

## Review on Personalized Activity Notification and Feedback

Srujana Sri<sup>1</sup>, Dr. E. Padmalatha<sup>2</sup>, Mareddy Tanvi<sup>3</sup>

<sup>1</sup>Chaitanya Bharathi Institute of Technology, Hyderabad

<sup>2</sup>Associate professor, Chaitanya Bharathi Institute of Technology, Hyderabad

<sup>3</sup>Chaitanya Bharathi Institute of Technology, Hyderabad

**ABSTRACT:** The News Aggregator is a personalized, real-time news and placement update service specially designed for students. It will be really hard to maintain in this digital era with relevant information and employment opportunities owing to information overload without the exact solutions in due time. It covers an application needed by a centralized system that provides both educational and professional content, well-curated toward individual academic or career interests. The platform employs the use of ML and NLP to analyze behavior and preferences about individuals. The use of a combination of RSS feeds and APIs allows for real-time updates, and user-based collaborative filtering improves the accuracy of suggestions. Advanced NLP techniques, such as topic modeling (LDA), sentiment analysis (LSTM), and summarization, are used to process news articles and placement updates iteratively, thus improving the relevance over time. The News Aggregator streamlines access to crucial information, thereby promoting academic and professional development of students with the customized news feed and placement alerts on time to prepare them for emerging opportunities.

**KEYWORDS:** Personalized recommendations, Real-time updates, Collaborative filtering, Placement alerts, RSS feeds, APIs

### 1 INTRODUCTION

A centralized application is proposed, which can be used as a platform to deal with the increasing requirements of personalized and real-time updates in the student's academic and professional lives. With the increasing amounts of information, it becomes difficult for students to keep track of news related to their placement and extracurricular events. This app bridges this gap by employing the latest technologies, such as machine learning and natural language processing, to provide specific content and updates according to one's preferences.

The platform offers more than regular solutions by having a structured quiz during sign up, which means the system can identify the user preferences and personalize his experience from day one. Once logged in, students will find a carefully crafted feed of academic updates, college events, and placement opportunities that are all easily accessible through one interface. This is complemented by real-time notifications that never allow students to miss important updates: job openings, application deadlines, or upcoming campus activities. By bringing together the aspects of modern UI design, robust back-end services, intelligent data processing, and real-time alerts, the application simplifies access to information and enhances educational and professional growth for its user students. This is a comprehensive solution designed to save the need for too much time, improve engagement, and empower a student to make the right decisions for their future.

### 2 LITERATURE SURVEY

#### 2.1 Personalized Recommendation Service in University Libraries using Hybrid Collaborative Filtering Recommendation System

Authors: Tao Pan

The paper here presents a university library hybrid-based collaborative filtering system for recommendation design. It bridges two major traditional CFR system shortages: data sparsity and the cold-start problems. The work combines content filtering, user-based collaborative filtering and the K-means clustering algorithm together to improve and enhance the overall recommendation accuracy with efficiency.

##### 2.1.1 Methodology.

The proposed hybrid approach integrates multiple techniques: User-Based Collaborative Filtering (CF):

Constructs a user-item interaction matrix to calculate similarities between users based on their borrowing patterns. Measures similarity using cosine similarity. Generates recommendations by finding the nearest neighbors of a user.

K-Means Clustering: Addresses the sparsity of the user-item matrix by grouping similar users into clusters. Uses cluster centroids and Pearson correlation for better similarity measurement. This reduces computational complexity, as it seeks neighbors within the clusters rather than across the whole dataset.

Content-Based Filtering (CBF):

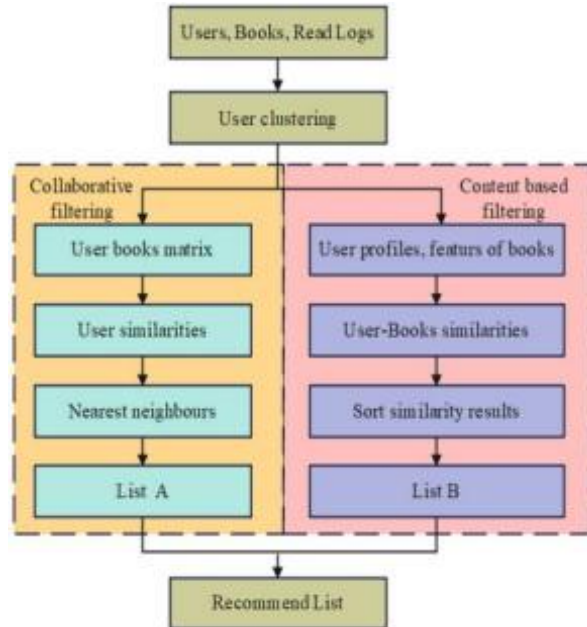
These are recommended items based on attributes such as title, author, and keywords. User profiles are built up based on borrowing history and specialization. Matches the user's

preferences to features of items and returns the most relevant items to recommend. Hybrid Model:

Combines the strength of both CF and CBF. Uses item similarity and past ratings to fill in missing values in the user-item matrix. Incorporates tags (labels) and time factors for dynamic, accurate predictions.

#### 2.1.2 Limitations.

Scalability Issues: Although the K-means clustering reduces the computation overhead, there is a scalability problem for extremely, large and dynamic data sets.



**Figure 1: Workflow of the proposed hybrid CFR system**

Real-Time Adaptation: The updates to the user-item matrix and clustering results in the system, which may not work efficiently for real-time recommendations.

Limited Flexibility: The model has limited flexibility for different user behaviors and changes in library collections.

Cold-Start Problem: While the content-based approach reduces the problem, the system may still struggle with entirely new users or items that have no interaction history. Static Data: The assessment was done on static data, so the findings do not really apply to performance in dynamic or ever-changing situations.

## 2.2 Multi-Agent Personalized Recommendation System in E-Commerce based on User

Authors: Dr. Nagagopiraju Vullam, Dr. M Venkateswara Rao, Khader Basha Sk, Roja D, Venkateswara Reddy B, Sai Srinivasa Vellela This paper presents a Multi-Agent Personalized Recommendation System for e-commerce websites, with emphasis on improving the accuracy of recommendation and user satisfaction. The system exploits user clustering and multi-agent technology to produce personalized recommendations by analyzing user interest and browsing behavior. Unlike the traditional collaborative filtering, this method relies on objective features such as user

demographics and past activities instead of subjective preferences.

#### 2.2.1 Methodology.

The proposed system works as follows a multi-agent architecture. The system utilizes a multi-agent design consisting of agents such as:

Recommendation Engine Agent: Central engine generating recommendations

User Profile Management Agent: Builds and updates user profiles based on user browsing and purchase history.

Data Mining Agent: Extracts insights regarding user behavior in light of decision trees, association rules, and neural networks Evaluation Feedback Agent: Collects feedback meant for refining recommendations

User Interface Agent: The User Interface agent facilitates user interactions and collects feedback.

User Clustering: Users are clustered based on objective features such as browsing frequency, purchase categories, and interaction history. Clustering reduces the search space for finding neighbors, thus improving efficiency.

Content-Based Filtering: Analyzes product features and user interests for recommendations. Suggests products similar to those previously interacted with by the user.

Collaborative Filtering Enhancement: Integrates feedback to address sparsity issues in user-item matrices. Offline evaluations improve the model by increasing the density of collaborative filtering data.

Feedback and Refinement: User feedback is collated and documented in evaluation records. The system dynamically changes as user preferences are changed.

2.2.2 Limitations. Dependence on Offline Evaluations: The system depends on offline evaluations, which might limit its ability to respond to real-time user interactions and feedback.

In general, it complicates multi-agent design due to a huge amount of careful coordination involved. This increases potential inefficiencies and computational overhead in the entire scheme.

Cold-Start Problem: The system doesn't explicitly state how it deals with new users or products without having any prior data.

Cluster Granularity: The quality of user clustering significantly affects the recommendation, and badly designed clusters can lead to misleading results.

Scalability Challenges: Like the first paper, the system would struggle to be efficient when dealing with very large datasets or a highly diversified set of user behaviors in big e-commerce systems.

## 2.3 Media Personalized Recommendation System Based on Network Algorithm

Authors:Wendan Jiang

To challenge the issue of information overload in platforms like Weibo, a paper presents a Media Personalized Recommendation System, based on network algorithm. It analyzes user interest to give more precise and

personalized marketing content by identifying their interest and helps users achieve media communication and data analysis for information management. It has four primary modules: media data acquisition, marketing information management, personalized recommendation, and media communication analysis.

### 2.3.1 Methodology.

The system is structured into four major modules:

**Media Data Acquisition Module:** Collects and processes user data, for example, basic information, forwarding, and comments. Data acquisition incorporates simulated login and web crawlers. Filters irrelevant data and performs text processing such as Chinese word segmentation to make data usable.

**Marketing Information Management Module:** Handles advertising content by gathering data through web crawlers in set parameters. Executes elementary operations such as addition, deletion, and modification of advertising information.

**Personalized Recommendation Module:** Matches marketing information with user interest models by computing similarity. Recommends the top N marketing items based on similarity scores, generating a ranked recommendation list.

**Media Communication Analysis Module:** Analyzes and visualizes communication results for marketing content. Tracks information propagation and displays results via visual methods to assess the influence and authenticity of communication.

### 2.3.2 Limitations.

**Keyword Expansion Issues:** The keyword expansion approach adopted (mutual information) is error-prone because of the influence of the word segmentation system and the use of synonyms.

**User Interest Model Limitations:** Users who access the system with loose or sparse access histories require large time windows to train interest, which lowers the real-time adaptability.

**Overlapping Categories:** Some categories are overlapping (for example, automobiles and advertising), which weakens the concentration and effectiveness of the recommendations.

**Partial System Implementation:** This leaves the complete system unrealized or untested online, thus severely limiting practical validation due to time constraints.

## 2.4 Push4Rec: Temporal and Contextual Trend-Aware Transformer Push Notification Recommender

**Authors:** Chu-Chun Yu, Ming-Yi Hong, Chiok-Yew Ho, Che Lin  
The purpose of this research work is to promote user engagement based on the accuracy of Click-Through Rates through the integration of user temporal and contextual preferences. The authors stress the need to understand user click behavior and preferences, especially when trends are rapidly changing. Push4Rec employs pivotal learners that assess click behavior and capture user preferences

effectively. It also features a gating network that manages the significance of personal interests and current trends, ensuring relevance and timeliness of recommendations. This model stresses user privacy as its processes do not involve personal data and user IDs. The authors argue the effectiveness of Push4Rec with the demonstration of better performance of the model over benchmark models when tested on a real-world dataset, setting a new benchmark in personalized recommendation systems.

### 2.4.1 Methodology.

The Push4Rec model's methodology is divided into several essential elements to better the prediction of CTR in push notifications. There are three principal learners included: TIL (Temporal Interest Learner), CIL (Contextual Interest Learner), and TAL (Trend-Aware Learner).

**TIE:** This is a component that processes time-related features such as click time intervals, impression time intervals, and the time from

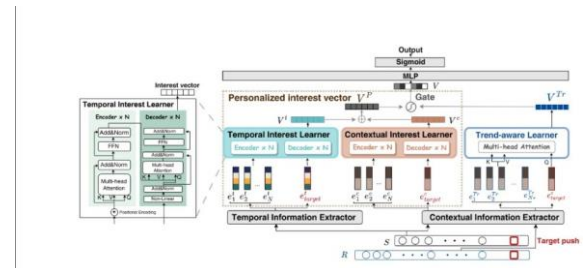


Figure 2: The Architecture of Push4Rec

impression to click. Other categorical features include the day of the week and hour of the day that are represented as a temporal embedding.

**Contextual Information Extractor (CIE):** CIE uses pre-trained language models, such as BERT or GPT-2, to extract contextual features from the titles of the pushed messages. The output representations are integrated through average pooling to form a contextual embedding.

**Temporal/Contextual Interest Learners (TIL and CIL):** Both learner types utilize a transformer architecture to incorporate user preference capture. TIL emphasizes the temporal aspect, while the contextual aspect is accounted for by the CIL as it produces vectors for both the temporal as well as the contextual embeddings.

**Trend-Aware Learner (TAL):** This model returns the top-N items by computing recent clicks using contextual embeddings in order to determine the trend vector and current popular items.

**Gating Network:** A gating network is used to control the flow of information between the personalized interest vector and the global trend vector, enabling the model to adaptively weigh the importance of personal interests versus trends in the final prediction.

### 2.4.2 Limitations.

**Complacency with Historical Data:** Since the user preferences tend to lean to a trend that emerges, the actual benefit of such models will lessen. The model becomes dependent on the historical click data accumulated.

Authors: Dr. Garima Sinha, Subhamoy Mandal, Owais Khan,  
Varanasi Akash, Karan Raj Purohit, Chetan Harawat.

through the user-friendly dashboard. The application integrates notification categorization techniques to enable filtering and prioritizing messages based on their importance and urgency, enhancing the overall experience for the users. The authors also point out that a user-friendly UI/UX design is necessary to ensure that users can easily navigate the application and access relevant information.

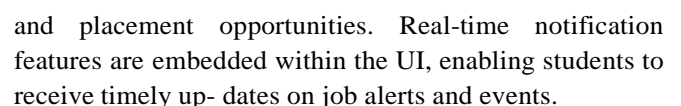
The methodology of Beep application is to provide an easy-to-use alert system for engineers within an organization. This design approach covers the following steps.

User Interface Development: A user interface is developed that lets users log in or sign up; after the sign-up, the user will be redirected to a dashboard with all the notifications. Users can click on any of the notifications to know more and raise queries for particular notifications.

Memory limitations of the system: Current systems lack the power to store many messages from the server side sent between the client and server.

Apps that are Unified: The paper really goes into details of each of the three major modules/sub-modules in the sections of User Authentication, and User Profile, and even greater things within User Interface.

**User Interface Design:** The user interface (UI) of the application is crafted using cross-platform frameworks such as Flutter or React Native to ensure accessibility across multiple devices. During the sign-up process, students complete a quiz designed to capture their academic, professional, and extracurricular preferences. This data is used to personalize the user experience, with the landing page displaying tailored content such as academic news, college events,



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**Srujana Sri <sup>1</sup>, ETJ Volume 10 Issue 04 April 2025**



extracurricular activity information. The backend processes these data inputs, forwarding them to the database and machine learning modules for further analysis.

**Database Management:** The database is implemented using Post-greSQL or MongoDB, facilitating efficient data storage and retrieval. The structure is divided into clear segments like user data, quiz data, and content data. User data holds individual profiles, quiz responses, and personalization preferences. The quiz data maintains the questions and results that can serve as the primary foundation for serving customized content. Content data incorporates academic articles, placement notifications, and extracurricular activities. This will enable the system to have a good repository from which it can base its recommendations and alerts.

**Machine Learning and NLP Module:** The machine learning (ML) and natural language processing (NLP) module forms the core of the personalization system. Data collected from external APIs and user interactions is preprocessed to remove inconsistencies and ensure a structured format. ML algorithms analyze user behavior through collaborative filtering techniques to identify preferences and generate recommendations. Content segmentation categorizes data into academic, placement, and extracurricular segments. NLP techniques such as topic modeling, sentiment analysis, and summarization enhance the relevance and clarity of the displayed content. The module ensures each user receives a highly personalized and engaging experience.

**Notification Service:** [4] Real-time notifications are managed through services like Firebase Cloud Messaging (FCM) or OneSignal. The notification system is configured to deliver alerts about job opportunities, placement updates, and upcoming college events. These alerts help students stay informed without needing to manually search for updates. The system ensures the timely delivery of critical information, empowering students to take advantage of academic and professional opportunities as they arise.

**System Integration and Deployment:** The application integrates all components—UI, backend services, database, ML and NLP modules, and notification services—into a cohesive system. The integrated system undergoes rigorous testing to ensure functionality, scalability, and performance.[2] Deployment on cloud platforms such as AWS or Google Cloud guarantees high availability and scalability, supporting seamless operations even with a growing user base. This integration ensures the application delivers an efficient, user-friendly experience while meeting the academic and professional needs of students.

#### 4 CONCLUSION

The personalized recommendation system for students proposed in this research combines different technological frameworks and methodologies in the enhancement of academic and professional experience. User-centric design, through a sign-up quiz, collects students' academic,

professional, and extracurricular preferences, thus assuring that the content will be highly relevant to the students by providing proper academic news, college events, and placement opportunities.

In addition, the back-end is designed to be considerably more powerful so that copious data can be processed quickly and updated in real-time, which corresponds with what is already known in collaborative filtering and content-based recommendation systems. The structured database will allow proper saving and retrieval of user information, thus increasing the power of personalized recommendations provided to the user.

What powers the application is a combination of machine learning and natural language processing module that analyzes user behavior and preference using techniques such as topic modeling and sentiment analysis. This way students receive relevant information with their interests.

Real-time notification services alert students regarding important events such as job openings and college events, making it stress-free as far as the information overload is concerned. This proactive notification system helps to empower student nominations to attend academic and professional opportunities.

Finally, their integration and deployment onto cloud platforms guarantee high availability and scalability as the user base increases. Overall, the personalized recommendation system not only curbs information overload but also positions education better towards an improved education experience; it keeps the student body more informed and engaged toward success.

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