

Retraction

Retracted: An Effective Approach for Modular Community Detection in Bipartite Network Based on Integrating Rider with Harris Hawks Optimization Algorithms

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] B. Fahad Alkhamees, M. A. A. Mosleh, H. AlSalman, and M. Azeem Akbar, "An Effective Approach for Modular Community Detection in Bipartite Network Based on Integrating Rider with Harris Hawks Optimization Algorithms," *Journal of Mathematics*, vol. 2021, Article ID 9511425, 16 pages, 2021.

Research Article

An Effective Approach for Modular Community Detection in Bipartite Network Based on Integrating Rider with Harris Hawks Optimization Algorithms

Bader Fahad Alkhamees ¹, **Mogeeb A. A. Mosleh** ², **Hussain AlSalman** ³,
and **Muhammad Azeem Akbar**⁴

¹Department of Information Systems, College of Computer and Information Sciences, King Saud University, Riyadh 11543, Saudi Arabia

²Faculty of Engineering and Information Technology, Taiz University, Taiz 6803, Yemen

³Department of Computer Science, College of Computer and Information Sciences, King Saud University, Riyadh 11543, Saudi Arabia

⁴Lappeenranta-Lahti University of Technology (LUT), Department of Software Engineering, Lappeenranta 53851, Finland

Correspondence should be addressed to Mogeeb A. A. Mosleh; mogeebmosleh@taiz.edu.ye

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The strenuous mining and arduous discovery of the concealed community structure in complex networks has received tremendous attention by the research community and is a trending domain in the multifaceted network as it not only reveals details about the hierarchical structure of multifaceted network but also assists in better understanding of the core functions of the network and subsequently information recommendation. The bipartite networks belong to the multifaceted network whose nodes can be divided into a dissimilar node-set so that no edges assist between the vertices. Even though the discovery of communities in one-mode network is briefly studied, community detection in bipartite networks is not studied. In this paper, we propose a novel Rider-Harris Hawks Optimization (RHHO) algorithm for community detection in a bipartite network through node similarity. The proposed RHHO is developed by the integration of the Rider Optimization (RO) algorithm with the Harris Hawks Optimization (HHO) algorithm. Moreover, a new evaluation metric, i.e., h-Tversky Index (h-TI), is also proposed for computing node similarity and fitness is newly devised considering modularity. The goal of modularity is to quantify the goodness of a specific division of network to evaluate the accuracy of the proposed community detection. The quantitative assessment of the proposed approach, as well as thorough comparative evaluation, was meticulously conducted in terms of fitness and modularity over the citation networks datasets (cit-HepPh and cit-HepTh) and bipartite network datasets (Movie Lens 100 K and American Revolution datasets). The performance was analyzed for 250 iterations of the simulation experiments. Experimental results have shown that the proposed method demonstrated a maximal fitness of 0.74353 and maximal modularity of 0.77433, outperforming the state-of-the-art approaches, including h-index-based link prediction, such as Multiagent Genetic Algorithm (MAGA), Genetic Algorithm (GA), Memetic Algorithm for Community Detection in Bipartite Networks (MATMCD-BN), and HHO.

1. Introduction

Naturally, the complex systems are deemed to be divided into multiple communities or modules. Usually, in order to represent the networks, the said communities or modules are labeled as clusters of compactly linked nodes with scarce

links to the nodes of other clusters. Complex network models have several representations, including one-mode network, bipartite network, and multimode network, but the existence of a bipartite network is very close to a natural phenomenon when especially modeling association relations between two different classes of real-world objects. In a

bipartite network, there are two different kinds of nodes. The existence of the edges between nodes is conditional such that if connecting nodes are associated with other types. Bipartite networks maintain rich information regarding the entire network being modeled and share important statistical properties like clustering coefficient as their single-mode form. Many real-world applications include the P2P network, entertainment and audience network, research coordination network, and items lending network.

Community detection holds an essentially significant contribution in many complex networks, especially an important class, i.e., bipartite networks. Community identification and dichotomy characteristics in a bipartite network not only reveal details about the hierarchical structure of a multifaceted network but also assist in better understanding of the core functions of the network and subsequently information recommendation. The bipartite networks belong to the multifaceted network whose nodes can be divided into a dissimilar node-set so that no edges assist between the vertices. Even though the discovery of communities in one-mode networks is briefly studied, community detection with bipartite networks is not studied.

Community detection is a trending research domain in the field of network science that poses the ability to offer vision to the fundamental structure and provides impending functions to the networks. Numerous real-world models like the Internet, food webs, social relationships, and biological systems are considered complex networks [1, 2]. The community is represented as a complex network which is described as the collection of nodes which are sturdily linked to one another but sporadically linked to nodes that are present external to the set [3]. The algorithms based on community detection are developed for recognizing the nodes, modules, or clusters inside the network that are more likely to interrelate among themselves than with the other network. This process is carried out when the nodes belong to the same community whereas it performs differently when the node belongs to other communities [4]. The social network using the attribute nodes is given by the bipartite graph and the extracted bicomunities are revealed later like other communities in bipartite bibliographic network which is employed for citation recommendation [4, 5]. The bipartite network is also known as two-mode network or the affiliation network wherein the nodes are divided into two different collections that involved upper and lower nodes. Here, each edge is adapted to connect the upper nodes to the lower nodes. Here, no edges exist between the two upper nodes and no edges lie between lower nodes [6]. The bipartite network offers an insight exemplification between two disjoint groups using the applications that range between the citation networks, disjoint groups, collaboration networks, and ecological networks. Here, the bipartite graph contains specific coverage property also termed as maximum matching [7].

Bipartite networks can be epitomized in the real-world scenarios considering two different categories of objects that involved movie-actor relation and paper-reference relation. The dichotomy physiognomies of the target network assist in disclosing more details than the single model networks [5]. The bipartite networks provide statistical properties in their single-

mode form which helps to define nodes of two parts of single model network and the original bipartite network offers the degree distribution and clustering coefficient to handle more information using the real network being modeled with single model version [4]. The network model is broadly employed in the reality, and the researchers provided bipartite network-related research using real-time application, cooperation network, and P2P exchange network [8]. There exist two ways for curving the relation of different object classes which involved projection method and nonprojection method [8]. The projection method projects the two parts of bipartite network considering certain nodes to evaluate further study. Similarity-based strategies are the frequently employed link prediction strategies wherein each pair of nodes considers proximity score, described based on network structure which implies that two nodes are similar if they pose higher structural similarities [9]. The proposed approach [10] is a heuristic method based on modularity optimization and demonstrated high quality of the community detection in terms of modularity in bipartite networks. The efficiency and effectiveness of Louvain algorithm had been proved by several applications.

Numerous techniques of community detection are designed to recognize the community structure. The near-optimal or optimal values of some criteria are generated by good partition. Moreover, the good separation also reveals the organization using community structure with different resolutions [11]. Conventionally, hierarchical clustering and graph partitioning strategies like agglomerative algorithms and disruptive counterparts are used for solving the issues of community detection [12]. In [13], modularity is delineated to measure the quality of partitions. Corrêa et al. [14] followed a complex network approach for word sense disambiguation. Through community detection in input-output bipartite graphs (BGs), Tang and Daoutidis [15] proposed the network decomposition for distributed control. In order to discover the necessary patterns in the IP traffic, Viard et al. [16] used cliques in bipartite link streams. Huang et al. [17] presented a novel link prediction for large scale miRNA-lncRNA interaction network in the BG. Rechner et al. [18] introduced the uniform sampling of the BGs with degrees in suggested intervals. Based on theory of complex network, Guan et al. [19] offered a service-oriented deployment policy of end-to-end network slicing. Bian and Deng [20] carried out the research to identify the influential nodes in complex networks. Gao et al. [21] wrote a paper; titled "an adaptive optimal-Kernel time-frequency representation-based complex network method for characterizing fatigued behavior using the SSVEP-based BCI system." Huang et al. [22] carried out a survey on techniques of community detection in multilayer networks. Rostami et al. [23] presented a genetic algorithm for feature selection that is based on a novel community detection, Li et al. [24] proposed the convex relaxation techniques for community detection, and Joo et al. [25] utilized the community detection for studying the stream gauge network grouping. The modularity is employed to reflect the fraction of edges using the communities related to the amount of edges developed using communities. Here, the method devised a null model, which utilizes the nodes degree for computing the uncertainty of edges that are established between the nodes.

Moreover, the modularity with high value specifies good partition, thereby maximizing the standard using optimization method [26]. However, it is obstinate to determine the precise optimal solution for the issues. Thus, many approximate techniques are designed for community detection. In [13], greedy method was devised for community detection. The algorithm showed effective performance and is considered as an efficient algorithm for detecting the nodes similarities. The Louvain algorithm contained two important processes. In the initial phase, using the community of each node, the modularity is optimized locally. The node with the same communities is aggregated and is considered as supernode and forms the novel coarse-grained network. The process is repeatedly performed using concentrated networks considering modularity to devise the node movement contained in network. Even though Louvain algorithm and modularity-based strategies pose certain drawbacks, they are still extensively utilized to evaluate real-world issues [27].

The principal purpose of this research is to devise a technique for community detection in bipartite network based on the node similarity. Here, the h-Tversky Index (h-TI) measure is newly designed by modifying h-index based on Tversky index for computing node similarity. This method is based on the similarity measures between nodes that exploit the bipartite networks. The algorithm holds the cycles for connection to maximize the similarity between nodes in order to define the communities. Then, the community detection is performed based on the proposed Rider-Harris Hawks Optimization algorithm (RHHO) and modularity. The RHHO introduced in this study is developed by integrating Rider Optimization (RO) algorithm with the Harris Hawks Optimization (HHO) algorithm. In addition, the fitness is newly devised considering modularity and proposed h-Tversky Index (h-TI) for evaluating the node similarity. The aim of modularity is to enumerate the integrity of specific division of network to evaluate the accuracy of the proposed community detection.

The major contributions are enlisted as follows:

- (i) Proposing RHHO for community detection: the proposed RHHO algorithm is a novel derivation which is achieved by the combination of RO and HHO algorithms, for community detection
- (ii) Proposing h-Tversky Index (h-TI) for node similarity: the similarity between the nodes is evaluated by integrating h-index and Tversky similarity index

Rest of the sections of this article is arranged as follows. Section 2 describes the strategies of conventional community detection that are used in the literature and challenges faced, which motivated developing the proposed technique. The objective model of community detection using bipartite graph is illustrated in Section 3. The method introduced for community detection through proposed RHHO is described in Section 4. The results of the introduced RHHO are compared with other techniques in Section 5 and finally, Section 6 provides the conclusion.

2. Motivations

The problem of community detection is NP-hard, since people have utilized different techniques to address the optimization problem. Therefore, precise algorithms like swarm evolutionary algorithms (EAs) and intelligence algorithms are employed for community detection, but the convergence of the global optimal solution needs more time. The limitation linked with modularity is identified, which is termed as resolution limits. Moreover, the modularity fails to determine the community structure for fewer nodes. The aforementioned limitations stood as the motivation for designing a novel community detection model in bipartite networks.

2.1. Literature Survey. The techniques based on eight existing community detection algorithms using bipartite network are illustrated. Zhou et al. [9] designed two h-index-based link prediction techniques using the citation network. Here, the h-type index was adapted for computing the significant nodes using the citation network. Moreover, the accuracy of prediction was found better but the method was inapplicable with other types of networks to enhance the performance of system. Gmati et al. [4] designed Fast-Bi community detection (FBCD) for detecting the community in social network using the node attributes. The goal of the model is to discover the maximum matching using bipartite graph for minimizing the complication. The method failed to use other kinds of bipartite network like directed, weighted, or dynamic network for determining the community structure. Che et al. [28] devised memetic algorithm, namely, MATMCD-BN for community detection using two-mode networks. The method employed conventional string-driven representation strategy for chromosome representation. Here, population initialization method was devised using bipartite network for enhancing the convergence rate. Moreover, the density-based bipartite modularity function was devised using the fitness function. However, the method failed to determine more than one node. Chang et al. [7] designed overlapping community detection strategy considering complete bipartite graph using microbipartite network Bi-EgoNet (CBG and BEN), which combined the benefits of both bipartite graph and the Bi-EgoNet for generating the best community structure. However, the method failed to evaluate associated issues faced by the bipartite network considering Bi-EgoNet. Sun et al. [29] designed BiAttractor for determining the two-mode communities using bipartite networks. The method was computed on the basis of distance dynamics attractor model. Even though the method precisely determined the two-mode communities of bipartite network in less time, it failed to discover community detection considering heterogeneous network, multilevel network, and temporal network. Li et al. [3] designed quantitative function for determining the community structures considering bipartite network. Moreover, the Heuristic and Adapted Label Propagation Algorithm (BiLPA) was devised to optimize the

quantitative function using huge scale bipartite networks. However, some of the data of bipartite network were missing in the obtained proposed network. Zhou et al. [10] designed a method for community detection using the bipartite network. Here, the expansion of bipartite modularity was designed and Louvain algorithm was devised. The Louvain algorithm adapted indigenous moving heuristic to unfold the complete hierarchical structure of the network. In addition, the Laplacian dynamics was considered for analyzing the constancy of community structure but failed to develop community-enabled recommendation model. Xue et al. [30] designed a method for addressing the cold start issue for community detection considering bipartite graph. At first, the decoupled normalization strategy was used to extract the inclination patterns considering the ratings. Moreover, two incremental community detection methods were devised for capturing the interesting shifts based on missing method of rating. However, the technique was unsuccessful in using the pairwise constraints for semisupervised learning for the enhancement of system's performance.

2.2. Challenges. The challenges confronted by the conventional techniques for developing a method for effective community detection are portrayed as follows:

- (i) Another drawback confronted by the community detection method is weighted modularity. Here, the weighted modularity was only effective on networks in which all connections are positive. However, these methods failed to create modules in weighted networks for devising negative and positive link strengths [26].
- (ii) Determining the structure of networks is beneficial for illustrating their formulation function and performance and is considered a significant issue in community detection [1].
- (iii) In [30], the Incremental Group-Specific model was designed for community detection. However, the empirical analysis was not performed for offering a reasonable explanation to simplify the grouping method and failed to combine valuable topological information.
- (iv) In [9], h-index-based link prediction method was developed using the citation network. Still, it did not consider the h-index and Tversky similarity indices and the Salton to improve performance.
- (v) Bipartite networks fit in the category of complicated networks, whose vertices are distributed into two alienated collections of vertices, such that there do not exist any edges between vertices of the same collections/set, and edges only subsist between nodes of different collections. Even though, in one-mode networks, the community discovery is widely studied, the community detections in bipartite networks have not been studied due to the fact that the projection loses important information of the original bipartite network.

3. Objective Model for Community Detection

Community detection is a fundamental tool employed for discovering valuable information that is hidden over complex networks. Numerous community detection techniques for bipartite networks are devised considering different viewpoints. However, the efficiency of these techniques worsens when the community structure turns ambiguous. Improving the community structure is a complicated task. The bipartite network is an essential class of complex networks in real-world systems, wherein each node is of different types, and no two nodes are the same type. For example, a bipartite network that has three communities is shown in Figure 1.

As bipartite networks pose community structure and the communities are independent of one another, that helped to expose indefinite functional modules. The analysis and detection of these communities from the bipartite network offer a means for functional classification of the bipartite network. Community detection is a challenging task considering bipartite networks due to the fact that the community detection problem is NP-hard. The algorithm makes the issue of community detection into a combinatorial optimization issue.

Modularity is widely applied for the evaluation of the quality of a specific partition of a network into communities. Moreover, modularity reflects the extent, relative to a null model network, to which edges are formed within communities instead of between them. Further, the bipartite modularity measures are proposed, which could be useful in the recognition of communities in bipartite networks. In turn, the model is newly devised that would have the same number of nodes and degree distribution as that of the original network while the edges of the node are replaced.

Assume a bipartite graph which is modeled as an undirected graph $G = (D, I)$ where D represents set of nodes and I indicates a set of edges. The node-set D is expressed as $D = \{X \cup W\}$ where X and W indicate the types of node X and type W . The set of edges is represented as I . The edges pose the ability to connect different types of nodes, which are modeled as edges $n_{ef} \in I (b_e \in X; s_f \in W)$, and $|I|$ indicate the number of edges in a bipartite graph. The detection of community in a bipartite graph is expressed as $G = (D, I) = (X \cup W, I)$ which is employed to partition G into subgraphs, modeled as $G_e = (X_e \cup W_e, I_e)$ where $e = \{1, 2, \dots, o\}$ and o is a total number of communities.

3.1. Bipartite Modularity for Detecting Similarity between Nodes. The modularity [31] is devised to quantify the integrity of a specific part in the provided network and is considered as a widespread benchmark index to compute the accuracy in community detection. The community structure is defined as a model that arranges the edges in a statistically surprising manner. Assume g_j represents the degree of node j and E indicates a total number of edges. The probability of edge being presented between node j and node q is represented as $(g_j g_q / 2E)$. The modularity quantifying the number of edges based on newly devised model can be expressed as

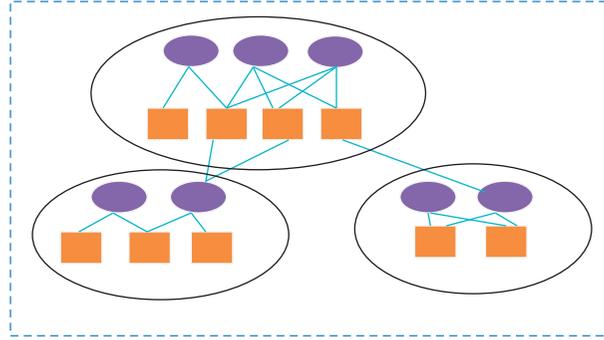


FIGURE 1: A bipartite network having three communities.

$$M = \frac{1}{2E} \sum_{j=1}^S \sum_{q=1}^S \left(T_{jq} - \frac{g_j g_q}{2E} \right) \eta(r_j r_q), \quad (1)$$

where M represents the sum of difference over all groups, S indicates network size, T_{jq} indicates the adjacent relation between node j and node q , g_j indicates the degree of node j , and g_q represents the degree of node q , η represents a function that acquires a value 1 if $r_j = r_q$ and receives value 0 otherwise, E indicates the number of edges, and r_q indicates the group of node q . Here, the value of M varies between -1 and 1 , and the larger value of Q indicates a more precise division of network in communities. A bipartite network with S nodes can be represented as duality $(x, y) \ni x + y = S$ where x and y indicate two types of nodes such as $\{1, 2, \dots, x, x+1, \dots, S\}$, where leftmost x indicates one type of node and rightmost x indicates other types of nodes. The bipartite modularity that considers a community of specific type of node in the network is given as

$$M_r = \frac{1}{E} \sum_{j=1}^q \sum_{q=x+1}^S \left(T_{jq} - \frac{g_j g_q}{E} \right) \eta(r_j r_q). \quad (2)$$

The unipartite network can be expressed as a bipartite one, and the bipartite network can recover the modularity of the given network. If each node j is represented by two nodes K_j and L_j and each edge $j-q$ is represented by two nodes $K_j - L_q$ and $K_q - L_j$, then the unipartite network with S nodes and E edges is converted into a corresponding bipartite network with $2S$ nodes and $2E$ edges. Moreover, the bipartite network is considered a massive class of networks that offers a solution for dealing with community structure detection. The bipartite modularity is served as a standardized goal for detecting communities using optimization.

3.2. Proposed h-Tversky Index (h-TI) for Node Similarity. In this research, a novel h-Tversky similarity index is proposed by combining the Tversky index with h-index [9] for computing the similarity between two nodes. The Tversky index is a similarity measure used for comparing the variant with respect to the prototype. The Tversky index is considered as a generalization of the Dice coefficient and Tanimoto coefficient. On the other hand, the h-index is a term utilized for discovering the significance of a node

considering a citation network. The h-index is also termed as lobby index, which is devised on the basis of Schubert's h-index. The nodes with high degree neighbors are strengthened by h-index, which has been discovered. Thus, the combination of Tversky index and h-index is defined to evaluate the similar nodes in order to improve the network performance. The proposed h-Tversky similarity index is represented as

$$G_{jq} = \frac{\theta |\Gamma_j \cap \Gamma_q|}{\theta |\Gamma_j \cap \Gamma_q| + \alpha |\Gamma_j \setminus \Gamma_q| + \beta |\Gamma_q \setminus \Gamma_j|}. \quad (3)$$

The values of the similarity function in the above form are bounded to unit interval $[0, 1]$. This formula generalizes numerous common similarity functions for suitable values of parameters, θ , α , β , and choice of the interval scale function. For instance, if $\theta = \alpha = \beta = 1$ Tversky index is the same as Jaccard index or Jaccard similarity coefficient. When $\theta = 1$ and $\alpha = \beta = 0.5$, Tversky's formula turns out to be the same as the Dice similarity coefficient. Here, $\alpha = t_j$ and $\beta = t_q$, $\Gamma_j \cap \Gamma_q$ represents a set of common neighbors of nodes j and q , α corresponds to the weight of prototype and β denotes the weight of variant, t_j represents the h-index of a node j , and t_q specifies the h-index of a node q . Here, the h-index of a node j is expressed as

$$t_j = Y(C_{j1}g_1, \dots, C_{jq}g_q, \dots, C_{qS}g_S), \quad (4)$$

where S indicates a total number of nodes, C_{jq} represents the adjacency matrix, and g_q indicates the degree of node j neighbors.

4. Proposed Rider-Harris Hawk Optimization (RHHO) for Community Detection

The goal of community detection is to generate high quality community structures. To attain the goal, a novel h-Tversky Index (h-TI) is used, which combines h-index and Tversky similarity index for determining the nodes similarity. Based on the similarities, the community detection is performed considering the proposed RHHO algorithm. The proposed RHHO is designed by integrating RO [32] and HHO [33]. Here, the proposed RHHO algorithm is employed to determine the communities in multifaceted networks, which are done on the basis of optimizing the network modularity.

The proposed RHHO is a novel population initialization method, which is useful for accelerating population convergence. In addition, the fitness function, namely, h-Tversky similarity index, is newly devised for computing the individuals from the population.

4.1. Bipartite Graph. Consider a bipartite graph which is represented as a graph $G = (D, I)$ where D represents nodes' set and I indicates edges' set. The nodes' set D is expressed as $D = \{X \cup W\}$ where X and W indicate the node of type X and type W . The set of edges is represented by I . The edges pose the ability to connect different types of nodes, which are modeled as edges $n_{ef} \in I (b_e \in X; s_f \in W)$ and $|I|$ indicates the number of edges in a bipartite graph. The detection of community in a bipartite graph is expressed as $G = (D, I) = (X \cup W, I)$, which is employed to partition G into subgraphs, which are modeled as $G_e = (X_e \cup W_e, I_e)$ where $e = \{1, 2, \dots, o\}$ and o is the total number of communities.

4.2. Determination of Node Similarity. The similarity is defined as a metric utilized for computing the amount of closeness between two pairs of nodes. Numerous node similarity measures based on the local information are described in the literature, which showed a different performance for determining the community structure from the complicated networks. However, the proposed method computes the node similarity in the network using a fitness function derived by the bipartite modularity and h-Tversky similarity index. Here, the fitness function is considered as a maximization function and is expressed as

$$F = \frac{M_a + M_G}{2}, \quad (5)$$

where M_a indicates a bipartite modularity and M_G represents the proposed h-Tversky similarity index considering a specific community structure. The proposed h-Tversky similarity index that considers a community of specific type of node in the network is given as

$$M_G = \frac{1}{E} \sum_{j=1}^q \sum_{q=x+1}^s (G_{jq}) \eta(r_j r_q), \quad (6)$$

where E represents a number of edges and η represents a function that acquires value 1 if $r_j = r_q$ and acquires value 0 otherwise, G_{jq} represents proposed h-Tversky similarity index, r_j indicates a group of node j , and r_q indicates a group of the node q .

4.3. Algorithmic Steps of Proposed Rider-Harris Hawk Optimization (RHHO) Algorithm. The HHO [33] is modified using the RO algorithm [32] wherein the update rule of HHO is updated based on the update rule of bypass rider in RO algorithm, thus obtaining the new algorithm, an RHHO, which is used to perform the community detection optimally. Basically, HHO is inspired by the chasing behavior of Harris hawks. The HHO provides a smoother transition

among the exploitation and exploration and helps to boost the exploratory behavior. Moreover, the quality of solutions is improved during a number of iterations. The HHO algorithm is effective in handling the difficulties of search space with local optimal solutions. On the other hand, the RO algorithm is inspired by riders racing to reach a particular destination. Simultaneously, the usual RO algorithm displays good global optimal convergence. Based on the imaginary ideas and thoughts, nothing like the other nature-inspired and artificial computing algorithms, RO algorithm works in the fictional computing platform. In RO algorithm, the optimization behavior depends on four groups of riders, each presenting particular characteristics. The overtaking rider derives the new update rule in the HHO algorithm by using the RO algorithm. The advantages of bypass include the faster convergence with greater global neighborhoods. Hence, in the current RHHO, the optimal global convergence is enhanced at the maximal iteration. The algorithmic steps of the introduced RHHO are defined as follows.

4.3.1. Step 1: Initialization. First is initialization of population that is denoted as Z with total d rabbits, where $1 \leq c \leq d$,

$$Z = \{Z_1, Z_2, \dots, Z_c, \dots, Z_d\}, \quad (7)$$

where d is total solution, and Z_c indicates the c th solution.

4.3.2. Step 2: Determination of Fitness Function. The success rate or fitness of the solution is computed on the basis of bipartite modularity and proposed h-Tversky similarity index, which is elaborated in Section 4.2. Hence, the solution's fitness is depicted in equation (3).

4.3.3. Step 3: Determination of Update Position. The scheme of selection in an HHO [33] algorithm helps to progressively update the position to attain an improved position. Moreover, Harris' hawks enclose the anticipated prey by updating their places. In such circumstances, the current place updates the solution space as

$$Z(v+1) = Z_{\text{rab}}(v) - H|\Delta Z(v)|, \quad (8)$$

where $z(v+1)$ indicates the position of hawks in next iteration, $Z_{\text{rab}}(v)$ indicates the position of rabbit, $\Delta Z(v)$ specifies the difference between position vector of rabbit and current location of prey, and H represents the energy of prey.

$$Z(v+1) = Z_{\text{rab}}(v) - H|Z_{\text{rab}}(v) - Z(v)|, \quad (9)$$

where $Z(v)$ indicates the current position vector. Assuming $Z_{\text{rab}}(v)$ as positive, the above equation is represented as

$$Z(v+1) = Z_{\text{rab}}(v) - H(Z_{\text{rab}}(v) - Z(v)). \quad (10)$$

Here, the updated position of the bypass rider according to RO algorithm [32] is utilized in the process of update for maximizing the rate of success by finding the position of bypass rider. The bypass riders trail a common route without

stalking the foremost rider. The bypass rider's equation given by riders is represented as

$$Z(v+1) = \mu[Z(v) * \gamma(w) + Z(v) * [1 - \gamma(w)]], \quad (11)$$

where ϑ and ℓ denote the random digits between 0 and 1, inclusive, κ and μ are random digits, and k indicates the iterations. Assume $\mu = r$; the equation is rewritten as

$$Z(v+1) = \mu Z(v) * \gamma(w) + \mu Z(v)[1 - \gamma(w)], \quad (12)$$

$$Z(v+1) = Z(v)[\mu\gamma(w) + \mu[1 - \gamma(w)]], \quad (13)$$

$$\begin{aligned} Z(v+1) &= Z_{\text{rab}}(v) - H\left(Z_{\text{rab}}(v) - \frac{Z(v+1)}{[\mu\gamma(w) + \mu[1 - \gamma(w)]]}\right), \\ Z(v+1) - \frac{HZ(v+1)}{\mu\gamma(w) + \mu[1 - \gamma(w)]} &= Z_{\text{rab}}(v) - H(Z_{\text{rab}}(v)), \\ Z(v+1) \left[1 - \frac{H}{\mu\gamma(w) + \mu[1 - \gamma(w)]}\right] &= Z_{\text{rab}}(v) - H(Z_{\text{rab}}(v)), \\ Z(v+1) \frac{\mu\gamma(w) + \mu[1 - \gamma(w)] - H}{\mu\gamma(w) + \mu[1 - \gamma(w)]} &= Z_{\text{rab}}(v) - H(Z_{\text{rab}}(v)). \end{aligned} \quad (15)$$

The final equation is given by

$$Z(v+1) = \frac{\mu}{\mu - H} [Z_{\text{rab}}(v) - H(Z_{\text{rab}}(v))]. \quad (16)$$

4.3.4. Step 4: Determining the Best Solution. If the solution acquired the minimal fitness value, then it is the best solution. Furthermore, the parameters of the update of a rider are crucial in order to conclude the best solution.

4.3.5. Step 5: Termination. Repeat the steps in anticipation of the iteration reaching the maximum count.

5. Results and Discussion

The analysis of the community detection model using the proposed RHHO is demonstrated in this section with an effective comparative analysis to prove the effectiveness of the proposed model.

5.1. Experimental Setup. The proposed method is executed in a system running Windows 8 OS with 4 GB of RAM, Intel core i-3 processor, and the implementation is carried out in Python.

5.2. Database Description. The nodes for the experimentation are taken from the datasets, namely, the citation networks dataset [34] and the bipartite network dataset [35]. The description for each is given below.

$$Z(v) = \frac{Z(v+1)}{[\mu\gamma(w) + \mu[1 - \gamma(w)]]}. \quad (14)$$

Substituting equation (14) in (10), the update equation derived is

5.2.1. Citation Networks Dataset. The experimentation is performed on a citation network dataset wherein the node denotes papers and edges denote citations. The citation network dataset can be employed for clustering the network and for studying the influence of citation networks to determine the most influential papers. Here, cit-HepPh and cit-HepTh are the two datasets used for performing the community detection:

- (a) Analysis based on cit-HepPh: the cit-HepPh network is an instance of citation network dataset data that can be temporal, directed, or labeled with 34,546 nodes and 421,578 edges. The cit-HepPh network data is employed in the Arxiv High Energy Physics paper citation network.
- (b) Analysis based on cit-HepTh: the cit-HepTh network data can be directed, temporal, or labeled with 27,770 nodes and 352,807 edges. The cit-HepTh network data is employed in the Arxiv High Energy Physics paper citation network.

5.2.2. Bipartite Network Dataset. The experimentation is performed on a bipartite network dataset wherein the network consists of two distinct node types, and all edges connect a node of the first type with a node of the second type. Here, Movie Lens 100 K was acquired from the official website (<https://grouplens.org/datasets/movielens/>), and the American Revolution network was obtained from the website (http://konect.cc/networks/brunson_revolution/) with two public datasets employed for performing the community detection.

- (a) Analysis based on Movie Lens 100 K: this bipartite network consists of ten million movie ratings wherein the left nodes are users, and the right nodes are movies. An edge connecting the user and a movie represents the user who has rated the movie with the rating value attached to the edge.
- (b) Analysis based on American Revolution: the bipartite network consists of membership information of thirty-six people in five organizations considering the period before the American Revolution. The list consists of well-known people like American activist Paul Revere. Here, the left nodes indicate persons, and the right nodes denote organizations. Here, the edge linking the person and the organization reveals that the person is a member of the organization.

5.3. Simulation Results. The simulation results of proposed community detection model considering citation network dataset and bipartite network dataset are illustrated in Figures 2 and 3.

5.3.1. Citation Networks Dataset. In this section, we analyze the simulation results of community detection based on citation networks datasets. Figure 2 elaborates the simulation results of the proposed community detection model using citation network dataset considering cit-HepPh and cit-HepTh datasets.

Figure 2(a) describes the original network using the cit-HepPh dataset and the communities identified considering the original network with the cit-HepPh dataset described in Figure 2(b). In Figure 2(b), green, red, and blue are the nodes representing different communities. Figure 2(c) elaborates the original network using the cit-HepTh dataset, and the communities detected by the original network using the cit-HepTh dataset are described in Figure 2(d). In Figure 2(d), green, red, and blue are the nodes with different communities present in the original network.

5.3.2. Bipartite Network Dataset. This section explains the simulation results of community detection based on bipartite networks datasets. Figure 3 elaborates the simulation results of the proposed community detection model using a bipartite network dataset considering Movie Lens 100 K and American Revolution datasets.

Figure 3(a) describes the original network using the Movie Lens 100 K dataset and the communities identified considering the original network with Movie Lens 100 K dataset described in Figure 3(b). In Figure 3(b), green, red, and blue represent different communities. Figure 3(c) elaborates the original network using the American Revolution dataset, and the communities detected by the original network using the American Revolution dataset are described in Figure 3(d). In Figure 2(d), green, red, and blue are the nodes with different communities' present in the original network.

5.4. Performance Analysis. The performance analysis of the proposed RHHO considering citation network dataset and bipartite network dataset is illustrated considering fitness and modularity measures.

5.4.1. Performance Analysis Based on Citation Networks Dataset Using cit-HepPh. Figure 4 illustrates the performance analysis of RHHO method using the cit-HepPh based fitness and modularity measures. The analysis of RHHO based on the fitness metric is portrayed in Figure 4(a). When the iteration is 1, the corresponding fitness values computed by the proposed RHHO with population = 5, 10, 15, 20, 25, and 30 are 6.628186, 0.000010, 0.000014, 0.000018, 0.000024, and 0.000035. Likewise, when the iteration is 250, then the corresponding fitness values computed by the proposed RHHO with population = 5, 10, 15, 20, 25, and 30 are 0.0059, 0.0182, 0.8430, 0.8771, 0.9431, and 0.9958, respectively. The analysis of the RHHO based on the modularity metric is illustrated in Figure 4(b). When the iteration is 1, the corresponding modularity values computed by proposed RHHO with population = 5, 10, 15, 20, 25, and 30 are 0.00038, 0.00113, 0.00274, 0.00327, 0.00422, and 0.00455. Likewise, when the iteration is 250, then the corresponding modularity values computed by proposed RHHO method with population = 5, 10, 15, 20, 25, and 30 are 6 0.62139, 0.65143, 0.65208, 0.65385, 0.66975, and 0.67397, respectively.

5.4.2. Performance Analysis Based on Citation Networks Dataset Using cit-HepTh. Figure 5 illustrates the performance analysis of the proposed RHHO using cit-HepTh based fitness and modularity measures. The analysis of the proposed RHHO based on the fitness metric is portrayed in Figure 5(a). When the iteration is 1, the corresponding fitness values computed by proposed RHHO with population = 5, 10, 15, 20, 25, and 30 are 8.7459, 0.000012, 0.000018, 0.000030, 0.000031, and 0.000068. Likewise, when the iteration is 250, then the corresponding fitness values computed by proposed RHHO with population = 5, 10, 15, 20, 25, and 30 are 0.0011, 0.0020, 0.9203, 0.9586, 0.9681, and 0.9932, respectively. The analysis of the proposed RHHO based on the modularity metric is illustrated in Figure 5(b). When the iteration is 1, the corresponding modularity values computed by proposed RHHO with population = 5, 10, 15, 20, 25, and 30 are 0.00146, 0.00177, 0.00211, 0.00346, 0.00361, and 0.00390. Likewise, when the iteration is 250, then the corresponding modularity values computed by proposed RHHO with population = 5, 10, 15, 20, 25, and 30 are 0.5954, 0.6006, 0.6270, 0.6306, 0.6391, and 0.6855, respectively.

5.4.3. Performance Analysis Based on Bipartite Network Dataset Using Movie Lens 100 K. Figure 6 illustrates the performance analysis of the proposed RHHO using Movie Lens 100 K-based fitness and modularity measures. The analysis of the proposed RHHO based on the fitness metric is portrayed in Figure 6(a). When the iteration is 1, the

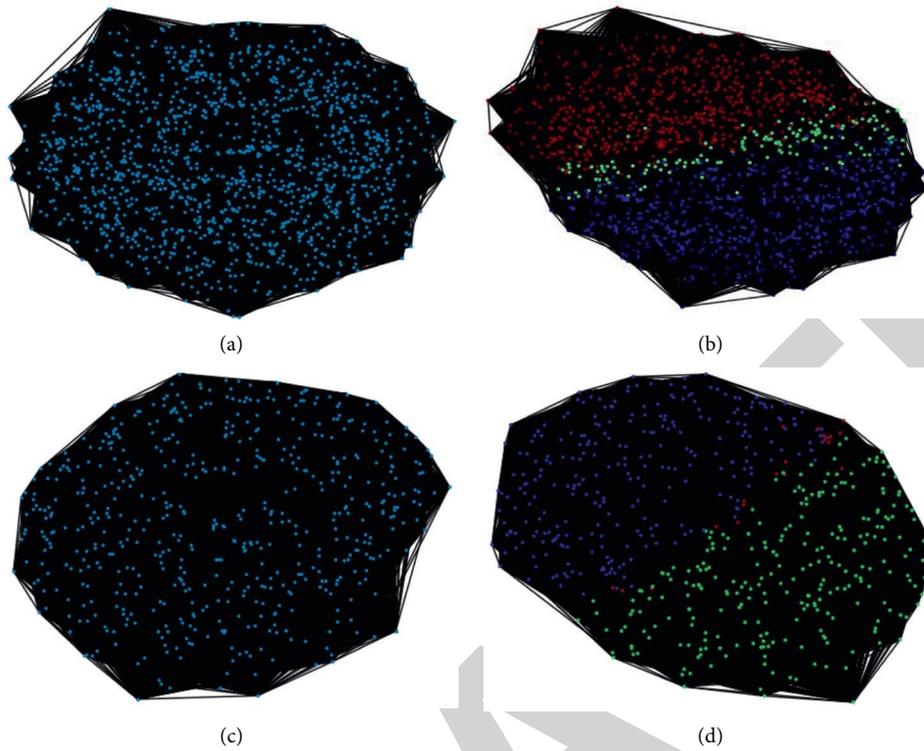


FIGURE 2: Analysis based on citation networks dataset using (a) original network using cit-HepPh dataset; (b) community detection using cit-HepPh dataset; (c) original network using the cit-HepTh dataset; (d) community detection using the cit-HepTh dataset.

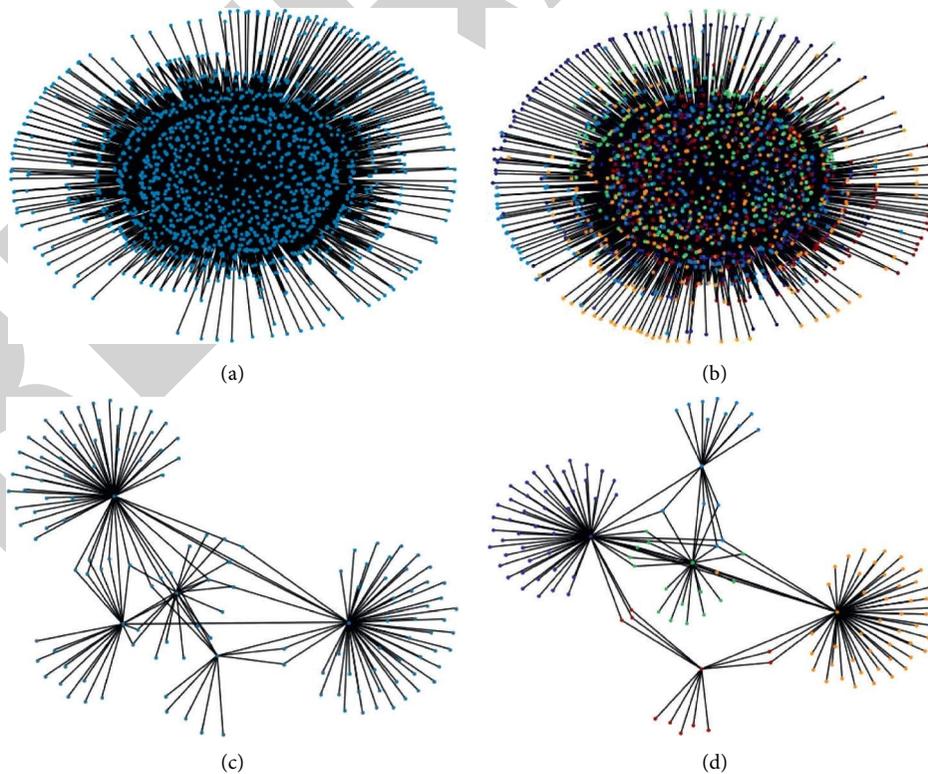


FIGURE 3: Analysis based on bipartite networks datasets using (a) original network using the Movie Lens 100 K dataset; (b) community detection using the Movie Lens 100 K dataset; (c) original network using the American Revolution dataset; (d) community detection using the American Revolution dataset.

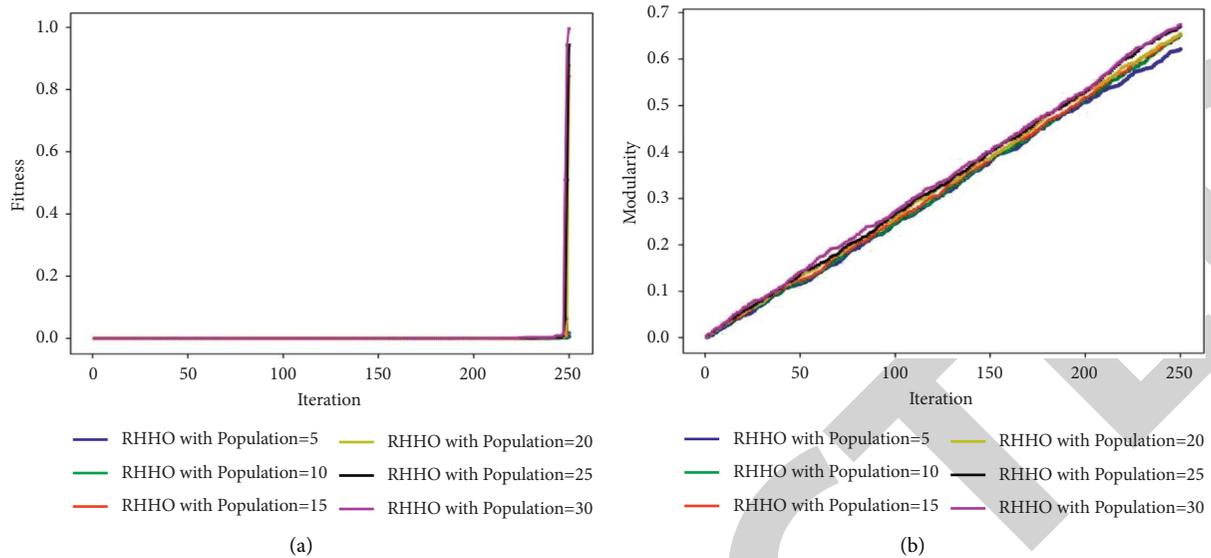


FIGURE 4: Performance analysis of proposed RHHO method using the cit-HepPh considering (a) fitness and (b) modularity.

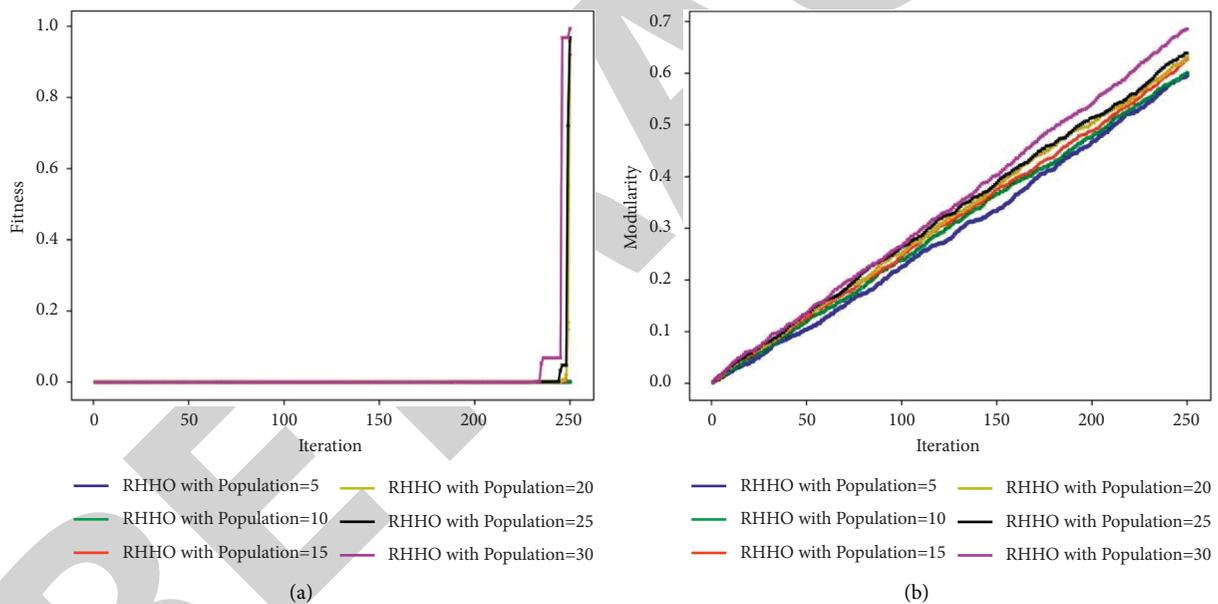


FIGURE 5: Performance analysis of proposed RHHO using the cit-HepTh considering (a) fitness and (b) modularity.

corresponding fitness values computed by proposed RHHO with population = 5, 10, 15, 20, 25, and 30 are 0.0000061, 0.000010, 0.000012, 0.000016, 0.000031, and 0.000063. Likewise, when the iteration is 250, then the corresponding fitness values computed by proposed RHHO with population = 5, 10, 15, 20, 25, and 30 are 0.00076, 0.00576, 0.07740, 0.88287, 0.97519, and 0.99201, respectively. The analysis of the proposed RHHO based on the modularity metric is illustrated in Figure 6(b). When the iteration is 1, the corresponding modularity values computed by proposed RHHO with population = 5, 10, 15, 20, 25, and 30 are 0.000419, 0.00204, 0.00213, 0.00284, 0.00303, and 0.00376. Likewise, when the iteration is 250, then the corresponding

modularity values computed by proposed RHHO with population = 5, 10, 15, 20, 25, and 30 are 0.6069, 0.6205, 0.6398, 0.6404, 0.6542, and 0.6790, respectively.

5.4.4. Performance Analysis Based on Bipartite Network Dataset Using American Revolution. Figure 7 illustrates the performance analysis of the proposed RHHO using American Revolution-based fitness and modularity measures. The analysis of the proposed RHHO based on the fitness metric is portrayed in Figure 7(a). When the iteration is 1, the corresponding fitness values computed by proposed RHHO with population = 5, 10, 15, 20, 25, and 30 are

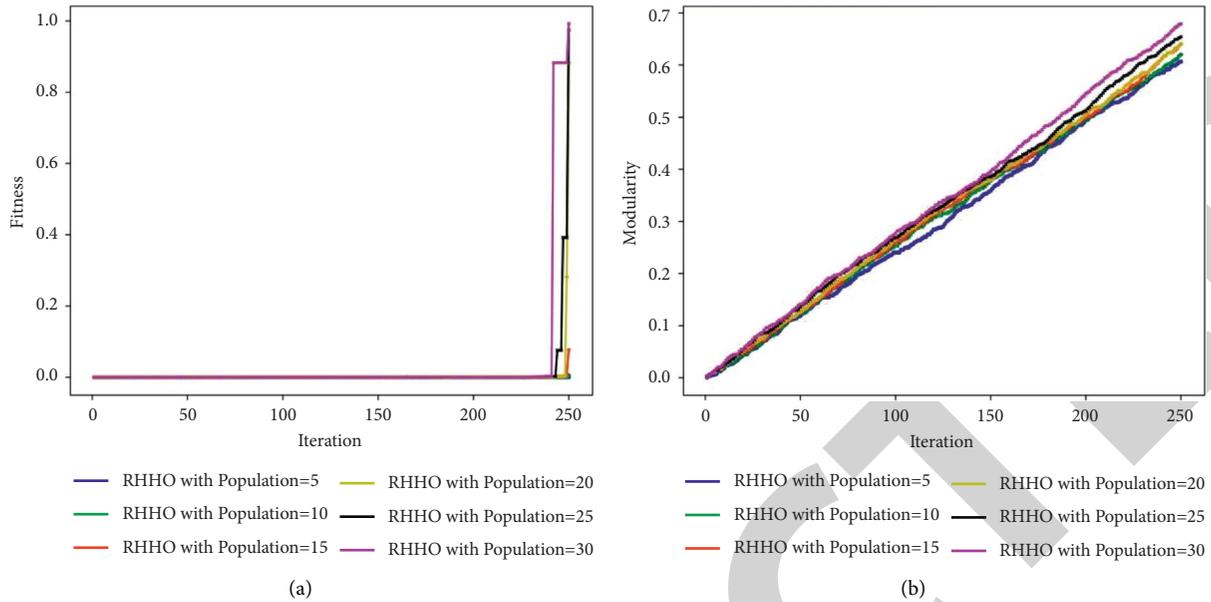


FIGURE 6: Performance analysis of proposed RHHO using Movie Lens 100 K considering (a) fitness and (b) modularity.

0.000021, 0.000026, 0.000036, 0.000044, 0.000051, and 0.00040. Likewise, when the iteration is 250, then the corresponding fitness values computed by proposed RHHO with population = 5, 10, 15, 20, 25, and 30 are 0.0016, 0.0017, 0.0069, 0.5085, 0.9140, and 0.9962, respectively. The analysis of the proposed RHHO based on the modularity metric is illustrated in Figure 7(b). When the iteration is 1, the corresponding modularity values computed by proposed RHHO population = 5, 10, 15, 20, 25, and 30 are 0.00023, 0.00300, 0.00311, 0.00327, 0.00436, and 0.00496. Likewise, when the iteration is 250, then the corresponding modularity values computed by proposed RHHO with population = 5, 10, 15, 20, 25, and 30 are 0.57925, 0.61982, 0.64765, 0.65844, 0.66412, and 0.67721, respectively.

5.5. Competing Methods. The methods, such as h-index-based link prediction [9], MAGA [31], GA [36], MATMCD-BN [28], and HHO [33], are employed for the comparison with the proposed RHHO.

5.6. Comparative Analysis. The comparative analysis of the proposed model is performed by evaluating the performance of other techniques based on fitness and modularity. The analysis is conducted by varying the number of iterations.

5.6.1. Analysis Based on Citation Networks Dataset Using cit-HepPh. Figure 8 illustrates the analysis of the methods using cit-HepPh based fitness and modularity measures. The analysis of the methods based on the fitness metric is portrayed in Figure 8(a). When the iteration is 1, the corresponding fitness values computed by h-index-based link prediction, MAGA, GA, MATMCD-BN, HHO, and proposed RHHO are 0.0000513, 0.00183, 0.47324, 0.48179, 0.50100, and 0.51568. Likewise, when the iteration is 250, the

corresponding fitness values computed by h-index-based link prediction, MAGA, GA, MATMCD-BN, HHO, and proposed RHHO are 0.130475, 0.574730, 0.59360, 0.60131, 0.64708, and 0.66048, respectively. The analysis of methods based on modularity metric is illustrated in Figure 8(b). When the iteration is 1, the corresponding modularity values computed by h-index-based link prediction, MAGA, GA, MATMCD-BN, HHO, and proposed RHHO are 0.000759, 0.00109, 0.00138, 0.00190, 0.00211, and 0.00285. Likewise, when the iteration is 250, the corresponding modularity values computed by h-index-based link prediction, MAGA, GA, MATMCD-BN, HHO, and proposed RHHO are 0.36686, 0.37422, 0.37475, 0.38952, 0.39476, and 0.77560, respectively.

5.6.2. Analysis Based on Citation Networks Dataset Using cit-HepTh. Figure 9 illustrates the analysis of the methods using cit-HepTh based fitness and modularity measures. The analysis of the methods based on the fitness metric is portrayed in Figure 9(a). When the iteration is 1, the corresponding fitness values computed by h-index-based link prediction, MAGA, GA, MATMCD-BN, HHO, and proposed RHHO are 0.000118, 0.00095, 0.36191, 0.40654, 0.43435, and 0.48270. Likewise, when the iteration is 250, the corresponding fitness values computed by h-index-based link prediction, MAGA, GA, MATMCD-BN, HHO, and proposed RHHO are 0.36032, 0.51114, 0.54192, 0.55247, 0.63780, and 0.69778, respectively. The analysis of the methods based on modularity metric is illustrated in Figure 9(b). When the iteration is 1, the corresponding modularity values computed by h-index-based link prediction, MAGA, GA, MATMCD-BN, HHO, and proposed RHHO are 0.000375, 0.00083, 0.00101, 0.00120, 0.00134, and 0.00298. Likewise, when the iteration is 250, the corresponding modularity values computed by h-index-based

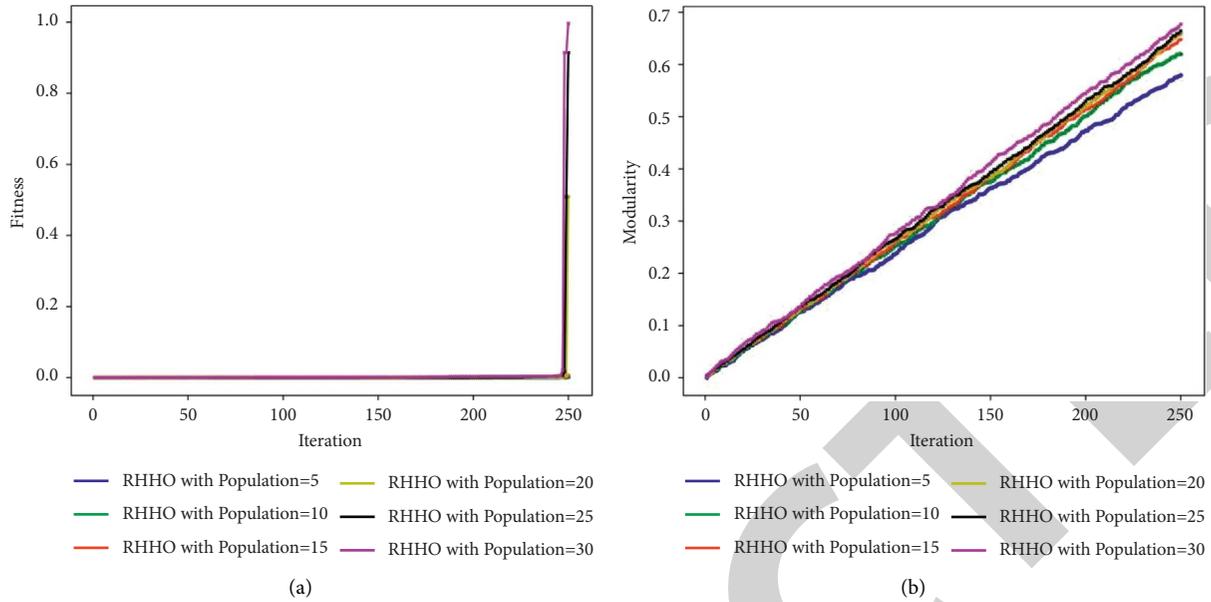


FIGURE 7: Performance analysis of proposed RHHO method using the American Revolution considering (a) fitness and (b) modularity.

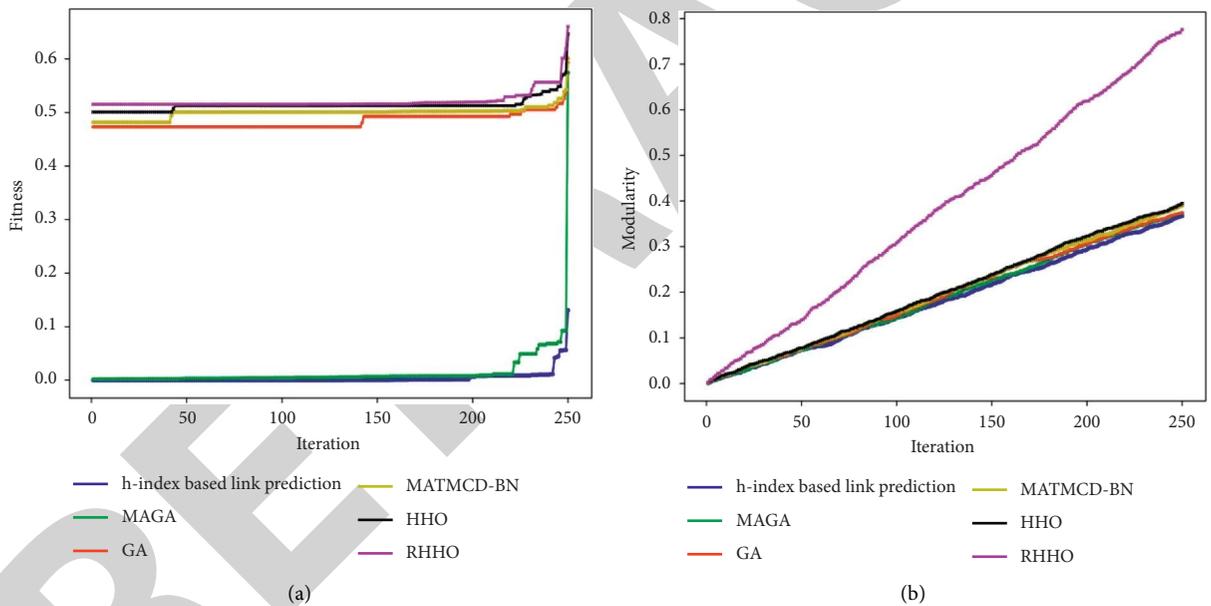


FIGURE 8: Analysis of methods using the cit-HepPh considering (a) fitness and (b) modularity.

link prediction, MAGA, GA, MATMCD-BN, HHO, and proposed RHHO are 0.34853, 0.37638, 0.37948, 0.38210, 0.38734, and 0.77807, respectively.

5.6.3. *Analysis Based on Bipartite Network Dataset Using Movie Lens 100 K.* Figure 10 illustrates the analysis of the methods using Movie Lens 100 K-based fitness and modularity measures. The analysis of the methods based on the fitness metric is portrayed in Figure 10(a). When the iteration is 1, the corresponding fitness values computed by h-index-based link prediction, MAGA, GA, MATMCD-BN, HHO, and proposed RHHO are 0.000035, 0.00069, 0.39608,

0.41400, 0.41713, and 0.49527. Likewise, when the iteration is 250, then the corresponding fitness values computed by h-index-based link prediction, MAGA, GA, MATMCD-BN, HHO, and proposed RHHO are 0.04802, 0.31454, 0.52216, 0.58928, 0.64062, and 0.68944, respectively. The analysis of the methods based on modularity metric is illustrated in Figure 10(b). When the iteration is 1, the corresponding modularity values computed by h-index-based link prediction, MAGA, GA, MATMCD-BN, HHO, and proposed RHHO are 0.00035, 0.00129, 0.00163, 0.00168, 0.00196, and 0.00553. Likewise, when the iteration is 250, then the corresponding modularity values computed by h-index-based link prediction, MAGA, GA, MATMCD-BN, HHO, and

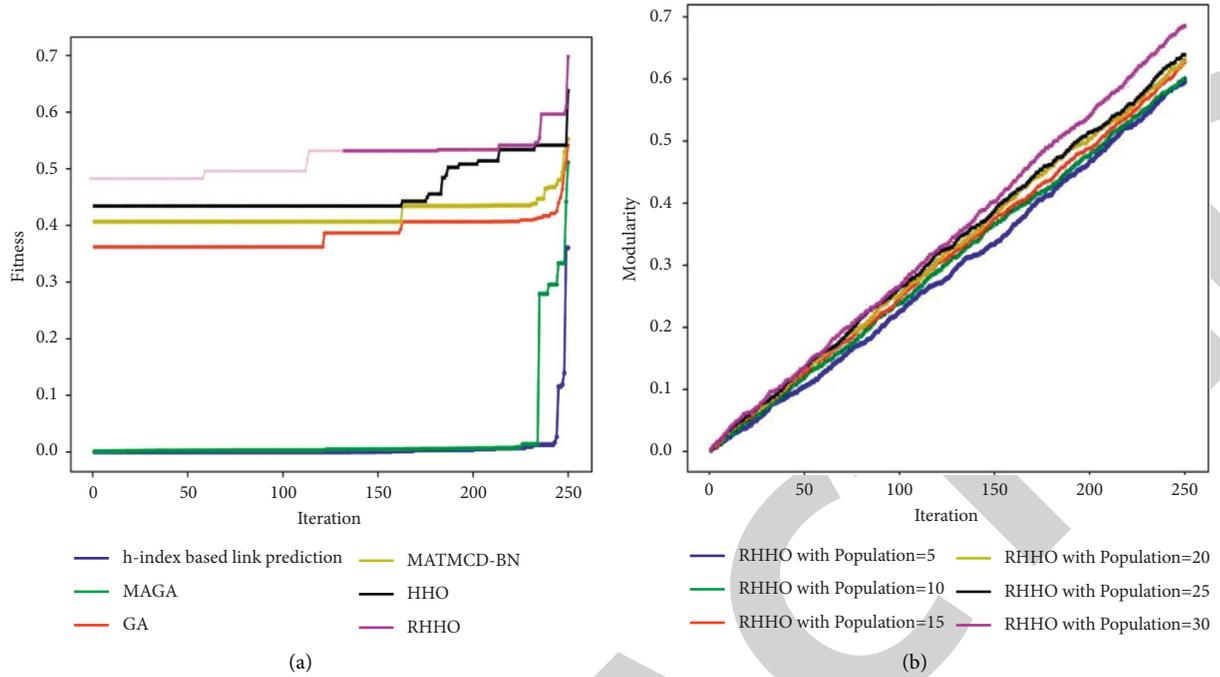


FIGURE 9: Analysis of methods using the cit-HepTh considering (a) fitness and (b) modularity.

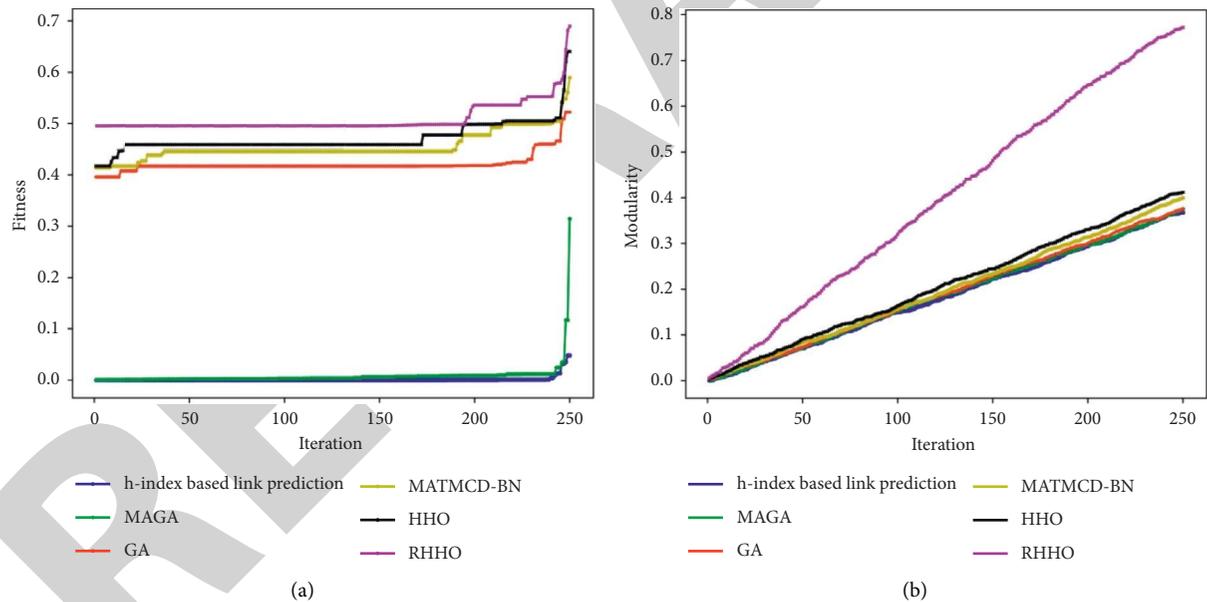


FIGURE 10: Analysis of methods using the Movie Lens 100 K considering (a) fitness and (b) modularity.

proposed RHHO are 0.36727, 0.37546, 0.37596, 0.39952, 0.41170, and 0.77191, respectively.

5.6.4. *Analysis Based on Bipartite Network Dataset Using American Revolution.* Figure 11 illustrates the analysis of the methods using Movie Lens 100 K-based fitness and modularity measures. The analysis of the methods based on the fitness metric is portrayed in Figure 11(a). When the iteration is 1, the corresponding fitness values computed by

h-index-based link prediction, MAGA, GA, MATMCD-BN, HHO, and proposed RHHO are 0.00053, 0.00142, 0.23572, 0.26296, 0.3476, and 0.4756. Likewise, when the iteration is 250, then the corresponding fitness values computed by h-index-based link prediction, MAGA, GA, MATMCD-BN, HHO, and proposed RHHO are 0.31137, 0.36367, 0.47276, 0.64272, 0.73190, and 0.74353, respectively. The analysis of the methods based on modularity metric is illustrated in Figure 11(b). When the iteration is 1, the corresponding modularity values computed by h-index-based link

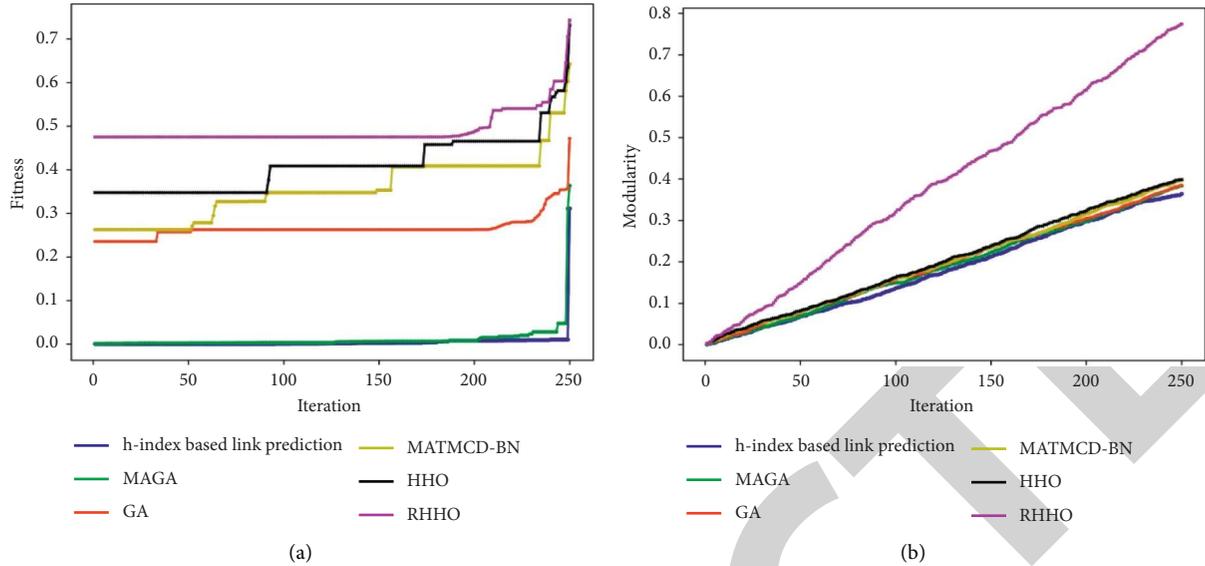


FIGURE 11: Analysis of methods using the American Revolution considering (a) fitness and (b) modularity.

TABLE 1: Comparative results of proposed RHHO method with other existing methods in terms of modularity and fitness.

Dataset	Metrics	h-index-based link prediction	MAGA	GA	MATMCD-BN	HHO	Proposed RHHO
cit-HepPh	Fitness	0.130475	0.574730	0.59360	0.60131	0.64708	0.66048
	Modularity	0.36686	0.37422	0.37475	0.38952	0.39476	0.77560
cit-HepTh	Fitness	0.36032	0.51114	0.54192	0.55247	0.63780	0.69778
	Modularity	0.34853	0.37638	0.37948	0.38210	0.38734	0.77807
Movie Lens 100 K	Fitness	0.04802	0.31454	0.52216	0.58928	0.64062	0.68944
	Modularity	0.36727	0.37546	0.37596	0.39952	0.41170	0.77191
American Revolution	Fitness	0.31137	0.36367	0.47276	0.64272	0.73190	0.74353
	Modularity	0.36400	0.38391	0.38523	0.39717	0.39896	0.77433

prediction, MAGA, GA, MATMCD-BN, HHO, and proposed RHHO are 0.000207, 0.00116, 0.00190, 0.00217, 0.00224, and 0.00275. Likewise, when the iteration is 250, then the corresponding modularity values computed by h-index-based link prediction, MAGA, GA, MATMCD-BN, HHO, and proposed RHHO are 0.36400, 0.38391, 0.38523, 0.39717, 0.39896, and 0.77433, respectively.

5.7. Comparative Discussion. Table 1 deliberates the comparative analysis of proposed RHHO with other existing methods in terms of modularity and fitness. The analysis is done by considering citation network and bipartite network dataset. Considering cit-HepPh, the maximal fitness is computed by proposed RHHO with 0.66048 whereas the fitness values of existing h-index-based link prediction, MAGA, GA, MATMCD-BN, and HHO are 0.130475, 0.574730, 0.59360, 0.60131, and 0.64708. The maximal modularity is computed by proposed RHHO with 0.77560 whereas the modularity values of existing h-index-based link prediction, MAGA, GA, MATMCD-BN, and HHO are 0.36686, 0.37422, 0.37475, 0.38952, and 0.39476, respectively. Likewise, considering cit-HepTh, the maximal fitness is 0.69778, and maximal modularity is 0.77807. Based on Movie Lens 100 K, the maximal fitness is 0.68944, and

maximal modularity is 0.77191. Similarly, considering American Revolution, the maximal fitness is 0.74353 and maximal modularity is 0.77433. It is also observed that the proposed RHHO outperformed other methods with maximal fitness of 0.74353 and maximal modularity of 0.77433 considering American Revolution network, respectively.

6. Conclusion

In the complex network structure, including bipartite networks, community detection is a major critical task. Community identification in a bipartite network not only reveals details about hierarchical structure of multifaceted network but also assists in better understanding of the core functions of the network and subsequently information recommendation. This paper presents a community detection method in a bipartite network considering the node similarity measure. In order to check the similarity of nodes, the h-Tversky measure is newly designed by modifying h-index based on Tversky index. In addition, a novel algorithm Rider-Harris Hawks Optimization (RHHO) is devised for community detection and developed by integrating RO and HHO algorithms to speed up the rate of convergence in the algorithm. The fitness is newly devised considering modularity and proposed h-Tversky index for

evaluating the node similarity. The purpose of incorporating modularity in the fitness function is to quantify the goodness of specific division of network to compute the precision of the proposed community detection. The proposed method showed effective performance with maximal fitness of 0.74353 and maximal modularity of 0.77433 using American Revolution network from bipartite network dataset. It can be utilized in machine learning discipline to detect groups with similar characteristics and properties inside a stock market or a social network like a bipartite network and then extract these groups for different reasons. In future, the MapReduce approach can be employed for determining the overlapping communities where more than one node is shared between the communities.

Data Availability

The Movie Lens 100 K dataset is publicly available at <https://grouplens.org/datasets/movielens/> and American Revolution network dataset is publicly available at http://konect.cc/networks/brunson_revolution/.

Conflicts of Interest

The authors declare no conflicts of interest about the publication of this research article.

Acknowledgments

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