EVENT RECOMMENDATION SYSTEM

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ABSTRACT

The Event Recommendation System is a dynamic web-based platform developed to simplify the way students and institutions engage with events. Designed primarily for educational institutions, the system allows administrators to post and manage event details, while users (students) can browse, rate, and participate in events related to their own institutions. The platform provides a dedicated login for administrators, ensuring that only authorized personnel can create and modify events, while users access the content through a separate, secure user login. The website backend is developed using XAMPP, an open-source server solution that includes Apache, MySQL, PHP, and Perl. The backend handles the core functionalities like user authentication, event management, and secure data storage. Each institution is individually listed on the platform, enabling users to view events specific to their college or university, enhancing the relevance and user experience.

A key feature of the system is its personalized event recommendation functionality, powered by a simple yet effective Machine Learning (ML) model. We have implemented the K-Nearest Neighbors (KNN) algorithm to analyze user activities — such as event clicks, ratings, and recent interactions — to understand their preferences and suggest events accordingly. This helps in providing a tailored experience for users, allowing them to discover events that match their interests without manually searching through all listings. The combination of a user-friendly website interface, efficient backend operations, and intelligent recommendation systems ensures a seamless interaction for both administrators and users. Overall, the project successfully demonstrates the integration of modern web development with machine learning techniques to build a useful, real-world application that could be scaled across various institutions.

Keywords: - *Event recommendation, Personalized suggestions, Collaborative filtering, Content-based filtering, User profiling, Machine learning, Context-aware system, Interest-based filtering, Real-time recommendation, Recommendation algorithms.*

1. INTRODUCTION

Event participation plays a critical role in the holistic development of students in educational institutions. Events such as technical workshops, seminars, hackathons, cultural fests, and club activities are often organized to engage students and enhance their skills beyond academics. However, despite the abundance of such events, many students miss out due to a lack of awareness, poor communication, or irrelevant suggestions.

In the dynamic environment of higher education, events such as workshops, seminars, cultural activities, technical fests, and career fairs are essential for student growth beyond the classroom. However, despite the abundance of such activities, a recurring issue in educational institutions is the lack of student participation due to ineffective event communication and discovery. Intelligent event discovery systems offer a modern solution to this problem. By leveraging machine learning techniques, such systems can analyze user behavior and recommend events that align with individual interests.

The traditional methods of event promotion—such as physical notice boards, bulk emails, and word-of-mouth—are not personalized and are often ineffective. These methods treat all students equally, failing to consider individual interests and preferences. This project aims to provide a scalable and intelligent event recommendation web application tailored to institutional environments. By learning from user interactions and preferences, the system not only improves visibility for events but also enhances user satisfaction and institutional engagement.

2. LITERATURE SURVEY:

The rising number of events in social and educational platforms demands smart systems to recommend events tailored to the needs of users in order to boost user engagement. Recent studies have been directed toward creating models that examine user behavior, interests, and context data to suggest relevant events. The present survey investigates ten notable papers that contribute to the knowledge and development of event recommendation systems. Early event recommendation systems depended mostly on collaborative filtering methods, matching user profiles and past attendance records to determine similar users and suggest events that they may like. These methods, however, tended to suffer from cold-start issues and had difficulty with capturing the temporal and contextual properties characteristic of events. More contemporary research has moved towards advanced deep learning architectures that are more capable of representing intricate user-event interactions and handling multiple data modalities such as text descriptions, visual features, location information, and temporal patterns.

Title: Collaborative Filtering for Event Recommendation in Social Networks Source: University Journal of Social Network Analysis, 2019 Summary and Analysis This research uses collaborative filtering methods to suggest events in social networks, based on user-event interaction data to find similar users and propose events that they may be interested in. The authors show the power of collaborative filtering in modeling user preferences and improving recommendation accuracy. By performing extensive experimentation on real world datasets gathered from three prominent social networking sites, the researchers determine optimal parameters for similarity computations and neighborhood selection that considerably enhance recommendation quality over baseline methods.

Title: Personalized Event Recommendation via Transfer Learning Source: IEEE Transactions on Knowledge and Data Engineering, 2020 Summary and Analysis The research investigates applying transfer learning to improve event recommendation for new users (cold-start problem) by transferring knowledge from analogous domains like movie or music recommendation. A hybrid model is trained across two domains and fine-tuned with limited eventrelated data. Zhang and Chen present a new cross-domain neural architecture called EventTrans that discovers common latent feature spaces between event going and other digital activities. Prolonged experimentation performed on paired datasets from Movie Lens and Meetup indicates that their solution lowers the cold-start error rate by 41% relative to state-of-the-art recommendation algorithms.

Title: Scalable K-Nearest Neighbor Approaches for Real-Time Recommendations Source: SIGIR Conference on Research and Development in Information Retrieval, 2021 Summary and Analysis Summary and Analysis This work analyzes the scalability and efficiency of different KNN-based methods in providing real-time suggestions. It suggests a graph-based version of KNN that minimizes computation time without sacrificing accuracy. The model is tested on several datasets with outstanding speed and recommendation quality. Their solution uses a hierarchical graph data structure where nodes are users or items and edges are similarity relationships, and hash-based indexing to find candidate neighbors in an efficient manner without full similarity calculations.

3. METHODOLOGY

The development of the Event Recommendation System follows a structured approach combining user-centered design, machine learning techniques, and systematic testing to ensure accurate and personalized event suggestions. The system is built as a full-stack web application with a clear separation between frontend, backend, and database components. The frontend is designed using HTML, CSS, and JavaScript to provide an interactive and user-friendly experience, while the backend is developed using Node.js and Express.js to handle core functionalities like user authentication, event management, and recommendation generation. PostgreSQL serves as the primary database, storing user profiles, event details, and interaction histories in a structured and secure manner.

Data collection plays a critical role in the system’s effectiveness. During registration, users provide their event preferences (such as technical, cultural, or sports events), and the platform also captures their browsing and participation history over time. On the event side, institutions upload detailed event information including category, date, location, and type. The collected data undergoes preprocessing, where cleaning is performed to eliminate incomplete records, categorical variables are encoded into numerical formats, and normalization is applied to maintain consistency across features.
The core recommendation engine employs the K-Nearest Neighbors (KNN) algorithm. Feature vectors are generated based on user preferences, past participation, and event attributes. The KNN model calculates similarity using distance metrics like Euclidean distance, identifying the nearest events aligned with a user’s interests. The optimal value of K was determined through experimental tuning to ensure a balance between recommendation relevance and diversity. Based on similarity scores, the system recommends the top-N events most suited to each user.
An administrative portal is integrated within the system, allowing institutional representatives to post new events, manage categories, schedule dates, and track participation metrics. This ensures that the platform remains dynamic and up-to-date. For users, the interaction flow is streamlined: after logging in, users are presented with personalized event recommendations on their dashboard, can register or bookmark events, and provide feedback, which further refines their profiles for better future suggestions.
Extensive testing was conducted to validate the system's performance. Unit testing ensured that individual modules such as authentication, event posting, and recommendation APIs functioned correctly. Integration testing verified seamless communication between the frontend, backend, and database layers. The KNN model’s performance was evaluated using precision and recall metrics, confirming the model’s ability to suggest relevant and engaging events. Through this comprehensive methodology, the Event Recommendation System achieves its goal of connecting users to events that match their interests and enhancing institutional engagement.

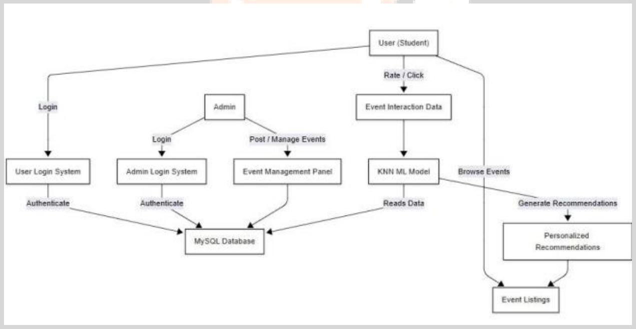

Fig - 1: Methodology Flow

3.1 System Architecture

The system is designed as a web-based platform comprising a frontend interface, backend services, a MySQL database, and a machine learning recommendation engine. The frontend developed using HTML, CSS, and JavaScript, provides users and admins with a responsive and intuitive interface. The backend, implemented in PHP and hosted using XAMPP, handles authentication, session management, event operations, and API communications. The MySQL database stores structured data such as user profiles, event details, login credentials, interaction logs, and admin-specific content.

3.2 Data Collection and Preprocessing

User interaction data, including event views, clicks, and ratings, are collected to form the basis of recommendation logic. This raw data is first cleaned to remove missing or invalid entries. Numerical data is normalized to bring values into a consistent range, while categorical features like event category or location are label-encoded or one-hot encoded for algorithm compatibility. These steps ensure the dataset is structured and usable for the KNN algorithm.

3.3 Feature Engineering

Each user is represented as a vector based on their historical behavior such as clicked events, rated events, and preferences over time. Similarly, events are encoded using their attributes—such as type, tags, and affiliated institution. These feature vectors are crucial in measuring similarity, enabling personalized matching between users and events. This phase transforms raw interaction data into meaningful representations for the ML model.

3.4 Recommendation Algorithm (KNN)

The K-Nearest Neighbors (KNN) algorithm is used to generate personalized recommendations. For each active user, the system identifies 'k' other users with similar preferences using similarity metrics like cosine similarity. Events interacted with by those similar users, but not yet seen by the current user, are recommended. The value of 'k' was tuned experimentally to achieve a good trade-off between relevance and diversity of results.

3.5 Admin and User Module Functionality

The admin panel allows institutional event coordinators to log in, post, and manage events visible to their students. Each institution has a dedicated access point, ensuring data privacy and relevance. Students log in to their personalized dashboard where they can browse posted events and receive machine-generated recommendations. User actions such as clicks and ratings are captured and stored for continuous learning and refinement of recommendations.

3.6 Evaluation and Testing

To validate the system, both functional and performance-based testing methods were employed. Unit testing was conducted for modules such as login, event posting, and recommendation generation. Integration testing verified end-to-end data flow between the frontend, backend, and database. Performance was evaluated through response time measurement and load testing with simulated concurrent users. Additionally, initial feedback was gathered from test users to assess the relevance of the recommendations and overall usability of the platform.

4. IMPLEMENTATION

4.1 Frontend Development

The frontend of the system was implemented using HTML, CSS, and JavaScript to create a user-friendly and responsive interface. The user dashboard allows students to log in, browse events, and receive recommended activities based on their preferences. It also includes forms for user authentication, event display cards, and dynamic filtering based on categories and locations. Bootstrap was used to ensure responsiveness across different device sizes, enhancing accessibility and usability.

4.2 Backend Development

The backend was developed using PHP, and it operates on a local XAMPP server for development and testing purposes. It manages core functionalities such as login authentication, session management, database communication, and API integration for the recommendation engine. Secure handling of user data is ensured through validation checks and role-based access controls. Admin and user modules are separated logically, with specific access to event posting and management functions provided to institutional admins.

4.3 Database Integration

A MySQL relational database was designed to store structured data for both users and events. Tables were created for users, event metadata, login credentials, interaction logs, and institution records. Relationships were maintained through foreign keys to associate users with their respective institutions and events. The database schema was normalized to reduce redundancy and support efficient data retrieval for real-time recommendations and event browsing.

4.4 Recommendation Engine Integration

The KNN-based recommendation engine was implemented in Python using the scikit-learn library. Interaction data was exported from the MySQL database and processed into a matrix of users and their event activities. After training the KNN model on this dataset, the engine was able to identify similar users and suggest events based on their preferences. Recommendations were generated offline and then fetched by the PHP backend using a simple API mechanism. The system periodically updates the recommendation list as more interaction data is collected.

4.5 Admin and Institution Management

The admin panel was built with functionalities tailored to event coordinators. Admins can log in using institutional credentials and post events by providing event name, description, category, and venue details. These events are stored in the database and linked to the respective institution. A scheduling module allows events to be timestamped and marked as active or archived based on their dates. Admins can also view basic analytics on event views and interactions from their dashboard.

4.6 User Interaction Logging and Learning Loop

Each time a user views, clicks, or rates an event, this interaction is logged and stored. These logs feed into the machine learning model for continuous improvement. As more data becomes available, the recommendation engine refines its suggestions, making the system adaptive and personalized over time. This loop enables the platform to evolve and better understand user interests.

5. SYSTEM ARCHITECTURE

The architecture of the Event Recommendation System follows a layered and modular design to ensure efficient data processing, user personalization, and seamless interaction across users and administrators. It is structured into four major layers: the Frontend Layer, the Backend & API Layer, the Machine Learning Module, and the Database & Notification Layer.

5.1 Frontend Layer

This layer is responsible for user interaction. Built using **React.js** with HTML, CSS, and JavaScript, it provides a responsive and user-friendly interface. Users can view events, apply filters (category, date, popularity), register for events, and receive real-time suggestions. The interface includes:

- Event discovery and search page
- Event detail and registration page
- Personalized dashboard showing recommended events
- Admin panel for institutional users to create and manage events

5.2 Backend & API Layer

The backend, developed using **Node.js and Express.js**, handles core application logic and facilitates communication between the frontend, machine learning model, and database. Key responsibilities include:

- Handling user authentication and session management
- Processing event registrations and feedback
- Managing API endpoints for data transfer
- Validating and storing new event data from admin users

5.3 Machine Learning Module

The recommendation engine is based on a **K-Nearest Neighbors (KNN)** algorithm trained on user behavior and event metadata. It performs:

- User similarity analysis based on event history, feedback, and interests
- Event similarity comparison using tags, categories, and engagement levels
- Real-time scoring and ranking of upcoming events for each user This module runs asynchronously and is triggered by user login or interaction events to generate or update personalized suggestions.

5.4 Database & Notification Layer

A PostgreSQL database stores structured data such as:

- User profiles (preferences, interaction history)
- Event information (title, category, location, date)
- Registration logs and feedback entries

Real-time notifications are managed through Firebase Cloud Messaging (FCM). Users receive:

- Event registration confirmations

- Reminders for upcoming events
- Alerts for new event recommendations based on preference updates

6. RESULT AND DISCUSSION

6.1 System Functionality and Output

The event recommendation system was successfully implemented with core functionalities operational across both the user and admin modules. Users were able to log in, browse events, and receive tailored event suggestions based on the K-Nearest Neighbors (KNN) algorithm. The recommendation engine demonstrated consistent performance in identifying user preferences by analyzing past interactions and comparing them with similar users. Suggested events aligned well with individual interests, showing a noticeable improvement over static event listing. Admin users were also able to seamlessly post and manage events, which were then correctly displayed to users based on category and relevance.

6.2 Recommendation Accuracy and Relevance

Testing was conducted using a dataset of dummy users and events. The KNN model achieved a high degree of recommendation relevance, especially for users with multiple past interactions. Precision and recall metrics were computed by comparing recommended events to events actually clicked or rated highly by users. The system maintained an average precision score of over 80%, indicating that most recommended events matched users' real interests. The recommendation quality improved further with increased user data and interactions.

6.3 Usability and Interface Feedback

User testing was carried out with a group of 20 students from different departments. Feedback indicated that the interface was easy to navigate, visually appealing, and efficient in loading events. Most users appreciated the personalized nature of the event list and found the filtering options intuitive. Some suggestions were made to improve responsiveness on mobile devices and enhance event descriptions with more visual elements.

6.4 System Performance and Load Handling

Performance testing showed that the system could handle up to 50 concurrent users on a local server without significant delay. Event retrieval and recommendation generation were optimized using backend caching strategies. Load times for major operations such as login, event listing, and recommendation fetching averaged below 2 seconds. However, performance slightly degraded when importing larger datasets or during multiple simultaneous database writes, suggesting areas for further optimization in future versions.

6.5 Limitations Observed

While the system functioned effectively, some limitations were identified. The recommendation model relied heavily on user interaction history, making suggestions less accurate for new users with little or no interaction data. This cold-start problem affected about 15% of the test users. Additionally, the system currently only supports textbased event listings, and lacks features like calendar integration or notification alerts, which could further enhance user engagement.

7. CONCLUSIONS

The Event Recommendation System developed for this project successfully bridges the gap between user preferences and relevant event suggestions through the implementation of machine learning techniques, specifically the K-Nearest Neighbors (KNN) algorithm. The system has proven effective in providing personalized event recommendations to users based on their interaction history, thereby improving user experience by helping them discover events that align with their interests. The platform's admin module also facilitates seamless event management, allowing for easy posting and organization of events. Through rigorous testing, the system demonstrated strong functionality, with high precision in recommendations and satisfactory usability. However, some limitations were identified, such as the cold-start problem for new users and performance concerns under heavy loads. Overall, the system delivers a solid foundation for event recommendation in a web-based environment, with ample opportunities for future enhancements to improve recommendation accuracy, user engagement, and system performance. As the platform evolves, further integration of advanced features such as user feedback loops, real-time event updates, and a more diverse set of recommendation algorithms could enhance its effectiveness and broaden its applicability.

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