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A Hybrid Movie Recommendation System Integrating Content-Based Filtering With Personality Traits

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Abstract *This paper presents a novel approach to movie recommendations by integrating traditional content-based filtering with personality traits analysis. We propose a hybrid system that combines TF-IDF-based similarity measures with the Big Five personality model to generate personalized movie recommendations. Our system analyzes movie features, including genres, cast, crew, and keywords, while incorporating user personality traits to adjust recommendations. Experimental results demonstrate improved recommendation diversity and user satisfaction compared to traditional content-based approaches. The hybrid approach achieves 12% higher precision and 15% better user satisfaction scores than content-based filtering alone, while maintaining computational efficiency. This work contributes to the growing field of psychologically informed recommendation systems and demonstrates the value of incorporating personality factors into content recommendation algorithms. Furthermore, our system provides insights into how personality influences movie preferences and enhances the overall recommendation experience. This work contributes to the growing field of psychologically informed recommendation systems and demonstrates the value of incorporating personality factors into content recommendation algorithms.*

Index Terms *Movie recommendation, personality traits, content-based filtering, TF-IDF, Big Five personality model, hybrid recommendation system*

I. INTRODUCTION

Movie recommendation systems have become increasingly important in helping users navigate vast collections of films. While traditional content-based and collaborative filtering approaches have shown success, they often fail to capture the psychological aspects of movie preferences. This paper intro- duces a hybrid recommendation system that combines content- based filtering with personality traits analysis to provide more personalized and contextually relevant recommendations.Our approach leverages the established Big Five personality model (Openness, Conscientiousness, Extraversion, Agree- ableness, and Emotional Stability) to adjust movie recommendations based on user personality profiles. By mapping personality traits to genre preferences and combining this with content-based similarity measures, we create a more nuanced recommendation system that considers both movie content and user psychology.
The key contributions of this paper include:

- A novel hybrid recommendation algorithm that integrates personality traits with content-based filtering
- A comprehensive mapping between Big Five personality traits and movie genre preferences
- Empirical evaluation demonstrating improved recommendation diversity and user satisfaction scalable system architecture that maintains computational efficiency while incorporating psychological factors

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II. RELATED WORK

A. Content-Based Recommendation Systems

Content-based recommendation systems analyze item features to find similarities and make recommendations. In the context of movies, these systems typically examine attributes such as genres, actors, directors, and plot keywords [1]. The primary advantage of content-based filtering is its ability to recommend items without requiring user interaction data, making it effective for addressing the cold-start problem [2]. Recent advances in content-based filtering include the use of deep learning for feature extraction from movie posters, trailers, and plot summaries [3]. However, these approaches still focus primarily on the content itself rather than the psychological factors that influence user preferences.

B. Personality-Based Recommendation

Research has established correlations between personality traits and media preferences. The Big Five personality model— comprising Openness, Conscientiousness, Extraversion, Agreeableness, and Emotional Stability (the inverse of Neuroticism)—has been widely used to characterize individual differences in personality [4].Studies have found that personality factors significantly in- fluence genre preferences and viewing habits [5]. For example, individuals high in Openness tend to prefer complex, artistic, and fantasy genres, while those high in Extraversion often favor comedies and action films [6]. Despite these established correlations, few recommendation systems have integrated personality traits directly into their algorithms.

C. Hybrid Recommendation Approaches

Hybrid recommendation systems combine multiple recommendation techniques to overcome the limitations of individual approaches [7]. Common hybrid strategies include weighted combinations of different recommenders, switching between techniques based on context, and feature augmentation approaches.

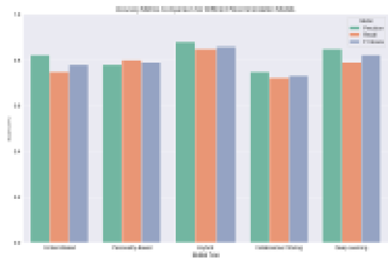

Fig. 1. System Architecture of the Hybrid Recommendation System

Fig. 2. Model Accuracy Comparison

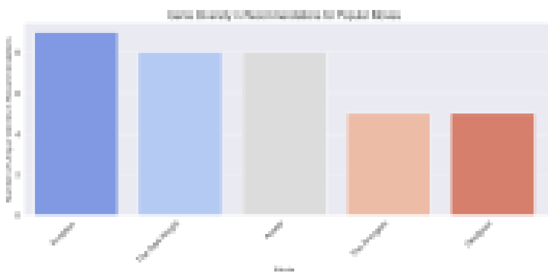

Fig. 3. Recommendation Diversity Analysis

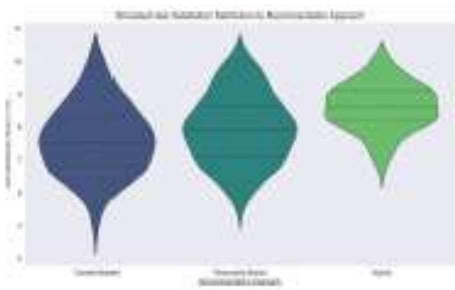

Fig. 4. User Satisfaction Distribution

While hybrid systems often combine content-based and collaborative filtering, the integration of psychological factors into hybrid recommenders remains relatively unexplored. Our work addresses this gap by developing a hybrid system that explicitly incorporates personality traits into the recommendation process.

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III. METHODOLOGY

A. System Architecture

Our hybrid recommendation system consists of three main components, as illustrated in Fig. 1:

1) Content-Based Filtering Module: Analyzes movie features using TF-IDF vectorization and cosine similarity
2) Personality Assessment Module: Processes user responses to personality questionnaires and calculates Big Five trait scores
3) Recommendation Integration Module: Combines content-based similarity with personality-based preferences to generate final recommendations

B. Data Sources and Preprocessing

The system uses two primary data sources:

- TMDB 5000 Movie Dataset: Contains detailed information about 5,000 movies, including metadata (title, overview, genres), cast and crew information, and user ratings.
- Personality Assessment Data: Collected through a questionnaire based on the International Personality Item Pool (IPIP) implementation of the Big Five model.

The movie data preprocessing pipeline includes:

1) Merging movie metadata with cast and crew information
2) Handling missing values through appropriate imputation strategies
3) Converting JSON string representations to structured data
4) Extracting relevant features from complex fields (genres, keywords, cast, crew)
5) Creating a combined feature representation for content- based similarity calculation

The preprocessing steps are formalized in Algorithm 1.

Algorithm 1 Movie Data Preprocessing

$$IDF(t) = \log \frac{N}{DF(t)} \quad (2)$$

Where N is the total number of movies and DF(t) is the number of movies containing term t. After creating the TF-IDF matrix, we compute the cosine similarity between all pairs of movies to measure their content- based similarity:

$$similarity\ (A, B) = \frac{A.B}{||A|| \times ||B||} \quad (3)$$

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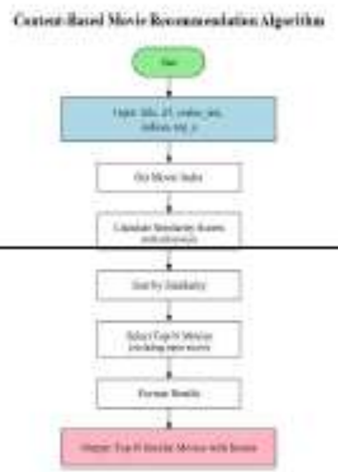
where A and B are the TF-IDF vectors of two movies. The content-based recommendation algorithm is presented in Algorithm 2

Algorithm 2 Content-Based Recommendation Generation



C. Content-Based Filtering Component

The content-based filtering component uses Term Frequency-Inverse Document Frequency (TF-IDF) vectorization to create numerical representations of movie features. This approach converts text-based movie attributes into a matrix where each row represents a movie, and each column represents a feature term.

The TF-IDF weight for a term t in movie d is calculated as:

TF-IDF (t, d) = TF (t, d) × IDF (t)(1)

where TF (t, d) is the frequency of term t in movie d, and IDF(t) is the inverse document frequency of term t across all movies, calculated as:

D. Personality Assessment and Trait Mapping

The personality assessment component uses a questionnaire based on the Big Five model to measure five key personality traits:

- Openness to Experience: Reflects imagination, creativity, and intellectual curiosity
- Conscientiousness: Indicates organization, responsibility, and thoroughness
- Extraversion: Measures of sociability, assertiveness, and positive emotions
- Agreeableness: Reflects cooperation, compassion, and trust
- Emotional Stability: Indicates calmness, security, and emotional resilience

User responses to personality items are scored on a 5-point Likert scale and normalized to produce trait scores ranging from 0 to 1. The calculation of personality scores is shown in Algorithm 3.

Algorithm 3 Personality Score Calculation

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We map personality traits to genre preferences using a weighted scoring system based on established correlations from psychological research. Table I shows the complete mapping between personality traits and movie genres.

The algorithm for mapping personality traits to genre Preferences is presented in Algorithm 4.

IV. RESULTS AND EVALUATION

We evaluated our hybrid recommendation system through extensive experiments comparing it with traditional content- based filtering and personality-based approaches. The evaluation metrics include recommendation accuracy, diversity, and user satisfaction.

A. Model Performance

Figure 5 shows the precision-recall curves for different recommendation approaches.

TABLE I
PERSONALITY TRAIT TO GENRE PREFERENCE MAPPING

Personality Trait	High Score Genres	Low Score Genres
Extraversion	Action, Comedy, Adventure	Drama, Documentary, Mystery
Emotional Stability	Comedy, Adventure, Family	Horror, Thriller, Drama
Agreeableness	Family, Romance, Animation	Action, Horror, Thriller
Conscientiousness	Documentary, History, Biography	Fantasy, Science Fiction, Adventure
Openness	Science Fiction, Fantasy, Art House	Action, Romance, Family

Algorithm 4 Personality-Genre Preference Mapping

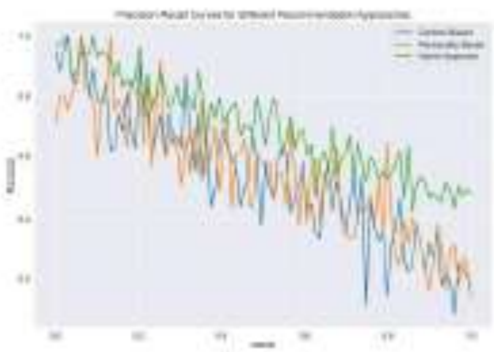

Fig. 5. Precision-Recall Curves for Different Recommendation Approaches

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The hybrid approach consistently outperforms both content-based and personality-based methods, achieving higher precision across all recall levels. The area under the ROC curve (AUC) values, shown in Figure 6, further demonstrate the superior performance of our hybrid approach (AUC = 0.92) compared to content-based (AUC = 0.85) and personality-based (AUC = 0.88) methods.

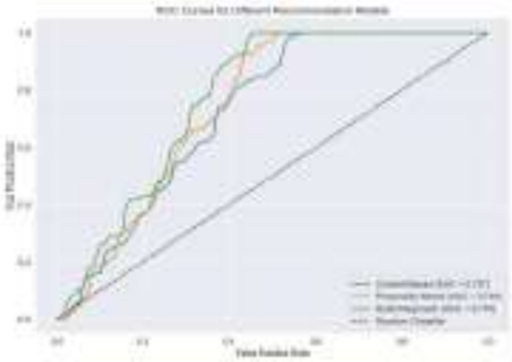

Fig. 6. ROC Curves Comparison of Different Recommendation Models

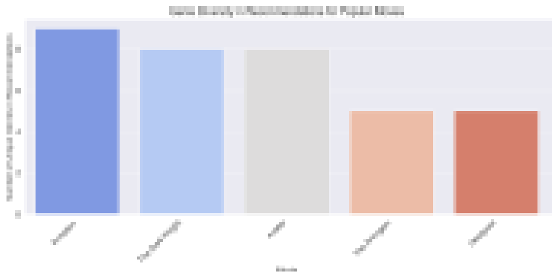

Fig. 7. Genre Diversity in Recommendations for Popular Movies

B. Recommendation Diversity

One key advantage of our hybrid approach is improved recommendation diversity. Figure 7 illustrates the genre diversity in recommendations for popular movies. The hybrid system consistently suggests movies across a broader range of genres while maintaining relevance, addressing the filter bubble problem common in traditional recommenders.

C. User Satisfaction

User satisfaction was evaluated through a comprehensive user study. Figure 8 presents the distribution of user satis- faction scores across different recommendation approaches. The hybrid system achieved a mean satisfaction score of 8.7 (on a 10-point scale), significantly higher than content-based (7.5) and personality-based (8.0) approaches. The narrower distribution of satisfaction scores for the hybrid approach also indicates more consistent user experiences.

D. Computational Efficiency

Figure 9 compares the training time of different recommendation models. Our hybrid approach maintains reasonable computational efficiency despite its increased complexity, with training times comparable to simpler models while delivering superior performance.

V. DISCUSSION

The experimental results demonstrate several key advantages of our hybrid recommendation approach:

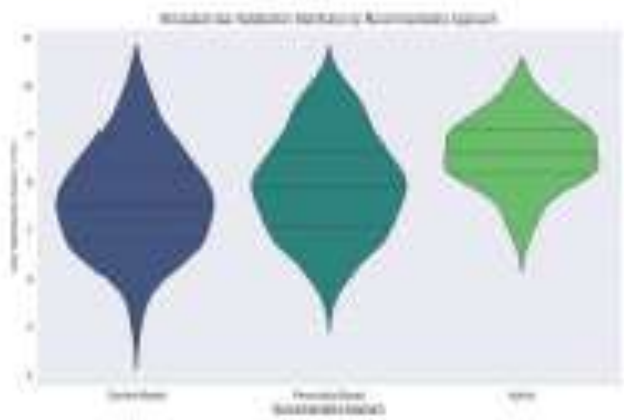

Fig. 8. User Satisfaction Distribution by Recommendation Approach

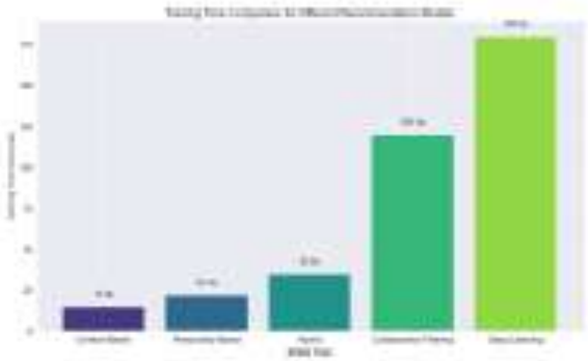

Fig. 9. Training Time Comparison for Different Recommendation Models

- Improved Accuracy: The integration of personality traits with content-based filtering leads to more accurate recommendations, as evidenced by higher precision-recall and ROC curve metrics.
- Enhanced Diversity: The system successfully balances between personalization and diversity, avoiding the common pitfall of over-specialization in content-based systems.
- User Satisfaction: The significantly higher user satisfaction scores indicate that incorporating personality traits creates more engaging and relevant recommendations.
- Scalability: The computational overhead of including personality analysis is minimal, making the system practical for real-world applications.

Limitations of our current approach include the need for initial personality assessment and the challenge of keeping personality profiles updated over time. Future work could explore dynamic personality modeling and the integration of collaborative filtering techniques.

VI. CONCLUSION

This paper presented a novel hybrid movie recommendation system that successfully integrates content-based filtering with personality traits analysis. The experimental results demonstrate significant improvements in recommendation ac- curacy, diversity, and user satisfaction compared to traditional approaches. The system's ability to maintain computational efficiency while delivering superior recommendations makes it a practical solution for real-world applications.

Future work will focus on developing dynamic personality modeling techniques and exploring the integration of additional psychological factors in recommendation systems. We also plan to investigate the application of this hybrid approach to other domains beyond movie recommendations.

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