learning approaches by margins of 12–23%. The framework is validated through integration into a working web-based travel planning application.

KEYWORDS

Personalized route planning; graph neural networks; multi-objective optimization; MOVNS-A* algorithm; travel recommendation system; stacking regression; tourist itinerary.

Introduction

The rapid growth of the global tourism industry has generated an enormous demand for intelligent, context-aware travel planning systems. Modern travelers no longer accept generic itineraries; instead, they seek highly personalized experiences that reflect their unique interests, physical capabilities, budget constraints, and schedule preferences [1,2]. According to the World Tourism Organization (UNWTO), the number of international tourist arrivals reached 1.4 billion in 2023, and user-generated travel data is growing exponentially across digital platforms [3].

Traditional route planning systems predominantly employ deterministic, single-objective algorithms such as the Traveling Salesman Problem (TSP) heuristics or Dijkstra's shortest-path algorithm. While computationally efficient, these approaches cannot accommodate multiple competing objectives — such as maximizing visit quality while minimizing travel time and cost — nor can they adapt to the heterogeneous preference profiles of individual users [4,5]. Recommendation systems offer a complementary perspective by leveraging collaborative filtering or content-based methods to suggest tourist attractions, yet

Recent advances in deep learning, particularly Graph Neural Networks (GNNs), have shown remarkable promise in modeling complex, non-Euclidean relationships inherent to user-item interaction data [7,8]. Meanwhile, multi-objective metaheuristics such as Variable Neighborhood Search (VNS) have demonstrated competitive performance on tourism-specific vehicle routing and orienteering problems [9]. However, no unified framework has yet combined GNN-based preference modeling, multi-objective metaheuristic route optimization, and satisfaction prediction into a coherent, end-to-end personalized planning pipeline.

This paper addresses this gap by proposing an integrated intelligent framework for personalized travel route planning, evaluated in the context of tourism in Uzbekistan — a rapidly growing destination with rich cultural and historical attractions. The key contributions of this work are as follows:

1. A GNN-based recommendation algorithm that encodes user–attraction interaction graphs with contextual node features to generate personalized ranked lists of tourist objects.
2. A hybrid MOVNS-A* algorithm that integrates multi-objective variable neighborhood search with A* heuristic pathfinding to solve the multi-constraint itinerary optimization problem.
3. A Stacking Regression ensemble model for predicting user post-visit satisfaction, enabling proactive itinerary refinement.
4. A real-world dataset of 15,420 tourist trajectories from Uzbekistan used for training, evaluation, and ablation studies.

2. Related Work

2.1. Personalized Recommendation Systems for Tourism

Early tourism recommendation systems relied on collaborative filtering (CF) [10] and content-based filtering (CBF) [11] techniques. Matrix factorization methods, such as Singular Value Decomposition (SVD) and Non-negative Matrix Factorization (NMF), extended CF by learning latent user and item feature vectors from sparse rating matrices [12]. However, these methods struggle with cold-start users and fail to capture the sequential, graph-structured nature of tourist trajectories.

Deep learning approaches have improved recommendation quality substantially. Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks have been applied to model

sequential point-of-interest (POI) check-in data [13]. More recently, attention-based transformers have been employed for next-POI prediction tasks [14]. Nevertheless, these approaches model user sequences in a linear chain topology, ignoring the rich, heterogeneous relational structure among users, attractions, time slots, and spatial locations.
GNN-based methods address this limitation by operating directly on graph-structured data. LightGCN [15] demonstrated that simple graph convolutions over user-item bipartite graphs achieve state-of-the-art collaborative filtering performance. Graph Attention Networks (GAT) [16] further improve this by learning adaptive edge weights. In the tourism domain, specific GNN variants incorporating spatial embeddings and temporal context have shown promising results [17,18], but none have been directly integrated with downstream route optimization.

2.2. Multi-Objective Route Planning for Tourism

The Tourist Trip Design Problem (TTDP) is a generalization of the orienteering problem [19], where the goal is to select and sequence a subset of locations to maximize total utility subject to time and budget constraints. Exact methods such as branch-and-bound are computationally intractable for realistic instances. Consequently, metaheuristics have been widely adopted.
Variable Neighborhood Search (VNS) has been successfully applied to single-objective TTDP variants [20]. Multi-objective extensions (MOVNS) using Pareto dominance and archive management have been proposed for problems with two or three conflicting objectives [21]. A* search, widely used in navigation systems, provides admissible and optimal shortest paths but does not naturally accommodate multiple objectives or user preference weights [22]. Hybrid approaches combining A* with local search have been explored in logistics contexts [23] but have not been applied to personalized tourism route planning with GNN-derived preference scores.

2.3. User Satisfaction Prediction

Predicting user satisfaction in tourism has been approached through sentiment analysis of reviews [24], regression on rating data [25], and more recently, multi-modal deep learning combining visual and textual content [26]. Ensemble methods, particularly stacking (meta-learning) regressors, have shown superior generalization compared to individual models in related domains [27]. However, their application to closed-loop satisfaction-driven itinerary refinement remains understudied.

3. Materials and Methods

3.1. Dataset and Preprocessing

The dataset used in this study was compiled from three sources: (i) the Uzbekistan Tourism Portal (UzTour), containing 38,720 registered tourist profiles and 215,430 attraction visit logs spanning 2018–2024; (ii) OpenStreetMap (OSM) for geographic coordinates and road network data; and (iii) Google Places API for attraction attributes (category, rating, average visit duration, price range). After deduplication, missing value imputation (using median imputation for numerical features and mode imputation for categorical features), and outlier removal (z-score threshold $|z| > 3.5$), the final dataset comprised 15,420 user trajectories covering 1,847 distinct tourist attractions across 14 cities.
User profiles were constructed from demographic attributes (age, travel party type, origin country), revealed preferences (historical attraction categories, average spending, preferred visit duration), and

contextual factors (travel season, trip purpose). Attraction features included 12 categorical and 8 numerical attributes. The user–attraction interaction graph G = (V, E) was built with user nodes U and attraction nodes A as vertex sets, and weighted edges encoding interaction strength (rating, visit frequency, dwell time).

Table 1. Summary statistics of the UzTour dataset.

Attribute	Value	Notes
Total user profiles	38,720	Registered tourists
Trajectories (after filtering)	15,420	Used for training/testing
Distinct attractions	1,847	14 cities
Avg. attractions per trajectory	6.3 ± 2.1	Range: 2–18
Avg. user rating (1–5)	3.87 ± 0.94	
Coverage period	2018 – 2024	6 years
Avg. trip duration (hours)	18.4 ± 7.2	Multi-day included

3.2. GNN-Based Personalized Attraction Recommendation

Let $G = (V, E, X)$ be the user–attraction heterogeneous graph, where $V = U \cup A$ is the node set ($|U|$ users and $|A|$ attractions), E represents interaction edges, and X is the node feature matrix. The recommendation model employs a multi-layer Graph Attention Network (GAT) architecture with the following message-passing scheme:

For each layer l, the updated node embedding $h_v^{(l+1)}$ is computed as:

$$h_v{}^{(l+1)} = \sigma\left(\sum_{u \in N(v)} \alpha_{vu}{}^{(l)} \cdot W^{(l)} \cdot h_u{}^{(l)}\right) \quad \text{[Eq. 1]}$$

where $N(v)$ is the neighborhood of node v, $W^{(l)}$ is the learnable weight matrix at layer l, $\alpha_{vu}^{(l)}$ is the attention coefficient computed via a two-layer feed-forward network with softmax normalization, and σ is the LeakyReLU activation function. The attention coefficient is defined as:

$$\alpha_{vu}{}^{(l)} = \mathrm{softmax}_u\left(\mathrm{LeakyReLU}\left(a^T\left[W^{(l)}h_v \parallel W^{(l)}h_u\right]\right)\right) \quad \text{[Eq. 2]}$$

Initial node features $h_v^{(0)}$ for user nodes encode demographic and preference vectors (dimension $d_u = 64$), while attraction node features encode categorical embeddings and normalized numerical attributes (dimension $d_a = 64$). A two-layer GAT ($L = 2$) with 8 attention heads in the first layer and a single head in the second layer was found optimal through cross-validation. The model is trained with BPR (Bayesian Personalized Ranking) loss to maximize the score gap between visited and unvisited attractions for each user.

The recommendation score $s(u, a)$ for user u and attraction a is computed as the inner product of their final-layer embeddings: $s(u, a) = h_u^{(L)} \cdot h_a^{(L)}$. Top-$K$ attractions are selected using a diversity-aware re-ranking step that penalizes geographic clustering via a Maximal Marginal Relevance (MMR) criterion .

3.3. Hybrid MOVNS-A* Route Optimization

Given a set of recommended attractions $R = \{a_1, \ldots, a_K\}$ for user u, with associated scores $s(u, a_i)$, geographic coordinates, opening hours, visit durations, and entrance fees, the multi-objective route planning problem is formulated as:

$$\text{Maximize} \quad f_1(\pi) = \sum_{a_i \in \pi} s(u, a_i)$$

$$\text{Minimize} \quad f_2(\pi) = \text{total travel time (transit + dwell time)}$$

$$\text{Minimize} \quad f_3(\pi) = \text{total cost (transport + entrance fees)}$$

Subject to: (i) time window constraints per attraction, (ii) total trip budget B, (iii) total trip duration $T_{\max}$, and (iv) accessibility constraints per user profile.

The solution space is the set of feasible ordered subsequences (itineraries) π of R. The proposed MOVNS-A* algorithm operates as follows:

5. Initialization: Generate an initial Pareto archive P using a greedy construction heuristic weighted by $\frac{s(u,a_i)}{d(\text{prev},a_i)}$, where $d(\cdot)$ is road network distance computed via A*.
6. Neighborhood structures: Five neighborhood operators are defined — (N1) single attraction swap, (N2) two-opt reversal, (N3) attraction insertion, (N4) attraction removal+reinsert, (N5) segment relocation.
7. A* integration: Travel times between consecutive attractions are computed on-demand using A* on the OSM road network graph with a Euclidean heuristic. Results are cached to reduce computational overhead.
8. Pareto dominance update: After each perturbation, non-dominated solutions are added to P and dominated solutions are removed. Crowding distance is used for archive size management.
9. Solution selection: A weighted sum aggregation with user-specified preference weights (w_1, w_2, w_3) selects the final itinerary from P.

3.4. Stacking Regression for Satisfaction Prediction

To enable proactive itinerary refinement, a Stacking Regression model is trained to predict the user's post-visit satisfaction score y ∈ [1, 5] for a proposed itinerary π. The stacking ensemble comprises three base learners: (L1) Gradient Boosting Regressor (XGBoost), (L2) Random Forest Regressor, and (L3) a two-layer Multilayer Perceptron (MLP). The meta-learner is Ridge Regression trained on out-of-fold predictions of the base models via 5-fold cross-validation.

Input features to the ensemble include: (i) itinerary-level aggregates (total score, total time, total cost, diversity index), (ii) user profile vector, (iii) sequence-level statistics (number of attractions, average inter-attraction distance, category entropy), and (iv) temporal context (season, day of week, holiday indicator). A total of 47 features are used after feature importance analysis and recursive feature elimination.

4. Results

4.1. Recommendation Performance

The GNN recommendation model was compared against five baselines: (B1) Popularity-based ranking, (B2) User-based Collaborative Filtering (UCF), (B3) Matrix Factorization (MF-BPR), (B4)

LSTM-based sequential recommendation, and (B5) LightGCN. The dataset was split into train/validation/test sets at 70/10/20 ratio, stratified by user. Evaluation metrics include Precision@K, Recall@K, and Normalized Discounted Cumulative Gain (NDCG@K) for K ∈ {5, 10}.

Table 2. Recommendation algorithm comparison (K = 10).

Algorithm	Precision@10	Recall@10	NDCG@10	F1@10
B1: Popularity	0.521	0.387	0.498	0.444
B2: UCF	0.634	0.502	0.601	0.561
B3: MF-BPR	0.692	0.558	0.671	0.619
B4: LSTM-Rec	0.731	0.603	0.716	0.661
B5: LightGCN	0.789	0.654	0.774	0.716
Proposed GNN-Rec	**0.847***	**0.718***	**0.831***	**0.777***

** Statistically significant improvement over all baselines ($p < 0.05$, paired t-test).*

The proposed GNN-Rec achieves the highest performance across all metrics, with a 7.3% improvement in Precision@10 and a 7.4% improvement in NDCG@10 over the best-performing baseline (LightGCN). The use of attention coefficients allows the model to dynamically weight the importance of neighboring nodes, capturing fine-grained preference patterns that static embedding methods cannot represent.

4.2. Route Optimization Performance

The MOVNS-A* algorithm was evaluated against four route optimization baselines: (R1) Greedy Nearest Neighbor (GNN-Route), (R2) Standard A* with preference weights, (R3) NSGA-II (a popular multi-objective evolutionary algorithm), and (R4) Single-objective VNS. Performance was measured using Hypervolume (HV), Spread (Delta), and GD+ (Generational Distance Plus) for multi-objective quality, as well as user preference satisfaction rate for practical quality.

Table 3. Route optimization algorithm comparison.

Algorithm	HV (↑)	Spread Δ (↓)	GD+ (↓)	Satisfaction Rate
R1: Greedy NN	0.431	0.724	0.312	63.2%
R2: A* Weighted	0.502	0.651	0.278	69.8%
R3: NSGA-II	0.618	0.523	0.201	74.5%
R4: Single VNS	0.571	0.589	0.234	71.3%
Proposed MOVNS-A*	**0.764***	**0.412***	**0.149***	**83.7%***

** Statistically significant improvement over all baselines ($p < 0.05$, Wilcoxon signed-rank test).*

The MOVNS-A* algorithm produces a 23.6% improvement in Hypervolume over NSGA-II, indicating a substantially better approximation of the true Pareto front. The integration of A* for accurate travel time estimation critically contributes to this performance: without it, sub-optimal edge weights cause route suggestions that violate time window constraints in 18.3% of test cases.

4.3. Satisfaction Prediction Performance

The Stacking Regression model was evaluated on a held-out test set of 3,084 trajectories with ground-truth satisfaction scores. Evaluation metrics are RMSE, MAE (Mean Absolute Error), and R^2 (coefficient of determination).

Table 4. User satisfaction prediction model comparison

Model	RMSE (↓)	MAE (↓)	R^2 (↑)
Linear Regression	0.581	0.463	0.512
Random Forest	0.423	0.337	0.714
XGBoost	0.389	0.301	0.748
MLP Regressor	0.412	0.324	0.729
Stacking Ensemble	**0.312***	**0.247***	**0.834***

** Best performance; significant vs. best individual model ($p < 0.05$).*

The Stacking Regression model achieves an RMSE of 0.312 and R^2 of 0.834, outperforming all individual base learners. Feature importance analysis reveals that itinerary-level diversity index, average GNN attraction score, and total trip duration are the three most predictive features, collectively accounting for 41.2% of the model's variance explanation.

5. Discussion

The results demonstrate that the proposed integrated framework consistently outperforms modular and single-algorithm baselines across all evaluation dimensions. The key insight is that the three components are mutually reinforcing: GNN-derived preference scores improve the quality of the initial greedy solution that seeds MOVNS-A*, while satisfaction prediction provides an actionable feedback signal that can be used to re-rank Pareto-optimal routes in real time.

A notable finding is the significant contribution of the A* travel time module to route feasibility. Prior work on TTDP has frequently used Euclidean or haversine distances as proxies for travel time, which introduces systematic errors of 15–35% in urban environments with irregular road networks. Our results confirm that accurate travel time estimation is not merely a quality-of-life improvement but a correctness requirement: routes constructed with Euclidean distance proxies violated time window constraints in 18.3% of test cases, which would render them useless in practice.

The performance advantage of the Stacking Regression model over individual base learners aligns with the broader meta-learning literature. However, we observe that gains are more pronounced when the base learners exhibit diverse error patterns: XGBoost excels for users with rich historical data (low

cold-start), Random Forest performs better for novel users, and MLP captures non-linear interactions among temporal features. The ridge meta-learner effectively weights these complementary strengths.
Several limitations should be noted. First, the dataset is geographically constrained to Uzbekistan, and generalization to destinations with different tourism infrastructure (e.g., sparse public transport, high-density urban environments) requires further validation. Second, the GNN model's training complexity scales quadratically with the number of edges in the interaction graph; incremental training strategies should be explored for larger datasets. Third, real-time re-planning during the trip — triggered by unexpected events such as attraction closures or weather changes — is beyond the scope of the current framework and constitutes an important direction for future work.

6. Conclusion

This paper presented an intelligent framework for personalized travel route planning that unifies GNN-based attraction recommendation, multi-objective MOVNS-A* route optimization, and Stacking Regression satisfaction prediction. Experimental results on a real-world Uzbekistan tourism dataset demonstrate statistically significant improvements over all tested baselines, with Precision@10 of 0.847, Hypervolume improvement of 23.6% over NSGA-II, and satisfaction prediction R^2 of 0.834. The framework has been validated through integration into a functional web-based travel planning application, confirming its practical viability. Future work will explore real-time dynamic replanning, cross-regional transfer learning, and multi-modal (image, text, sensor) user preference modeling.

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