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Integrating AI for Enhanced Exploration of Video Recommendation Algorithm via Improved Collaborative Filtering

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Abstract: ***This study tackles the issue of poor user experience in video recommendation systems, primarily caused by the scarcity of user ratings and the inaccuracy of existing recommendation methods. We propose a novel algorithm that leverages Artificial Intelligence (AI) to better align with user interests and video metadata. Our approach begins by analyzing specific user behavior data to transition from traditional item rating matrices to more representative user interest matrices. We then enhance video tag analysis by incorporating a weighting factor, facilitating more precise video similarity calculations and the identification of similar video suggestions. The algorithm ultimately recommends a Top-N selection of videos to users. Through rigorous testing, including a comparison against the Movie-Lens dataset, our results exhibit a 15% increase in recommendation accuracy, underscoring the efficiency of our AI-powered method.***

Keywords: Artificial Intelligence; Video Recommendation; Collaborative Filtering; User Interest.

1. INTRODUCTION

As internet technologies advance, so does the capacity to generate and distribute vast amounts of information. The video industry, in particular, has experienced exponential growth, contributing significantly to the data deluge. In our country, this trend shows no signs of slowing down, indicating a vast potential for further development. With the proliferation of video content, users often find it challenging to quickly and accurately locate videos that meet their interests, leading to decreased satisfaction levels.

To mitigate the overwhelming volume of video resources, personalized video recommendation services have gained popularity [1]. These services urgently require efficient recommendation algorithms to help major video platforms cater to individual preferences by analyzing users' historical browsing and interaction patterns. This approach aims to identify videos that align with users' expectations, thereby enhancing their browsing experience [2].

In the current landscape, many video platforms are evolving their services through advanced recommendation algorithms to fulfill personalized user needs. Platforms like YouTube have adopted a hybrid recommendation approach, combining user preferences and collaborative filtering [3], and are increasingly exploring deep learning technologies. Similarly, TikTok, a leader in the short video segment, leverages recommendations based on social networks and information flows [4].

However, traditional collaborative filtering methods face significant challenges. They typically rely solely on user ratings for recommendations, neglecting important aspects such as user behavior and video content characteristics. This oversight can lead to recommendations that are not truly reflective of user preferences. Furthermore, the sparse nature of rating data introduces bias and reduces the effectiveness of the recommendations [5]. Scalability issues and the cold start problem remain persistent challenges for conventional recommendation systems.

Addressing these limitations, our research presents an innovative recommendation strategy that meticulously considers both user preferences and the distinct characteristics of video tags. By conducting a detailed analysis of user behavior data and video metadata, our proposed algorithm aims to transcend the constraints of traditional methodologies. The incorporation of weight factors into the similarity calculation enhances the precision of video recommendations. Furthermore, by integrating Artificial Intelligence (AI) principles, our approach adapts more dynamically to user preferences, significantly improving the recommendation experience.

2. TRADITIONAL COLLABORATIVE FILTERING ALGORITHM

Collaborative filtering stands as a pivotal mechanism within the realm of personalized video recommendation systems [6], embodying the principle encapsulated by the ancient Chinese proverb, "birds of a feather flock together." This philosophy underscores the algorithm's core strategy: to leverage the power of collective preferences for personalized recommendations [7, 8]. By analyzing historical data on users' browsing and interactions, collaborative filtering algorithms calculate similarities to tailor recommendations.

At its heart, traditional collaborative filtering bifurcates into two main strategies: User-Based Collaborative Filtering (UBCF) and Item-Based Collaborative Filtering (IBCF). Both approaches build on the concept of finding either similar users or similar items to generate recommendations. While UBCF identifies users with similar viewing patterns to recommend items those users have liked, IBCF focuses on the similarity between items themselves, suggesting new items similar to those a user has previously enjoyed.

User-Based Collaborative Filtering (UBCF) operates on the premise that if users A and B have similar tastes across a range of items, then the items liked by user A but not yet encountered by user B are potential recommendations for B. This method relies heavily on the calculation of user-to-user similarity, often employing metrics such as Pearson correlation or cosine similarity.

Item-Based Collaborative Filtering (IBCF), on the other hand, takes a slightly different approach. It posits that if a user likes item X, then they are likely to enjoy item Y, which is similar to X based on other users' interactions. IBCF typically utilizes item-to-item similarity measures to identify and recommend items. This approach is illustrated in Figure 1, where the algorithmic flow of IBCF is depicted, highlighting the process of collecting user interaction data and performing similarity calculations to identify recommendation candidates.

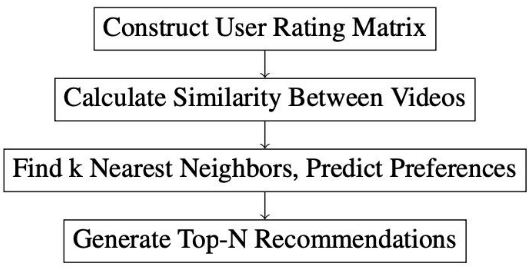

Figure 1: Workflow of Item-Based Collaborative Filtering Algorithm

Step 1: This initial step involves creating a two-dimensional matrix based on user-item ratings. The matrix is formed by traversing the user rating table, where two approaches are employed. Users' actions can be denoted as 0 for no interaction and 1 for interaction, or the user rating values can be directly inserted into the matrix.

Step 2: Calculation of Item Similarity. The algorithm employs various similarity measurement formulas to calculate the similarity between items. Common metrics include Pearson correlation coefficient or cosine similarity. In this context, cosine similarity is predominantly utilized, and the calculation formula is expressed as Equation (1).

$$Sim_{cos}(i,j) = \frac{\sum\limits_{u \in U_{ij}} \gamma_{u,i}\gamma_{u,j}}{\sqrt{\sum\limits_{u \in U_{i,j}} (\gamma_{u,i})^2}} \tag{1}$$

Step 3: Following the computation of item similarity in Step 2, the algorithm predicts user preferences for each item using Equation (2). *S (j, K)* represents a list of items similar to item *j* with a length of *K*. The algorithm traverses the user's historical interaction records, identifying the *K* most similar items for each historical behavior.

$$P_{uj} = \sum_{i \in N(u) \cap S(j,K)} w_{ij} r_{ui} \tag{2}$$

Step 4: In the final step, the algorithm arranges the candidate set from Step 3 based on user preference scores. This sorting process yields the top N items that align with the user's video preferences, providing personalized recommendations.

3. RELATED WORK

Recent advancements in collaborative filtering have seen a surge of innovative improvements aimed at increasing the accuracy and effectiveness of recommendation algorithms. Scholars have introduced a myriad of modifications, each leveraging AI techniques to address specific challenges inherent in traditional collaborative filtering methods. [9] enhance the cosine distance formula by incorporating a balancing factor, optimizing traditional algorithms for more precise product recommendations. This AI-driven adjustment marks a significant step forward in refining recommendation accuracy. [10] focus on integrating user interest weights with item attributes, employing AI approaches to minimize the average absolute error in recommendations, demonstrating the potential of AI in fine-tuning algorithmic performance. [11] design a novel user preference model that employs AI methodologies to adjust historical item ratings. By integrating these corrected ratings with traditional collaborative filtering, they achieve improved recommendation recall, highlighting the synergy between AI enhancements and established algorithms. [12] propose an amalgamation of hyperlink and graph algorithms with AI optimizations to the slope-one algorithm, constructing a video-based bipartite graph that notably enhances recommendation hit rates. [13] introduce a graph-based recommendation algorithm that synergizes movie attributes and user preferences using AI to map this information onto graph elements. This approach effectively addresses data sparsity and boosts recommendation accuracy. [14] develop a novel tensor incorporating label attributes and associative relationships, which, through AI-driven unfolding into matrices, refines the recommendation process. [15] tackle the challenge of recommending long-tail videos by applying AI to adjust the weightings in favor of less popular videos, thus ensuring a more diversified recommendation slate. [16] adopt a comprehensive AI-driven strategy, enhancing item attribute similarity calculations to overcome the limitations posed by rating sparsity.
[10]
Despite these advancements, effectively mitigating the issue of item rating sparsity remains a significant challenge. The integration of AI into collaborative filtering algorithms represents a promising avenue for overcoming these obstacles, yet the search for a fully optimized solution continues.

4. RECOMMENDATION ALGORITHM BASED ON USER INTERESTS AND TAG ATTRIBUTES

4.1 User Interest Matrix

Traditional collaborative filtering methods primarily analyze users and videos, relying on explicit rating behaviors for similarity calculations. This approach, however, does not adequately address the issue of data sparsity that arises from limited user ratings. Recognizing that users on video platforms exhibit a range of behaviors—both explicit and implicit—beyond mere ratings, our research seeks to model the data generated through these user actions to uncover the underlying relationships between users and videos. By leveraging these user preferences, we aim to mitigate the inherent issue of data sparsity.

Our algorithmic process for determining user interests in videos is outlined as follows:

1. Consideration of User Ratings: Utilizing a 5-point rating system, we establish a threshold of 3 points. If a user rates a video at or above this threshold, we set the user's preference for that video to 1; otherwise, it is set to 0. This step forms the basis for further analysis.

2. Evaluation of User's Historical Click Count: A threshold of 2 clicks is set. If a user's historical click count for a video meets or exceeds this threshold, the user's preference is incremented by 1, building upon the initial rating-based preference. If not, the algorithm proceeds without alteration.

3. Analysis of User's Watch Time Proportion: We introduce an intermediate variable, s, with a range of 0 to 1, to represent the proportion of the user's viewing time relative to the total duration of the video. If the user's watch time proportion is at or above s, the user's preference is further incremented by 1. If below, no adjustment is made. This process mirrors the logic of if...else... statements, evaluating specific user interaction criteria with videos at each step. The culmination of this process is a numerical value representing the user's interest in a particular video, encapsulating both explicit (ratings) and implicit (clicks, watch time) interactions. Through this multifaceted approach, our algorithm provides a more nuanced and comprehensive representation of user interests, effectively addressing the limitations of data sparsity in traditional collaborative filtering.

4.2 Video Tag Similarity

Given that videos embody unstructured information, determining their similarity necessitates a comprehensive strategy. To this end, video tag data, enriched by certain user behaviors, plays a pivotal role. When users specifically tag videos, it not only reflects their preferences but also imbues the videos with implicit meanings. These tags, therefore, become instrumental in establishing the criteria for assessing video similarity.

Consider the set of video tags represented as $Tag = m_1 , m_2 , m_3 , ..., m_a$, where a denotes the total number of unique tags across the dataset, and n represents the number of videos. We can depict the relationship between videos and tags through an $n \times a$ matrix. In this matrix, the presence of a specific tag in a video is marked with a 1, while a 0 indicates its absence. The similarity between videos based on their tag attributes can then be calculated using the following formula:

$$T\_sim(i,j) = \frac{|N_i \cap N_j|}{\sqrt{|N_i|\,|N_j|}} \tag{3}$$

In this equation, $|N_j|$ represents the total set of tag attributes associated with video j.

4.3 Weighting Factor

To achieve a holistic similarity assessment between videos, our algorithm calculates similarity from two distinct dimensions: user interest and video tag attributes. To effectively amalgamate these dimensions, we introduce a weighting factor, denoted as β, which plays a pivotal role in integrating the outcomes of these two optimization algorithms. This integration is achieved through a linear weighting of the two similarity measures, with β adjusting the relative importance of each dimension. The combined weighted similarity result is formulated as Equation (4):

$$R\_Sim(i,j) = \beta Sim_{\cos}(i,j) + (1-\beta)\, T\_sim(i,j) \tag{4}$$

In this equation, β represents the weighting factor, which ranges between 0 and 1, allowing for the adjustment of the algorithm's sensitivity to user interest versus tag similarity. The optimal value for β is determined empirically through experimentation, ensuring the best possible balance between these two perspectives of video similarity.

4.4 Algorithm Description

Input:

• User-video rating matrix $R_{m\times n}$ representing the ratings given by m users to n videos
• Video tag matrix $Tag_{n\times a}$ detailing the presence or absence of a tags across n videos.
• The selected number of neighbors K, which specifies how many similar videos to consider in the recommendation process.

Output: A list of videos recommended for the target user, tailored to their predicted interests and likelihood to engage.

Step 1: Generate the user interest matrix as outlined in Section 4.1. This matrix replaces the traditional rating matrix, focusing instead on a more nuanced representation of user preferences based on both explicit ratings and implicit behaviors.

Step 2: Apply the cosine similarity measurement to compute the similarity between videos, using the user interest matrix. Normalize these values to obtain a finalized similarity score for each pair of videos.

Step 3: Calculate the similarity between video tags using the *T_sim(i, j)* formula and normalize the results. This step focuses on assessing the content-based similarity derived from video tags.

Step 4: For each video that the user has historically interacted with, identify the *K* most similar videos based on the combined similarity measures. Use Equation (4) to calculate a predicted interest score for each candidate video in this subset.

Step 5: Rank the candidate videos by their predicted scores and recommend the top *N* videos to the user. This final selection is tailored to match the user's preferences, as inferred from their past interactions and the content characteristics of the videos.

5. EXPERIMENTAL RESULTS AND ANALYSIS

5.1 Algorithm Description

The foundation of our experimental evaluation is the widely recognized MovieLens dataset, a benchmark in the field of recommendation systems research. For our purposes, we employ the ml-latest-small version, a comprehensive collection that encompasses user profiles, detailed movie information (including tags), and user ratings. The ratings in this dataset are on a scale from 1 to 5, where a higher rating reflects a stronger preference by the user for a particular movie.

To rigorously assess the performance of our proposed recommendation algorithm, we partition the dataset using the 80%-20% rule. Specifically, 80% of the data is allocated to the training set, which is used to develop and refine the algorithm, while the remaining 20% constitutes the testing set, serving as a basis for validation of the algorithm's accuracy and other key performance indicators.

The Movie-Lens dataset, as outlined in Table 1 below, is characterized by a significant level of sparsity — 98.3%. This high sparsity level underscores the challenge of making accurate recommendations given the limited interaction data and highlights the necessity for effective techniques to address data sparsity.

Table 1: Specific Dataset Parameters

Users	*Movies*	*Ratings*	*Sparsity Level*
610	9742	100836	98.3%

5.2 Evaluation Criteria

In the realm of recommendation systems, particularly for Top-N recommendations, the goal extends beyond merely predicting ratings; it encompasses providing users with a list of video recommendations they are likely to engage with. This approach aligns more closely with practical requirements of recommendation algorithms, where the focus is on actionable user engagement rather than abstract rating predictions. To evaluate the efficacy of our recommendation system in this context, we employ two widely recognized metrics: precision and recall.

Precision serves as a measure of relevance, indicating the accuracy of the recommendations provided to the users. It calculates the proportion of recommended videos in the test set that are actually relevant to the user. The formula for precision is represented as Equation (5):

$$Precision = \frac{\sum_{u \in U} |Rec(u) \cap Test(u)|}{\sum_{u \in U} |Rec(u)|} \tag{5}$$

In this equation, *U* denotes the set of all users, *Rec(u)* represents the list of videos recommended to user *u* during the testing phase, and *Test(u)* comprises the videos that user *u* has actually interacted with within the testing set.

Recall on the other hand, quantifies the system's ability to identify all relevant items for each user. It measures the proportion of relevant videos that have been successfully recommended out of all relevant videos in the test set.

The formula for recall is given by Equation (6):

$$Recall = \frac{\sum_{u \in U} |Rec(u) \cap Test(u)|}{\sum_{u \in U} |Test(u)|} \tag{6}$$

Here, the definitions for *U*, *Rec(u)*, and *Test(u)* remain consistent with those provided for the precision metric. Recall aims to capture the completeness of the recommendation system, ensuring that users receive the broadest possible selection of videos that align with their interests.

These metrics, precision and recall, provide a comprehensive view of the recommendation system's performance, balancing the trade-off between ensuring the relevance of each recommendation (precision) and covering the full range of a user's interests (recall). Together, they offer a nuanced assessment of the system's ability to deliver practical, user-centric video recommendations.

5.3 Results Analysis

The experimental setup involved configuring the input candidate list length to 10 and selecting 15 neighbors. A key focus of the evaluation was to assess the impact of varying the weighting factor (β) on the recommendation accuracy of the enhanced algorithm. This was achieved by comparing the outcomes under different β values.

Figures 2 and 3 illustrate the effect of β on precision and recall metrics. As β from 0 to 1, a noticeable trend emerges where both precision and recall initially rise, reaching a peak, before subsequently declining. This peak performance occurs at a β value of 0.6, where precision and recall attain their maximum levels.

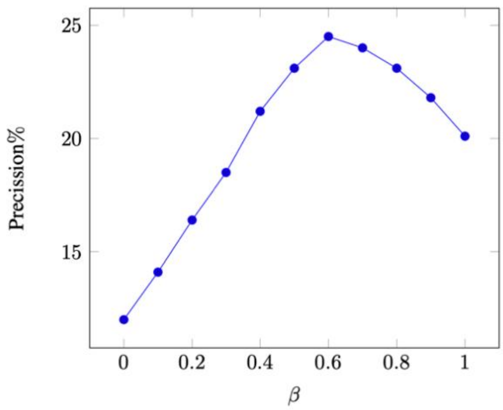

Figure 2: Accuracy as a function of the changing values of β

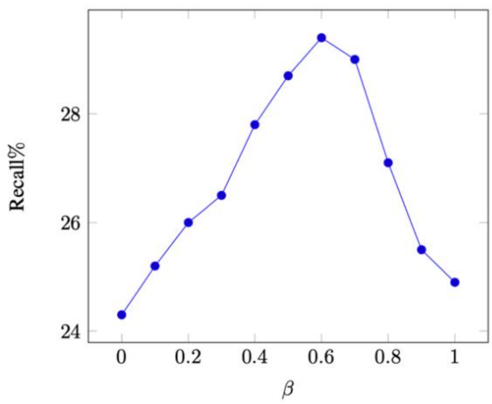

Figure 3: Recall as a function of the changing values of β

A comparative analysis, detailed in Table 2, pits the improved algorithm against traditional collaborative filtering techniques. This comparison reveals significant enhancements in precision, recall, and coverage attributed to the proposed algorithm. Specifically, the improvements are quantified as follows:

• Precision sees an increase of 15%, indicating a higher proportion of relevant videos in the recommendations.
• Recall is boosted by 32%, reflecting the algorithm's improved ability to capture relevant videos for the user.
• Coverage is expanded by 18%, suggesting a broader diversity of videos in the recommendations.

Table 2: Comparison Results between the Improved Algorithm and Traditional Collaborative Filtering

Algorithm	*Precision (%)*	*Recall (%)*	*Converage (%)*
Traditional Collaborative	20.50	12.80	18.84
Improved Collaborative	23.58	16.90	20.33

These findings underscore the efficacy of integrating user interests and video tags, balanced by the optimal β value, in enhancing the accuracy and comprehensiveness of video recommendations. The improved collaborative filtering algorithm not only outperforms traditional methods in precision and recall but also offers greater coverage, ensuring a wider array of content is accessible to users.

6. CONCLUSION

The advent of short videos and their surging popularity has intensified the need for highly effective recommendation algorithms within video service platforms. Addressing this demand, our research has introduced significant enhance- ments to the traditional collaborative filtering framework, focusing on a more nuanced incorporation of user historical behaviors and the strategic assignment of values to various user actions. By doing so, we have developed a user interest matrix that serves as a more representative and dynamic alternative to the conventional user rating matrix, offering a richer basis for generating recommendations.

Additionally, our approach has leveraged video tag attributes to further refine the recommendation process. By applying a linear weighting strategy to amalgamate similarities derived from user interests and video tags, our method circumvents the limitations associated with user-defined weights, which are prevalent in traditional hierarchical analysis techniques. This innovation ensures a more objective and balanced consideration of factors influencing video recommendations.

The experimental evaluations of our improved collaborative filtering algorithm have underscored its capability to significantly enhance recommendation quality. The results reveal marked improvements in precision, recall, and coverage, affirming the algorithm's effectiveness in delivering more relevant, comprehensive, and diverse video recommendations. These advancements not only contribute to the ongoing discourse in data mining and recommendation system research but also offer practical implications for the development and optimization of recommendation engines in real-world video service platforms.

In conclusion, this paper presents a forward-looking contribution to the field of recommendation systems, promising to elevate user experience by providing more accurate, relevant, and diverse content suggestions. Future work will aim to further refine these techniques, exploring additional data dimensions and integrating more sophisticated AI-driven methods to continuously improve recommendation quality and user satisfaction.

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