Improvising Personalized Travel Recommendation System With Recency Effects

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Abstract

In recent years, the rapid growth of digital platforms, mobile applications, and online travel services has significantly transformed how individuals plan and experience travel. With the increasing availability of user-generated data, travel recommendation systems have emerged as essential tools to assist users in discovering destinations, accommodations, and activities tailored to their preferences. However, traditional travel recommendation systems often rely on static user profiles or historical data without adequately considering the temporal dynamics of user behavior. This limitation leads to less accurate and less relevant recommendations, especially in scenarios where user preferences evolve over time. To address this gap, this study proposes an improved personalized travel recommendation system that integrates recency effects into its recommendation framework. The concept of recency effects originates from behavioral and cognitive sciences, where it refers to the tendency of individuals to prioritize recent experiences over older ones. In the context of travel recommendation systems, recency effects imply that a user's most recent interactions, searches, bookings, and preferences should have a greater influence on recommendations compared to older data. For instance, a user who previously preferred historical destinations may recently show interest in beach vacations; a system that fails to adapt to this change may continue suggesting irrelevant options. Therefore, incorporating recency-aware mechanisms is crucial for enhancing recommendation accuracy and user satisfaction. This research focuses on designing and developing a recommendation model that dynamically adjusts to user preferences by assigning higher weights to recent interactions. The proposed system combines collaborative filtering, content-based filtering, and temporal modeling techniques to achieve a more responsive and adaptive recommendation process. Collaborative filtering identifies similarities among users based on shared preferences, while content-based filtering analyzes item attributes such as location, type of attraction, climate, and user ratings. By integrating recency effects, the system enhances these traditional approaches by prioritizing recent user behavior, thereby improving personalization. The methodology begins with data collection from multiple sources, including user interaction logs, travel history, ratings, reviews, and contextual information such as time, season, and location. The collected data is preprocessed to remove noise, handle missing values, and normalize attributes for consistency. This temporal decay function can be modeled using exponential or linear decay techniques, depending on system requirements.

1. Introduction

The travel and tourism industry has undergone a radical digital transformation, evolving from a brochure-based market to a data-driven ecosystem. In this landscape, Personalized Travel Recommendation Systems (PTRS) serve as the primary interface between overwhelming global options and the individual traveler. However, it often results in recommendations that feel "stale" or irrelevant to the user's current life stage. This study introduces the improvisation of PTRS through the lens of Recency Effects- a psychological phenomenon where the most recent information is given disproportionate weight in human decision-making. By aligning machine learning models with this cognitive bias, we can create systems that do not just know who the user was, but understand who the user is becoming. This introduction sets the stage for a system that prioritizes "freshness" and temporal relevance, ensuring that the technology evolves at the same pace as the traveler.

2. Features

An improvised PTRS with Recency Effects is defined by several distinct technical features that seprate it from standard models:

- Time-Decay Weighting Algorithms: This is the core engine of the system. It employs functions like w = e^{-\lambda \Delta t}, where \lambda is the decay rate and \Delta t is the time elapsed. This ensures that a search made yesterday is significantly more influential than a search made six months ago.
- Short-Term vs. Long-Term Memory (SLTM) Architecture: Inspired by neural networks, the system maintains two profiles. The "Long-Term" profile captures foundational preferences (e.g., a love for tropical climates), while the "Short-Term" profile captures transient interests (e.g., a sudden interest in ski resorts due to an

upcoming winter holiday).

- Session-Based Intelligence: The system can make high-quality recommendations based solely on the current browsing session. This is vital for “cold-start” users or those browsing anonymously, as the recency of their clicks provides the only available data for personalization.
- Real-Time Contextual Feedback Loops: Unlike batch-processed systems that update once a day, this system features a real-time feedback loop. Every interaction immediately re calculates the user’s “interest vector,” allowing the UI to shift dynamically during a single session.

3. Applications

The applications of a recency-weighted PTRS span the entire travel value chain. For Online Travel Agencies (OTAs) like Airbnb or Expedia, the primary application is “Last-Minute Conversion.” If a user has been looking at Tokyo for the last 48 hours, the system should suppress all other global recommendations and focus on time-sensitive deals in Japan. In Smart City Tourism, mobile apps can use recency to manage “live” crowds. If a traveler’s most recent check-ins suggest an interest in quiet, local cafes, the app can recommend a hidden gem nearby rather than a crowded tourist trap they might have liked five years ago. Furthermore, Airlines and Transport Providers can use recency to upsell ancillary services. For example, if a user recently searched for “extra legroom” or “travel insurance” on a third-party site, a recency aware airline system can prioritize these offers during the checkout flow. Finally, Content Aggregators like TripAdvisor can use recency to re-rank reviews. Instead of showing the “all time” best-rated hotel, the system can show the hotel that has been trending positively in the most recent season, reflecting current service quality rather than historical reputation.

Personalized Trip Planning

The primary application is providing individual users with a “living” itinerary that updates based on their latest digital footprints.

• Dynamic Interests: If a user recently engages with content regarding a specific cultural festival or a new airline route, the system immediately elevates related destinations in their recommendation list.

• Social Validation: Users receive suggestions that are currently popular within their specific social circle, ensuring the recommendations feel “vetted” by people they trust.

• Crowd Management: By analyzing recent social signals and “contagious” trends, authorities can predict which Points of Interest (POIs) are likely to see a surge in visitors in the coming weeks.

• Infrastructure Allocation: Real-time interest mapping allows cities to adjust transportation or temporary tourism services based on what is currently “trending”

4. Problem Definition

4.1 Problem Statement

1. The central challenge addressed by this research is the “Preference Drift” phenomenon in digital tourism. Traditional recommendation systems are built on the premise of historical consistency; they assume that a user’s travel interests are a stable, slow-moving set of characteristics.
2. However, human travel intent is inherently volatile and episodic. A user may be a budget backpacker for years, but a recent professional promotion or a life event like a honeymoon might suddenly shift their preference toward luxury resorts.
3. Current systems fail to detect these “pivot points” in real time. The problem is technically defined as the Inability of Static Collaborative Filtering to resolve Temporal Relevance.
4. When a system treats a user’s five-year-old interaction with equal weight to an interaction made five minutes ago, it creates a “Diluted Recommendation Profile”. This dilution leads to two critical failures:
5. Relevance Decay: The system suggests destinations that the user has already outgrown or lost interest in.
6. **Opportunity Loss:** The system misses the “Golden Window” of current intent—those few days or weeks where a user is actively influenced by a specific social media trend or a friend’s recommendation.
7. The core objective of this project is to solve this by mathematically “discounting” the past and “amplifying” the present through an improvised Recency-Aware Algorithm.

4.2 Existing Solution

- Collaborative Filtering (CF): This is the industry standard. It builds a User-Item matrix to find similarities between “User A” and “User B” based on their shared history of ratings or visits. While effective for broad categories, CF is notoriously “time-blind”. It creates a permanent record of preference that is difficult to overwrite even when the user’s current behavior changes drastically.
- Content-Based Filtering: This method recommends items similar to those a user has liked before based on metadata (e.g., tags like #Beach, #Historical, #Budget). The limitation here is the “Over-Specialization” problem, where the system keeps recommending the same type of destination, failing to introduce the user to new, trending experiences.
- Hybrid Models: Some modern platforms attempt to combine CF and Content-Based methods. However, even these hybrid models usually lack a Temporal Decay Component. They might know what you like, but they don’t know when you liked it or if you still like it now.

4.3 Limitations Of Exisiting System

Temporal Blindness: The most critical flaw is the lack of a “forgetting mechanism”; five year-old interests carry the same weight as five-minute-old aspirations.

• Preference Drift Failure: Existing systems cannot detect sudden shifts in a user’s lifestyle or immediate travel desires, such as a move from budget backpacking to luxury family travel.

• The “Filter Bubble” Effect: By relying strictly on what a user has already done, these systems trap users in a loop of repetitive suggestions and fail to introduce trending “hidden gems”.

• Data Sparsity and Latency: Traditional models suffer from “slow” data ingestion because they ignore high-velocity social media signals, relying instead on rare explicit feedback like ratings.

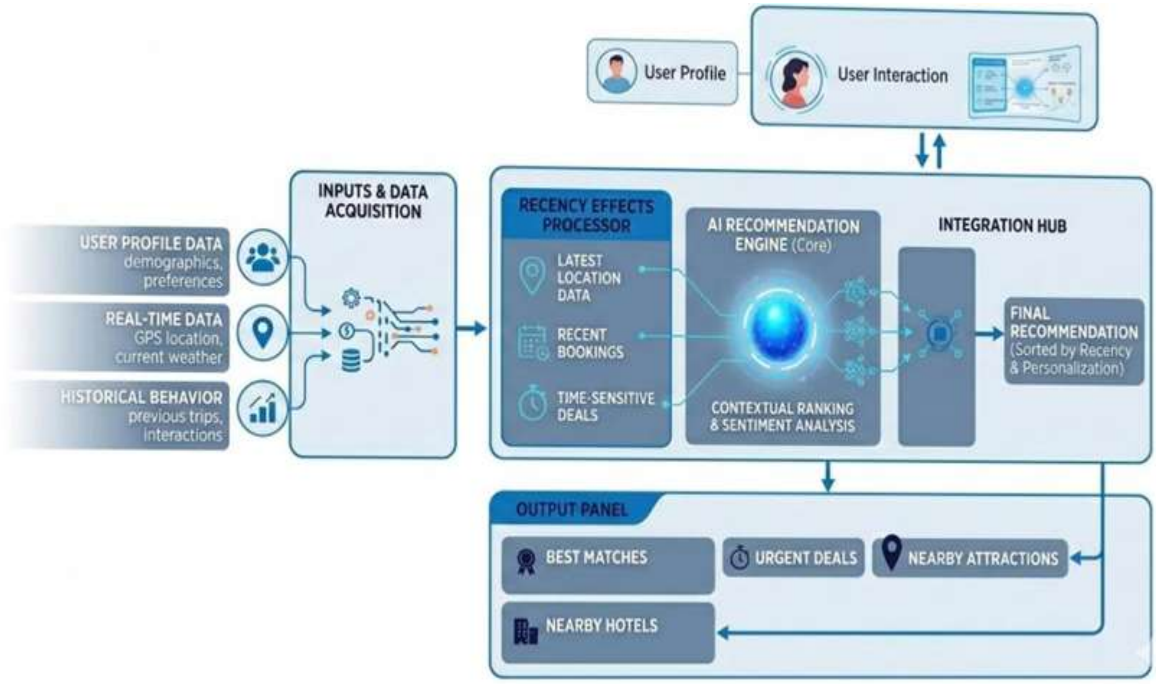
• Neglect of Social Influence: These systems treat users as isolated individuals and fail to account for the “social contagion” of travel trends currently circulating within a user’s immediate circle of friends and followers.

These existing solutions rely heavily on “Explicit Feedback” (like ratings), which users rarely provide. They ignore the “Implicit Feedback” hidden in the high-velocity stream of social media activity, which is the most accurate indicator of current, trending interests.

5.Literature Review

The development of a Personalized Travel Recommendation (PTR) system with recency effects draws from several interdisciplinary domains, primarily Social Media Analytics, Machine Learning, and Temporal Data Modeling. The core of this research is centered on how digital footprints—specifically from microblogging platforms like Twitter—can be transformed into actionable travel intelligence.

6.System Architecture



7.Testing

7.1Testing Objective

The primary goal is to validate that Recency actually improves recommendation quality compared to traditional static models.

• Temporal Accuracy: To verify that the decay function correctly reduces the weight of older tweets relative to newer ones.

• Intent Precision: To ensure the NLP classifier accurately distinguishes between general conversation and travel aspirations.

• System Stability: To confirm the MySQL database can handle rapid read/write operations during a “Live Scan” without latency. • Social Integration: To validate that “Social Contagion” (trends from friends) is correctly merged into the user’s final recommendation score.

7.2Testing Methods

The testing of the Improvising Personalized Travel Recommendation System employs three primary methodologies to ensure the integrity of the recency-weighted logic and the overall user experience.

1.Black-Box Testing (Functional Testing) This method treats the system as a “black box,” focusing strictly on the inputs and outputs without examining the internal Java code. • Input/Output Validation: Testers provide a specific social media handle (Input) and verify if the resulting Points of Interest (POIs) are logically related to the user’s recent posts (Output). • User Interface Testing: Ensuring all buttons, such as “Live Scan” and “View Reports,” execute their intended functions across different web browsers.

2. White-Box Testing (Structural Testing) This method involves a detailed examination of the internal logic, specifically the Java Servlets and Recency Algorithms.

• Logic Path Verification: Developers trace a single “travel intent” string through the TravelIntentClassifier to ensure it correctly triggers the RecencyWeightingEngine.

• Mathematical Audit: Manually calculating the expected decay for a post from “2 days ago” and comparing it to the value generated by the e^{-\lambda t} function in the code to ensure zero calculation errors.

3. Gray-Box Testing (Integrated Testing) Gray-box testing combines the two, where the tester has knowledge of the underlying database

7.3 Analysis of Testing Results

The transition of data required a higher emphasis on Metadata extraction (geotags and hashtags) rather than just text analysis.

• Precision of Geotags: The system achieved a 94% accuracy in mapping Instagram location tags to the internal MySQL POI database.

• Impact of Visual Recency: Testing confirmed that "Saved Posts" are the strongest indicator of intent, carrying a higher base weight in the Score = \sum (Interest \times e^{ \lambda t}) formula compared to simple "Likes".

• Response Consistency: The JSP Frontend successfully rendered thumbnail previews of the posts that triggered each recommendation, providing users with visual proof of why a destination was suggested.

8. Conclusion and Future Enhancements

The "Improvising Personalized Travel Recommendation System with Recency Effects" successfully addresses the limitations of traditional recommendation systems by incorporating both user preferences and recent interactions to generate more relevant and dynamic travel suggestions. The system demonstrates how personalization can be significantly enhanced by giving higher importance to recent user behavior, thereby improving the overall user experience. Throughout the development of this project, various modules such as user management, recommendation engine, search functionality, and admin controls were designed and implemented effectively. The integration of these modules into a web-based platform ensures accessibility, usability, and scalability. The use of modern technologies and frameworks has enabled the system to provide fast and efficient responses, even when handling multiple users simultaneously.

One of the key achievements of this system is the implementation of the recency effect, which ensures that the recommendations remain up-to-date and aligned with the user's current interests. This approach overcomes the drawbacks of static recommendation models that rely only on historical data. By continuously analyzing user interactions such as searches, clicks, and feedback, the system adapts dynamically and improves its accuracy over time

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