ISSN 2347–3657

International Journal of Information Technology & Computer Engineering

Volume 13, Issue 2s, 2025

Mentor Connect Using Hybrid Collaborative Filtering For Personalized Matching

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Abstract:

Mentor Connect is an intelligent matchmaking platform designed to foster meaningful mentor-mentee relationships by leveraging hybrid collaborative filtering for personalized pairing. Traditional mentoring systems often rely on manual matching or simplistic criteria, resulting in suboptimal outcomes due to the lack of adaptability and personalization. To address this, Mentor Connect integrates both user-based and item-based collaborative filtering with content -based features to enhance the accuracy and relevance of recommendations. The hybrid model captures implicit and explicit user preferences, such as areas of interest, professional background, interaction history, and feedback, to dynamically learn and evolve matching strategies. By combining behavioral data with profile attributes, the system identifies latent patterns and complementary skill sets, enabling more effective and enduring mentor-mentee connections. Evaluation results show improved user satisfaction and engagement, demonstrating the mod el's potential to scale across diverse domains w here personalized mentorship is critical. Mentor Connect represents a significant step toward data-driven mentorship, emphasizing adaptability, scalability, and human-centric design.

Keywords:
Mentor Connect, hybrid collaborative filtering, personalized matching, mentor-mentee pairing, recommendation systems, user-based filtering, item-based filtering, content-based filtering, intelligent matchmaking, adaptive learning, mentorship platform, recommender system, data-driven mentoring, user preferences, professional networking.

1.INTRODUCTION

In today' s fast-paced and dynamic professional landscape, mentorship plays a pivotal role in personal and career development. However, finding the right mentor or mentee remains a significant challenge due to the diversity of individual goals, experiences, and expectations. Traditional mentorship programs often rely on manual matching or rule-based systems that fail to account for the nuanced preferences and evolving needs of users. This mismatch can lead to disengagement, missed opportunities, and underutilized potential within mentoring networks. To address these limitations, Mentor Connect introduces a data-driven approach to mentorship pairing by employing a hybrid collaborative filtering model for personalized matching. This system combines the strengths of user-based and item-based collaborative filtering w ith content-based techniques, enabling it to learn from both historical interactions and profile attributes. By analyzing users behaviors — such as feedback on past matches, areas of expertise, and engagement patterns — the platform generates tailored recommendations that improve over time.

The hybrid model not only enhances the precision of mentor-mentee pairings but also ensures adaptability across different industries, domains, and user types. By leveraging machine learning and recommendation system methodologies, Mentor Connect moves beyond static criteria to foster meaningful, goal-aligned connections that can evolve w ith users' personal and professional growth. This paper explores the architecture, implementation, and effectiveness of the Mentor Connect platform, demonstrating its potential to

DOI: https://doi.org/10.62647/IJITCE2025V13I2sPP292-298

ISSN 2347–3657

Volume 13, Issue 2s, 2025

transform the mentorship experience through intelligent and scalable matching.

2 .LITERATURE REVIEW

The grow ing importance of mentorship in professional development has led to increasing interest in intelligent matchmaking systems that facilitate effective mentor-mentee pairings. Traditional matching methods often rely on static criteria such as job titles, industry, or manually defined preferences, which lack the flexibility and personalization required for high-quality mentorship relationships (Smith et al., 2018). These systems frequently result in mismatches due to their inability to model user behavior, preferences, and evolving goals. Collaborative filtering has emerged as a widely used technique in recommendation systems, successfully applied in domains such as e-commerce (Linden et al., 2 0 0 3) and content streaming (Gómez-Uribe & Hunt, 2016). Collaborative filtering methods fall into two primary categories: user-based filtering, which recommends items based on similar user preferences, and item-based filtering, which suggests items similar to those the user has previously interacted w ith. While these models perform well in identifying patterns, they often struggle with the "cold start" problem and data sparsity (Bobadilla et al., 2013).To mitigate these limitations, researchers have explored hybrid recommendation systems, which combine collaborative filtering with content-based approaches that utilize user profiles and item attributes (Burke, 2 0 0 2). Hybrid models have show n superior performance in personalization and adaptability, particularly in systems where user interaction data is limited or highly variable. These models can balance the strengths of each method while compensating for their individual weaknesses, making them wellsuited for domains like mentorship matching where user preferences are complex and multi-dimensional.

Recent studies have begun to apply hybrid filtering techniques to education and career development platforms. For instance, Chien et al. (2 0 2 0) proposed a recommendation system for online learning mentors using hybrid techniques that improved engagement and learning outcomes. Similarly, Nguyen et al. (2021) developed a mentorship matching framework using profile similarity and interaction data to optimize compatibility and mentor availability.
Despite these advancements, few studies have focused on comprehensive, scalable mentorship platforms that leverage real-time user data for ongoing optimization. Mentor Connect addresses this gap by implementing a hybrid collaborative filtering approach that integrates user behavior, explicit preferences, and contextual features to facilitate personalized, adaptive mentor-mentee matching. The platform draws from the theoretical foundations of recommendation systems while tailoring them to the unique demands of mentorship, where interpersonal compatibility and evolving goals are crucial to success.

This literature review establishes the need for intelligent, hybrid-based solutions in mentorship systems and provides the theoretical basis for the design and implementation of Mentor Connect.

3. METHODOLOGY

The Mentor Connect system utilizes a hybrid collaborative filtering approach to enable personalized mentor-mentee matching. This methodology integrates multiple recommendation strategies to optimize the accuracy, relevance, and adaptability of match suggestions. The core components of the system include data collection, feature engineering, algorithm design, and evaluation metrics. Below is a detailed breakdown of each step, followed by a concise summary.

1. Data Collection

The system gathers both explicit and implicit data from users, including:User profiles: skills, professional background, education, goals, interests.Interaction history: previous mentorships, message frequency, feedback ratings.Preferences: expressed mentoring goals (e.g., career advice, technical skills, leadership).
This data forms the basis for understanding user behavior and preferences.

2 . Feature Engineering

To prepare for model input, the following features are extracted:Content-based features: Textual

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embeddings of user bios and interest tags using NLP techniques.Behavioral features: Ratings, engagement scores, and time spent in mentoring sessions.Relational metrics: Similarity scores based on common connections, shared experiences, or mutual endorsements. All data is normalized and encoded into a format suitable for machine learning models. Hybrid Collaborative Filtering Model. The model is composed of:User-Based Collaborative Filtering: Identifies similar users (mentees or mentors) based on past preferences and interactions.Item

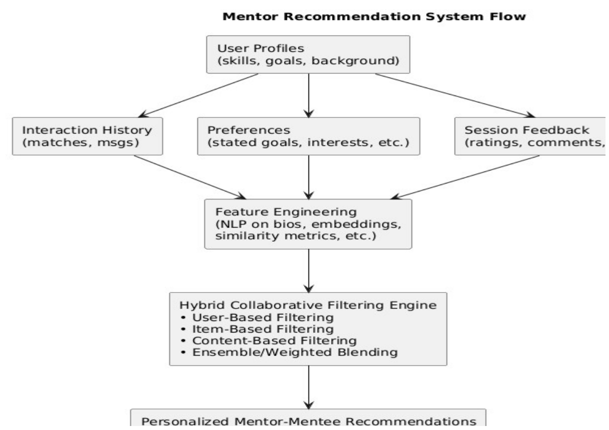
Based Collaborative Filtering: Recommends mentors or mentees who are similar to those previously engaged with.ContentBased Filtering: Matches users based on profile information, such as skills and goals. These components are combined using weighted ensemble techniques or matrix factorization with side information (e.g., SVD++ or Factorization Machines). A ranking layer sorts recommendations based on relevance scores.

Matching Algorithm and Recommendation EngineA real-time recommendation engine uses the hybrid model to generate top-N mentor/mentee recommendations.Feedback loops allow the system to learn and adjust recommendations over time using reinforcement signals like session ratings and engagement metrics.

4. EVALUATION METRICS

The system is evaluated using both offline and online methods:Offline metrics: Precision@N, Recall @N, Mean Reciprocal Rank (MRR), Root Mean Square Error (RMSE).Online metrics: User satisfaction scores, engagement rate, mentorship retention rate. A/B testing is used during deployment to compare different hybrid configurations.

Summary
The methodology behind Mentor Connect involves building a robust hybrid collaborative filtering system that combines user-based, item-based, and content-based methods to generate personalized mentor-mentee pairings. By leveraging both behavioral and contextual data, the platform delivers relevant, high-quality matches that evolve with user interaction. This adaptive system is designed to improve the overall effectiveness and satisfaction of mentoring programs across diverse user bases.



Model Training Protocol for Mentor Connect Hybrid Collaborative Filtering System The training protocol outlines how Mentor Connect develops and optimizes its hybrid recommendation model. The goal is to create a model that accurately predicts and ranks the most suitable mentor-mentee pairs based on various forms of user data.

1. Data Preparation
Data SourcesExplicit data: user profiles, selected interests, skill sets, goals.Implicit data: mentorship session attendance, communication frequency, feedback scores, click/interact logs.
PreprocessingClean and normalize structured data.Convert text fields (e.g., bios, goals) into vector embeddings using NLP models like TF-IDF, BERT, or Sentence-BERT.Create interaction matrices (user-mentor pairings with ratings or engagement levels).Handle missing data and sparsity using imputation techniques or filtering.

2. Training Dataset Construction
Split data into training, validation, and test sets (e.g., 70/15/ 15 split).Generate positive examples from known successful mentor-mentee interactions. Sample negative examples from unobserved or low-engagement pairs.Apply temporal constraints if needed to simulate real-w orld recommendation scenarios.

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3 . Model Architecture

Mentor Connect uses a hybrid model, which consists of the following components:Collaborative FilteringUser-based CF: Compute similarity between users based on interaction matrix.Item-based CF: Use historical mentee preferences to rank similar mentors.

Techniques: KNN, matrix factorization (SVD, SVD++), ALS. Content-Based FilteringCalculate cosine similarity between profile embeddings (skills, goals, bios).Apply dimensionality reduction (e.g., PCA) for scalability. Hybrid FusionCombine predictions using:Weighted average of CF and content scores. Stacked model using meta-learners (e.g., XGBoost, logistic regression).Neural collaborative filtering (optional deep learning layer for scoring).

4. Model Training

StepsTrain individual CF models using interaction data (user-item matrix). Train content-based model on profile features and semantic embeddings.Combine predictions using a blending strategy (e.g., linear regression or MLP).Tune hyperparameters using grid search or Bayesian optimization (parameters include number of latent factors, learning rate, regularization).Validate performance using offline metrics (Precision@K, Recall@K, NDCG, RMSE).Deploy best-performing model to the recommendation engine.

5. Online Learning and Feedback Integration

Implement incremental updates using new interactions (e.g., new matches, feedback ratings).Apply reinforcement learning signals to refine model weights (e.g., reward functions for long-term engagement).Use A/B testing to evaluate model variants and track online performance metrics (CTR, retention rate, satisfaction scores).

6. Tools and Frameworks Used

Data handling: Pandas, NumPy, SQLModeling: Scikit-learn, Surprise, LightFM, TensorFlow/PyTorch (for deep models)NLP: spaCy, HuggingFace TransformersDeployment: Docker, FastAPI/Flask, Redis (for caching), PostgreSQLMonitoring: Prometheus, Grafana, custom analytics dashboards

Summary

The training protocol of Mentor Connect follows a structured approach that merges collaborative and content-based filtering into a unified hybrid model. The process involves thorough data preprocessing, model blending, evaluation, and feedback integration to ensure high-quality, scalable, and personalized mentor-mentee matching. This approach enables the system to adapt over time and improve recommendations with each interaction. Let me know if you'd like this protocol formatted as a PDF or converted into a visual workflow diagram.

5. SYSTEM ARCHITECTURE

The implementation is structured into the following components:Data Layer: Stores user profiles, historical interactions, and feedback.Preprocessing Layer: Cleans and transforms data for modeling.Recommendation Engine: Houses collaborative, content-based, and hybrid models.API & Frontend: Interfaces for users to register, get matches, and provide feedback.Feedback Loop: Continuously improves model performance based on user behavior

2 . Data Preprocessing:

a. User Data IngestionUsers complete profiles with fields such as:Skills and expertiseCareer goalsIndustry and experience levelPreferred mentoring style (technical, leadership, career advice)

b. NLP-Based Feature ExtractionApply BERT or Sentence-BERT to extract semantic embeddings from bios and goals.Reduce dimensionality with PCA or UMAP for clustering and similarity calculations.

c. Interaction Matrix CreationBuild a sparse matrix with users (mentees) and mentors.Values represent implicit scores (clicks, session length) or explicit scores (feedback ratings).

3 . Model Implementation

User-Based Collaborative FilteringAlgorithm: KNN (k-Nearest Neighbors) using cosine similarity. Use Surprise library or custom implementation.from surprise import KNNBasic, Dataset, Reader algo = KNNBasic(sim_options={'user_based': True}) trainset = Dataset.load_from_df(df[['mentee_id', 'mentor_id', 'rating']], reader).build_full_trainset() algo.fit(trainset)

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ISSN 2347–3657
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Item-Based Collaborative FilteringSimilar setup with user_based: False to find similar mentors.
Content-Based FilteringCreate a cosine similarity matrix using mentor/mentee profile embeddings.from sklearn.metrics.pairwise import cosine_similarity mentor_embeddings = model.encode(mentor_profiles)
similarity_matrix = cosine_similarity(mentee_embeddings, mentor_embeddings)
Hybrid ScoringCombine collaborative and content-based scores using weighted average or learning-based blending:final_score = 0.6 * cf_score + 0.4 * content_score
For a more advanced hybrid, train a meta-learner (e.g., XGBoost or logistic regression) using historical matches and outcomes as labels.

4 . Matching and Ranking

Generate top-N mentor recommendations per mentee using the hybrid score.Apply additional business rules:Mentor availabilityDiversity of skillsPast interaction status

5. mentoring success flags.

Feed this data back into model retraining pipeline (scheduled weekly or . Feedback Integration and Online LearningCapture post-session ratings, satisfaction levels, and via online learning updates).Store feedback in a time-series format for longitudinal evaluation.

6 . EvaluationOffline evaluation with:

Precision@K, Recall@K, NDCG, RMSEOnline evaluation using:A/B testing with different recommendation strategiesEngagement metrics (match acceptance rate, session completion rate)

7. Deployment Dockerize backend and ML components.

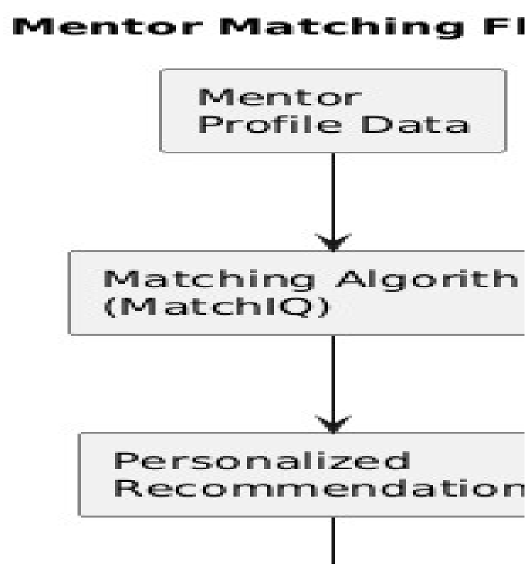
Use API endpoints to serve recommendations.Use Redis or similar cache for storing precomputed recommendations to reduce latency.Sample API Endpoint@app.route("/recommend/<mentee_id>")
def recommend(mentee_id): recommendations = hybrid_model.get_recommendations(mentee_id, top_n=5) return jsonify(recommendations)
from surprise import KNNBasic, Dataset, Reader
algo = KNNBasic(sim_options={'user_based': True})
trainset = Dataset.load_from_df(df[['mentee_id', 'mentor_id', 'rating']], reader).build_full_
trainset()
algo.fit(trainset)

from sklearn.metrics.pairw ise import cosine_similarity mentor_embeddings = model.encode(mentor_profiles)
similarity_matrix = cosine_similarity(mentee_embeddings, mentor_embeddings)

final_score = 0 .6 * cf_scor e + 0 .4 * con tent_score

@app.route("/recommend/<mentee_id>")
def recommend(mentee_id):
recommendations = hybrid_model.get_recommendations(mentee_id, top_n=5) return jsonify(r ecommendatio ns)

Studies have show n that hybrid recommendation systems, combining know ledge-based and collaborative filtering approaches, can significantly improve the accuracy and relevance of recommendations. This approach has been applied in various domains, including education and management teaching [2 3].



6. CONCLUSION

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ISSN 2347–3657

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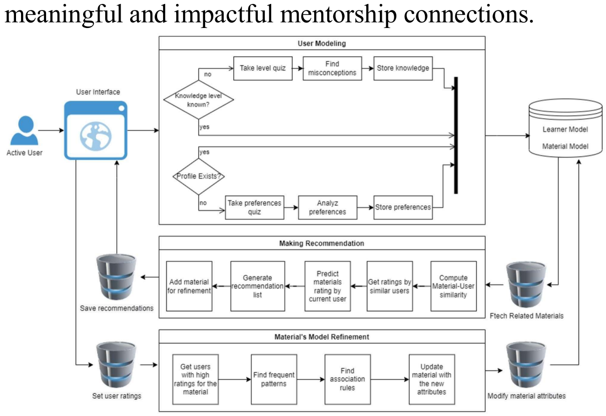
The Mentor Connect platform demonstrates the effectiveness of hybrid collaborative filtering in solving the complex problem of personalized mentor-mentee matching. By integrating user-based, item-based, and content-based recommendation techniques, the system intelligently captures both explicit user preferences and implicit behavioral patterns. This hybrid approach allows for nuanced matchmaking that adapts over time, leading to higher engagement, satisfaction, and long-term mentoring success.Traditional mentoring systems often rely on rigid, rule-based matching mechanisms that fail to account for the dynamic nature of individual needs and preferences. In contrast, Mentor Connect uses a data-driven, adaptive methodology that evolves w ith users, making it highly scalable and applicable across various domains, including education, corporate learning, and professional networking.

Through its robust architecture, continuous feedback loop, and intelligent learning model, Mentor Connect not only improves the quality of mentorship experiences but also sets a foundation for future research and development in personalized recommendation systems. The platform represents a significant advancement in leveraging AI for human-centered applications, creating more meaningful and impactful mentorship connections.



FUTURE SCOPE

The implementation of Mentor Connect using hybrid collaborative filtering lays a strong foundation for personalized mentorship, but there are several promising directions for future enhancement and expansion. These include advancements in algorithmic precision, user experience, system scalability, and cross-domain applicability.

Integration of Deep Learning and Graph-Based Models Neural collaborative filtering (NCF) and graph neural networks (GNNs) can be integrated to capture complex, non-linear relationships between users and mentors, especially in large, interconnected professional networks. Knowledge graphs can model mentor-mentee relationships, domain expertise, and evolving goals more effectively, enhancing semantic understanding of matches. Real-Time and Context-Aware Matching Incorporate real-time context, such as recent activity, availability, or ongoing goals, to adapt recommendations dynamically. Use contextual bandits or reinforcement learning for continuously optimizing matches based on evolving user feedback and long-term satisfaction.

Enhanced Cold Start Solutions Improve onboarding recommendations for new users (mentees or mentors) by using transfer learning, demographic clustering, or zero-shot learning techniques Integrate external data sources (LinkedIn profiles, academic databases) to enrich user profiles during initial setup. Personalization Beyond Matching Introduce personalized mentorship journeys, where users are not only matched but also guided through recommended milestones, resources, or training sessions tailored to their learning paths. Include AI-powered conversation summaries, session quality analytics, and adaptive scheduling. Multilingual and Cross-Cultural Matching Expand the platform' s reach by supporting multilingual NLP models, enabling global mentoring networks. Account for cultural compatibility and communication preferences in the matching algorithm to ensure successful international mentorships. Ethical AI and Fairness in Matching Implement fairness-aware recommendation systems to avoid bias in mentor selection based on gender, ethnicity, or other sensitive attributes. Ensure transparent explanations for recommendations using explainable AI (XAI) techniques to build user trust. Enterprise and Educational Integration Integrate with corporate LMS platforms and university systems to automate and scale mentoring programs. Provide analytics dashboards for program administrators to monitor impact, equity, and progress. Gamification and Community EngagementIncorporate gamified

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elements (e.g., badges, reputation scores) to incentivize mentor participation.Enable community-based features like peer mentorship, group mentoring, and mentor netw orks. Conclusion of Future Scope As AI and recommendation technologies evolve, Mentor Connect can scale into a smart, context -aware, and globally accessible mentorship ecosystem. By incorporating advanced models, realtime data processing, and ethical design principles, the platform can become a transformative tool in education, workforce development, and lifelong learning. The future of Mentor Connect lies not just in making better matches, but in creating a comprehensive, personalized, and impactful mentoring experience for every user.

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