COMP9727 Project Design

Project Title: Sydney Go: A Personalized Travel Recommender System

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1. Scope

1.1 Domain and Motivation

Sydney Go is a system that recommends personalized travel itineraries for tourists visiting Sydney. The application's functionality encompasses the mitigation of information overload and the optimization of trip planning efficiency. It accomplishes this by generating daily itineraries that are customized to align with the user's preferences.

The system has been developed for the purpose of highlighting both iconic landmarks and hidden local gems by analyzing location metadata, user interests, and contextual constraints such as travel time and budget.

1.2 Target Users

The system is designed to appeal to a diverse range of visitors, including first-time visitors, families with children, solo travelers on a budget, and food enthusiasts seeking to explore Sydney.

These users frequently exhibit a paucity of local knowledge and seek curated, hassle-free planning experiences that balance sightseeing, dining, and convenience.

1.3 System Interface and Interaction Flow

The application interface has been designed with mobile users in mind. Upon launching the application, users are prompted to select their interests from a range of options including, but not limited to, nature, art and food. The system then generates a daily itinerary comprising five to seven items.Each item includes a brief description, an estimated visit duration, and a navigation link via Google Maps. Users are able to save items, skip items, or rate items. These interactions are then fed back into the system in order to refine recommendations. It is imperative to note that user feedback will be stored locally and synchronised with the backend on a daily basis. This process serves to update user profiles and enhance future itineraries.

1.4 Mockup Sketches

The system features three main screens:

1. Interest Selection: Users pick tags such as “beach”, “museum”, “food”.
2. Day Plan and Feedback: A timeline-style itinerary with attractions, restaurants, and hotels.Users can rate plan.
3. Profile: Users can edit preferences, or view past itineraries.

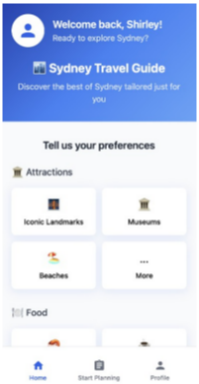

Figure1

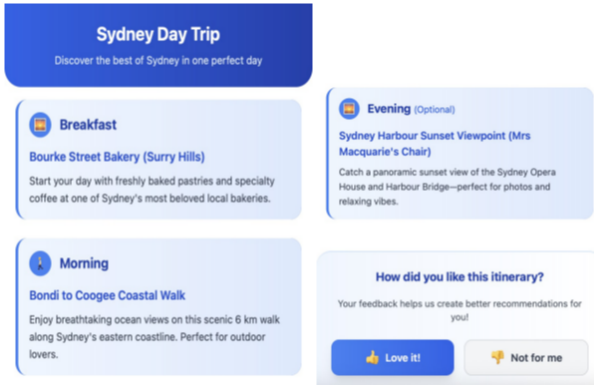

Figure2–3

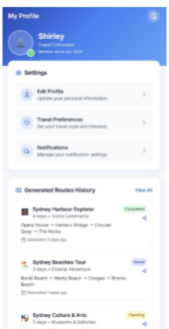

Figure4

Figure1: Users have the option to select points of interest, including attractions and types of food that align with their preferences.

Figure2: The system generates travel recommendation itineraries for the users through their choices.

Figure3: Users have the option to view previously generated travel itineraries.

1.5 Dynamic Scenario & Cold Start Strategy

The system uses content-based filtering for cold starts. In the context of new items, the system utilises metadata, including tags and proximity to existing popular locations. The recommendation model is subject to periodic updates, which are based on user interactions that are uploaded at the conclusion of each day. In dynamic use cases (e.g. real-time changes or user rerouting), pre-computed recommendations are adjusted using user location and recent behaviour.

1.6 Brief Business Model

Generation of revenue can be achieved through affiliate marketing with local attractions and restaurants, or through in-app premium features such as the "local expert itinerary". Additional monetisation options include the provision of ad placements to local businesses and the implementation of tiered subscriptions with enhanced features (e.g., downloadable offline itineraries, real-time updates).

2. Dataset(s)

2.1 Dataset Overview

To build a robust and realistic travel recommender system for Sydney, we utilize three complementary datasets to capture point-of-interest (POI) details, user-generated ratings, and transportation context:

1.OpenStreetMap (OSM): For extracting geographic and categorical data of POIs.

2.Yelp Open Dataset: For user reviews and ratings (simulated for Sydney).

3.Transport for NSW Open Data: For understanding travel distances and constraints between locations.

This combination allows us to recommend attractions, restaurants, and hotels based not only on relevance, but also proximity and transportation feasibility.

2.2 Source and Format

1. OpenStreetMap (OSM POIs via Overpass API)

Format: JSON/GeoJSON

Content: Names, tags (e.g., tourism=attraction, amenity=restaurant), lat/lon, category, popularity.

2. Yelp Open Dataset

Format: JSON (business, review, user entities)

Content: Star ratings, review texts, business categories, approximate geo-locations.

Note: Since Sydney data is limited in Yelp, this data will be used to simulate realistic review patterns and feedback signals.

3. Transport for NSW — Open Data API

Format: CSV and REST API

Content: Real-time transit info, travel times between suburbs/locations, route availability, transfer infomation.

Used for: Estimating feasible travel windows and planning geographically efficient itineraries.

2.3 Fields for Recommendation

Dataset	Field	Usage in Recommendation
OpenStreetMap	name, category, lat/lon, tags	Identifying and categorizing POIs
Yelp Open Dataset	stars, review_text, category	Filtering by user rating, deriving sentiment
Transport for NSW — Open Data API(TfNSW)	route_time, distance, from/to	Evaluating movement cost between locations

2.4 Preprocessing Plan

1.OSM POIs: Extract relevant POIs within the Sydney bounding box. Clean up inconsistent tag labels (e.g., unify "cafe" and "coffee shop"). Group by category.

2.Yelp Reviews: Extract review statistics and sentiment (using TextBlob or VADER). Map categories to OSM schema where possible.

3.TfNSW Routes: Parse data into a travel cost matrix between key POIs and group by zone to avoid unrealistic jumps between far locations.

2.5 Limitations of the Dataset

OSM data is crowdsourced and may have incomplete tags or coverage biases (e.g., overrepresentation of touristy areas).

Yelp dataset does not directly contain Sydney businesses. However, it will be used as a proxy dataset to simulate rating behavior and text sentiment structure.

TfNSW data is real-time and granular but may require aggregation and estimation (e.g., average weekday travel time) for stable use in itinerary generation.

3. Method(s)

3.1 Recommender System Types Considered

The Sydney Go system integrates both Content-Based Filtering (CBF) and Collaborative Filtering (CF) to form a hybrid recommender system that supports both cold-start scenarios and evolving personalization. Compared to using either method alone, a hybrid system better accommodates diverse user needs and data sparsity issues. Additionally, contextual factors (e.g., visit duration, location proximity) may be incorporated later as extensions, potentially making the system context-aware.

3.2 Method 1: Content-Based Filtering

This method relies on matching user preferences with the attributes of places (e.g., “museum”, “outdoor”, “family-friendly”, “mid-range”). For example, a user selecting interests like “art” and “history” will receive recommendations tagged accordingly in the POI database.A user profile vector is generated from selected tags and refined through interaction feedback. The similarity between user and item profiles is computed using cosine similarity or TF-IDF weighted keyword matching.

3.3 Method 2: Collaborative Filtering

This approach leverages the behaviors of similar users, using user-based or item-based k-nearest neighbors (kNN). For instance, if multiple users who liked Bondi Beach also highly rated the Royal Botanic Garden, the latter may be recommended to new users with similar profiles. To implement this, we will create a user-item rating matrix derived from simulated feedback data (e.g., likes, skips, ratings), and apply standard memory-based collaborative filtering techniques.

3.4 Method 3: Hybrid Approach

The hybrid system integrates both CBF and CF, dynamically adjusting their weights based on system stage and data availability. Cold Start Phase: Emphasis on content-based scores as user interaction data is limited.Post-Interaction Phase: Shift to incorporate collaborative scores as user similarity becomes computable. A linear score combination is used: final_score = $\alpha \cdot$CBF_score + $(1-\alpha) \cdot$CF_score, where α decreases over time.We also consider fallback mechanisms: if collaborative filtering fails due to data sparsity, content-based scores serve as default.

3.5 Justification of Method Suitability

CBF ensures initial personalization based on explicit interests and is ideal for new users. CF exploits collective intelligence and provides novelty through indirect exploration. Hybrid enhances robustness, balances diversity and accuracy, and adapts to the user lifecycle. Given the nature of travel planning (low frequency, high variation), a flexible hybrid model is the most pragmatic solution.

3.6 Plan for Method Selection & Evaluation

All three methods will be implemented and compared using offline metrics (see Section 4). Content-Based Filtering will serve as the baseline, due to its independence from user behavior history. Experiments will vary parameters such as the weight α, similarity thresholds, and rating cutoffs.Performance will be assessed over simulated user sessions to evaluate recommendation stability, novelty, and responsiveness to feedback.

4. Evaluation

4.1 Offline Evaluation Metrics

To evaluate the recommendation quality on historical and simulated interaction data, we will use the following top-N ranking metrics:

Precision@5: Measures the proportion of relevant items in the top 5 recommendations.

Recall@5: Captures the ability of the system to retrieve relevant items from the user's full preference set.

NDCG@5 (Normalized Discounted Cumulative Gain): Evaluates the relevance of recommended items with respect to their position in the list.

These metrics reflect both accuracy and ranking quality, critical in short-list recommendation like itinerary generation. A user-item interaction matrix will be generated through simulated behavior logs (e.g., saved items = positive signal), and metrics will be averaged across a representative user sample.

4.2 System Evaluation Metrics

In addition to offline metrics, user-centric evaluation will be conducted through interaction logging and subjective surveys:

Click-through rate (CTR): Percentage of recommended items that users interact with (e.g., expand, view details, add to itinerary).

Skip rate: Frequency of negative feedback, indicating irrelevance.

Session diversity score: Proportion of distinct categories (e.g., art, food, outdoor) per itinerary.

User satisfaction score: Collected via Likert-scale questionnaires post-simulation, measuring perceived relevance, variety, and planning efficiency.

These indicators help assess real-world usability and perception beyond pure accuracy.

4.3 Discussion of Tradeoffs & Metric Prioritization

While Precision@K is intuitive and easy to interpret, it lacks nuance regarding ranking position. NDCG provides a better measure of rank-sensitive quality, especially useful for travel sequences where earlier items (e.g., breakfast spots) are more critical. User feedback offers qualitative validation and highlights personalization effectiveness. In this project, we prioritize NDCG and user satisfaction over recall or diversity, as users care more about “what is shown first” and “how useful it feels” than exhaustive coverage.

4.4 Computational Requirements and Efficiency

To ensure responsiveness on mobile devices and scalability, the system is optimized through:

Daily caching of top-N recommendations based on current user profile and geolocation.

Batch retraining of the recommendation model weekly, using accumulated interaction logs (ratings, skips, etc.).

Lightweight inference pipeline using pre-computed embeddings and similarity scores.

Cold-start handling via low-cost content filtering without external API calls.

Real-time computation is avoided on the client side to preserve performance and battery life.

4.5 User Study Design

A simulated user study will be conducted with 5—10 participants (students or volunteers) using a Figma-based prototype. The procedure includes:

1. Participants specify their interests and are shown a 3-day itinerary.
2. They review the itinerary and interact with items (save, skip, rate).
3. A brief post-session questionnaire is collected, covering:
    - Relevance of recommendations
    - Perceived novelty and personalization
    - Planning time saved
    - Overall satisfaction (1—5 scale)

The study does not require ethics approval and serves to guide iterative refinement of both algorithm and UI.