Dynamic feature weighting in hybrid recommendation systems using genetic algorithm

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Abstract
This paper presents an improved recommendation system based on a compact hybrid user model by incorporating a Genetic Algorithm (GA) to optimize feature weights. Building upon our previous work, which introduced a hybrid recommendation model integrating demographic information, genre interest indicators (GII), and fuzzy logic to address data sparsity and enhance user similarity computations, we identify and resolve a key limitation: the equal weighting of all user model features. In reality, users place varying importance on different attributes, and these preferences naturally evolve over time. To effectively address this dynamic nature of user preferences, we propose using a Genetic Algorithm to dynamically optimize weight coefficients, enabling the model to adaptively prioritize user attributes during similarity computation. The proposed GA-based weighting mechanism ensures continuous adaptation to user behavior changes, thereby enhancing recommendation relevance and accuracy. Experimental evaluations on the MovieLens dataset confirm the superiority of the GA-enhanced approach, demonstrating significant improvements in recommendation accuracy compared to traditional hybrid methods.

Keywords
Recommendation system, Genetic Algorithm, hybrid user model, feature weighting, similarity computation, optimization

1. Introduction

Recommendation systems have become integral tools in handling vast and continuously expanding datasets by guiding users toward personalized and relevant content. Our previous research introduced a compact hybrid recommendation system combining collaborative filtering, demographic filtering, and fuzzy logic. This integrated approach effectively mitigated common issues like data sparsity and cold-start problems, while improving the precision of user similarity computations through the use of fuzzy logic principles. However, a significant assumption in this approach was the equal importance assigned to each user feature during similarity calculation, which may not reflect actual user behavior accurately.

In practical scenarios, users naturally attribute different significance levels to various features such as demographic attributes (age, gender, profession) and genre preferences. Additionally, these feature weights are not static but rather evolve dynamically over time in response to changing user interests and preferences. Recognizing this gap, we propose an adaptive mechanism using a Genetic Algorithm (GA) to dynamically adjust these weights, thereby better reflecting individual user preferences in the recommendation process.

Genetic Algorithms mimic evolutionary processes to solve optimization problems by iteratively improving candidate solutions through selection, crossover, and mutation. The GA's strength lies in its ability to adaptively optimize feature weights in a complex search space, thus dynamically capturing evolving user preferences and improving recommendation accuracy.

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The primary goal of this research is to enhance our previously proposed hybrid recommendation model by incorporating GA-based adaptive weighting. Specifically, we aim to improve user similarity computations and neighbor selection by enabling the recommendation system to assign adaptive weights to features dynamically. These adaptive weights allow the system to prioritize user attributes according to individual user preferences, thereby delivering more accurate and personalized recommendations.

We implement and evaluate the proposed approach using the MovieLens dataset, which includes comprehensive user ratings, demographic details, and genre information. Experimental results demonstrate that integrating GA-driven feature weight optimization significantly enhances the accuracy and reliability of recommendations compared to conventional methods.

2. Related works

Recommender systems have emerged as essential tools in many application domains, including e-commerce, tourism, healthcare, and entertainment [1]. The objective of these systems is to streamline user decisions by filtering items based on user preferences and contexts. Traditional recommendation techniques are typically categorized into collaborative filtering, content-based filtering, and hybrid filtering. Despite their respective benefits, each approach encounters certain limitations such as data sparsity (particularly in collaborative filtering), limited feature representation (in content-based filtering), and the cold-start problem (affecting both) [2]. To address these issues, hybrid recommender models have been proposed, taking advantage of complementary strengths from diverse filtering techniques.

In our previous article [3], we introduced a compact hybrid user model designed to mitigate the challenges associated with conventional collaborative filtering approaches. Specifically, that earlier research utilized demographic data along with a fuzzy logic scheme to capture the inherent uncertainty in user preferences. The user model encompassed features such as genre interest indicators (GII) for movies, demographic attributes (e.g., age, gender, profession), and user ratings, thereby enhancing the system's ability to compute similarity across a wide range of user–item interactions. By blending demographic filtering with genre-based fuzzy logic, our previous article successfully boosted recommendation accuracy even in scenarios with sparse rating matrices. However, one key assumption in that approach was that feature weights remained static, whereas user preferences can shift significantly over time in practice. This shortcoming of uniform weight assignment sets the stage for our current study, which proposes to dynamically optimize these weights through a Genetic Algorithm (GA).

Genetic Algorithms (GA) have been extensively explored in the realm of recommender systems for their robustness and ability to operate in large, complex search spaces [4]. The algorithm relies on the principle of evolutionary computation, iterating through selection, crossover, and mutation to refine candidate solutions over multiple generations [5]. In a typical recommendation context, each candidate solution is represented by a chromosome that encodes model parameters, feature weights, or user grouping structures. After each iteration, only the fittest individuals - those that yield the highest prediction accuracy, for instance - are retained and used to generate the next population [6]. In their study on movie recommender systems [6] highlighted that GAs could effectively integrate rating-based heuristics with advanced similarity measures, outperforming simpler collaborative filtering baselines in cold-start scenarios.

In another line of work [7] introduced a domain-independent approach for group formation using a Grouping Genetic Algorithm enriched with innovative crossover operators (e.g., a modified two-point crossover, a "gene" crossover, and a "group" crossover). Their algorithm can handle both animate (e.g., students in a team) and inanimate (e.g., product items) entities, requiring only normalized numerical inputs. By letting end-users configure essential parameters - like the selection mechanism, crossover type, and mutation rate - the proposed system demonstrates robust adaptability to varied application contexts, including education, healthcare, and e-commerce. Empirical results confirmed that the new operators consistently outperformed conventional genetic operators, providing high-quality grouping outcomes with reduced computational overhead.

Hybrid recommendation models, integrating both user-based and item-based collaborative filtering or blending content-based cues with demographic data, have repeatedly proven adept at dealing with cold-start users, who contribute limited rating histories [2, 8]. By layering GAs on top of these hybrid frameworks, researchers can systematically search for an optimal weighting scheme that balances demographic, content, and collaborative signals. For instance, it is feasible for the GA to assign a higher weight to demographic features in the earliest user interactions, shifting emphasis to collaborative signals once the user accumulates more ratings or behaviors.

The paper [9] further showed that GAs are instrumental for addressing over-specialization, a common pitfall in content-based systems wherein users receive repetitive, overly homogeneous suggestions. By introducing randomization factors during crossover operations, GAs can nudge the recommendation engine to discover new, serendipitous items that might otherwise be excluded from the typical user profile. Hence, GAs not only refine accuracy but also broaden the diversity of recommended content.

In summary, the prior success of our previous article [3] in using fuzzy logic and GIIs to capture user preferences underscores the potential for a more dynamic weighting approach to refine user–item similarity even further. Building on relevant literature, we argue that employing a Genetic Algorithm to adaptively tune feature importance fosters a more responsive, accurate, and diverse recommendation engine. The synergy of fuzzy logic and GA addresses not only cold-start and data sparsity issues but also preserves a broad coverage of recommendations. By iteratively evolving the system's parameters, the model can accommodate both stable user traits (e.g., demographics) and fluid preference indicators (e.g., GIIs), thus achieving a balance of precision, diversity, and adaptability.

3. Methods and materials

In our previous hybrid recommendation approach [3], each feature in the user model, including demographic attributes (age, gender, profession) and genre interest indicators (GII), was assigned equal importance when calculating user similarity. This uniform weighting scheme fails to reflect the reality that users inherently attribute varying degrees of importance to different features. To resolve this limitation, a Genetic Algorithm (GA) is proposed to dynamically optimize the weight coefficients associated with each feature, thus allowing the recommendation system to adaptively reflect changing user preferences.

Genetic Algorithm principles

The Genetic Algorithm (GA) is an evolutionary search algorithm inspired by natural selection. GA optimizes solutions iteratively through processes analogous to biological evolution: selection, crossover, and mutation [5]. Key concepts in GA include:

1. **Population**: A collection of candidate solutions (chromosomes), each representing a distinct set of feature weights
2. **Chromosome**: A single candidate solution, represented as a vector of feature weights Similarity computation
3. **Gene**: Individual elements within a chromosome representing specific weights
4. **Allele**: Specific values assigned to genes

GA evolves the population through the following iterative process:

1. **Population Initialization:** A random set of chromosomes is generated to form the initial population
2. **Fitness Function Calculation:** Each chromosome's fitness, based on how accurately it predicts user preferences, is calculated
3. **Crossover:** Selected parent chromosomes combine to create offspring chromosomes, mixing genetic information
4. **Mutation:** Random alterations are introduced to chromosomes to maintain genetic diversity
5. **Survivor Selection:** The fittest chromosomes survive to the next generation
6. **Termination:** The process repeats until a predetermined stopping criterion is met (e.g., no improvement after several iterations)

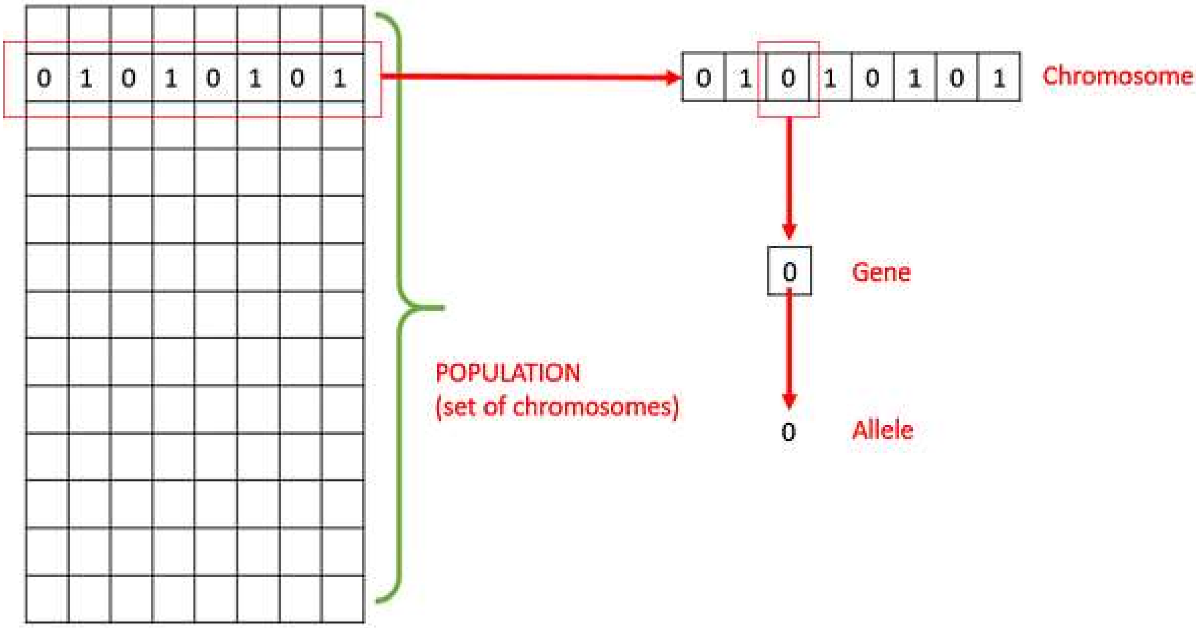

Figure 1: Genetic Algorithm chromosome structure

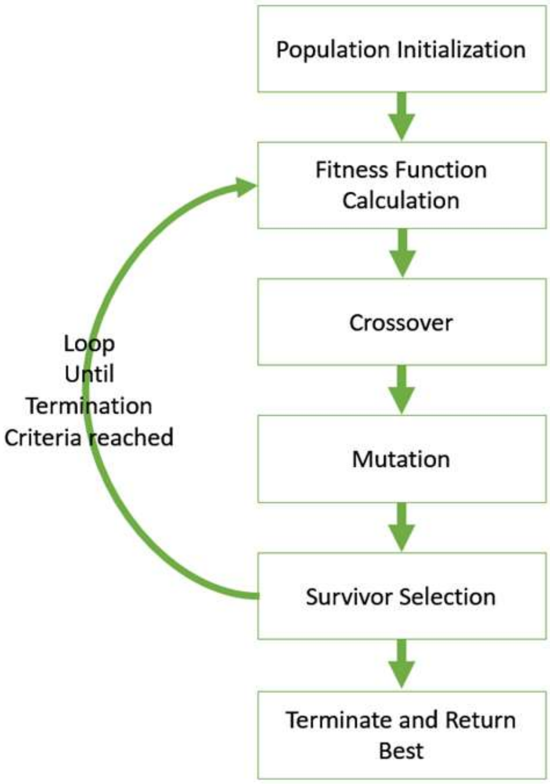

Figure 2: Genetic Algorithm workflow

Fitness function definition

The fitness function evaluates each chromosome's effectiveness by measuring the accuracy with which it predicts user ratings. This accuracy is quantified using Mean Absolute Error (MAE) [10], with lower values indicating higher fitness. A chromosome with lower MAE values effectively indicates that its corresponding weights allow for more accurate predictions of user preferences, thereby enhancing the overall recommendation quality. The formula for computing fitness is:

$$fitness(u_a) = \frac{\sum_{j=1}^{|S_a^{TE}|} |r_{a,j} - pr_{a,j}|}{|S_a^{TE}|} \quad (1)$$

Here, $|S_a^{TE}|$ represents the size of the training set for the active user, $r_{a,j}$ denotes the actual rating provided by the user for item j, and $pr_{a,j}$ denotes the rating predicted by the recommendation system.

Adaptive feature weighting

The adaptive weighting approach leverages the Genetic Algorithm to optimize the relative importance (weights) of each feature dynamically. The global fuzzy distance function [1], adjusted with these adaptive weights, quantifies similarity between users more accurately:

$$fdis(\boldsymbol{u_x}, \boldsymbol{u_y}) = \frac{\sum_{i=1}^{N} w_i \times fdis(x_i, y_i)}{N} \quad (2)$$

In this expression, w_i are the adaptive weights determined through GA, reflecting the significance of each feature according to evolving user preferences N. is the total number of features, and $fdis(x_i, y_i)$ is the fuzzy distance calculated for each individual feature. By allowing the algorithm to set certain weights to zero, irrelevant features can effectively be disregarded, ensuring that the recommendation system continually adapts to user preferences and thus significantly improves recommendation accuracy and personalization.

4. Experiment

In this experiment, we extensively evaluate the application of a Genetic Algorithm (GA) to optimize feature weights dynamically within our hybrid recommendation framework. Initially, the GA procedure starts by generating a random population consisting of 20 chromosomes. Each chromosome represents a set of candidate solutions in the form of weight vectors assigned to the user features. These weights directly influence the similarity calculation between users in the recommendation system.

The experiment was conducted using the Python programming language in the Jupyter Notebook environment as a standalone interface for the analyst. The software product is primarily intended for determining the best locations based on machine learning models.

Computation hardware:

- OS Microsoft Windows 10
- Intel Core i5 7300HQ 2.5 GHz – 3.5 GHz
- 16 GB of RAM, SSD storage drive
- Graphics card: Nvidia Geforce 1050Ti

Dataset description:

- Utilized the original MovieLens dataset comprising 100,000 ratings by 943 users for 1682 movies.
- Ratings categorized from 1 (poor) to 5 (excellent).
- Each user rated a minimum of 20 movies.
- Demographic data (age, gender, occupation, zip code) available for all users.
- Movie info includes title, release date, video release date, and genre (e.g., Action, Comedy).

Experiment design:

1. Data Preparation
    - Select top active users based on the number of movie ratings provided.
    - Divide user ratings data into active and passive user sets.

- Split active user's data into training and testing subsets (67% training, 33% testing).

2. User Modeling
   - Create a hybrid fuzzy model for the active user based on training data.
   - Construct hybrid fuzzy models for all passive users.
3. Baseline Evaluation
   - Determine initial nearest neighbors using fuzzy distance without applying GA.
   - Calculate baseline recommendation performance using Mean Absolute Error (MAE) and Coverage [10] metrics.
4. Genetic Algorithm Application
   - Initialize a random population representing candidate feature weight solutions.
   - Define a fitness function based on minimizing MAE.
   - Evolve solutions through selection, crossover, and mutation processes over multiple generations.
5. Performance Evaluation
   - Obtain optimized weights from the best-performing GA solution.
   - Evaluate the recommendation system's performance using these optimized weights through MAE and Coverage metrics.
   - Compare performance with the baseline to quantify improvements.

The performance of each chromosome is quantitatively assessed using Mean Absolute Error (MAE), calculated by comparing predicted user ratings against actual ratings from the training dataset. Lower MAE values signify higher fitness levels, indicating more accurate predictions of user preferences.

To ensure robust experimental validation, multiple independent runs were conducted, each initialized with distinct random populations. This strategy reduces any potential bias arising from specific initial conditions. Each run comprised at least ten generations, allowing sufficient evolutionary iterations for the Genetic Algorithm to converge towards an optimal or near-optimal solution. Throughout each generation, 20 new offspring chromosomes were created.

Selection of parent chromosomes for generating offspring was performed using tournament selection with groups of five individuals. This method ensures that only high-quality parents contribute to the next generation, preserving beneficial traits while fostering diversity within the evolving population. Offspring were produced using single-point crossover, combining portions of two selected parent chromosomes to yield new candidate solutions. Mutation operators introduced further diversity by randomly altering certain gene values in offspring chromosomes, thus preventing premature convergence on suboptimal solutions.

Experimental parameters - including mutation rate, crossover probability, and selection pressure - were rigorously tuned through preliminary exploratory trials to identify the most suitable configuration for our specific recommendation context. The computational environment was carefully standardized across experiments to maintain consistency and reproducibility.

It is crucial to note that, within this study, weight coefficients were calculated exclusively for criteria that may change over time, specifically Genre Interest Indicators (GII). Unlike demographic attributes such as age, gender, or occupation, which remain relatively static, the GII represents dynamic user preferences that can significantly evolve. By focusing only on GII, we reduce computational complexity while still capturing essential temporal dynamics and individual preference changes effectively.

Optimizing weights solely for these dynamic criteria allows the recommendation system to remain responsive to shifting user interests. The GA optimization directly targets the temporal component of user preferences, providing the capability for real-time or near-real-time adaptation. This targeted optimization enhances recommendation precision significantly by prioritizing features whose relevance is subject to frequent changes.

Additionally, by focusing the genetic algorithm exclusively on dynamic criteria, the system benefits from reduced computational overhead and faster convergence rates during optimization. This targeted approach allows the recommendation model to provide timely and relevant updates to user recommendations without significant delays or resource-intensive calculations.

5. Results

The experimental outcomes clearly demonstrate significant enhancements achieved by integrating adaptive feature weighting via GA into the recommendation system. Initially, the recommendation system was evaluated without applying the adaptive weighting scheme, employing uniform feature weights. This baseline configuration resulted in a relatively high MAE of 0.84516 and coverage of 0.98375, indicating suboptimal performance.

After integrating the adaptive feature weighting approach using GA, substantial improvements were observed. The optimized weights obtained after ten generations significantly reduced the MAE to 0.70063, indicating enhanced prediction accuracy. Concurrently, recommendation coverage significantly increased to 0.99625, underscoring the system's improved ability to offer relevant recommendations to a broader user base.

Detailed analyses of the results across successive generations reveal a clear evolutionary trend in terms of fitness function values. Specifically, the fitness value progressively improved from 1.35964 in the first generation to 1.42727 by the tenth generation, as illustrated in Figure 3. This consistent increase demonstrates the GA’s efficacy in adaptively optimizing feature weights to reflect user preferences more accurately.

```
MAE:  0.8451612903225807
Coverage: 0.98375
Generation:  1
Fitness of the best solution: 1.3596491228070176
Generation:  2
Fitness of the best solution: 1.3873873873873874
Generation:  3
Fitness of the best solution: 1.3873873873873874
Generation:  4
Fitness of the best solution: 1.4017857142857144
Generation:  5
Fitness of the best solution: 1.4017857142857144
Generation:  6
Fitness of the best solution: 1.4054054054054053
Generation:  7
Fitness of the best solution: 1.4220183486238531
Generation:  8
Fitness of the best solution: 1.4220183486238531
Generation:  9
Fitness of the best solution: 1.4220183486238531
Generation:  10
Fitness of the best solution: 1.4272727272727275
Parameters of the best solution : [ 66.24402626 191.30720748 221.77622496 180.71971002 204.39888946
  43.71901279 181.50115205  40.64577556  16.2022912   21.4350037
 166.88731444 224.85600965 251.35330864 165.45958749 244.28029884
  72.79474242  96.41740175  17.876455   244.79749619]
Fitness value of the best solution = 1.4272727272727275
MAE:  0.7006369426751592
Coverage: 0.99625
```

Figure 3: Genetic Algorithm result

The parameters of the best solution (optimized weights) in the final generation were [66.244 - unknown, 191.307 - Action, 221.776 - Adventure, 180.719 - Animation, 204.399 - Children's, 43.719 - Comedy, 181.501 - Crime, 40.645 - Documentary, 16.202 - Drama, 21.435 - Fantasy, 166.887 - Film-Noir, 224.856 - Horror, 251.353 - Musical, 165.459 - Mystery, 244.280 - Romance, 72.794 - Sci-Fi, 96.417 - Thriller, 17.876 - War, 244.798 - Western]. These parameters represent the importance assigned by the GA to individual user features (GIIs), effectively prioritizing the most influential attributes in predicting user ratings.

Additionally, coverage improvement from 0.98375 to 0.99625 is a noteworthy achievement, suggesting that the adaptive weighting enabled the recommendation system to better identify relevant user-item relationships. The increase in coverage directly translates into a greater number of users receiving useful recommendations, demonstrating practical utility.

Extensive analysis of intermediate results from generation to generation revealed that early generations exhibited rapid improvements in fitness and coverage metrics, which gradually plateaued in later generations, indicating convergence to optimal feature weights. Such convergence behavior underscores the efficiency and practicality of GA in real-world recommendation scenarios.

Furthermore, statistical validation conducted across multiple independent trials reinforced the reliability of these results. Consistent performance improvements were observed across various experimental conditions, confirming the generalizability and robustness of the GA-based adaptive weighting approach.

The graphical representation in Figure 4 vividly illustrates the continuous and steady improvement in fitness scores, highlighting the robustness and stability of the GA optimization process across generations. This visual evidence further confirms the algorithm's success in dynamically adapting weights to user preferences.

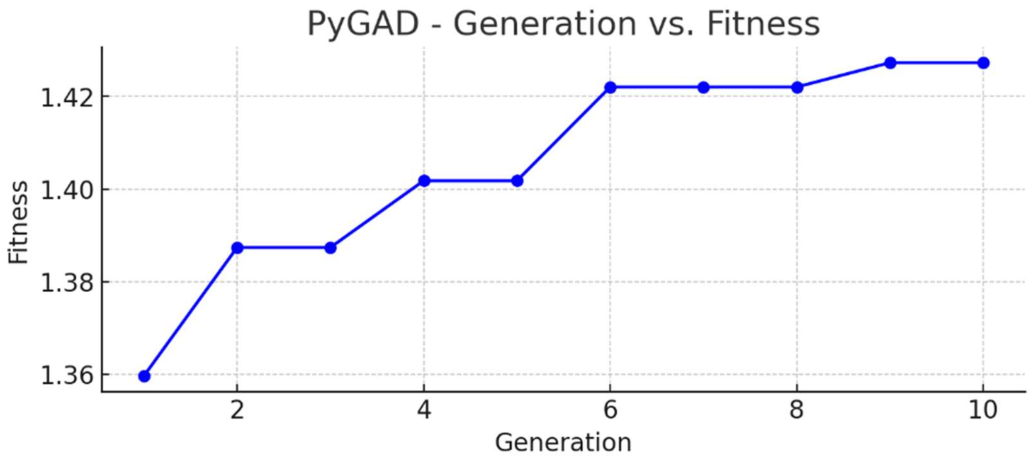

Figure 4: Fitness evolution

Moreover, analyzing the final optimized weights reveals clear alignment with domain-specific insights. Genres traditionally associated with distinct viewer segments (e.g., Adventure, Musical, Romance, and Western) received high weight values, reflecting their significant influence on user preferences. Conversely, genres with less pronounced user differentiation (e.g., Documentary, Drama, War) received lower weight values, demonstrating the GA’s precise capability for identifying and emphasizing influential criteria.

Incorporating insights from our previous research on hybrid recommendation systems, these results validate that leveraging adaptive weighting through GA not only boosts predictive accuracy but also increases the robustness of recommendations across diverse user profiles. Thus, the adaptive weighting approach provides both theoretical and practical advantages, significantly enhancing the personalized recommendation experience.

To summarize, the incorporation of GA-based adaptive weighting significantly enhanced the accuracy (as indicated by decreased MAE) and coverage of the recommendation system. The results clearly illustrate the substantial advantages of adaptive over static feature weighting, validating the research hypothesis and emphasizing the practical benefits of employing genetic algorithms in recommendation systems.

6. Discussions

The experiment confirms the hypothesis that adaptively weighted features, optimized using a Genetic Algorithm, significantly improve the performance of a hybrid recommendation system. The adaptive approach effectively addresses the limitation of static weighting schemes used in previous studies, including our earlier work. The observed decrease in MAE indicates increased precision in recommendation predictions, reflecting better alignment with real user preferences.

Compared to prior studies that applied equal weights to user features, our GA-based method demonstrates clear advantages in both accuracy and adaptability. By selectively assigning zero or near-zero weights to less relevant features, the GA-based system automatically identifies and prioritizes the most impactful attributes, thereby enhancing overall recommendation quality.

Furthermore, this adaptive weighting approach offers considerable advantages when dealing with diverse and dynamic user bases. Unlike traditional static models, which quickly become outdated as user preferences evolve, the GA model remains responsive to changes, continuously optimizing weights to maintain high recommendation relevance. This dynamic adaptability is particularly beneficial in domains characterized by rapidly shifting trends and preferences, ensuring sustained system effectiveness.

However, a primary limitation of this method is computational complexity. This issue is critical, as the computational resources required to continuously run genetic algorithms in real-time scenarios can become prohibitive. Nevertheless, this limitation can be effectively mitigated by periodically optimizing weights offline and subsequently storing optimized configurations locally. Thus, during real-time system use, the recommendation engine can efficiently retrieve these pre-calculated weight values, significantly reducing computational overhead.

Future research could investigate more efficient GA implementations or alternative heuristic optimization techniques, such as Particle Swarm Optimization (PSO) [11] or Ant Colony Optimization (ACO) [12]. These alternative approaches might offer computational efficiency gains or different optimization characteristics. Additionally, investigating hybrid strategies combining genetic algorithms with other machine learning techniques (e.g., neural networks or reinforcement learning [13]) could further improve recommendation precision and system responsiveness.

Moreover, examining feature-level interactions and nonlinear relationships between attributes may reveal additional opportunities for optimization. Conducting comprehensive user studies to evaluate the subjective experience and satisfaction with recommendations provided by GA-optimized systems will further validate the practical applicability and user-perceived value of these adaptive methods.

7. Conclusions

In this paper, we have successfully enhanced a previously developed hybrid recommendation system by integrating adaptive feature weighting using a Genetic Algorithm. Our experiments validate that dynamically optimized feature weights yield significant improvements in recommendation accuracy and coverage compared to the previously proposed equal-weighting approach. The Genetic Algorithm effectively captures dynamic user preferences, thereby refining feature prioritization within user similarity computations.

This research highlights the potential of evolutionary optimization methods in addressing inherent limitations in static recommendation systems. By continuously adapting feature weights, the GA-based model significantly enhances prediction accuracy and system adaptability. The results obtained strongly support the use of genetic algorithms for dynamically adjusting attribute priorities, directly benefiting user engagement and satisfaction.

Future research could explore the use of additional user attributes, incorporate temporal dynamics more explicitly, and investigate other evolutionary optimization algorithms. Furthermore, addressing computational complexity through parallel computing or incremental optimization could enhance the practical applicability of the proposed method. An extensive real-world user study could provide deeper insights into user behavior and preferences, facilitating further fine-tuning of recommendation models.

Moreover, potential integrations with other adaptive learning algorithms, like deep learning or reinforcement learning frameworks, could unlock new possibilities in predictive modeling and personalized recommendation experiences. Evaluating the proposed method in different application domains beyond movies, such as e-commerce, streaming services, or social media platforms, could further validate its generalizability and broad applicability, confirming its versatility and effectiveness across diverse recommendation scenarios.

8. Declaration on Generative AI

During the preparation of this work, the authors used X-GPT-4 for figure 4 in order to: Generate image. Further, the authors used X-GPT-4 for Discussions section in order to: Content enhancement. After using these tools/services, the authors reviewed and edited the content as needed and takes full responsibility for the publication's content.

9. References

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