International Journal of Computing and Digital Systems
ISSN (2210-142X)
Int. J. Com. Dig. Sys. #, No.# (Mon-20..)

A Novel Weight-based Fish School Search Approach for Hierarchical Network Clustering

Abuzer Hussein Ibrahim1, *. Mohamed Ahmed BOUDREF 2. Lyes BADIS 3

[1]LIM Laboratory, Department of Computer Science, Akli Mohand Oulhadj University of Bouira
Bouira, Algeria. h.abouzer@univ-bouira.dz

[2]LIM Laboratory, Department of Mathematics, Akli Mohand Oulhadj University of Bouira Bouira, Algeria.
m.boudref@univ-bouira.dz

[3]LIM Laboratory, Department of Computer Science, Akli Mohand Oulhadj University of Bouira, Bouira, Algeria.
l.badis@univ-bouira.dz

* Correspondence email:
h.abouzer@univ-bouira.dz

Abstract

Networks consist of interconnected nodes and edges that depict entities and their relationships. In social network clustering, nodes are grouped into clusters based on their connectivity, to identify communities. However, community detection methods have not yet leveraged the Weight-based Fish School Search algorithm, which is one of the promising approaches to finding community structure. In this paper, we aim to apply a specific class of FSS-Based algorithm, which is weighted FSS, to network clustering. We have developed a unique hierarchical network clustering method that leverages the Weight-based Fish School Search algorithm (WFSSC). This methodology focuses on maximizing weights to enhance the modularity function, leading to the identification of community structures in unipartite, undirected, and weighted networks. The process involves iterative network splitting and the construction of a dendrogram, with the optimal community structure determined by selecting the cut that maximizes modularity. Our method employs the modularity function for an objective assessment of the community structure, aiding in optimal network division. We evaluated our methodology on known and unknown network structures, including a network generated using the LFR model to assess its adaptability to different community structures. The performance was measured using metrics such as NMI, ARI, and FMI. The results demonstrated that our methodology exhibits robust performance in identifying community structures, highlighting its effectiveness in capturing cohesive communities and accurately pinpointing actual community structures.

Keywords -Clustering, Weight-based Fish School Search algorithm, Community Detection, Modularity function, Network structures

E-mail:author's email

1. Introduction

Network theory involves nodes connected by edges, representing entities and their interactions. For example, in biological networks [1], nodes represent species, and edges depict predator-prey relationships, aiding in understanding ecosystems. Communication networks [2] use nodes to symbolize devices like telephones, and edges represent communication links, optimizing network design. Supply chain networks [3] utilize nodes for locations and edges for supply routes, optimizing logistics. In citation networks [4], nodes represent scientific papers, and edges represent citations, aiding in understanding scientific fields. The network is represented as a graph G (V, E), with V as nodes/vertices and E as edges/links [5].
In social network clustering [6], nodes are grouped based on their connectivity patterns, determined by the links or edges that connect them. Clusters form from nodes with stronger connections, while nodes with weaker connections are placed separately [7]. Clustering techniques help discover groups revealing social substructures like cliques [8], subgroups, or communities, providing insights into social interactions and identifying influential individuals or groups [9]. In molecular biology [10], clustering methods identify protein communities, aiding in functional group discovery. In transportation networks[11], clustering identifies highly interconnected nodes for efficient traffic planning. Methods like Modularity-based [12], Spectral [13], and Hierarchical clustering [14] [15] can be used for effective network structuring.
Maximizing modularity is complex due to its computational intractability, often requiring heuristic algorithms [16]. Modularity maximization aims to increase interconnectedness within communities while minimizing it between different communities, revealing network structures [17]. Our work enhances modularity through the Weight-based Fish School Search algorithm [18]. This algorithm segments networks iteratively, maximizing the modularity function. Our methodology, employing the Weight-based Fish School Search algorithm (WFSSC), offers an innovative strategy for identifying community structures within networks. The modularity function acts as the objective function during clustering, evaluating clustering solutions.
The paper is logically structured, with the second section covering background and related works, the third highlighting the contribution (WFSSC), the fourth detailing our experiment and results, and the fifth concluding and discussing future work.

2. Background and Related Works

2.1 Community Detection

In complex networks, communities are groups of nodes tightly interconnected with each other, holding shared characteristics or functions [19]. Detecting these communities is crucial for various applications, with modularity optimization being a widely used method. This approach maximizes the density of links within communities compared to connections between them, thus enhancing partition quality [20].
Hierarchical clustering is another popular method for community detection [21]. It constructs a partition hierarchy by merging or splitting communities based on similarity measures, revealing both macro and micro-level patterns within the network [22]. This technique allows

E-mail:author's email

flexible exploration of community structure at different levels of granularity, even identifying nested communities [23].

Hierarchical clustering offers a systematic framework for uncovering hidden structures within complex networks, facilitating a deeper understanding of network organization and efficiency [24]. Its applications span various fields, including social network analysis, biology, neuroscience, information retrieval, recommendation systems, and anomaly detection [25].

Despite advancements, challenges like overlapping communities, weighted networks, and noisy data persist [23]. Addressing these challenges will further enhance community detection methods and their practical applications.

Our method, WFSSC, utilizes modularity to identify communities in structured networks. It maximizes modularity, indicating the most natural division of the network into communities with stronger internal connections than external ones.

2.2 Modularity

In [26], Newman and Girvan introduced modularity as a crucial metric for assessing graph partitioning into communities. Initially designed for undirected graphs, subsequent research [27]extended its applicability to directed and weighted graphs. Modularity transcends disciplinary boundaries, serving as a fundamental tool for understanding complex systems, especially in community detection within diverse network contexts [28].

Community detection in networks often involves modularity maximization, where modularity measures how a network deviates from a random network with the same degree distribution concerning intra-community edges. The objective is to group nodes into communities with the highest modularity score [29] [20]. This entails identifying clusters of nodes with stronger internal connections than external ones. Modularity maximization algorithms iteratively move nodes between communities, optimizing modularity until the best division of the network into communities is achieved.

Modularity maximization offers several advantages for community detection. It is a versatile method adaptable to networks of various sizes and types. Additionally, it can determine the optimal number and size of communities without prior information, facilitating an unbiased exploration of the community structure [30].

The adjacency matrix presents the network, with ‘0’ denoting the absence of an edge and ‘1’ denoting its presence. A membership variable’ indicates whether a node belongs to community 1 or 2. The modularity function is calculated as $Q = c_i e(c_i) - a(c_i)^2$ where $e(c_i)$ is the observed fraction of edges inside communities and $a(c_i)$ is the expected ratio

$$Q = \frac{1}{(2m)} \sum_{vw} \left[A_{ij} - \frac{K_i K_j}{(2m)} \right] \delta(C_i, C_j) = \sum_{i=1}^{c} (e_{ii} - a_i{}^2) \qquad (1)$$

where

$$\delta(c_i, c_j) = \begin{cases} 1 & if\ c_i = c_j \\ 0 & otherwise \end{cases}$$

the graph's adjacency matrix has Aij as the entry in the i row and j column, it is determined if there is an edge between vertex i and vertex j the degrees of the vertices i and j are ki and kj respectively, e_{ii} Observed fraction of edges within community and a_i representing intra-community connections the graph has a total of m edges, and each group is divided into k groups $(c1 \ldots \ldots \ldots, k)$

2.3 Weight-based Fish School Search Algorithm

The Weight-based Fish School Search algorithm (WFSS) is a metaheuristic optimization technique that draws inspiration from the collective behavior of fish school search (FSS) [31]. It was developed as a novel approach to tackle complex optimization problems, offering an alternative to traditional optimization algorithms. By emulating the behavior of fish schools, WFSS aims to efficiently explore the search space and find optimal solutions.

In WFSS, a population of fish called a "school," is used to explore the search area and uncover the optimal solution. Each fish in the school has a potential solution to the issue. The position of a fish corresponds to a candidate solution, and the fitness of a fish represents the quality of that solution [32].

The main idea behind WFSS is to mimic the collective behavior of fish schools, where individual fish adjust their positions based on the positions of their neighbors. This collective behavior helps the school to explore the search space efficiently and converge toward the optimal solution.

The key concept in WFSS is the weight factor, which determines the influence of each fish on the movement of its neighbors. The fitness of each fish is used to calculate the weight factor, with fitter fish having a higher weight. This allows the fitter fish to have a stronger influence on the movement of the school. WFSS uses a number of operators to simulate the behavior of fish schools, including:

1. **Individual components of the movement**

Within the Fish School Search (FSS), the individual movement operator plays a pivotal role. This operator enables each fish to navigate independently within the search space, following a positive gradient. The movement involves updating each fish's position through a formula that incorporates a random displacement. Notably, the new position is accepted only if it leads to an enhancement in the fish's fitness. This fitness is determined by evaluating the objective function specific to the optimization problem at hand. Otherwise, the fish remains in its current position. This individual movement stage is repeated iteratively for each fish in the school, allowing them to explore the search space and potentially improve their positions and fitness [33]. using the formula

$$x_i(t+1) = x_i(t) + rand(-1,1)step_{ind} \quad (2)$$

Where $x_i(t)$ and $x_i(t+1)$ The fish's status was both before and after the individual movement operator. in that order. $rand(-1,1)$ is a number that is randomly distributed and uniform, with a range from -1 up to 1 and $step_{ind}$ parameter that sets the highest distance for this movement. The updated location, denoted as $x_i(t+1)$, is adopted by the fish exclusively if it results in an improvement in the fish's fitness. In cases where this condition is not met, the fish maintains a similar position and does not change.

$$x_i(t+1) = x_i(t) \quad (3)$$

2. **Feeding Operator**

The feeding operator is a critical element in the Fish School Search, it models how fish increase or decrease their weight depending on the quality of their food source, which is determined by the objective function value [34]. The feeding operator updates the weight of each fish according to the following formula:

$$W_i(t+1) = W_i(t) + \frac{\Delta f_i}{max(|\Delta f_i|)} \quad (4)$$

where $W_i(t)$ is the weight of the fish at iteration t, Δf_i The difference in objective function values between the current and previous ones, and $max(|\Delta f_i|)$ The absolute value that is the highest of Δf_i among all fish.

The feeding operator ensures that fish with better objective function values will have higher weights, and vice versa. This affects the individual and collective movements of the fish, as well as the termination criterion of the algorithm [35].

3. **Link Formation Rule**

The Link Formation Rule in the Fish School Search plays a crucial role in connecting fish within the school. Fish that successfully improve their fitness through individual movement are more likely to establish links. Additionally, fish with higher weights, indicating better food source quality, also tend to form connections. These links facilitate information sharing among the fish, enabling them to collectively explore and adapt to the evolving search space [36].

Link Formation Rule dictating how fish establish connections based on their movements and food source quality. This fosters collaboration within the school, enhancing the search for optimal solutions.

4. Collective Instinctive Movement

The Collective Instinctive Movement is a fundamental aspect of the Fish School Search, shaping the behavior of fish within the school. Drawing inspiration from the collective behavior of fish schools, this movement involves calculating the average of individual movements. The resulting vector represents the weighted average of the displacements observed by each fish. As a result, fishes that have experienced greater improvements act as attractors, drawing other fishes towards their position. Following the vector computation, every fish is motivated to move by this collective instinct, fostering collaboration and coordinated exploration within the school [37].

The search space can have a balance between exploration and exploitation thanks to this mechanism, as it encourages fish to move towards areas where other fish have found success, while still maintaining some degree of randomness and individuality in their movements1. This can lead to more efficient and effective search processes, as it leverages both individual successes and collective knowledge within the school [38].

$$x_{ij}(t+1) = x_{ij}(t) + \alpha\left(\frac{\Delta x_{ij}\Delta f\left(\overrightarrow{x_l}\right)L\Delta x_{ij}\Delta f\left(\overrightarrow{x_l}\right)}{\Delta f\left(\overrightarrow{x_l}\right)+L\Delta f\left(\overrightarrow{x_l}\right)}\right) \quad (5)$$

5. The Collective Volitive Movement

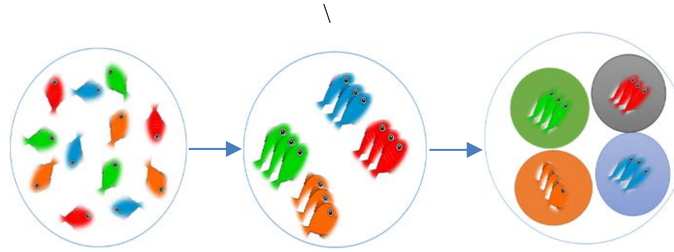
The Collective Volitive Movement is an operator that regulates the exploration and exploitation search process and is influenced by the school's ability.

The algorithm calculates the barycenter of the fish school, influencing exploration and exploitation. If the total weight increases, fishes move towards the barycenter, focusing on promising areas and improving solution quality [39].

The search space can have a balance between exploration and exploitation through this mechanism. It encourages fish to move towards areas where other fish have found success, while still maintaining some degree of randomness and individuality in their movements1. This can lead to more efficient and effective search processes, as it leverages both individual successes and collective knowledge within the school [40].

$$B_i(t) = \frac{x_{ij}W_i(t) + Lx_{lj}W_i(t)}{W_i(t) + LW_l(t)} \quad (6)$$

\



a. Initial Distribution b. Group Formation c. Final Grouping

Fig1. The three stages of the Weighted Fish School Search (WFSS) algorithm are: a. Initial Distribution: Fish are randomly distributed, moving independently towards the positive gradient in the search space. Their weights are adjusted based on the quality of their food source. b. Group Formation: Over time, similar fish form small groups guided by the Link Formation Rule and Collective Instinctive Movement, moving towards areas where other fish have found success. c. Final Grouping: The final grouping is based on fish weights. All fish will move towards the barycenter if the school's total weight increases, leading to a final grouping based on high weight.

Algorithm 1: WFSS Algorithm

```
// Initialization
InitializePopulation()
EvaluateFitness()
InitializeWeights()
// Iterative Process
while TerminationCriterionNotMet() do:
 // Individual Movement
for each fish in the school:
newPosition = CalculateNewPosition(fish)
if FitnessImproves(newPosition):
UpdatePosition(fish, newPosition)
// Feeding Operator
UpdateWeights()
// Link Formation Rule
FormLinks()
// Collective Instinctive Movement
CalculateWeightedAverage()
UpdatePositions()
// Collective Volitive Movement
CalculateBarycenter()
MoveTowardsBarycenter()
// Termination
TerminateAlgorithm()
```

2.4 Related Works

In this review, we will discuss key contributions that highlight the use of modularity and artificial intelligence (AI) algorithms in community detection. Community detection is an evolving field that focuses on identifying and analyzing structures in complex networks.

The first study [41] employs a statistical model-based approach to cluster diverse networks, using a hierarchical agglomerative algorithm and automated model selection. Challenges like the label-switching problem are addressed, with effectiveness demonstrated on synthetic and ecological networks. The secondary, method [42] employs a weighted clustering ensemble for adaptive partitioning of multilayer brain networks, achieving optimal module detection and promising insights into Alzheimer's disease connectomes. Also, the study [43] introduces a hierarchical method using the Tabu Search algorithm to detect community structures in networks by splitting the network into subgraphs until each node is a community, Finally, the study [44] introduces a new network-based community detection algorithm using cosine similarity for edge weights, employing a bottom-up approach with modularity-based merging, and evaluates its performance against other algorithms using various metrics. Our proposed WFSSC approach extends the paradigm of hierarchical community detection introduced in the related work. While previous studies have explored hierarchical methods such as those based on Tabu Search and cosine similarity, our approach introduces the Weight-based Fish School Search algorithm to enhance the efficiency and accuracy of community detection. By combining insights from existing methodologies with innovative AI-driven techniques, the WFSSC approach represents a promising advancement in the field of community detection in complex networks.

3. The Proposed WFSSC Approach (Weight-based Fish School Search Algorithm Clustering)

Our methodology is primarily intended for networks that are unipartite, undirected, and weighted. Nevertheless, it possesses the potential to be expanded to identify community structures in other network types, such as unweighted or directed networks.

We've developed an innovative network clustering technique that leverages the power of artificial intelligence through the Weight-based Fish School Search algorithm, with a primary emphasis on hierarchy.

Community detection methods that are hierarchical, either divisive or agglomerative, work by splitting or merging clusters. Divisive methods, such as Edge Density [45] and Topological measures [46], eliminate edges based on criteria like density, centrality, or clustering coefficient to uncover subgraphs that are densely connected as communities and improve community separation.

our methodology takes a different route. We employ a network-splitting strategy that hinges on maximizing weights to improve the modularity function. This distinctive approach enables us to pinpoint community structures that achieve maximum modularity. What sets us apart is our reliance on Weight-based Fish School Search algorithm to execute this splitting process.

In our methodology, we employ a division hierarchical technique Beginning with a network, we divide it into two separate networks that have high modularity. after that splitting process is repeated iteratively until each cluster contains one vertex. Subsequently, we construct a dendrogram to visualize the hierarchical relationships within the network. In our approach to community structure detection, we employ the modularity function to guide us in choosing the optimal dendrogram cut. WSSC stops the process of splitting when the graph G has been disconnected, which implies that each node of G represents a community. Subsequently, a dendrogram is constructed, and the most optimal community structure $\pi = \{c1, \ldots, ck\}$ is determined such that $\bigcup k\ i{=}1 = V$ and $ci \neq \emptyset$, $ci \cap cj = \emptyset$ (for $i, j = 1 : k$).

Algorithm 2: WFSSC Method

1. Input: G = (V, E) - The input graph with vertices V and edges E.
2. Result cluster - The resulting cluster (dendrogram, π)
3. Cluster ← G;
4. π ← cluster;
5. repeat
6. Set_cluster ← π
7. for each cluster in set _cluster do
8. π' ← Weigh Fish School Search(cluster);
9. π' splits the cluster into subsets;
10. cluster = cluster1 +cluster2;
11. Update π';
13. Adjust the matrix for the final dendrogram.
14. end for
15. until |π| ≥ |V|
16. return cluster that maximizes Q;
17. Return the final dendrogram;

4. Performance measure

We tested WFSSC on known and unknown network topologies. In our analysis, we compare our method with many other established methodologies, such as DS-LPA [47], SCD [48], ERGM [49], OSLOM [50], Infomap [51], Label propagation(LPA) [52], Louvain [53], and Fastgreedy method [54], Our approach successfully identified communities that exhibited superior clarity and cohesiveness compared to those discovered by the other methods. We assessed the performance and effectiveness of our method using four measures: the Modularity(Q), normalized mutual information, adjusted rand index (ARI), and Fowlkes-mallows index (FMI).

4.1 Normalized Mutual Information (NMI)

the normalized Mutual Information (NMI) [55] metric was proposed for the comparative assessment of community-based screening techniques. NMI is a widely used measure of community quality and is a good predictor of humanannotated ground-truth communities. You'll need a confusion matrix N, with rows representing the actual communities and columns representing the identified communities. Each component Nij in the matrix represents the count of nodes belonging to the actual community I that are present in the discovered community j. This confusion matrix allows us to quantify the overlap and agreement between the two sets of communities. The NMI measure employs information theory principles to evaluate the similarity between the partitions. It calculates the mutual information between the real and found communities, taking into account the distribution of nodes across the communities. The NMI measure captures the shared information and dependence between the partitions by considering the probabilities of nodes belonging to specific communities.

$$I(A,B) \frac{-2\sum_{i=1}^{c_A}\sum_{j=1}^{c_B} N_{ij}\, log(N_{ij}N/N_{i.}N_{.j})}{\sum_{i=1}^{c_B} N_i\, log(N_i/N)+\sum_{j=1}^{c_B} N_{.j}\, log(N_{.j}/N)} \qquad (7)$$

In this context, CA represents the actual community count, while CB indicates the identified community count. Ni signifies the sum of elements in the ith row vector of Nij matrix, and $N.j$ identifies the sum for column j. When our method aligns perfectly with the actual community structure, I (A, B) attains its highest value of 1, indicating a perfect match. Conversely, if the discovered communities are unrelated to the actual ones, the NMI value drops to 0, signifying no similarity. When the identified community structure is somewhat similar but not identical to the actual structure, the NMI value falls between 0 and 1, indicating partial agreement.

4.2 Adjusted Rand Index (ARI)

When it comes to evaluating the similarity between two data clustering, the adjusted rand index (ARI) [56] is a valuable tool. The ARI formula enhances the rand index by incorporating chance into the evaluation. It thoroughly scrutinizes how pairs of data points are assigned, taking into account their similarity or dissimilarity in both the predicted and true clustering.

$$ARI \frac{(RI-Expected_{RI})}{(max(RI)-Expected\_RI)} \qquad (8)$$

The ARI score is designed to approach 0.0 for random labeling, reach exactly 1.0 when the clustering is a perfect match, and potentially drop as low as -0.5 for completely discordant clustering.

The ARI exhibits symmetry, implying that swapping the input clustering has no impact on the score. It falls within the range of -1 to 1, where 1 signifies complete concordance, 0 represents a chance-level agreement, and -1 denotes absolute discord.

. Professionals in machine learning, data mining, and pattern recognition frequently turn to the ARI as a fundamental tool for appraising the performance of clustering algorithms.

4.3 Fowlkes-Mallows Index (FMI)

(7)

The Fowlkes-Mallows Index (FMI) [57] is a statistical metric frequently utilized in clustering analysis to assess the quality of clustering outcomes or the effectiveness of clustering algorithms. It quantifies the similarity between two different clustering or partitions of a dataset, taking into account both precision and recall, two important metrics in information retrieval and classification. The FMI is computed using the formula:

$$FMI = TP \,/\, \sqrt{\left(\left((TP+FP)(TP+FN)\right)\right)} \qquad (9)$$

In this context, TP is employed to indicate true positives, FP is utilized for false positives, and FN is designated for false negatives. The Fowlkes-Mallows Index (FMI) has a scale from 0 to 1, with values approaching 1 indicating a stronger agreement between the clustering. It is especially useful when comparing different clustering algorithms or assessing the quality of a clustering algorithm's output. Overall, the FMI provides a balanced measure for evaluating clustering performance.

4.4 Computer-generated networks

To assess the effectiveness of our method, we put it through rigorous testing using computer-generated grids. These synthetic networks come with predefined community structures, making them an ideal testbed for evaluating the precision and robustness of community detection algorithms, specifically WFSSC. We harnessed the Lancichinetti–Fortunato–Radicchi (LFR) benchmark model, as suggested by [58], to generate networks tailored to our desired community structures. This comprehensive evaluation allows us to gauge WFSSC's proficiency in accurately uncovering and delineating community structures.

The LFR model stands as a widely recognized framework for fashioning networks with diverse attributes, including power-law degree distributions, community structures, and even overlapping communities. Within our study, we employed the LFR model to construct a network comprising 128 nodes. The degree exponent distribution was set at 2, governing the node-to-link ratio, while the community size distribution exponent was fixed at 3, dictating community sizes. With an average degree of 16, we quantified the actual connections in relation to potential ones within the network. This network featured three distinct communities, with the mixing parameter varying from 0.1 to 0.9, exerting an impact on interconnectivity among these communities. In our methodology, we defined the fitness function as the modularity function and established 1000 food sources, accompanied by a maximum iteration limit of 5000 for optimizing WFSSC.

5. Experiment and results

In this section, we delve into diverse social networks to evaluate our method's effectiveness, providing detailed descriptions below. These networks offer valuable insights into varied social dynamics and structures on the following networks: The Zachary club network [59], American College football [60], The Dolphin Social Network [61], The Book about US Politics Network [62], Amazon [63], Les Miserable Network [64], The Jazz Collaboration Network [65], The HIV network [66], The Contiguous USA [67] network. Table 1 summarizes the fundamental characteristics of real benchmark networks, including the number of nodes (|V|), the number of edges (|E|), the average degree (〈k〉), and community structure (CS) is known or unknown

Table 1: Shows a complete picture of networks

Networks	*CS*	|*V*|	|*E*|	〈*k*〉	*Main Focus*
Zachary	Known	34	78	4.58	Karate club conflict analysis.
Football	Known	115	613	10.66	College football network analysis.
Dolphin	Known	62	159	5.12	Dolphin social dynamics analysis.
Book	Known	105	441	8.4	2004 US election book themes.
Miserable	Unknown	77	245	6.36	Victor Hugo's character network.
Jazz	Unknown	198	2742	27.69	Jazz collaboration dynamics
HIV	Unknown	40	41	2.05	Early HIV spread in USA contacts.
USA	Unknown	48	107	4.45	Geographical connectivity analysis.
Amazon	Unknown	334863	925872	5.52	network for co-purchasing products.

Table 2. Presents the results related to the network's performance.

Methods	**Karate**		**Football**		**Books**		**Dolphins**		**Amazon**	
	|C|	NMI	|C|	NMI	|C|	NMI	|C|	NMI	|C|	NMI
DS-LPA	4	**0.53**	20	**0.64**	4	**0.48**	3	**0.52**	259	**0.09**
SCD	3	**0.55**	10	**0.84**	2	**0.50**	5	**0.59**	1362	**0.63**
ERGM	3	**0.22**	14	**0.17**	4	**0.21**	2	**0.07**	120	**0.03**
OSLOM	2	**0.1**	22	**0.54**	12	**0.39**	7	**0.35**	80	**0.39**
Infomap	2	**0.59**	12	**0.92**	6	**0.49**	5	**0.53**	17296	-
Louvain	4	**0.50**	9	**0.85**	5	**0.50**	4	**0.49**	5813	**0.01**
LPA	2	**0.1**	10	**0.83**	3	**0.48**	4	**0.47**	22496	**6.35**
Fastgreedy	3	**0.69**	5	**0.65**	3	**0.53**	3	**0.41**	220	**0.06**
WFSSC	2	**0.87**	12	**0.94**	**3**	**0.57**	8	**0.60**	170	**0.54**

Table 3 displays the modularity values for networks exhibiting community structures.

Methods	Karate	Football	Books	Dolphins	Amazon
	Q	**Q**	**Q**	**Q**	**Q**
DS-LPA	0.37	0.41	0.47	0.42	0.79
SCD	0.39	0.58	0.45	0.40	0.88
ERGM	0.06	0.03	0.02	0.01	0.60
OSLOM	0.37	0.18	0.09	0.14	0.68
Infomap	0.37	0.60	0.52	0.52	0.82
Louvain	0.41	0.60	0.52	0.52	0.92
LPA	0.37	0.57	0.47	0.51	0.78
Fastgreedy	0.38	0.54	0.50	0.49	0.81
WFSSC	0.40	0.60	0.50	0.53	0.93

Table 4. Presents the ARI and FMI metrics for assessing the network's performance.

Methods	Karate		Football		Books		Dolphins		Amazon	
	ARI	FMI	ARI	FMI	ARI	FMI	ARI	FMI	ARI	FMI
DS-LPA	0.38	0.60	0.74	0.76	0.55	0.64	0.53	0.52	0.53	0.52
SCD	0.54	073	0.80	0.82	0.53	0.72	0.54	0.55	0.54	0.55
ERGM	0.16	0.22	0.06	0.09	0.02	-0.03	-0.11	0.04	-0.11	0.04
OSLOM	0.1	0.1	0.48	0.52	0.44	0.59	0.38	0.42	0.38	0.42
Infomap	0.35	0.71	0.89	0.90	0.53	0.69	-	-	-0.04	0.01
LPA	0.1	0.1	0.69	0.73	0.65	0.79	-	-	-	0.05
Louvain	0.22	0.59	0.70	0.74	0.64	0.77	-	-	0.01	0.07
Fastgreedy	0.54	0.77	0.42	0.54	0.63	0.77	-	-	-	0.02
WFSSC	0.69	0.80	0.82	0.84	0.91	0.94	0.62	0.84	0.62	0.84

Table 2 and Table 3 provide a comprehensive comparison of community detection methods across four diverse networks, utilizing key metrics like the number of clusters (|C|), modularity (Q), normalized mutual information (NMI), adjusted Rand Index (ARI) and Fowlkes-Mallows Index (FMI) to assess method effectiveness. The WFSSC method demonstrated significant performance across various networks. It achieved a reasonable level of agreement with the ground truth on the Karate network and high accuracy on the Football network. Although it performed moderately on the Books network, it excelled on the Dolphins network, outperforming other methods. These results underscore WFSSC's robustness and versatility in community detection across diverse networks

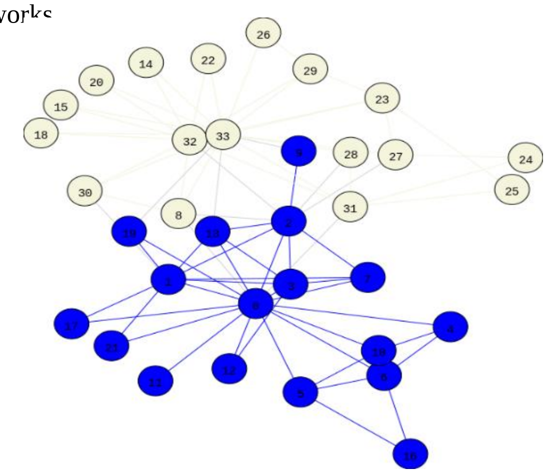


Fig .2 WFSSC identifies 2 clusters in the Zachary club network structure.

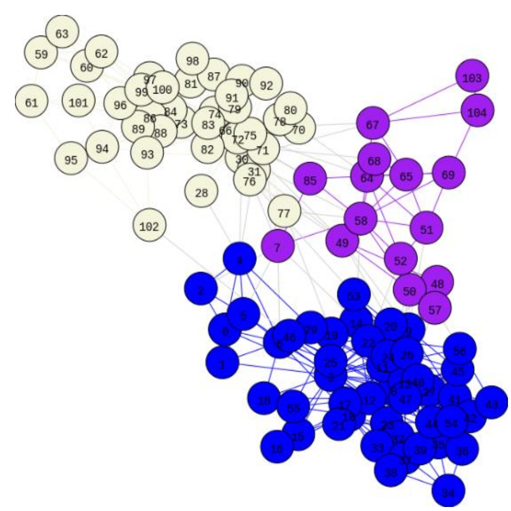


Fig. 3 WFSSC identifies 3 clusters in the structure of the Books about US politics.

WFSSC effectively discerned significant communities in the karate network (Fig 2) and identified three distinct clusters in the US politics book network (Fig 3). The high modularity and NMI values highlight its robust performance in community detection, offering insights into social dynamics and thematic clustering.

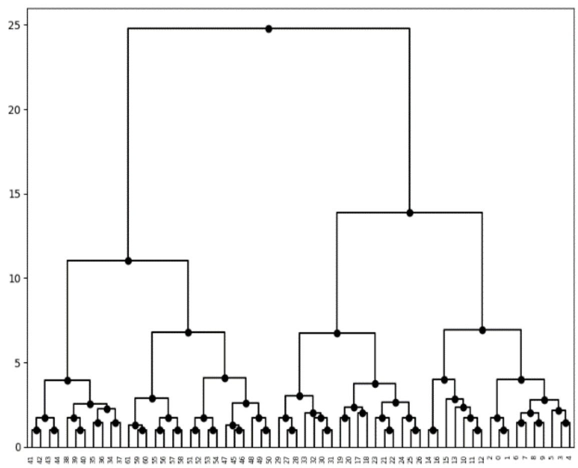


Fig. 4The dendrogram of the Dolphins network created by WFSSC.

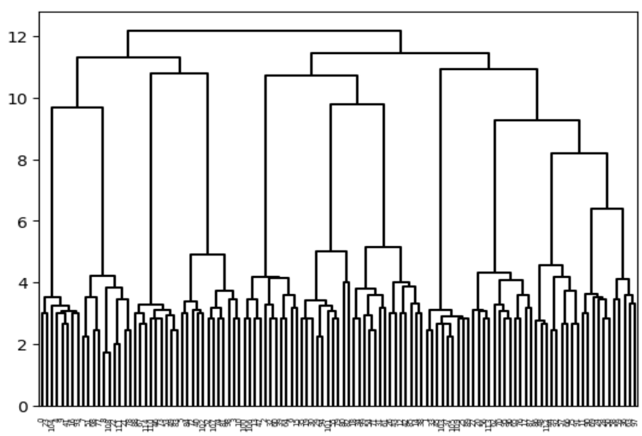


Fig. 5 The dendrogram of the football network created by WFSSC.

WFSSC's performance in clustering two networks, Dolphin and football, was exceptional. The Dolphin network (Figure 4) formed eight meaningful communities, revealing hierarchical clustering patterns via a dendrogram. In the football network (Figure 5), WFSSC partitioned it into 12 clusters with impressive accuracy. These results underscore WFSSC's effectiveness in accurately detecting communities within complex networks, offering valuable insights into their structural organization.

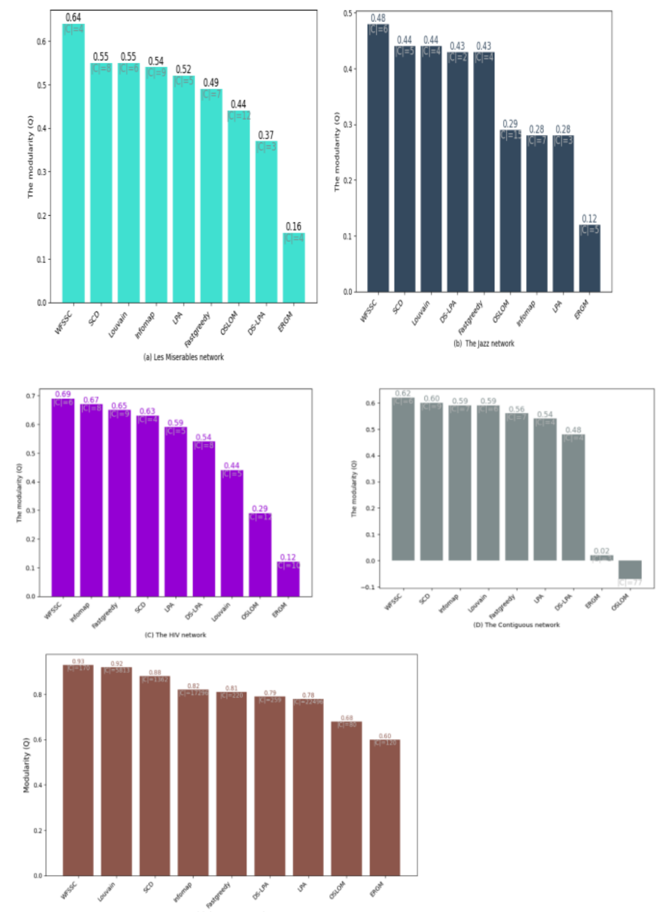


Fig. 6 Compares WFSSC with different unknown networks: (a) Les Miserable Network, (b) Jazz Network, (c) HIV Network, (D) USA Network, and (E) Amazon Network.

depicted in Fig 6, the WFSSC method was subjected to testing across various networks, consistently exhibiting superior performance in many instances. However, comparing WFSSC with methods like ERGM, LPA, and OSLOM proves complex due to the absence of a known community structure. While these methods may excel on certain networks, their performance varies on others, underscoring the challenge of identifying the most effective community detection approach. Furthermore, In this paper, we evaluate different algorithms in large network settings using the Amazon dataset (Fig E). The WFSSC algorithm emerges as a standout performer in the Amazon network, consistently achieving Q values above 0.90, surpassing other algorithms. However, the complex time complexity of these algorithms poses a significant challenge to their efficient operation in the Amazon network.

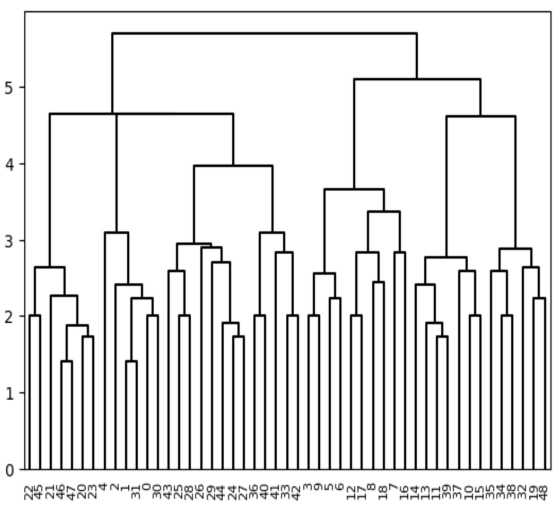


Fig. 7 The dendrogram of the USA network created by WFSSC.

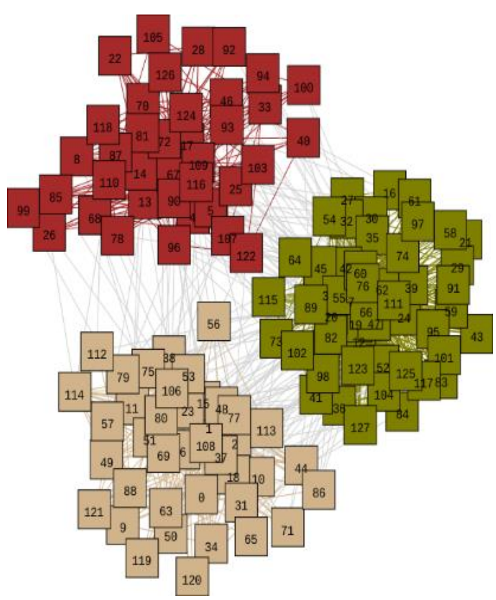


Fig. 8 WFSSC detects computer-generated networks at μ = 0.1

In Figure 7, WFSSC effectively partitioned an unknown USA network into six clusters with a high modularity score of 0.60, aided by a revealing dendrogram. In Figure 8, WFSSC accurately detected three clusters in computer-generated networks using μ = 0.1. These results highlight WFSSC's adaptability and precision in identifying meaningful communities across varied network scenarios, affirming its utility as a versatile tool for network analysis and community detection.

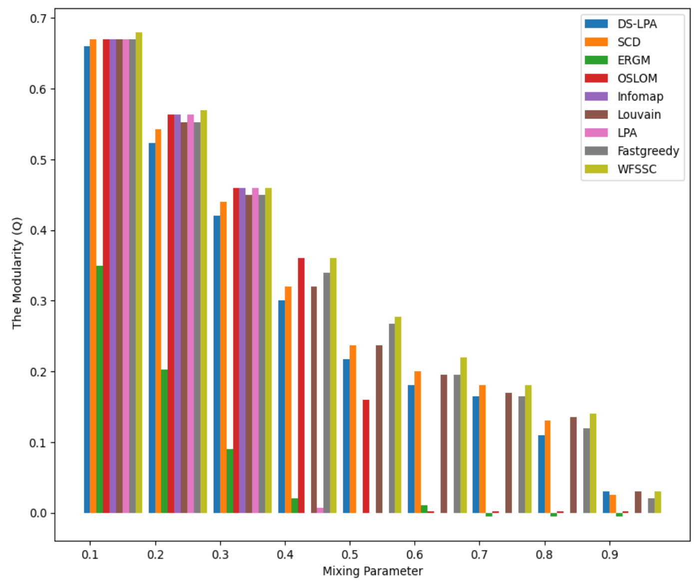


Fig.9 Modularity changes with the degree of inter-community mixing.

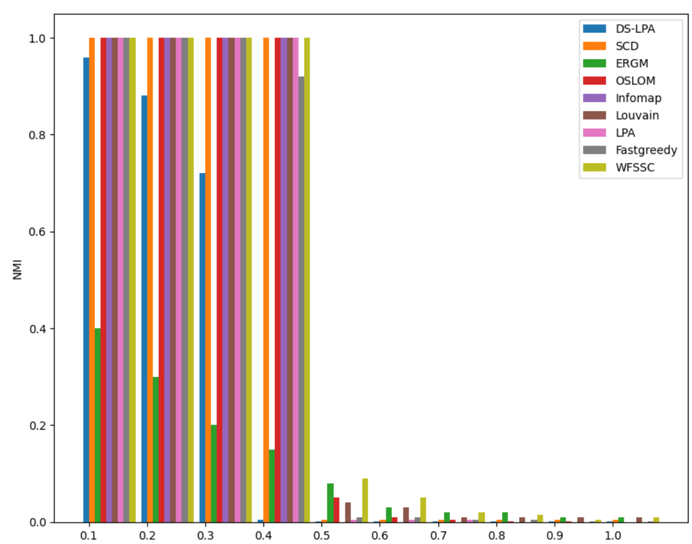


Fig.10 NMI changes with the degree of inter-community mixing.

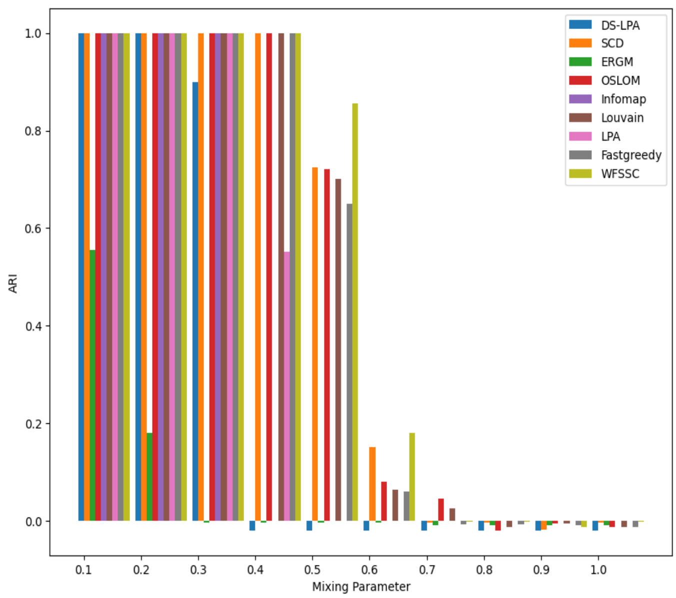


Fig.11 ARI changes with the degree of inter-community mixing.

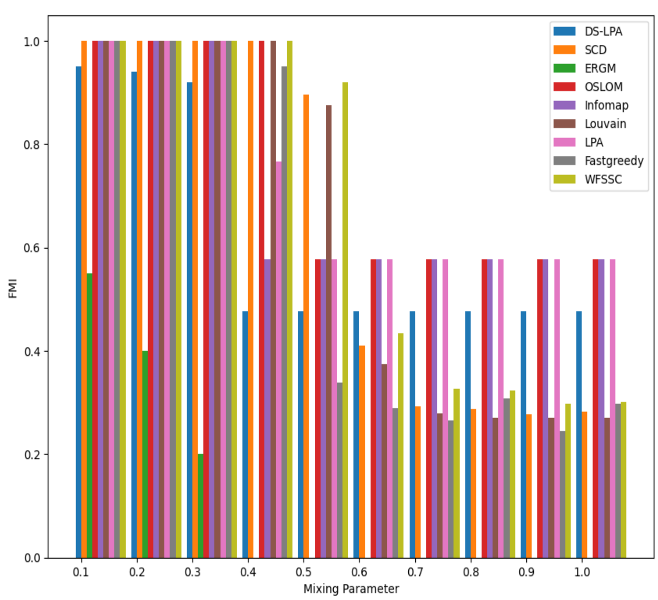


Fig.12 FMI changes with the degree of inter-community mixing.

The WFSSC method revealed a robust community structure in network analysis, according to [54], a network's community structure is significant when its modularity exceeds 0.3. This high modularity signifies densely connected communities. Figure 9 visually supports this, showcasing WFSSC's proficiency in unveiling cohesive communities. These findings validate WFSSC's effectiveness in detecting meaningful network communities, highlighting its value in network analysis and community detection compared with some methods such as ERGM, OSLOM, Informap, and LPA that give modularity values low or zero. Figure 10 provides a focused performance analysis of the WFSSC method concerning inter-community mixing. Initially, WFSSC achieved a perfect NMI of 1.0 with mixing parameters between 0.1 to 0.4, demonstrating precise community identification. On the contrary, some methods, such as DS-LPA, ERGM, and Fastgreedy, may not accurately identify the true community structure, particularly when μ is less than or equal to 0.4. When μ is greater than or equal to 0.5, detecting the true community structure becomes a challenge for all methods. However, the WFSSC method continues to outperform others in terms of accuracy, even under these conditions.

In Figure 11, we evaluate the performance of the WFSSC method for community detection under different levels of inter-community mixing, using the Adjusted Rand Index (ARI) as a measure. The WFSSC method shows excellent performance with a perfect ARI score of 1.0 for mixing parameters ranging from 0.1 to 0.4, indicating accurate community detection. For mixing parameters in the range of 0.5 to 0.6, WFSSC still maintains a robust ARI above 0.80. However, some methods like DS-LPA, ERGM, and Infomap yield an ARI value of zero or negative when the mixing parameters exceed 0.5, indicating their limitations in these scenarios.

In Figure 12, The WFSSC method demonstrates to outperform other methods, achieving a high Fowlkes-Mallows Index (FMI). This suggests that it excels in accurately detecting communities, especially when the network's mixing parameter is relatively high (μ less than 0.7) underscoring WFSSC's adaptability and strong performance in community detection across different network scenarios. In contrast, other methods such as

OSLOM, Infomap, and LPA may struggle or even fail to effectively detect communities under similar conditions.

6. Conclusion and future work

The methodology's core purpose revolves around its applicability to networks that share the traits of being unipartite, weighted, and undirected, but it can be expanded to other network types. It uses the Weight-based Fish School Search algorithm to identify community structures. Unlike other methods, it focuses on maximizing weights to improve the modularity function. The methodology employs a division hierarchical technique, dividing the network into separate networks iteratively until each cluster contains only one node. A dendrogram is then constructed to visualize the hierarchical relationships, and the cut in the dendrogram that maximizes the modularity function is chosen to identify the community structure. The WFSSC method has shown significant performance in various networks, achieving high accuracy and modularity values. It effectively detects communities within complex networks and offers valuable insights into their structural organization. The method has also demonstrated adaptability and precision in identifying meaningful communities across different network scenarios. Through comprehensive comparisons with alternative community detection approaches, the WFSSC method has consistently displayed its prowess in community detection, recording impressive results across metrics like modularity, normalized mutual information, and the adjusted Rand index. The Fowlkes-Mallows Index has also been used to evaluate the method's performance, and it consistently delivers high values. Overall, the WFSSC method is effective, versatile, and robust in detecting communities in networks. Future work involves expanding the methodology to different network types, exploring its potential in unweighted or directed networks, enhancing it with additional optimization techniques, and evaluating its performance on larger and more diverse networks for scalability and generalizability. Further development and refinement are needed to improve its effectiveness and applicability in community detection for example be applied WFSSC in cancer subtype classification [68] for identifying patient clusters and advancing targeted therapies and biomarker discovery.

Competing Interests

The authors have no competing interests to declare that are relevant to the content of this article.

Funding

The authors did not receive support from any organization for the submitted work.

References

[1] X. Kan *et al.*, “R-Mixup: Riemannian Mixup for Biological Networks,” *Proc. ACM SIGKDD Int. Conf. Knowl. Discov. Data Min.*, pp. 1073–1085, 2023, doi: 10.1145/3580305.3599483.

[2] M. Herrera, M. Sasidharan, S. Cassidy, and A. K. Parlikad, “Performance assessment of a communication infrastructure with redundant topology: A complex network approach,” *Comput. Networks*, vol. 228, no. March, p. 109747, 2023, doi: 10.1016/j.comnet.2023.109747.

[3] Z. Ardalan, S. Karimi, B. Naderi, and A. A. Khamseh, “Supply chain networks design with multi-mode demand satisfaction policy,” *Comput. Ind. Eng.*, vol. 96, pp. 108–117, 2016, doi: 10.1016/j.cie.2016.03.006.

[4] F. Radicchi, S. Fortunato, and A. Vespignani, “Models of Science Dynamics,” pp. 233–257, 2012, doi: 10.1007/978-3-642-23068-4.

[5] J. L. Gross *et al.*, “Graphical Measurement,” pp. 1063–1063, 2013, doi: 10.1201/b16132-63.

[6] M. Naderipour, M. H. Fazel Zarandi, and S. Bastani, *Fuzzy community detection on the basis of similarities in structural/attribute in large-scale social networks*, vol. 55, no. 2. Springer Netherlands, 2022. doi: 10.1007/s10462-021-09987-x.

[7] S. Sieranoja and P. Fränti, “Adapting k-means for graph clustering,” *Knowl. Inf. Syst.*, vol. 64, no. 1, pp. 115–142, 2022, doi: 10.1007/s10115-021-01623-y.

[8] V. D. F. M. Mathematik, “A Relevance Feedback

Approach for Social Network Clustering in the Context of Triangle Inequality Violations," 2023, doi: 10.26127/BTUOpen-6519.

[9] A. P. Logan, P. M. LaCasse, and B. J. Lunday, "Social network analysis of Twitter interactions: a directed multilayer network approach," *Soc. Netw. Anal. Min.*, vol. 13, no. 1, 2023, doi: 10.1007/s13278-023-01063-2.

[10] R. T. Schirra, N. F. B. dos Santos, K. K. Zadrozny, I. Kucharska, B. K. Ganser-Pornillos, and O. Pornillos, "A molecular switch modulates assembly and host factor binding of the HIV-1 capsid," *Nat. Struct. Mol. Biol.*, vol. 30, no. 3, pp. 383–390, 2023, doi: 10.1038/s41594-022-00913-5.

[11] A. Boukerche, Y. Tao, and P. Sun, "Artificial intelligence-based vehicular traffic flow prediction methods for supporting intelligent transportation systems," *Comput. Networks*, vol. 182, no. August, p. 107484, 2020, doi: 10.1016/j.comnet.2020.107484.

[12] J. Kim, S. Luo, G. Cong, and W. Yu, *DMCS : Density Modularity based Community Search*, vol. 1, no. 1. Association for Computing Machinery, 2022. doi: 10.1145/3514221.3526137.

[13] K. Rohe, S. Chatterjee, and B. Yu, "Spectral clustering and the high-dimensional stochastic block model," *Ann. Stat.*, vol. 39, no. 4, pp. 1878–1915, 2011, doi: 10.1214/11-AOS887.

[14] L. Infante, "Hierarchical Clustering: Objective Functions and Algorithms," *Rev. Mex. Astron. y Astrofis. Ser. Conf.*, vol. 14, no. 4, pp. 63–67, 2002, doi: 10.1145/3321386.

[15] P. Govender and V. Sivakumar, *Application of k-means and hierarchical clustering techniques for analysis of air pollution: A review (1980–2019)*, vol. 11, no. 1. Turkish National Committee for Air Pollution Research and Control, 2020. doi: 10.1016/j.apr.2019.09.009.

[16] U. Brandes *et al.*, "Maximizing Modularity is hard," no. September, 2006, [Online]. Available: http://arxiv.org/abs/physics/0608255

[17] S. Aref, M. Mostajabdaveh, and H. Chheda, "Heuristic Modularity Maximization Algorithms for Community Detection Rarely Return an Optimal Partition or Anything Similar," no. Iccs 2023, pp. 612–626, 2023, doi 10.1007/978-3-031-36027-5_48.

[18] F. B. L. Neto, I. M. C. Albuquerque, and J. B. M. Filho, "Weight-based Fish School Search algorithm for Many-Objective Optimization," vol. 1, pp. 1–5, 2017, [Online]. Available: http://arxiv.org/abs/1708.04745

[19] D. Jin *et al.*, "A Survey of Community Detection Approaches: From Statistical Modeling to Deep Learning," *IEEE Trans. Knowl. Data Eng.*, vol. 35, no. 2, pp. 1149–1170, 2023, doi: 10.1109/TKDE.2021.3104155.

[20] G. Contreras-Aso, R. Criado, G. Vera de Salas, and J. Yang, "Detecting communities in higher-order networks by using their derivative graphs," *Chaos, Solitons and Fractals*, vol. 177, no. November, p. 114200, 2023, doi: 10.1016/j.chaos.2023.114200.

[21] H. C. Rustamaji, W. A. Kusuma, S. Nurdiati, and I. Batubara, "Community detection with greedy modularity disassembly strategy," *Sci. Rep.*, pp. 0–17, 2023, doi: 10.1038/s41598-024-55190-7.

[22] M. A. Javed, M. S. Younis, S. Latif, J. Qadir, and A. Baig, "Community detection in networks: A multidisciplinary review," *J. Netw. Comput. Appl.*, vol. 108, pp. 87–111, 2018, doi: 10.1016/j.jnca.2018.02.011.

[23] Z. Lu and Z. Dong, "A Gravitation-Based Hierarchical Community Detection Algorithm for Structuring Supply Chain Network," *Int. J. Comput. Intell. Syst.*, vol. 16, no. 1, pp. 1–19, 2023, doi: 10.1007/s44196-023-00290-x.

[24] M. Latapy, "Density-Based Entropy Centrality for Community Detection in Complex Networks," *Comput. Commun.*, vol. 34, no. 5, pp. 607–608, 2022, doi: 10.1016/j.comcom.2010.10.015.

[25] N. Tatti and A. Gionis, "LNAI 8189 - Discovering Nested Communities," pp. 32–47, 2013.

[26] M. E. J. Newman and M. Girvan, "Finding and evaluating community structure in networks," *Phys. Rev. E - Stat. Nonlinear, Soft Matter Phys.*, vol. 69, no. 2 2, pp. 1–15, 2004, doi: 10.1103/PhysRevE.69.026113.

[27] M. E. J. Newman, "Fast algorithm for detecting community structure in networks," *Phys. Rev. E - Stat. Physics, Plasmas, Fluids, Relat. Interdiscip. Top.*, vol. 69, no. 6, p. 5, 2004, doi: 10.1103/PhysRevE.69.066133.

[28] F. Dörfler and F. Bullo, "Kron reduction of graphs with applications to electrical networks," *IEEE Trans. Circuits Syst. I Regul. Pap.*, vol. 60, no. 1, pp. 150–163, 2013, doi: 10.1109/TCSI.2012.2215780.

[29] R. Bhattacharya, N. Kumar, and S. Tripathi, "A community detection model using node embedding approach and graph convolutional network with clustering technique," *Decis. Anal. J.*, vol. 9, no. November, p. 100362, 2023, doi: 10.1016/j.dajour.2023.100362.

[30] W. H. Weir, B. Walker, L. Zdeborová, and P. J. Mucha, "Multilayer Modularity Belief Propagation to Assess Detectability of Community Structure," *SIAM J. Math. Data Sci.*,

vol. 2, no. 3, pp. 872–900, 2020, doi: 10.1137/19m1279812.
[31] C. J. A. B. Filho, F. B. de Lima Neto, A. J. C. C. Lins, A. I. Nascimento, and M. P. Lima, "Fish school search," *Stud. Comput. Intell.*, vol. 193, pp. 261–277, 2009, doi: 10.1007/978-3-642-00267-0_9.
[32] C. J. A. Bastos-Filho and A. C. S. Guimarães, "Multi-Objective Fish School Search," *Int. J. Swarm Intell. Res.*, vol. 6, no. 1, pp. 23–40, 2015, doi: 10.4018/ijsir.2015010102.
[33] R. P. Monteiro, L. F. V. Verçosa, and C. J. A. Bastos-Filho, "Improving the performance of the fish school search algorithm," *Int. J. Swarm Intell. Res.*, vol. 9, no. 4, pp. 21–46, 2018, doi: 10.4018/IJSIR.2018100102.
[34] A. Janecek and Y. Tan, "Feeding the fish - Weight update strategies for the fish school search algorithm," *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 6729 LNCS, no. PART 2, pp. 553–562, 2011, doi: 10.1007/978-3-642-21524-7_68.
[35] S. Jena, "FISH SCHOOL SEARCH : AN INTERVAL REPRESENTATION National Institute of Technology Rourkela," 2013.
[36] C. J. A. B. Filho, F. B. D. L. Neto, A. J. C. C. Lins, A. I. S. Nascimento, and M. P. Lima, "A novel search algorithm based on fish school behavior," *Conf. Proc. - IEEE Int. Conf. Syst. Man Cybern.*, no. February 2014, pp. 2646–2651, 2008, doi: 10.1109/ICSMC.2008.4811695.
[37] J. Connor, M. Joordens, and B. Champion, "Fish-inspired robotic algorithm: mimicking behavior and communication of schooling fish," *Bioinspir. Biomim.*, 2023, doi 10.1088/1748-3190/acfa52.
[38] L. Xie, T. Han, H. Zhou, Z. R. Zhang, B. Han, and A. Tang, "Tuna Swarm Optimization: A Novel Swarm-Based Metaheuristic Algorithm for Global Optimization," *Comput. Intell. Neurosci.*, vol. 2021, 2021, doi: 10.1155/2021/9210050.
[39] A. Bettinger, A. Brun, and A. Boyer, *Independent influence of exploration and exploitation for metaheuristic-based recommendations*, vol. 1, no. 1. Association for Computing Machinery, 2022. doi: 10.1145/3520304.3528972.
[40] H. L. Kwa, J. Leong Kit, and R. Bouffanais, "Balancing Collective Exploration and Exploitation in Multi-Agent and Multi-Robot Systems: A Review," *Front. Robot. AI*, vol. 8, no. February, pp. 1–25, 2022, doi: 10.3389/frobt.2021.771520.
[41] T. Rebafka, "Model-based clustering of multiple networks with a hierarchical algorithm," *Stat. Comput.*, vol. 34, no. 1, pp. 1–16, Feb. 2024, doi: 10.1007/S11222-023-10329-W/FIGURES/11.
[42] Z. Jiao, X. Ming, Y. Cao, C. Cheng, and S. H. Wang, "Module partitioning for multilayer brain functional network using weighted clustering ensemble," *J. Ambient Intell. Humans. Comput.*, vol. 14, no. 5, pp. 5343–5353, 2023, doi: 10.1007/s12652-019-01535-4.
[43] B. Saoud, "Community structure detection in networks based on Tabu search," *J. Control Decis.*, 2022, doi: 10.1080/23307706.2022.2146010.
[44] P. Çetin and S. Emrah Amrahov, "A new network-based community detection algorithm for disjoint communities," *Turkish J. Electr. Eng. Comput. Sci.*, vol. 30, no. 6, pp. 2190–2205, 2022, doi: 10.55730/1300-0632.3933.
[45] F. Bonchi, D. García-Soriano, A. Miyauchi, and C. E. Tsourakakis, "Finding densest k -connected subgraphs," *Discret. Appl. Math.*, vol. 305, pp. 34–47, 2021, doi: 10.1016/j.dam.2021.08.032.
[46] C. Suo, S. Oldham, B. Fulcher, L. Parkes, A. Arnatkevic, and A. Fornito, "Consistency and differences between centrality measures across distinct classes of networks," pp. 1–23, 2019.
[47] C. Li, H. Chen, T. Li, and X. Yang, "A stable community detection approach for complex network based on density peak clustering and label propagation," *Appl. Intell.*, vol. 52, no. 2, pp. 1188–1208, 2022, doi: 10.1007/s10489-021-02287-5.
[48] B. Škrlj, J. Kralj, and N. Lavrač, *Embedding-based Silhouette community detection*, vol. 109, no. 11. Springer US, 2020. doi: 10.1007/s10994-020-05882-8.
[49] A. Agarwal and L. Xue, "Model-Based Clustering of Nonparametric Weighted Networks With Application to Water Pollution Analysis," *Technometrics*, vol. 62, no. 2, pp. 161–172, 2020, doi: 10.1080/00401706.2019.1623076.
[50] A. Lancichinetti, F. Radicchi, J. J. Ramasco, and S. Fortunato, "Finding statistically significant communities in networks," *PLoS One*, vol. 6, no. 4, 2011, doi: 10.1371/journal.pone.0018961.
[51] M. Rosvall and C. T. Bergstrom, "Maps of random walks on complex networks reveal community structure," *Proc. Natl. Acad. Sci. U. S. A.*, vol. 105, no. 4, pp. 1118–1123, 2008, doi: 10.1073/pnas.0706851105.
[52] U. N. Raghavan, R. Albert, and S. Kumara, "Near linear time algorithm to detect community structures in large-scale networks," *Phys. Rev. E - Stat. Nonlinear, Soft Matter Phys.*, vol. 76, no. 3, pp. 1–11, 2007, doi: 10.1103/PhysRevE.76.036106.
[53] V. D. Blondel, J. L. Guillaume, R. Lambiotte, and

E. Lefebvre, “Fast unfolding of communities in large networks,” *J. Stat. Mech. Theory Exp.*, vol. 2008, no. 10, 2008, doi: 10.1088/1742-5468/2008/10/P10008.
[54] A. Clauset, M. E. J. Newman, and C. Moore, “Finding community structure in very large networks,” *Phys. Rev. E - Stat. Physics, Plasmas, Fluids, Relat. Interdiscip. Top.*, vol. 70, no. 6, p. 6, 2004, doi: 10.1103/PhysRevE.70.066111.
[55] L. Danon, A. Díaz-Guilera, J. Duch, and A. Arenas, “Comparing community structure identification,” *J. Stat. Mech. Theory Exp.*, no. 9, pp. 219–228, 2005, doi: 10.1088/1742-5468/2005/09/P09008.
[56] S. Zhang and H. S. Wong, “ARImp: A generalized Adjusted Rand Index for cluster ensembles,” *Proc. - Int. Conf. Pattern Recognit.*, no. June, pp. 778–781, 2010, doi: 10.1109/ICPR.2010.196.
[57] P. Taylor, E. B. Fowlkes, C. L. Mallows, B. Laboratories, and M. Hill, “A Method for Comparing Two Hierarchical Clusterings A Method for Comparing Two Hierarchical Clusterings,” no. April 2013, pp. 37–41, 2012.
[58] A. Lancichinetti, S. Fortunato, and F. Radicchi, “Benchmark graphs for testing community detection algorithms,” *Phys. Rev. E - Stat. Nonlinear, Soft Matter Phys.*, vol. 78, no. 4, pp. 1–6, 2008, doi: 10.1103/PhysRevE.78.046110.
[59] W. W. Zachary, “An Information Flow Model for Conflict and Fission in Small Groups,” *J. Anthropol. Res.*, vol. 33, no. 4, pp. 452–473, 1977, doi: 10.1086/jar.33.4.3629752.
[60] M. Girvan and M. E. J. Newman, “Community structure in social and biological networks,” *Proc. Natl. Acad. Sci. U. S. A.*, vol. 99, no. 12, pp. 7821–7826, 2002, doi: 10.1073/pnas.122653799.
[61] D. Lusseau, K. Schneider, O. J. Boisseau, P. Haase, E. Slooten, and S. M. Dawson, “The bottlenose dolphin community of doubtful sound features a large proportion of long-lasting associations: Can geographic isolation explain this unique trait?” *Behav. Ecol. Sociobiol.*, vol. 54, no. 4, pp. 396–405, 2003, doi: 10.1007/s00265-003-0651-y.
[62] N. G. Lada A. Adamic, “The Political Blogosphere and the 2004 U.S. Election: Divided They Blog.” Accessed: Nov. 22, 2023. [Online]. Available: https://sci-hub.se/https://doi.org/10.1145/1134271.1134277
[63] J. Leskovec, L. A. Adamic, and B. A. Huberman, “The dynamics of viral marketing,” *ACM Trans. Web*, vol. 1, no. 1, 2007, doi: 10.1145/1232722.1232727.
[64] D. E. Knutht, “The Stanford GraphBase: A Platform for Combinatorial Algorithms,” 1994.
[65] P. M. GLEISER and L. DANON, “Community Structure in Jazz,” *Adv. Complex Syst.*, vol. 06, no. 04, pp. 565–573, 2003, doi: 10.1142/s0219525903001067.
[66] J. Kunegis, “KONECT - The koblenz network collection,” *WWW 2013 Companion - Proc. 22nd Int. Conf. World Wide Web*, pp. 1343–1350, 2013.
[67] D. E. Knuth, “The Art of Computer Programming.” Accessed: Nov. 22, 2023. [Online]. Available: https://sci-hub.se/https://doi.org/10.1145/1388240.1388245
[68] “Get Trial | Encord.” Accessed: Mar. 15, 2024. [Online]. Available: https://encord.com/try-it-free/?&utm_campaign=cta-blog-medical-dark

Notes on Contributors

Abuzer Hussein Ibrahim holds a Master of Science degree in Computer Science from the University of Gezira, Sudan (2016). He was a lecturer at the University of AL-Butana, Sudan (2016). now a Ph.D. Student at Akli Mohand Oulhadj University of Bouira, Algeria.

Dr. BOUDREF Mohamed Ahmed is currently a lecturer and researcher at Bouira University. He obtained his Doctorate in Mathematics from Bejaia University in 2016. Actually, Dr. Boudref Mohamed Ahmed is a director of the Laboratory of Computer Sciences and Mathematics.

His research focuses actually on differential equations, optimization, and integral transforms.

Dr. Lyes BADIS is currently a professor and researcher at Bouira University. He obtained his Doctorate in Computing Sciences from Bejaia University in 2021. In 2008, Dr. BADIS completed his Master's degree at the High School of Computing Sciences (Oued Smar-Algiers). Before that, he earned his engineer's degree in Computer Engineering from the same institution in 2005. Dr. BADIS focuses actually on Artificial Intelligence (AI) and its practical applications in diverse domains such as social networks, the Internet of Things (IoT), and medical systems.