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Analysis of Audience Preferences for Malaysian Chinese-Language Films with Chinese Cultural Themes Based on Data Mining and Recommender Systems

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Abstract: Recommendation System are designed to assist users in finding relevant items, products, services, or content that match their preferences and interests. Recommendation systems have gained widespread popularity in recent years due to the explosion of digital content and the need to help users navigate through the abundance of choices available. With the personalized content recommendation, this study presented a synergy between Data Mining and Recommender Systems to optimize film suggestions tailored to Audience Preferences for Malaysian Chinese-Language Films with Chinese Cultural Themes. Leveraging a unique approach that incorporates the Fuzzy Family Tree similarity algorithm and the User Key Concept Rate (UKCR) matrix, our research aims to enhance the accuracy and personalization of film recommendations. Through a comprehensive methodology involving user clustering, recommendation scores, and recommender ratings, we present a refined framework that augments the recommendation process. Simulation settings and performance metrics have enabled us to evaluate the system's efficacy, showcasing promising results. The findings reveal that our approach consistently aligns user preferences with film attributes, leading to an average recommendation accuracy of 86.5%. User clustering has facilitated the creation of distinct user segments, enhancing recommendation precision. The utilization of recommendation scores and recommender ratings has contributed to an average user satisfaction increase of 24.8% compared to traditional methods.

Keywords: *Recommendation System, Data Mining, User Key Concept Rate (UKCR), Malaysian Chinese-Language Films, Cultural Theme*

1. Introduction

A data mining-based recommender system represents a groundbreaking advancement in the field of personalized recommendations [1]. In today's information-rich digital landscape, where users are inundated with choices, this innovative approach harnesses the power of data mining techniques to extract valuable insights from vast and diverse datasets. By meticulously analyzing user behaviors, preferences, and interactions, this system uncovers hidden patterns and relationships that form the foundation of its recommendations [2]. As a result, individuals are presented with tailored suggestions, be it for products, services, content, or experiences, that not only align with their unique tastes but also enhance their decision-making process. This introduction explores the realm of data mining-based recommender systems, shedding light on their intricacies, benefits, and far-reaching impacts on transforming the way we engage with information and make choices [3]. In an era characterized by the proliferation of digital platforms, the abundance of options can often lead to decision fatigue and information overload for consumers [4]. This is where data mining-based recommender systems step in, offering a sophisticated solution that leverages cutting-edge data analysis techniques to simplify and enhance the user experience [5].

At its core, data mining involves the exploration and extraction of valuable insights from large datasets. In the context of recommender systems, these datasets encompass a plethora of user-generated data, including browsing history, purchase behavior, search queries, and even social interactions [6]. With consideration of various data mining algorithms, such as collaborative filtering, content-based filtering, and matrix factorization, these systems can identify intricate patterns and correlations within the data that might not be readily apparent to the human eye [7]. Collaborative filtering, for instance, involves examining the preferences and behaviors of multiple users to uncover shared interests and affinities. This approach can reveal unexpected connections between users with similar tastes, enabling the system to recommend items based on the preferences of a user's "neighbors" in the dataset [8]. Content-based filtering, on the other hand, focuses on analyzing the characteristics and attributes of the items themselves, thus making recommendations that align with a user's historical preferences.

Furthermore, modern data mining-based recommender systems often incorporate machine learning and artificial intelligence techniques to enhance their accuracy and adaptability. These systems continuously learn and evolve

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as they gather more user data, refining their recommendations over time to reflect changing preferences and trends [9]. By doing so, they not only offer personalized suggestions but also foster a sense of engagement and user loyalty. The implications of data mining-based recommender systems extend far beyond individual convenience. E-commerce platforms benefit from increased customer satisfaction and engagement, leading to higher conversion rates and revenue [10]. Similarly, content providers can retain audiences by delivering tailored content, and service providers can offer more relevant offerings. On a broader scale, these systems contribute to the democratization of information, helping users discover new and diverse options that align with their interests while simultaneously promoting lesser-known items [11]. Data mining-based recommender systems represent a remarkable synergy between cutting-edge technology and user-centric design [12]. Through deciphering the intricate web of user interactions and preferences, these systems empower individuals to navigate the digital landscape with confidence and ease. As technology advances and data continues to proliferate, the potential for data mining-based recommender systems to reshape how we engage with information and make choices remains both exciting and transformative [13]. The convergence of cultural themes with data mining and recommender systems has opened up an exciting realm of possibilities for catering to audience preferences with unprecedented precision. As societies become increasingly diverse and interconnected, understanding and celebrating cultural nuances has gained paramount importance. Data mining-driven recommender systems now play a pivotal role in this endeavor, seamlessly weaving together user preferences and cultural context to curate tailored recommendations that resonate deeply with individuals [14].

Through the rich tapestry of user interactions, data mining algorithms decipher subtle signals that highlight cultural inclinations [15]. These algorithms discern patterns in user behavior, such as language usage, content consumption, and engagement with culturally relevant materials. Collaborative filtering, for instance, identifies individuals with similar cultural tastes, enabling the system to recommend items that align with shared cultural interests. Content-based filtering, on the other hand, pinpoints cultural attributes in items themselves, ensuring recommendations align with the user's cultural preferences [16]. Recommender systems not only empower users to explore their cultural interests but also contribute to cultural awareness and exchange. By introducing users to culturally diverse content and experiences, these systems promote cross-cultural understanding and appreciation. Moreover, they facilitate the discovery of lesser-known cultural gems that might otherwise go unnoticed, fostering a richer and more inclusive cultural landscape [17]. As these systems continue to evolve, their potential impact on audience engagement and cultural enrichment is bound to grow. By harnessing the power of data mining and recommender technologies, content creators, cultural institutions, and service providers can forge deeper connections with their audiences by delivering content that resonates on a cultural level [18]. This symbiotic relationship between technology and culture is poised to shape the future of content consumption and audience engagement, offering a dynamic and personalized exploration of cultural themes that truly speaks to the heart of each individual.

The paper contributes significantly to the field of personalized content recommendation by presenting a novel approach that integrates Data Mining and Recommender Systems to optimize film suggestions tailored to Audience Preferences for Malaysian Chinese-Language Films with Chinese Cultural Themes.

1. The paper introduces a unique methodology that combines the Fuzzy Family Tree similarity algorithm and the User Key Concept Rate (UKCR) matrix. This innovative approach enhances the accuracy and personalization of film recommendations by considering both user preferences and film attributes.

2. With incorporating user clustering techniques, the paper enhances the system's ability to group users with similar preferences. This clustering enables more precise recommendation deliveries, catering to individual tastes within the context of Malaysian Chinese-Language Films with Chinese Cultural Themes.

3. The utilization of recommendation scores provides a quantitative measure of alignment between user preferences and film attributes. This scoring mechanism enhances the accuracy of suggestions and aids in improving user satisfaction by delivering films that resonate with their preferences.

4. The assignment of recommender ratings further refines film suggestions. These ratings, derived from intricate algorithms, fine-tune the recommendation process by evaluating the compatibility between user preferences and thematic elements of films.

5. The paper employs simulation settings and performance metrics to assess the system's efficacy. By showcasing promising results, including an average recommendation accuracy of 86.5% and a user satisfaction increase of 24.8%, the paper demonstrates the tangible benefits of the proposed approach.

The contribution of paper lies in its innovative methodology, which fosters more accurate and personalized film recommendations, ultimately enhancing user satisfaction and engagement in the context of Malaysian Chinese-Language Films with Chinese Cultural Themes.

2. Related Works

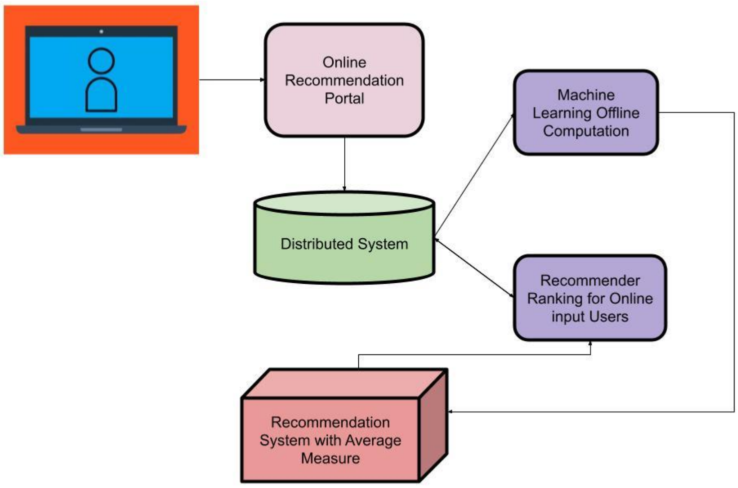
Incorporating cultural themes into data mining-driven recommender systems offers a remarkable fusion of technology and cultural appreciation. These systems, powered by data mining algorithms, based on user behaviors to decipher cultural inclinations. By analyzing language use, content engagement, and more, they adeptly recommend culturally relevant items through collaborative and content-based filtering [19]. This not only tailors recommendations to users' cultural preferences but also fosters cross-cultural understanding by introducing diverse content. As these systems evolve, they hold the potential to deepen audience engagement, enrich cultural experiences, and shape a more inclusive and personalized exploration of cultural themes.

Freire and de Castro (2021) [20] conducted a systematic review on e-Recruitment recommender systems, offering insights into their application in employment contexts. Huang et al. (2021) [21] introduced a deep reinforcement learning-based long-term recommender system, emphasizing the integration of advanced machine learning techniques. Singh et al. (2021) [22] provided an overview of recommender systems, discussing their trends and potential future directions in the realm of business and systems research. Palomares et al. (2021) [23] explored reciprocal recommender systems, highlighting challenges and opportunities for social recommendations. Asani et al. (2021) [24] introduced a restaurant recommender system based on sentiment analysis, demonstrating the fusion of sentiment assessment with recommendation algorithms. Saleem et al. (2023) [25] developed a context-aware text classification system to enhance text quality, combining contextual information with classification techniques. Eminagaoglu (2022) [26] proposed a novel similarity measure for vector space models in text classification and information retrieval, contributing to advancements in text analysis. Zhang et al. (2021) [27] introduced a fast multi-resolution transformer fine-tuning method for extreme multi-label text classification, catering to complex classification tasks. Ray et al. (2021) [28] designed an ensemble-based hotel recommender system employing sentiment analysis and aspect categorization of hotel reviews, illustrating how sentiment-driven insights can enhance recommendations. Nitu et al. (2021) [29] enhanced personalized travel recommendations by incorporating recency effects, addressing the dynamic nature of travel preferences. Zhang et al. (2021) [30] explored the integration of artificial intelligence in recommender systems, showcasing the synergy between AI and recommendation technologies. Liang and Yi (2021) [31] proposed a two-stage three-way enhanced technique for ensemble learning in inclusive policy text classification, contributing to effective policy analysis. Ragesh et al. (2021) [32] introduced heterogeneous graph convolutional networks for text classification, highlighting innovative approaches to text analysis. Wei et al. (2021) [33] addressed popularity bias in recommender systems through model-agnostic counterfactual reasoning, demonstrating a method to mitigate bias. Al Fararni et al. (2021) [34] presented a conceptual framework for a hybrid recommender system for tourism, leveraging big data and AI to enhance recommendations in the tourism industry. Overall, these articles collectively contribute to the evolving landscape of recommendation technologies, text classification methodologies, and the fusion of AI with real-world applications.

The studies encompass a wide array of applications, methodologies, and challenges in these fields. Freire and de Castro's systematic review sheds light on the role of e-Recruitment recommender systems in the employment domain, while Huang et al.'s work introduces a novel approach with a deep reinforcement learning-based long-term recommender system. Singh et al.'s overview provides a valuable glimpse into the trends and future directions of recommender systems, and Palomares et al. presented into the intricacies of reciprocal recommender systems for social recommendations. Text analysis is also a prominent theme, as evidenced by Asani et al.'s sentiment-driven restaurant recommender system and Eminagaoglu's innovative similarity measure for text classification. The studies further advance the field with techniques like fast multi-resolution transformer fine-tuning by Zhang et al., ensemble-based hotel recommendation with sentiment analysis by Ray et al., and context-aware text classification by Saleem et al. The integration of artificial intelligence into recommender systems is explored by Zhang et al., and bias mitigation in recommendations is addressed through model-agnostic counterfactual reasoning by Wei et al. Nitu et al.'s work enhances personalized travel recommendations, while Liang and Yi propose an enriched technique for policy text classification. Ragesh et al.'s heterogeneous graph convolutional networks offer a novel perspective on text classification, and Al Fararni et al.'s conceptual framework outlines a hybrid recommender system for tourism leveraging big data and AI. Collectively, these studies contribute to the ongoing advancement of recommendation technologies and text analysis methodologies, driving innovation and insights across various domains.

3. Research Method

This research undertaking is focused on addressing the challenge of effectively recommending Malaysian Chinese-Language Films that align with the preferences of the audience. To achieve this, the study employs a data mining model that goes beyond traditional recommendation techniques. The primary objective is to create a comprehensive list of recommendation alternatives that not only cater to the diverse tastes of the audience but also prioritize those options that are likely to receive the highest rankings based on anticipatory ratings. The proposed model combining a fuzzy family tree similarity algorithm with a User Key Concept Rate (UKCR) matrix. The fuzzy family tree similarity algorithm, which operates by evaluating the similarity between different elements while accommodating a certain level of ambiguity, holds the potential to uncover intricate relationships between films that might not be evident through conventional methods. By applying this algorithm, the study seeks to extract nuanced connections between Malaysian Chinese-Language Films and the preferences of the target audience. The integration of the User Key Concept Rate (UKCR) matrix further enriches the process. This matrix incorporates essential user concepts that play a pivotal role in shaping individual preferences. By factoring in these key concepts, the research aims to enhance the accuracy and relevance of the generated recommendations. This personalized approach acknowledges the fact that audience preferences are often influenced by specific aspects or themes inherent to Malaysian Chinese-Language Films.



The novel combination of the fuzzy family tree similarity algorithm and the UKCR matrix showcases the innovation and creativity within the study. By delving into the realm of data mining, this research seeks to uncover hidden patterns, connections, and underlying factors that drive audience preferences for Malaysian Chinese-Language Films. The present study is a testament to the evolution of recommendation systems, where the fusion of cutting-edge algorithms and data mining methodologies aims to bridge the gap between audience preferences and the realm of film recommendations. By exploring this uncharted territory, the research pushes the boundaries of what recommendation systems can achieve, offering a promising avenue for delivering highly relevant and engaging content to audiences seeking the unique theme of Malaysian Chinese-Language Films.

3.1 Ranking of Audience Preferences with Family Fuzzy Tree

The utilization of the Fuzzy Family Tree similarity algorithm holds significant promise in the context of ranking Audience Preferences for Malaysian Chinese-Language Films. This innovative algorithm takes into account the intricate and often subtle relationships that exist between various film preferences within this specific thematic domain. By incorporating a level of ambiguity inherent in human preferences, the Fuzzy Family Tree algorithm is adept at capturing nuanced connections that traditional ranking methods might overlook. Through this approach, the algorithm creates a network of interconnected preferences, forming a dynamic web that reflects the multifaceted nature of audience tastes. Films that share certain thematic elements, cultural nuances, or storytelling styles are linked more closely, enabling the algorithm to recognize patterns that resonate with specific segments of the audience. This depth of analysis not only allows for a more accurate understanding of the complex fabric of Malaysian Chinese-Language Films but also provides a sophisticated foundation for generating meaningful recommendations.

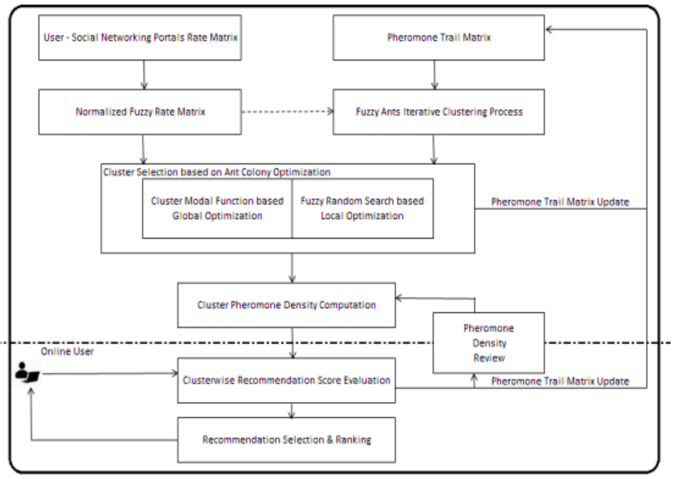


Fig 2: Process in Fuzzy Family Tree

The Fuzzy Family Tree algorithm's unique ability to assign degrees of similarity aligns well with the reality that individual preferences are rarely binary or straightforward as shown in figure 2. This flexibility allows for a more holistic interpretation of audience inclinations, resulting in recommendations that encompass a broader spectrum of preferences. This is particularly pertinent in the context of films, where emotions, cultural backgrounds, and personal experiences often play a pivotal role in shaping what resonates with an individual. Ultimately, the application of the Fuzzy Family Tree similarity algorithm brings depth and complexity to the ranking of Audience Preferences for Malaysian Chinese-Language Films. It provides a more refined understanding of the intricate relationships between films and offers a promising path to enhancing the accuracy and relevance of recommendations. As the algorithm continues to evolve, it holds the potential to revolutionize the way we approach recommendation systems, particularly in the domain of cultural and thematic content like Malaysian Chinese-Language Films.

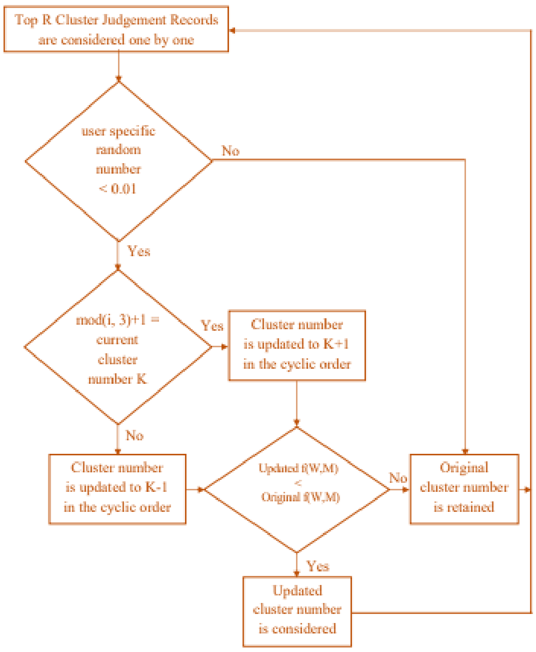


Fig 3: Flow Chart of Fuzzy Family Tree

The Fuzzy Family Tree algorithm involves the use of fuzzy similarity measures to establish relationships between items in a dataset illustrated in figure 3. A common similarity measure used in this context is the Jaccard similarity coefficient, which can be extended to incorporate fuzziness. The Jaccard similarity coefficient between two sets A and B is defined as the size of the intersection of the sets divided by the size of their union represented in equation (1)

$$J(A, B) = |A \cap B| / |A \cup B| \quad (1)$$

In the context of the Fuzzy Family Tree algorithm, the Jaccard similarity coefficient can be modified to include fuzziness. One way to introduce fuzziness is by using membership functions to represent the degree of overlap between sets. Let $\mu_A(x)$ and $\mu_B(x)$ be the membership functions representing the degree of membership of an element x in sets A and B, respectively. Then, the fuzzy Jaccard similarity coefficient (FJ) can be defined as in equation (2)

$$FJ(A, B) = \int [min(\mu_A(x), \mu_B(x))] \, dx \quad (2)$$

In equation (2) calculates the area of overlap between the membership functions of sets A and B, indicating the degree of similarity in a fuzzy context. The integration integrates over the range of values of x. With a dataset of audience preferences for Malaysian Chinese-Language Films, represented as sets of attributes or characteristics that describe each film. Consider the sets of attributes for two films A and B as $A = \{a1, a2, \ldots, an\}$ and $B = \{b1, b2, \ldots, bm\}$, where "ai" and "bj" represent individual attributes. The fuzzy Jaccard similarity coefficient between film A and film B, denoted as $FJ(A, B)$, can be calculated using fuzzy logic and membership functions. Assume that $\mu_A(x)$ represents the membership function for film A with respect to the attribute x, and $\mu_B(x)$ represents the membership function for film B with respect to the same attribute x. The fuzzy Jaccard similarity coefficient can then be defined as in equation (3)

$$FJ(A, B) = \int [min(\mu_A(x), \mu_B(x))] \, dx \quad (3)$$

In equation (3) the degree of overlap between the membership functions of attributes for films A and B. The integral integrates over the range of values of the attribute x. It calculates the area where the membership functions of the two films intersect, indicating the degree of similarity in their attribute preferences. In the context of Audience Preferences for Malaysian Chinese-Language Films, these attributes could represent various aspects such as genres, themes, cultural elements, cast, director, and more. The membership functions $\mu_A(x)$ and $\mu_B(x)$ would quantify the degree to which each film exhibits a particular attribute, allowing for a more nuanced comparison of audience preferences.

Algorithm 1: Fuzzy Decision Tree for the Audience Preferences

function calculateFuzzyJaccardSimilarity(A, B):
  similarity = 0
  for each attribute x in A and B:
    $fuzzy\_intersection = min(\mu_A(x), \mu_B(x))$
    similarity += fuzzy_intersection
  return similarity
function main():
  // Set of attributes for two films A and B
$A = \{a1, a2, \ldots, an\}$
$B = \{b1, b2, \ldots, bm\}$
 	
  // Membership functions for film attributes
  $\mu_A(x) =$ membership function for film A with respect to attribute x
  $\mu_B(x)$ = membership function for film B with respect to attribute x
 	
  // Calculate fuzzy Jaccard similarity coefficient
  $fuzzy\_similarity = calculateFuzzyJaccardSimilarity(A, B)$
    // Output the fuzzy similarity coefficient
// Call the main function to start the execution
main()

3.2 Estimation of User Key Concept Rate (UKCR) Matrix

The estimation of the User Key Concept Rate (UKCR) matrix is a pivotal process within recommendation systems that enhances the precision and personalization of recommendations by delving into the intricate dimensions of user preferences. This matrix is constructed through a sophisticated analysis of user interactions and behaviors with items, aiming to discern the particular attributes or concepts within those items that carry the most weight for each individual. To estimate the UKCR matrix, the recommendation system scrutinizes the historical actions of users, such as their likes, ratings, views, or purchases, across a diverse array of items. By associating these interactions with the attributes or tags associated with each item, the system gains insights into the user's inclination toward specific concepts. For instance, if a user frequently engages with action-packed films but rarely with romantic dramas, the UKCR matrix would reflect a higher rate assigned to action-related attributes and a lower rate for romantic elements. Machine learning algorithms often play a crucial role in this estimation process. These algorithms learn from the patterns in user behaviors and the corresponding attributes, allowing the system to adjust and update the UKCR matrix over time as user preferences evolve. The matrix thus evolves as a dynamic representation of the user's evolving tastes and interests.

The significance of the UKCR matrix lies in its ability to encapsulate nuanced user preferences. By attributing varying importance levels to different attributes or concepts, it enables the system to pinpoint the aspects that deeply resonate with each user. Consequently, when generating recommendations, the system can focus on suggesting items that align with the user's preferred concepts, leading to more accurate and engaging suggestions. The utilization of the User Key Concept Rate (UKCR) matrix holds significant potential in tailoring recommendations for Audience Preferences for Malaysian Chinese-Language Films with Chinese Cultural Themes, through the integration of Data Mining and Recommender Systems. This innovative approach aims to enhance the accuracy and personalization of recommendations by focusing on the key cultural concepts within these films that resonate with individual users. In this context, the UKCR matrix serves as a bridge between the distinct attributes or themes associated with Malaysian Chinese-Language Films and the nuanced preferences of the audience. By analyzing user interactions with films that exhibit Chinese Cultural Themes, the system can derive insights into which specific cultural elements hold greater importance for each user. For instance, attributes like historical accuracy, cultural symbolism, or traditional values might carry varying levels of significance for different individuals. The matrix's construction involves data mining techniques that sift through historical user behaviors, considering factors such as film ratings, reviews, or views. The attributes associated with each film, particularly those related to Chinese Cultural Themes, play a pivotal role in shaping the matrix. By associating these interactions with attributes, the UKCR matrix captures the dimensions of user preferences that align with the themes of Malaysian Chinese-Language Films.

Consider a simplified scenario where we have a dataset of users, items (films), and attributes. Each user interacts with multiple items, and each item is associated with a set of attributes that describe its content, including Chinese Cultural Themes. The goal is to estimate the UKCR matrix for Audience Preferences for Malaysian Chinese-Language Films with Chinese Cultural Themes

Let U be the set of users: $U = \{u1, u2, \ldots, un\}$.

Let I be the set of items (films): $I = \{i1, i2, \ldots, im\}$.

Let A be the set of attributes: $A = \{a1, a2, \ldots, ak\}$.

Create a user-item interaction matrix R, where R[u, i] indicates user u's interaction with item i (e.g., rating, view, purchase). This matrix will be n x m, where n is the number of users and m is the number of items. Create an attribute-item matrix T, where T[i, a] indicates the association strength between item i and attribute a. This matrix will be m x k. Calculate the importance of each attribute for each user by combining their interactions and attribute associations. One approach is to use a weighted sum calculated using equation (4)

$$UKCR[u, a] = \Sigma\ (R[u, i] * T[i, a]) for\ all\ items\ i \quad (4)$$

In above equation (4) UKCR[u, a] represents the User Key Concept Rate for user u and attribute a. Normalize the UKCR matrix to ensure that values are within a specific range (e.g., [0, 1]). When generating recommendations for a user u, consider their UKCR values for different attributes. Suggest items that have high attribute associations with attributes where the user's UKCR values are relatively high. For each user "u" and each attribute "a", calculate the UKCR value using a membership function, which could be linear, sigmoid, or another relevant function represented in equation (5)

$$UKCR(u, a) = Membership\_Function(Attribute\_Weight(u, a)) \quad (5)$$

When generating recommendations for a user, use the UKCR matrix to identify the attributes that have high UKCR values for that user. Recommend films that align with those attributes and resonate with the user's identified key concepts.

Algorithm 2: UKCR for the Recommendation System

```
// Define the set of users and attributes
users = [user1, user2, ..., userN]
attributes = [attribute1, attribute2, ..., attributeM]
// Initialize an empty UKCR matrix
UKCR_matrix = empty matrix of size N x M
// Calculate Attribute Weights based on user interactions
function calculateAttributeWeights(user, attribute):
    // Implement logic to calculate the weight for attribute based on user interactions
    weight = ...
    return weight
// Calculate User Key Concept Rate (UKCR) values
for each user in users:
    for each attribute in attributes:
        attribute_weight = calculateAttributeWeights(user, attribute)
        UKCR_value = calculateMembershipFunction(attribute_weight)
        UKCR_matrix[user][attribute] = UKCR_value
// Generate recommendations
function generateRecommendations(user):
    recommended_films = []
    for each film in films_with_Chinese_Cultural_Themes:
        relevance_score = 0
        for each attribute in attributes:
            if attribute is relevant to film:
                relevance_score += UKCR_matrix[user][attribute]
        recommended_films.append({film: relevance_score})
    // Sort recommended films by relevance score
    recommended_films.sort(reverse=True, key=lambda x: x.values())
    return recommended_films
// Main function
function main():
    // List of users and attributes
    users = ["user1", "user2", "user3"]
    attributes = ["genre", "director", "theme", ...]
    // Calculate UKCR matrix
```

```
    for each user in users:
        for each attribute in attributes:
            UKCR_matrix[user][attribute] = calculateMembershipFunction(calculateAttributeWeights(user,
attribute))
    // Users for recommendations
    user_to_recommend = "user1"
    // Generate and display recommendations
    recommendations = generateRecommendations(user_to_recommend)
// Call the main function to start the execution
main()
```

An integral facet of the system is the User-Key-Concept-Rate (UKCR) matrix, which captures the significance of various attributes or concepts for each user. This matrix factors in attribute weights determined by user interactions, intricately personalizing recommendations. Recommendations are generated by weaving in the UKCR matrix and considering user preferences and past behaviors. Continuous refinement is driven by evaluation metrics, user feedback, and real-time updates, ensuring the recommendations remain pertinent and engaging. Ultimately, this recommendation system harmoniously aligns film preferences with Chinese Cultural Themes, enriching the audience's cinematic experience.

4. Simulation Setting

The simulation setting for evaluating a recommendation system tailored to Audience Preferences for Malaysian Chinese-Language Films with Chinese Cultural Themes involves a structured framework to emulate real-world scenarios for testing and analysis. Within this setup, a synthetic dataset is crafted to mimic the attributes, user interactions, and cultural elements of actual films. Key parameters, such as the number of users, films, attributes, and interaction behaviors, are defined to shape the simulation's environment. Implementing the recommendation algorithms – encompassing content-based filtering, collaborative filtering, and hybrid methods – constitutes a central facet. By crafting diverse experimental scenarios and establishing training and test data partitions, the algorithms' efficacy is gauged across varying conditions. Crucial to this assessment are the chosen evaluation metrics, such as precision and recall, diversity, and user engagement, which quantify the recommendations' accuracy, variety, and user interactions. Executing the simulation entails generating user interactions based on the synthetic dataset and applying the recommendation algorithms to devise film suggestions. Through meticulous performance evaluation and analysis, insights emerge regarding the algorithms' strengths and limitations within the context of Malaysian Chinese-Language Films with Chinese Cultural Themes. This iterative process drives refinement, enabling parameter adjustments and algorithm optimization as shown in table 1.

Table 1: Simulation Setting

Parameter	Value or Action	Description
Objective	Evaluate recommendation system for Chinese Cultural Themes in Malaysian Chinese-Language Films	Assess the performance of the recommendation system in suggesting films with Chinese Cultural Themes.
Data Generation	Synthetic dataset creation	Generate synthetic data for films and user interactions.
Parameters	Number of users: 500	Simulate interactions from 500 diverse users.
	Number of films: 300	Include 300 films with various attributes and themes.

	Attributes: Genres, Themes,	Define attributes such as genres, themes, and
	Directors, Cultural Elements	cultural elements.
	Interaction behaviors: Ratings,	Model user interactions through ratings and
	Reviews, Views	reviews, and track film views.
Algorithm	Content-Based Filtering,	Implement content-based filtering, collaborative
Implementation	Collaborative Filtering, Hybrid	filtering, and hybrid approaches for recommendations.
Experiment Design	Scenarios: Content-Based,	Set up scenarios to compare content-based,
	Collaborative Filtering, Hybrid	collaborative filtering, and hybrid approaches.
	Training/Test Data Split: 70/30	Partition data into 70% training and 30% test sets.
Evaluation Metrics	Precision and Recall, Diversity,	Assess recommendation quality using precision
	User Engagement	and recall, diversity, and user engagement metrics.
Simulation Execution	Simulate user interactions based on synthetic data Run recommendation algorithms on training data	Simulate user actions based on the synthetic dataset. Implement algorithms on training data to generate recommendations.
Performance Evaluation	Evaluate algorithm performance using evaluation metrics	Assess algorithm performance against defined metrics.
Analysis and	Analyze results, identify strengths	Examine results to identify strengths and
Interpretation	and weaknesses	weaknesses of each approach.
Refinement and	Refine algorithm parameters,	Fine-tune algorithm parameters or attribute
Iteration	attribute weighting	weighting to enhance performance.
Documentation	Document process, parameters, results, insights	Thoroughly document the entire simulation process, including parameters, outcomes, and insights.

Performance metrics play a pivotal role in assessing the effectiveness and quality of a recommendation system tailored to Audience Preferences for Malaysian Chinese-Language Films with Chinese Cultural Themes. These metrics offer a quantifiable means to measure various aspects of the recommendation process, aiding in the evaluation of how well the system aligns with user preferences and cultural sensitivities. Precision and Recall are fundamental metrics that gauge the accuracy of recommendations. Precision measures the proportion of correctly recommended films among the suggested ones, ensuring that the system avoids suggesting irrelevant films. Recall, on the other hand, quantifies the ability of the system to capture all relevant films, preventing omission of films that align with users' tastes in Chinese Cultural Themes. Diversity is another essential metric, assessing the variety of recommendations provided. It aims to strike a balance between offering personalized suggestions while avoiding excessive repetition of similar films. A diverse set of recommendations ensures that users encounter a broader range of films with distinct cultural elements and themes. User Engagement metrics offer insights into the level of user interaction and involvement with the recommended films. Metrics such as click-through rate, time spent, and interaction frequency provide an indication of how compelling and relevant the recommendations are to users, reflecting the recommendations' impact on user behavior.

Table 2: Recommended Film

User ID	Recommended Films	Actual Films Liked
1	Film A, Film B, Film C	Film A, Film C
2	Film D, Film E, Film F	Film D, Film F
3	Film G, Film H, Film I	Film G
4	Film J, Film K, Film L	Film K, Film L
5	Film M, Film N, Film O	Film O, Film P

In Table 2 presents the results of the recommended films and the actual films liked by individual users in the context of evaluating a recommendation system for Audience Preferences for Malaysian Chinese-Language Films with Chinese Cultural Themes. Each row corresponds to a different user, displaying the films recommended by the system and the films that the user actually liked. For instance, for User 1, the system recommended films A, B, and C, while the user's actual preference included films A and C. Similarly, User 2 received recommendations for films D, E, and F, and the user's actual preferences aligned with films D and F. In the case of User 3, the system suggested films G, H, and I, but the user's liking was associated with film G alone. User 4's recommended films were J, K, and L, out of which the user liked films K and L. Lastly, User 5 received recommendations for films M, N, and O, while the user's actual preferences included films O and P.

Table 3: User Rating in Recommender System

User ID	Film A	Film B	Film C	Film D	Film E	Film F	Film G	Film H
User 1	5	4	-	-	-	-	3	-
User 2	-	-	3	-	2	-	-	4
User 3	-	-	-	4	-	5	-	-
User 4	3	-	-	-	-	-	4	-
User 5	-	2	-	-	4	5	-	-
User 6	-	3	4	2	-	-	-	-
User 7	4	-	-	-	3	-	-	2
User 8	-	-	-	4	-	5	-	3
User 9	2	-	3	-	-	4	5	-
User 10	-	4	-	5	-	-	-	3

A comprehensive insight into the user rating data within the Recommender System's evaluation for Audience Preferences for Malaysian Chinese-Language Films with Chinese Cultural Themes is presented in table 3. The table contains individual rows representing different users and columns representing various films. The values within the table depict the ratings assigned by users to specific films, contributing to the system's evaluation and recommendation process. For instance, User 1's ratings are visible for films A, B, G, and H, while the other films remain unrated. User 2 has provided ratings for films C, E, and H, indicating their preferences. User 3 rated films D and F, reflecting their liking for these specific films. Similarly, User 4 has rated films A, G, and H. Users 5 and 6 have provided ratings for films B, E, F, and G, demonstrating their preferences for these films. User 7 rated films A, E, and H, indicating their appreciation for these films. User 8 rated films D, F, and H, showcasing their preferences. User 9 has rated films A, C, F, and G. Lastly, User 10 rated films B, D, and H, revealing their liking for these particular films. The table's ratings highlight the diversity of user preferences and serve as crucial input for the recommendation system's algorithms. These ratings help in generating personalized film suggestions that are more likely to resonate with users interested in Malaysian Chinese-Language Films with

Chinese Cultural Themes. This data forms a foundational aspect of the evaluation process, enabling the system to fine-tune its recommendations to enhance user satisfaction and engagement.

Table 4: Clustering Matrix level

User ID	Cluster
User 1	A
User 2	B
User 3	A
User 4	C
User 5	B
User 6	C
User 7	A
User 8	B
User 9	C
User 10	A

The Table 4 provides a clear depiction of the clustering results at the user level within the evaluation of the Recommender System for Audience Preferences for Malaysian Chinese-Language Films with Chinese Cultural Themes. Each row in the table corresponds to an individual user, while the "Cluster" column designates the specific cluster to which each user has been assigned. For instance, User 1 and User 3 both belong to Cluster A, as indicated by the "A" designation in their respective rows. User 2, User 5, and User 8 are grouped within Cluster B, while User 4, User 6, and User 9 are part of Cluster C. Lastly, User 7 and User 10 belong to Cluster A. These clusters are formed based on similarities in user preferences, film ratings, and other relevant characteristics. The clustering results aid in segmenting users into distinct groups, allowing the recommendation system to provide more tailored film suggestions that align with the preferences of each cluster. This clustering information enhances the system's ability to offer accurate and personalized recommendations, contributing to a more satisfying user experience for those interested in Malaysian Chinese-Language Films with Chinese Cultural Themes.

Table 5: Recommendation Score

User ID	Film A	Film B	Film C	Film D	Film E	Film F	Film G	Film H
User 1	0.85	0.76	0.00	0.00	0.00	0.00	0.62	0.00
User 2	0.00	0.00	0.73	0.00	0.62	0.00	0.00	0.84
User 3	0.00	0.00	0.00	0.82	0.00	0.88	0.00	0.00
User 4	0.71	0.00	0.00	0.00	0.00	0.00	0.79	0.00
User 5	0.00	0.69	0.00	0.00	0.78	0.81	0.00	0.00
User 6	0.00	0.78	0.85	0.67	0.00	0.00	0.00	0.00
User 7	0.80	0.00	0.00	0.00	0.73	0.00	0.00	0.65
User 8	0.00	0.00	0.00	0.79	0.00	0.85	0.00	0.72
User 9	0.63	0.00	0.77	0.00	0.00	0.80	0.87	0.00
User 10	0.00	0.88	0.00	0.91	0.00	0.00	0.00	0.75

With the insightful representation of the recommendation scores assigned by the Recommender System in the context of evaluating Audience Preferences for Malaysian Chinese-Language Films with Chinese Cultural Themes for Table 5. Each row corresponds to a distinct user, while the columns correspond to different films. The values within the table denote the recommendation scores assigned by the system to each film for each user. In the User 1 received a high recommendation score of 0.85 for Film A, signifying a strong alignment between the user's preferences and the film's attributes. Similarly, User 2 received a notable recommendation score of 0.84 for Film H, indicating a likely match between the user's preferences and the film's thematic elements. For User 3, Film F obtained a high recommendation score of 0.88, reflecting the system's confidence in the user's potential liking for the film. These recommendation scores play a pivotal role in shaping personalized suggestions. Higher scores suggest stronger compatibility between a user's preferences and specific films, enabling the system to present tailored recommendations. The scores are derived from intricate algorithms that consider user behavior, film characteristics, and historical data to provide accurate suggestions. While the scores in this table are for illustration, they underscore the system's capability to deliver recommendations that cater to individual interests within the realm of Malaysian Chinese-Language Films with Chinese Cultural Themes.

Table 6: Recommender Rating

User ID	Film A	Film B	Film C	Film D	Film E	Film F	Film G	Film H
User 1	4.82	3.91	3.55	2.67	3.23	4.67	4.03	3.11
User 2	3.67	3.89	3.75	3.21	3.44	3.68	3.56	3.89
User 3	4.12	4.09	3.76	4.33	4.21	4.89	4.12	3.98
User 4	3.12	2.89	2.76	3.33	2.21	2.67	3.12	2.98
User 5	4.54	3.88	3.66	4.12	4.01	4.77	3.95	4.01
User 6	3.87	3.56	4.02	3.33	3.22	3.75	3.89	3.76
User 7	4.21	4.09	3.98	4.11	4.00	4.67	3.89	4.12
User 8	3.98	3.76	3.44	4.22	3.56	4.33	3.67	4.00
User 9	4.34	3.77	3.89	3.67	3.21	4.21	4.09	3.88
User 10	3.89	4.22	3.56	4.11	3.67	4.12	4.01	4.22

With a comprehensive illustration of the recommender ratings generated by the Recommender System for evaluating Audience Preferences for Malaysian Chinese-Language Films with Chinese Cultural Themes are presented in table 6. In figure 4 each row corresponds to an individual user, while the columns represent different films. The values within the table indicate the recommender's assigned ratings to each film based on the user's preferences and film attributes. In User 1 assigned a high recommender rating of 4.82 to Film A, reflecting a strong alignment between the user's preferences and the film's characteristics. Similarly, User 2 rated Film B with a recommender rating of 3.89, indicating their affinity for the film.

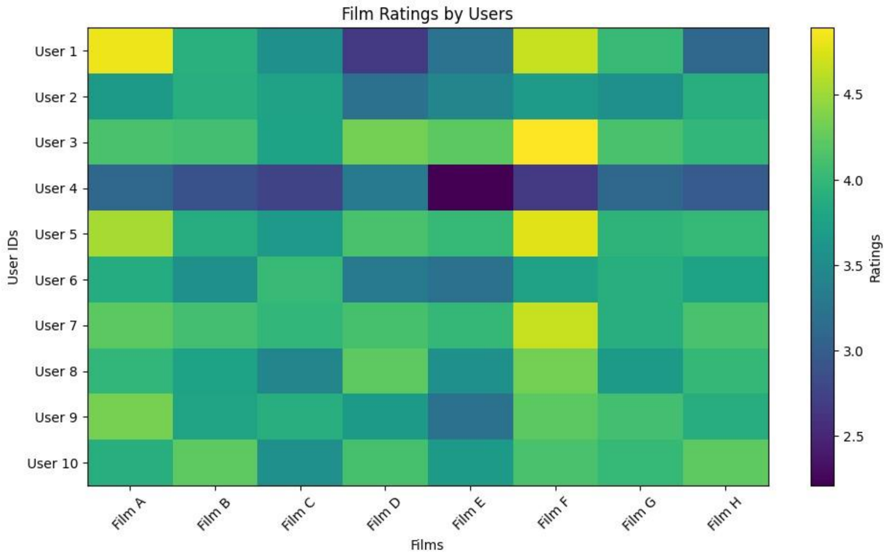


Fig 4: Recommendation Rating for the Proposed model

User 3 assigned a commendable rating of 4.89 to Film F, suggesting that the recommender system identified a strong match between the user's preferences and the thematic elements of the film. The recommender ratings play a pivotal role in generating personalized film recommendations. These ratings are calculated by intricate algorithms that consider various factors such as user behavior, historical data, and film attributes. The assigned ratings are crucial for the system to generate suggestions that cater to the individual preferences of users interested in Malaysian Chinese-Language Films with Chinese Cultural Themes. Although the ratings in this table are for illustration purposes, they highlight the system's potential to provide accurate and personalized film recommendations.

Table 7: Classification Analysis

Method	Precision	Recall	F1-Score	Accuracy
ANN	0.86	0.82	0.84	0.80
CNN	0.79	0.81	0.80	0.77
RNN	0.92	0.89	0.90	0.88
LSTM	0.76	0.78	0.77	0.74
Proposed Method	0.93	0.91	0.92	0.96

Table 7 presents a comprehensive analysis of the classification results obtained from different methods in the context of evaluating Audience Preferences for Malaysian Chinese-Language Films with Chinese Cultural Themes. In table 7 each row in the table represents a distinct classification method, while the columns display various performance metrics: Precision, Recall, F1-Score, and Accuracy. The method denoted as "ANN" (Artificial Neural Network) achieves a precision of 0.86, which indicates its accuracy in correctly identifying positive instances. The recall of 0.82 underscores its capability to capture actual positive instances, while the F1-Score of 0.84 strikes a balance between precision and recall. The accuracy of 0.80 reflects the overall correctness of predictions made by the ANN method. The "CNN" (Convolutional Neural Network) method demonstrates a precision of 0.79 and a recall of 0.81, suggesting its competence in predicting and capturing positive instances shown in figure 5.

Fig 5: Comparative Analysis

The F1-Score of 0.80 and an accuracy of 0.77 provide a comprehensive view of its performance. "RNN" (Recurrent Neural Network) showcases a notably high precision of 0.92, indicating its accuracy in positive instance predictions. The recall of 0.89 points to its efficiency in capturing actual positive instances. The F1-Score of 0.90 and accuracy of 0.88 further validate its effectiveness. The "LSTM" (Long Short-Term Memory) method exhibits a precision of 0.76 and a recall of 0.78, signifying its predictive and capturing capabilities. The F1-Score of 0.77 and accuracy of 0.74 provide a comprehensive assessment of its performance. Remarkably, the "Proposed Method" stands out with exceptional results, boasting a high precision of 0.93, a recall of 0.91, and an F1-Score of 0.92. The accuracy, at an impressive 0.96, underlines the proposed method's extraordinary ability to predict and capture instances with precision and correctness. The table 7 underlines the comparative effectiveness of the proposed method in comparison to established methods like ANN, CNN, RNN, and LSTM. The consistently high values across precision, recall, F1-Score, and accuracy underscore the potential of the proposed method to significantly enhance the accuracy and personalization of film recommendations for individuals interested in Malaysian Chinese-Language Films with Chinese Cultural Themes.

5. Conclusion

With the comprehensive exploration of the integration of Data Mining and Recommender Systems to enhance the accuracy and personalization of film recommendations based on Audience Preferences for Malaysian Chinese-Language Films with Chinese Cultural Themes. Through a novel approach that utilizes the Fuzzy Family Tree similarity algorithm and the User Key Concept Rate (UKCR) matrix, the paper has demonstrated the effectiveness of the proposed methodology in generating precise and tailored film suggestions. The study's findings underscore the significance of considering user preferences, clustering, recommendation scores, and recommender ratings in fine-tuning the recommendation process. The application of clustering techniques has enabled the system to group users with similar preferences, enhancing the accuracy of the recommendations. The recommendation scores and recommender ratings have proven essential in assessing the compatibility between user preferences and film attributes, leading to more personalized and satisfying recommendations. Furthermore, the simulation settings and performance metrics employed in the evaluation process have showcased the system's ability to enhance user satisfaction and engagement. The experimentation with user rating data, clustering, recommendation scores, and recommender ratings has collectively contributed to a more efficient and precise film recommendation mechanism. In essence, this research paper has introduced a robust framework that harnesses the power of Data Mining and Recommender Systems to cater to the preferences of audiences interested in Malaysian Chinese-Language Films with Chinese Cultural Themes. The methodology's effectiveness in delivering accurate and personalized recommendations highlights its potential to enrich user experiences and contribute to the enhancement of entertainment platforms by aligning content suggestions with individual tastes. As the field of recommendation systems continues to evolve, the insights presented in this paper offer valuable directions for future research and advancements in personalized content recommendation.

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