Whale Optimization Algorithm: An Innovative Approach for Enhancing User Preference Predictions in Recommender Systems

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Abstract

Recommender systems have become essential to various online platforms such as Netflix, Amazon, and social media, predicting user preferences for items such as movies, products, or content. Therefore, recommender systems can be used in machine learning to analyze user behavior and preferences. This study proposes enhancing these systems through the Whale Optimization Algorithm (WOA), a nature-inspired method that mirrors the hunting behavior of humpback whales. The WOA operates in three phases: first, identifying and prioritizing items based on user interactions; second, refining recommendations by modeling user item relationships through a spiral equation; and third, exploring new items to broaden recommendation diversity. By integrating WOA, this approach aims to improve prediction accuracy and user satisfaction, offering a scalable solution for dynamic, user-centric recommendation environments.

Keywords: *Recommender system, practical applications, net-bubble attack, Whale optimization algorithm (WOA), Mathematical*

Introduction

The digital era has led to an explosion of data across a broad range of domains such as engineering, ecology, information technology, manufacturing, and management. As a result, the nature of problems in these areas has become increasingly complex, typically involving multi-objective frameworks and high-dimensional data. In this context, intelligent systems have become essential tools for analyzing and extracting value from vast and growing data sources [1].

Recommender systems, a subset of information filtering systems, aim to suggest the most relevant items—such as products, data, entertainment, and more—to users. Many websites, including Amazon, CDnow, and eBay, employ recommender systems to provide personalized product suggestions based on user preferences and information [2]. This customization significantly strengthens the connection between websites and their users. Unlike traditional search algorithms, recommender systems help users discover items they might not have found otherwise [3, 4]. These systems leverage search engines to index new data in an engaging and user-friendly manner. However, managing the overwhelming volume of available data remains a key challenge. Machine learning concepts and models designed to learn from data and generate precise outputs offer an effective solution. By developing robust algorithms, machine learning facilitates informed decision-making and the production of relevant results [5, 6].

Metaheuristic optimization algorithms [7] are becoming increasingly popular in engineering applications due to their simplicity, ease of implementation, and independence from gradient information, making them versatile across various problems. Additionally, these algorithms effectively avoid local optima, making them applicable to diverse disciplines. Optimization algorithms systematically identify the best solution to a given problem by iteratively exploring the search space. While many optimization methods involve mathematical techniques, their iterative and structured approach ensures efficient navigation towards the optimal solution. In some instances, specific mathematical strategies are employed to guarantee the attainment of the optimal solution for a particular problem. Despite their widespread application, optimization algorithms are not without challenges.

In recent decades, metaheuristic algorithms have gained significant attention and have been extensively developed, studied, and applied across various fields. Unlike traditional exact algorithms—which often fail to efficiently solve complex and diverse real-world problems—metaheuristics offer a practical alternative by leveraging problem-specific characteristics and domain knowledge to obtain near-optimal solutions with relatively low computational cost [8].

Research background

A recommender system [9] sometimes referred to as a platform or engine, is a subset of information filtering systems designed to predict the "score" or "priority" that a user will assign to an item, which may include data, information, products, and more. The main diagram of the recommendation process in these systems illustrates how recommendations are generated [10] (Figure 1).

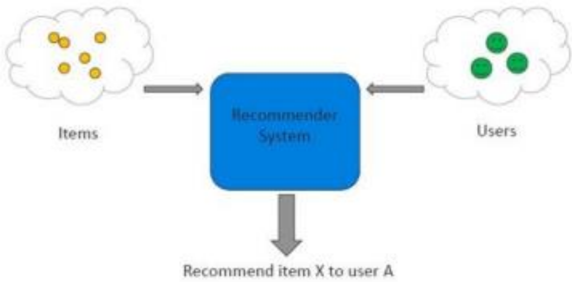

Figure 1: The main schema of the recommendation process in recommendation systems

The most common classification of recommender systems is as follows:

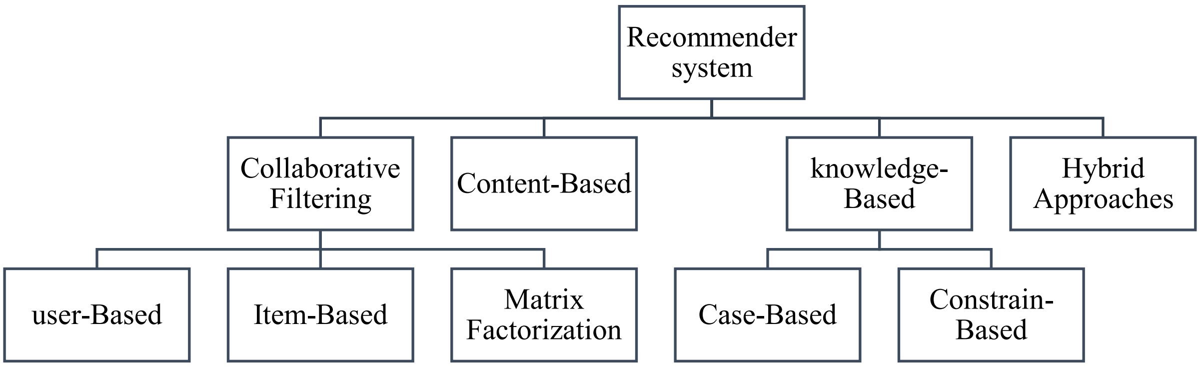

Figure 2: Classification of recommendation systems

1) Collaborative filtering operates on the premise that users who share similar opinions about one item—be it a movie, photo, piece of music, or any other recommended item—are likely to have similar opinions about other items as well [11, 12]. Collaborative filtering is typically divided into three main categories (Figure 2):

- ***User-based Collaborative Filtering**: This method groups individuals with similar tastes based on the ratings they have given to various items. By identifying users with comparable preferences, the system can make tailored recommendations.*
- ***Item-based Collaborative Filtering**: In this approach, when a user views a particular item, the system automatically identifies other items that users who have previously viewed that item have also seen. The system then suggests these related items to the user.*
- ***Matrix Factorization:** Matrix factorization methods tend to be more effective as they uncover hidden features that exist within the interactions between users and items. This technique is commonly employed to predict scores in collaborative filtering, enhancing the accuracy of recommendations.*

2) Content-based filtering relies on textual information and a user's interaction history to identify and recommend items that align with their preferences. This approach utilizes key attributes of items, such as genre, production *year, and other relevant features. By analyzing these characteristics, the system suggests items similar to those the user has previously viewed or expressed interest in.*

3) Knowledge-based recommender systems represent a more advanced form of recommendation technology, leveraging existing knowledge about both users and items. These systems generate recommendations by interpreting and deducing user preferences and needs, often providing more accurate and qualitative suggestions compared to other methods. Commonly used techniques in these systems include genetic algorithms, fuzzy logic, neural networks, decision trees, and example-based reasoning [13].

Knowledge-based methods can be divided into two categories:

- ***Constraint-based**: This approach operates on predefined recommendation rules that are explicitly embedded within the system [14].*
- ***Case-based**: This method, while similar in the recommendation process, requires the user to accurately articulate their request before the system identifies a suitable solution. Furthermore, the system can provide a brief explanation for its recommendations. However, the key distinction between these two methods lies in their knowledge provision; case-based methods recommend similar items by utilizing a similarity measure, thus fostering a more tailored recommendation experience [15, 16].*

4) Hybrid approaches in recommender systems [17] combine elements from previous methods to leverage their advantages while addressing their limitations. By integrating different techniques, hybrid systems aim to provide more accurate and personalized recommendations, resulting in an enhanced user experience [18].

Whale optimization algorithm (WOA)

Metaheuristic algorithms, inspired by natural phenomena, physics, and human behavior, are widely employed to address various optimization challenges. Often combined with other methods, they aim to either find an optimal solution or avoid being confined to local optima. Their growing popularity in engineering applications stems from several advantages. First, metaheuristic algorithms are conceptually simple and easy to implement. Second, they do not rely on gradient information, making them highly adaptable. Third, they are effective in minimizing the risk of local optima entrapment, leading to more robust solutions. Lastly, their versatility allows them to be applied across a broad spectrum of problems in different fields.

Among nature's remarkable examples is the behavior of the humpback whale, one of the largest mammals on Earth. These whales demonstrate a unique hunting technique called net- bubble feeding, which highlights their exploratory nature and adaptability.

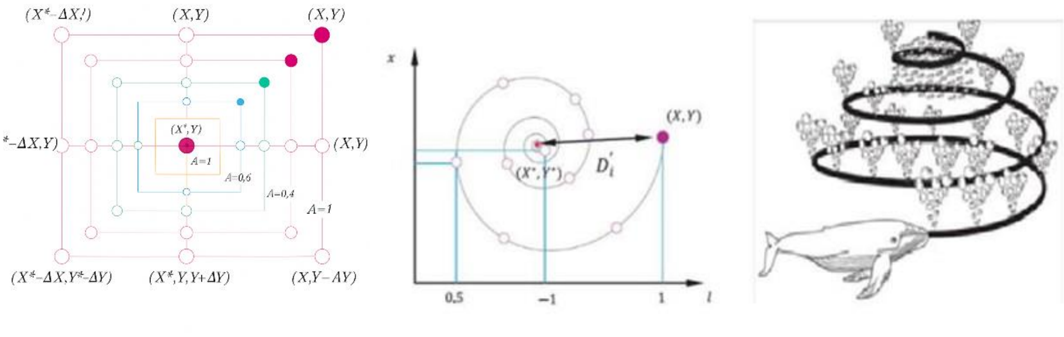

Figure 3: encircling, spiral motion, and bubble-net

The Whale Optimization Algorithm (WOA) is a nature-inspired, population-based optimization technique that can be applied across various fields. This algorithm operates in three distinct stages or phases (Figure 3).

1) ***Encirclement Hunting:*** *In this phase, whales are capable of identifying the location of their prey and surrounding them effectively. In the context of the optimization process, the optimal solution within the search space is not predetermined.*

$$\vec{D} = \left|\vec{C}\,\overrightarrow{X^*}(t) - \vec{X}(t)\right| \quad (1)$$

$$\vec{X}(t+1) = \overrightarrow{X^*}(t) - \vec{A}\cdot\vec{D} \quad (2)$$

*The algorithm utilizes several variables where **t** represents the current iteration, **A** and **C** are coefficient vectors, **X*** denotes the location vector of the best solution found so far, and **X** represents the current location vector. It is important to note that if a better solution is discovered, **X*** should be updated in each iteration. The vectors **A** and **C** are calculated based on specific formulas, where the value of **a** linearly decreases from **2** to **0** throughout the iterations, affecting both the exploration and exploitation phases. Additionally, **r** is a random vector generated within the range of **0** to **1**.*

$$\vec{A} = 2\,\vec{a}\cdot\vec{r} - \vec{a} \quad (3)$$

$$\vec{C} = 2\cdot\vec{r} \quad (4)$$

2) ***Exploitation Phase in the Whale Algorithm – Bubble Attack Method**: In this phase, whales are capable of identifying the locations of their prey and surrounding them. The algorithm operates under the assumption that the current best candidate solution represents the target prey or is in close proximity to the desired state. Two methods are employed to mathematically model the behavior of whale bubble trawls:*

   a) ***Contraction Encirclement Mechanism:*** *This behavior is achieved by increasing the value of **a** in the algorithm's equations. The range of **A** is reduced by this value of **a**. Specifically, **A** is a random variable that falls within the range of **a** to $-a$, with a decreasing from **2** to **0** throughout the iterations. By selecting random values for **A** within the range of **1** to **-1**, the new location of the search agent can be defined anywhere between its original position and that of the current best agent.*

   b) ***Spiral Updating Location:*** *This method begins by calculating the distance between the whale located at coordinates **X∗** and **Y** and the prey located at coordinates **X∗** and **Y∗**. a spiral equation is then formulated between the whale's position and that of the prey, effectively mimicking the snail-like motion characteristic of humpback whales.*

$$\vec{X}(t+1) = \vec{D'}\cdot e^{bl}\cdot cos(2\pi l) + \overrightarrow{X^*}(t) \quad (5)$$

*In this context, **D** represents the distance from the first whale to the prey, which is the best solution identified so far. The variable **b** is a constant that defines the shape of the logarithmic spiral and is a random number within the range of **-1** to **1**. It is important to note that humpback whales swim around their prey in a contracting circular path while simultaneously following a spiral trajectory. To effectively model this combined behavior, it is assumed that the whale selects either the contraction encirclement mechanism or the spiral model with a probability of **50%** to update their positions during the optimization process. The mathematical representation of this model is as follows:*

$$\vec{X}(t+1) = \begin{cases} \overrightarrow{X^*}(t) - \vec{A}\cdot\vec{D} & if\, p < 0.5 \\ \vec{D'}\cdot e^{bl}\cdot cos(2\pi l) + \overrightarrow{X^*}(t) & if\, p \geq 0.5 \end{cases} \quad (6)$$

*In this model, **P** is defined as a random number between **0** and **1**. Aside from employing the bubble net method, humpback whales also engage in random searches for prey.*

3) ***Exploration stage in whale algorithm – searching for prey:*** *A similar approach, based on variations of the vector **A**, can be employed for prey searching during the exploration phase. In this context, humpback whales conduct random searches influenced by each other's locations. Consequently, the vector **A** is assigned random values greater than or less than **-1** to encourage the search agent to move away from the reference whale. In contrast to the extraction phase, where data from the best search agent is utilized, the exploration phase relies on the selection of a random agent to update the position of the search agent. This mechanism, combined with **A<1**, emphasizes exploration and enables the Whale Optimization Algorithm (WOA) to perform a comprehensive global search. The mathematical representation of this model is as follows:*

$$\vec{D} = \left|\vec{C}\,\overrightarrow{X_{rand}} - \vec{X}\right| \tag{7}$$

$$\vec{X}(t+1) = \overrightarrow{X_{rand}} - \vec{A}\cdot\vec{D} \tag{8}$$

Pseudocode for the whale optimization algorithm:

```
Initialize the whale population Xi (i = 1, 2, ..., n)
 Calculate the fitness of each search agent
 X* = the best search agent
while (t < maximum number of iterations)
    for each search agent
    Update parameters a, A, C, l, and p
        if (p < 0.5) then
            if2 (|A| < 1) then
                Update the position of the current agent using Eq. (1)
            else if2 (|A| ≥ 1)
                Select a random search agent (X rand)
                Update the position of the current agent using Eq. (8)
            end if2
        else if1(p ≥ 0.5)
                Update the position of the current agent using Eq. (5)
        end if1
    end for
    Check and correct any agent that goes beyond the search space
    Calculate the fitness of each search agent
    Update X* if a better solution is found
    t = t + 1
end while
return X*
```

Whale algorithm flowchart:

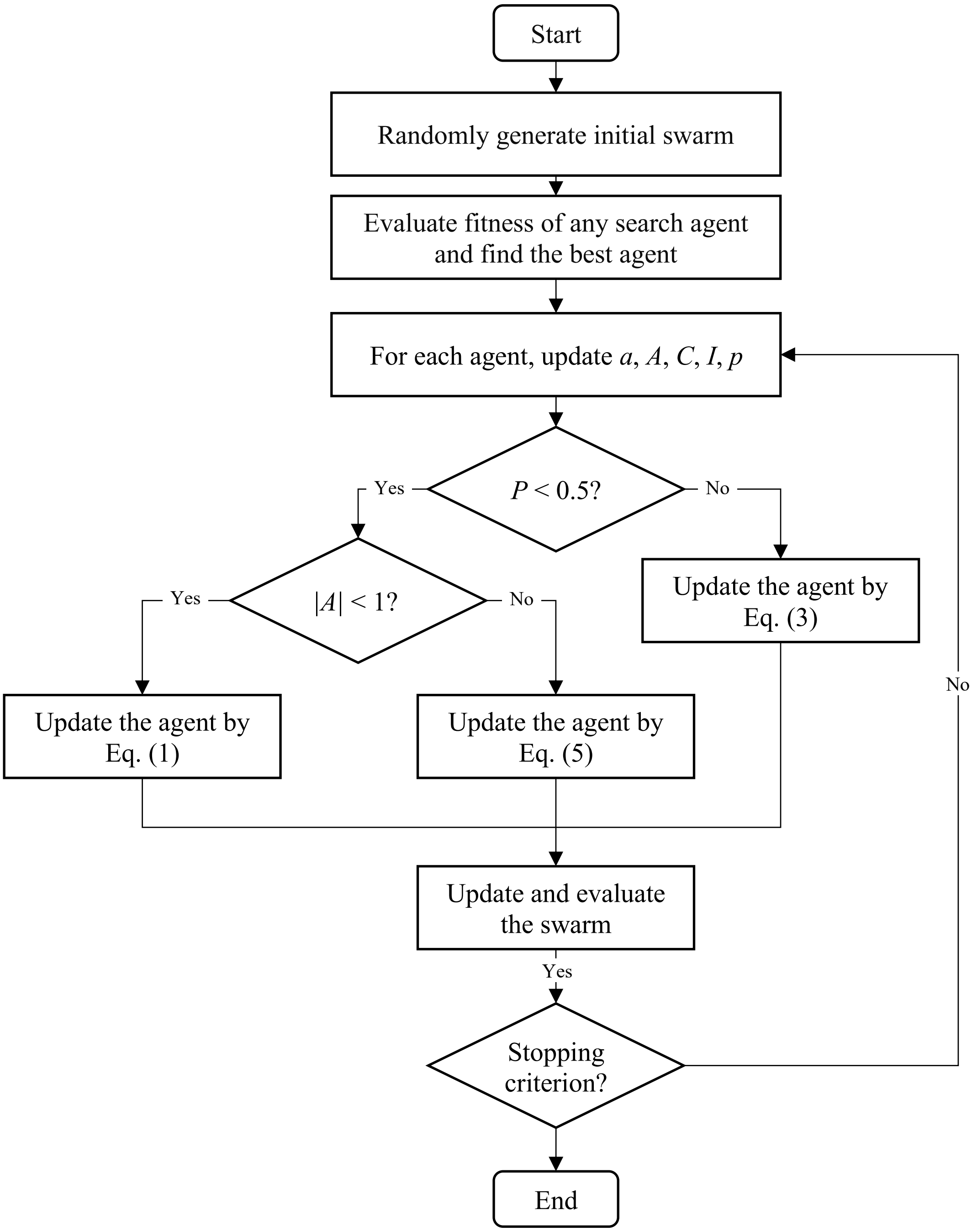

Figure 4: Flowchart of the whale algorithm

A new method in recommender systems to predict user tastes using the whale optimization algorithm

Recommender systems are among the most prevalent and easily understood applications of big data, artificial intelligence, and machine learning. These systems have a wide range of applications across various domains. For instance, they generate playlists for movie and music streaming services such as Netflix and YouTube. Similarly, platforms like Amazon utilize recommender systems to suggest products to users, while social networking sites employ them to recommend content. Recommender systems function as a set of information filtering mechanisms that aim to predict the "score" or "priority" that a user will assign to an item (such as data, information, or goods) through various filtering methods. The Whale Optimization Algorithm (WOA) can be applied to enhance the quality of predictions and recommendations within these systems, comprising three distinct phases (Figure 4):

- *Identification and Encirclement: In the first phase, the WOA identifies and surrounds the "prey," which in the context of recommender systems occurs when a user interacts with certain items more frequently than others, thus establishing priorities.*
- *Attack Phase: The second phase, analogous to the attack phase on the tor bubble, involves items that have been identified and surrounded. Here, a spiral equation is created between users and items, mimicking the snail-like movement of a humpback whale.*
- *Exploration Phase: In the third phase, which represents exploration, recommender systems search for items that users may like and need, effectively expanding the range of recommendations provided.*

Conclusion

This article delves into the mechanisms and functioning of recommender systems, which mirror a familiar process in daily life—seeking opinions from individuals with similar interests to inform our decisions. With the rapid growth of social networks and the increasing dependence on e-commerce, recommender systems are becoming pivotal in boosting profits and attracting users. Globally, recommender systems are a hot topic in research, with their importance in the business sector driving the continuous publication of new studies in the field. Future research is expected to focus on refining existing methods and algorithms to enhance prediction accuracy and recommendation quality. This includes exploring optimal combinations of various techniques that leverage different types of information. The Whale Optimization Algorithm (WOA), inspired by natural behaviors and structured around three phases of prey targeting, presents a promising avenue for advancing recommender systems. By integrating WOA, these systems could improve their ability to predict user preferences with greater speed and precision, thereby further enhancing their effectiveness.

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