SHORT-PAPER

From Bicliques to BiFlexi Cliques: A New Era of Bipartite Subgraph Discovery

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From Bicliques to Biflexi Cliques: A New Era of Bipartite Subgraph Discovery

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Abstract

Real-world bipartite communities tend to exhibit relaxed internal connectivity as their size increases, making traditional biclique models too restrictive for cohesive subgraph discovery. In this paper, we propose the Biflexi Clique, a novel bipartite subgraph model that employs flexible, size-adaptive degree thresholds based on sublinear constraints. Our approach dynamically adjusts connectivity requirements according to subgraph size, enabling the discovery of larger and more realistic cohesive structures. We prove that the Maximum Biflexi Clique problem is NP-hard and develop an efficient heuristic algorithm. Experimental results on real-world datasets demonstrate the effectiveness and scalability of our algorithm and the applicability of our model.

CCS Concepts

• **Information systems → Clustering**.

Keywords

Graph mining; Cohesive subgraph discovery

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1 INTRODUCTION

Many relationships in real-world systems are naturally captured as pairwise interactions, such as user–item associations, author–paper links, and actor–movie pairings. These interactions are effectively modelled using bipartite graphs, which connect two disjoint sets of nodes. Due to their expressiveness, bipartite graphs have been adopted in a wide range of applications [12, 14, 19, 30, 35], where discovering cohesive subgraphs is a fundamental task. As a result, cohesive subgraph discovery in bipartite networks has been extensively studied, leading to the development of various modelling approaches [16–18, 26, 31, 36].

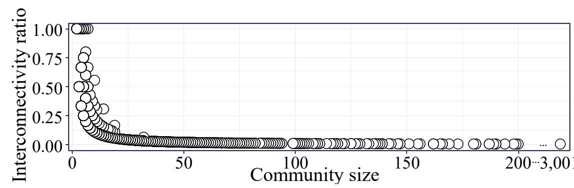

Figure 1: Community size vs Inter-connectivity ratio

Among these, the biclique model [21] characterises an all-to-all fully connected structure. This model captures the strictest form of connectivity and represents the densest possible substructure. On the other hand, the k-biplex model [26] relaxes this condition by allowing each node to miss up to k edges, thereby representing a most-to-most, near-complete structure. These models have been successfully applied in diverse tasks including recommendation [25], group analysis [27], and fraud detection [5].

Despite their usefulness, both models have structural limitations that reduce their effectiveness in real-world networks. They enforce degree requirements that grow linearly with subgraph size, imposing uniformly high connectivity regardless of scale. This conflicts with sociological research demonstrating that individuals typically maintain fewer connections as communities grow larger [7, 24]. Additionally, real networks commonly contain noise [15], making large, perfectly connected bicliques or biplexes rare in practice. These strict definitions miss realistic structural patterns and prevent the identification of larger subgraphs [4, 22], despite the fact that bigger subgraphs often carry more value and influence through network effects [9, 33].

To empirically validate the limitations of stringent subgraph models, we analyse the structural properties of communities in real-world networks, focusing on how internal connectivity varies with community size. As many cohesive subgraph models define structural tightness based on minimum degree thresholds [16–18], we adopt a similar formulation to ensure compatibility in comparison. Specifically, we define the interconnectivity ratio of a community C as $\frac{\delta(C)}{|C|-1}$, where $\delta(C)$ denotes the minimum number of internal connections per node within the community.

Figure 1 presents the results from the YouTube dataset [32], where each point represents a community. We observe a clear inverse relationship between community size and interconnectivity: small communities often form tightly knit structures resembling cliques, while larger ones exhibit a sharply declining ratio. Crucially, this behaviour reveals a fundamental flaw in the biclique

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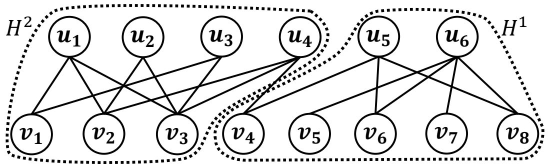

Figure 2: Toy example

and biplex models: their fixed degree constraints are blind to structural scale. As a result, they are biased towards identifying only small or trivially dense communities, overlooking the larger yet still significant groups that are prevalent in realistic settings.

Motivated by these findings, we introduce a new model, named the Biflexi Clique, which redefines connectivity requirements through a scale-aware lens. Instead of imposing strict and size-invariant thresholds, the Biflexi Clique enforces degree conditions that grow sublinearly with the size of the resultant subgraph. This flexible formulation is designed to capture the enough-to-enough connectivity principle, where cohesion is defined by a realistic and scalable notion of interaction density.

In this work, we define the maximum Biflexi Clique problem and prove that it is NP-hard, due to the complexity of searching under dynamically adjusted, size-dependent degree constraints. To address this challenge, we introduce an efficient heuristic method designed to identify large Biflexi Clique subgraphs. Experiments on real-world bipartite networks confirm the scalability and effectiveness of our approach, supporting its use in discovering structurally diverse and realistic communities across real-world graphs.

Our contributions are summarised as follows:

- **Scale-aware subgraph model:** We introduce Biflexi Clique, a relaxation of the biclique model that imposes sub-linear, size-dependent degree constraints, allowing for more realistic cohesive subgraph discovery in bipartite networks.
- **Theoretical complexity result:** We prove that the maximum Biflexi Clique problem is NP-hard, underlining the computational difficulty of finding optimal solutions.
- **Scalable discovery method:** We present an efficient heuristic algorithm for identifying large Biflexi Clique subgraphs and demonstrate its effectiveness and efficiency through experiments.

Reproducibility. https://github.com/tjhantj/Biflexi-Clique.git

2 BIFLEXI CLIQUE IN BIPARTITE GRAPHS

This section formally introduces the Biflexi Clique model, which generalises classical biclique and biplex formulations and proposes the Maximum Biflexi Clique problem.

Let $G = (U, V, E)$ be a bipartite graph, where U and V are disjoint node sets and E is the set of edges. For any subset $H \subseteq U \cup V$, let $H_U = H \cap U$ and $H_V = H \cap V$, and let $G[H]$ denote the subgraph induced by H. The edge set $E[H]$ consists of all edges between H_U and H_V, i.e., $E[H] = \{(u, v) \mid u \in H_U, v \in H_V\}$. For any node $w \in U \cup V$, let $N(w, G)$ denote its neighbours and $d(w, G) = |N(w, G)|$ denote its degree.

Definition 1 (Biflexi Clique). *Given a bipartite graph $G = (U, V, E)$ and a parameter $0 \le \tau \le 1$, the induced subgraph $G[H]$ is a Biflexi Clique if the following conditions hold:*

(1) Each node $u \in H_U$ satisfies $d(u, G[H]) \ge \lfloor |H_V|^\tau \rfloor$.
(2) Each node $v \in H_V$ satisfies $d(v, G[H]) \ge \lfloor |H_U|^\tau \rfloor$.
(3) The induced subgraph $G[H]$ is connected.

This formulation introduces flexible degree thresholds that scale sub-linearly with subgraph size. As a result, the Biflexi Clique can identify subgraphs that are too sparse to qualify as biclique or biplex, but still maintain strong enough connectivity to represent meaningful group structure.

Example 1. *Figure 2 illustrates two feasible Biflexi Clique subgraphs under $\tau = 0.7$. One subgraph H^1 consists of $H^1_U = \{u_5, u_6\}$ and $H^1_V = \{v_4, v_5, v_6, v_7, v_8\}$, where each node in H^1_U connects to at least $\lfloor 5^{0.7} \rfloor = 3$ nodes in H^1_V, and each node in H^1_V connects to at least $\lfloor 2^{0.7} \rfloor = 1$ node in H^1_U. This subgraph contains 7 edges. Another feasible subgraph $H^2 = \{u_1, u_2, u_3, u_4\} \cup \{v_1, v_2, v_3\}$ satisfies the same constraints and contains 9 edges, making it the maximum Biflexi Clique in this example graph.*

To generalise this intuition, we next formalise the Maximum Biflexi Clique problem and examine its theoretical hardness.

Problem definition 1 (Maximum Biflexi Clique). *Given a bipartite graph $G = (U, V, E)$ and a parameter τ, the Maximum Biflexi Clique problem aims to find a Biflexi Clique in G that contains the largest number of edges.*

Theorem 1. *The Maximum Biflexi Clique problem is NP-hard.*

Proof. We prove the NP-hardness of the Biflexi Clique problem via a polynomial time reduction from the classic biclique problem, which is known to be NP-complete [23].

We first define the decision version of the Biflexi Clique. Given a bipartite graph $G = (U, V, E)$, a parameter τ and a threshold m, does there exist a connected induced subgraph $G[H]$ such that (1) $\forall u \in H_U$, $d(u, G[H]) \ge |H_V|^\tau$; (2) $\forall v \in H_V$, $d(v, G[H]) \ge |H_U|^\tau$; and (3) $|E[H]| \ge m$. Note that if $\tau = 1$, degree constraints enforce that $G[H]$ should be a complete bipartite subgraph, i.e., biclique.

Let $I_{BC} = (G' = (U', V', E'), k)$ be an instance of the biclique problem where the task is to determine whether G' contains a biclique with at least k edges.

We construct an instance of the Biflexi Clique problem as follows:

- Let $G = G'$
- Set the parameter $\tau = 1$ and threshold $m = k$

We claim that G' contains a biclique H' with at least k edges if and only if G contains a Biflexi Clique H' under $\tau = 1$ with $|E[H']| \ge m$. ($\Rightarrow$) Suppose G' contains a biclique H' such that every $u \in H'_U$ is connected to all $v \in H'_V$ and $|E'[H']| \ge k$. Then, $G[H']$ is a Biflexi Clique with at least m edges satisfying the conditions under $\tau = 1$. ($\Leftarrow$) Suppose G contains a Biflexi Clique H' under $\tau = 1$ with $|E[H']| \ge m$. Then, each node in H'_U is connected to all $v \in H'_V$, and vice versa. Thus, $G'[H']$ is a biclique with $|E'[H']| \ge k$. Since the reduction is polynomial-time, the Maximum Biflexi Clique problem is NP-hard. □

3 MAXIMUM BIFLEXI PEELING ALGORITHM

We propose the Maximum Biflexi Clique Peeling (MBP) algorithm that aims to find the maximum Biflexi Clique in a bipartite graph.

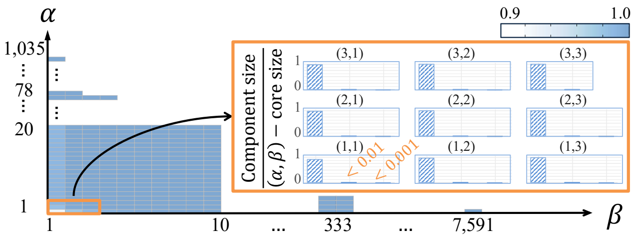

Figure 3: Component size ratio of (α, β)-core

The core idea is to iteratively refine candidate subgraphs while maintaining both connectivity and the scale-aware degree constraints defined by the Biflexi Clique model.

In real-world bipartite graphs, most nodes exhibit low degree due to the power-law distribution [10, 29, 37]. To efficiently construct candidates, we adopt the (α, β)-core [6] as an initial filter: a subgraph where every node in U (resp. V) has at least α (resp. β) neighbours in the opposite side. While an (α, β)-core may contain multiple components, we retain only the largest component.

To validate the safety of this approach, we performed (α, β)-core decomposition on real-world datasets and examined the proportion of each connected component within the entire (α, β)-core. Figure 3 shows the proportion occupied by the top three largest components in each (α, β)-core from the YouTube dataset [20]. The largest component of the $(1, 1)$ core represents more than 91% of the entire core. Moreover, the largest components of the remaining (α, β)-cores converge in proportion toward 1. This pattern was consistently observed in the GitHub dataset [13] as well, where each of the largest components achieved at least 91% proportion, except for the $(1, 1)$-core which showed 78%. These results demonstrate that examining only the largest component of each (α, β)-core is sufficient to discover substantially large Biflexi Clique structures.

Peeling process. The peeling algorithm iteratively removes non-articulation nodes with the smallest degree, ensuring that connectivity is preserved. If at any point a Biflexi Clique subgraph with more edges than the current maximum is discovered, the algorithm immediately returns it as the new maximum. Conversely, if the number of remaining edges drops below the current maximum, the process is terminated early to avoid unnecessary computation.

Algorithm 1: MBP algorithm(G, τ)

```
max ← 0; H_max ← ∅; S ← αβ-index(G);
// Q is sorted by edge size
Q ← findCandidates(G, τ, S, max, H_max);
while Q ≠ ∅ do
    H ← Q.pop();
    if |E[H]| ≤ max then
        break;
    max, H_max ← peeling(G, τ, H, max, H_max);
return H_max
```

Algorithm description. Algorithm 1 outlines the overall procedure of MBP. It iterates over increasing values of α and β to extract (α, β)-cores. For each core, it finds the largest connected component and verifies whether the subgraph satisfies the Biflexi Clique constraints. If the subgraph satisfies the condition, it is retained as a candidate for further processing.

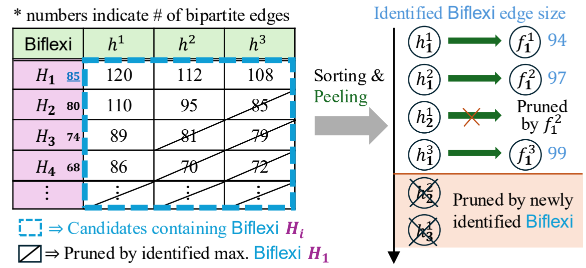

Figure 4: The MBP process

For each identified Biflexi Clique H_i, we construct adjacent candidates from neighbouring cores: We denote h_i^1 as $(\alpha-1, \beta-1)$, h_i^2 as $(\alpha-1, \beta)$, and h_i^3 as $(\alpha, \beta-1)$. These candidates are sorted by edge count and applied to a peeling procedure (Algorithm **??**) to extract a larger Biflexi Clique. Candidates yielding fewer edges than the current maximum are pruned.

Example 2. *Figure 4 illustrates the overall flow of MBP. Among the (α, β)-cores, H_1 is the largest feasible Biflexi Clique with 85 edges and is chosen as the initial maximum. Candidate subgraphs with more than 85 edges—specifically $\{h_1^1, h_1^2, h_1^3, h_2^1, h_2^2, h_3^1, h_4^1\}$—are selected for the peeling process. Applying peeling to h_1^2 yields a subgraph f_1^2 with 97 edges, which updates the current maximum. During the peeling in h_2^1, its edge count drops below 97, therefore, h_2^1 is pruned. Also, h_1^3 successfully produces f_1^3 with 99 edges, becoming the new maximum. Then, the remaining candidates $\{h_2^2, h_3^1, h_4^1\}$ are pruned, as their edge counts do not exceed 99. Ultimately, MBP returns f_1^3 as the final result.*

Time complexity. The time complexity of MBP is $O(|E|^{1.5} + \alpha^*\beta^*(|V| + |E| + |V| \log^2 |V|))$, where

- It takes $O(|E|^{1.5})$ to construct the (α, β)-core index [16].
- It takes $O(\alpha^* \cdot \beta^*)$ for the total number of core iterations, where α^* and β^* denote the maximum core indices on the U and V sides, respectively.
- It takes $O(|V|+|E|)$ to compute the largest connected component for each core.
- It takes $O(|V| \log^2 |V|)$ for peeling procedure, where $O(|V|)$ is the number of node-removal iterations and $\log^2 |V|$ is the cost of querying articulation points using dynamic connectivity [11].

4 EXPERIMENTS

Table 1: Real-world datasets

Datasets	$\lvert U\rvert$	$\lvert V\rvert$	$\lvert E\rvert$	d_{max}	d_{avg}
Leadership(**L**)	20	24	99	12	4.5
YouTube(**YT**)	94,238	30,087	293,360	7,591	4.7
Github(**GH**)	56,519	120,867	440,237	3,675	5.0
BookCrossing(**BC**)	105,278	340,523	1,149,739	13,601	5.2

4.1 Experimental Setup

To evaluate the proposed algorithm, we conduct extensive experiments to address the following research questions (**EQs**): (1) **Effectiveness**: How close are the results of our algorithm to the exact solution?; (2) **Effect of** τ: How does the value of τ influence the output of our algorithm?; (3) **Scalability**: How well does our algorithm scale with increasing input size?; (4) **Case study**: How applicable is the Biflexi Clique model in real-world applications?

4.2 Experimental Setting

Real-world datasets. Table 1 summarizes the characteristics of the real-world datasets used in our experiments, including the number of nodes, number of edges, maximum degree ($d_{\max}$), and average degree (d_{avg}). All datasets were obtained from KONECT [13].

Experimental environment. We implemented using Python. All experiments were conducted on a machine equipped with an Intel Xeon 6248R processor and 256GB of RAM, running Ubuntu 20.04.

4.3 Experimental Result

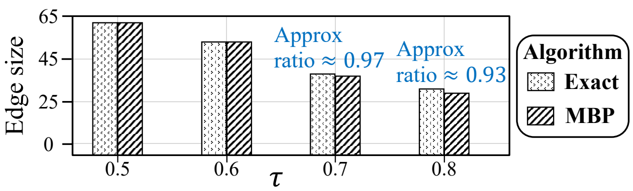

Figure 5: EQ1. Effectiveness

EQ1. Effectiveness. To evaluate the approximation quality of MBP, we conduct an experiment on the Leadership dataset [3], where all connected components are exhaustively enumerated through the method proposed in [2]. For each connected component, we check whether it qualifies as a Biflexi Clique under varying τ values. Among the components identified as feasible Biflexi Clique, we select the one with the largest edge size and compare it with the result produced by our MBP algorithm. As presented in Figure 5, MBP finds a Biflexi Clique with the same edge size as the exact solution for $\tau = 0.5$ and 0.6. Even for larger τ values, it achieves an approximation ratio exceeding 0.9 in terms of edge size. These results suggest that MBP has the potential to identify high-quality Biflexi Clique structures with substantial approximation guarantees.

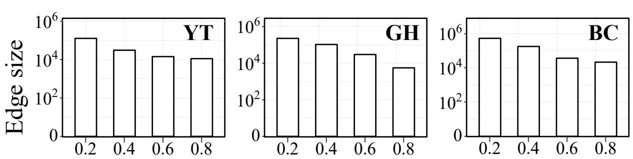

Figure 6: EQ2. Effect of τ

EQ2. Effect of τ. We analyse how the parameter τ affects the size of the resulting Biflexi Clique. Figure 6 presents the edge sizes for various τ values. Naturally, as τ increases, the minimum degree requirements become stricter, which consequently results in smaller subgraphs. This increased cohesiveness requirement means that fewer nodes can satisfy the stricter connectivity criteria, resulting in smaller subgraphs being retained after pruning. Furthermore, we observe that even small changes in τ lead to noticeable differences in edge size, showing that our model can flexibly control the level of connectivity. By adjusting a single parameter, users can find either larger, loosely connected cohesive subgraphs or smaller, more tightly connected ones, depending on their needs.

EQ3. Scalability. We evaluate the scalability of MBP using synthetic BNOC benchmark datasets [28]. Specifically, we generate bipartite graphs where both U and V sides contain the same number of nodes. The total number of nodes is scaled from $4,000$ to $64,000$ by doubling at each step. Figure 7 illustrates the running time of MBP across different graph sizes, for varying values of τ. The observed trend indicates a near-linear relationship between input size and running time. While some fluctuations appear for specific τ values, the overall runtime is not significantly affected by τ. This is because the pruning strategy effectively limits the number of candidate subgraphs regardless of τ. These results indicate MBP scales efficiently with increasing graph size and maintains stable performance across different τ values.

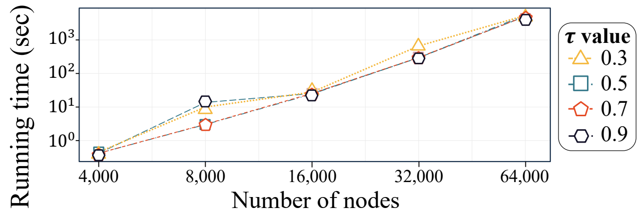

Figure 7: EQ3. Scalability

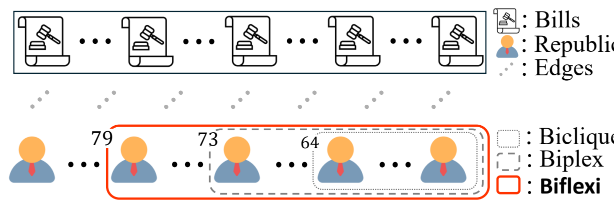

Figure 8: EQ4. Case study

EQ4. Case study. To illustrate the practical utility of our model, we conduct a case study using the House-Bill dataset [8], which represents a bipartite network between U.S. members of Congress and the bills they sponsored, with members labelled according to their party affiliation. In this bipartite network, an edge denotes the sponsorship of a bill. We focus on the Republican community and compare the subgraphs identified by maximum biclique [1], maximum 2-biplex [34], and Biflexi Clique with $\tau = 0.9$. Figure 8 illustrates the results: the biclique model identifies a subgraph of 64 members, the 2-biplex expands this to 73, and our Biflexi Clique captures 79 members, including 6 additional individuals excluded by the previous models. These results indicate that the Biflexi Clique can uncover larger, yet still cohesive communities that are not identified by conventional models constrained by rigid degree constraints.

5 CONCLUSION

We introduced the Biflexi Clique framework for cohesive subgraph discovery in bipartite networks, using a sub-linear, size-aware degree constraint. We proved that the Maximum Biflexi Clique problem is NP-hard and proposed efficient search strategies. We demonstrated through experiments that the Biflexi Clique outperforms biclique and biplex models in uncovering larger, more informative structures. Our results highlight the effectiveness of sub-linear degree thresholds. Future directions include enhancing efficiency and incorporating edge weights and node attributes.

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