An Exact Branch and Bound Algorithm with Symmetry Breaking for the Maximum Balanced Induced Biclique Problem

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Abstract. We show how techniques from state-of-the-art branch and bound algorithms for the maximum clique problem can be adapted to solve the maximum balanced induced biclique problem. We introduce a simple and effective symmetry breaking technique. Finally, we discuss one particular class of graphs where the algorithm's bound is ineffective, and show how to detect this situation and fall back to a simpler but faster algorithm. Computational results on a series of standard benchmark problems are included.

1 Introduction

Let G = (V, E) be a graph (by which we always mean finite, undirected and with no loops) with vertex set V and edge set E. A *biclique*, or complete bipartite subgraph, is a pair of (possibly empty) disjoint subsets of vertices $\{A, B\}$ such that $\{a, b\} \in E$ for every $a \in A$ and $b \in B$. A biclique is *balanced* if |A| = |B|, and *induced* if no two vertices in A are adjacent and no two vertices in B are adjacent. The maximum balanced induced biclique problem is to find a balanced induced biclique of maximum size in an arbitrary graph. We illustrate an example in Fig. 1.

Finding such a maximum is NP-hard [1, Problem GT24], both in bipartite and arbitrary graphs. A naïve exponential algorithm could simply enumerate every possible solution to find a maximum. Here we develop a branch and bound algorithm

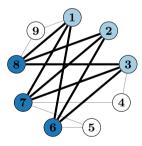


Fig. 1. A graph, with its unique maximum balanced induced biclique of size six, $\{\{1,2,3\},\{6,7,8\}\}$, shown in light and dark blue

with symmetry breaking that substantially reduces the search space. We believe that this is the first attempt at tackling this problem. We are not yet aware of any practical applications, but the problem is interesting from an algorithmic perspective.

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If G = (V, E) is a graph, we write V(G) for the vertex set V. The *neighbour*hood of a vertex v in a graph G is the set of vertices adjacent to v; we denote this $N_G(v)$. The *degree* of a vertex is the cardinality of its neighbourhood.

A graph G' = (V', E') is a subgraph of G = (V, E) if $V' \subseteq V$ and $E' \subseteq E$; the subgraph *induced by* V' is the subgraph with vertex set V' and all possible edges. A set of vertices, no two of which are adjacent, is called an *independent* set. A set of vertices, all of which are adjacent, is called a *clique*; the size of a maximum clique is denoted ω . A *clique cover* is a partition of the vertices in a graph into sets, each of which is a clique. We introduce the symbol $\ddot{\omega}$ for the size (i.e. |A| + |B|) of a maximum balanced induced biclique, which is always even (this simplifies comparisons with unbalanced biclique variants). A graph is *bipartite* if its vertices may be partitioned into two disjoint independent sets.

2 A Branch and Bound Algorithm

A very simple branch and bound algorithm for the maximum induced biclique problem is given in Algorithm 1. The algorithm works by recursively building up two sets A and B such that $\{A, B\}$ is a biclique. At each stage, P_a contains those vertices which may be added to A whilst keeping a feasible solution (i.e. each $v \in$ P_a is individually adjacent to every $b \in P_b$ and nonadjacent to every $a \in A$), and similarly P_b contains vertices which may be added to B. Initially, A and B are both empty, and P_a and P_b both contain every vertex in the graph (line 4).

At each recursive call to expand, a vertex v is chosen from P_a (line 8) and moved to be in A instead (lines 10 and 11). The algorithm then considers the implications of $v \in A$ (lines 12 to 17). A new P'_a is constructed on line 12 by filtering from P_a those vertices adjacent to v (since A must be an independent set), and a new P'_b is constructed on line 13 by filtering from P_b those vertices not adjacent to v (everything in B must be adjacent to everything in A).

Now if P'_b is not empty, we may grow *B* further. Thus we repeat the process with a recursive call on line 17, swapping the roles of *A* and *B*—we are adding vertices to the two sides of the growing biclique in alternating order.

Having considered the possibility of $v \in A$, we then consider $v \notin A$ (line 18). The algorithm loops back to line 8, selecting a new v from P_a , until P_a is empty. Finally, we backtrack by returning from the recursive call.

We keep track of the largest feasible solution $\{A_{max}, B_{max}\}$ that we have found so far; this is called the *incumbent*. Initially it is empty (line 3). Whenever we find a potential solution, we compare it to the incumbent (line 14), and if our new solution is larger then the incumbent is unseated (line 15). Note that at this point, the balance condition must be checked explicitly, since either |A| = |B|, or |A| = |B| + 1 could be true.

Knowing the size of the incumbent allows us to avoid exploring some of the search space—this is the bound part of branch and bound. The condition on line 9 checks how much further we can grow A and B: if there are not enough vertices available to potentially unseat the incumbent, search at the current position can be abandoned. (This is not a very good bound, and is only for illustrative purposes. We discuss a more sophisticated bound below.)

Algorithm 1. A simple, alternating branch and bound algorithm for the maximum balanced induced biclique problem.

```
1 simpleBiclique :: (Graph G) \rightarrow (Set of Integer, Set of Integer)
 2 begin
         (A_{max}, B_{max}) \leftarrow (\emptyset, \emptyset)
                                                // Initially our best solution is empty
 3
         expand(G, \emptyset, \emptyset, V(G), V(G), A_{max}, B_{max})
 \mathbf{4}
         return (A_{max}, B_{max})
 5
 6 expand :: (Graph G, Set A, Set B, Set P_a, Set P_b, Set A_{max}, Set B_{max})
 7 begin
          for v \in P_a do
 8
 9
               if |P_a| + |A| > |A_{max}| and |P_b| + |B| > |B_{max}| then
                   A \leftarrow A \cup \{v\}
                                                                                 // Consider v \in A
10
                   P_a \leftarrow P_a \setminus \{v\}
11
                   P'_a \leftarrow P_a \cap \overline{\mathrm{N}_{\mathrm{G}}(v)}
                                                          // Remove vertices adjacent to v
12
                  P'_b \leftarrow P_b \cap \mathcal{N}_{\mathcal{G}}(v)
                                                    // Remove vertices not adjacent to v
13
                   if |A| = |B| and |A| > |A_{max}| then
14
                    (A_{max}, B_{max}) \leftarrow (A, B) // We've found a better solution
15
                   if P'_h \neq \emptyset then
16
                    expand(G, B, A, P'_b, P'_a, B_{max}, A_{max})
                                                                              // Swap and recurse
\mathbf{17}
                   A \leftarrow A \setminus \{v\}
                                                                           // Now consider v \notin A
18
```

Improving the Algorithm. We now adapt Algorithm 1 to incorporate symmetry breaking, an improved bound based upon clique covers, and an initial sort order. The end result is Algorithm 2. We have explicitly designed the algorithm to permit a bitset encoding for the data structures. For the maximum clique problem, this technique has allowed an increase in performance of between two and twenty times, without altering the steps taken by the algorithm. We refer to work by San Segundo et al. [2,3] for implementation details.

Symmetry Breaking. The search space for Algorithm 1 is larger than it should be: it explores legal ordered pairs (A, B) of vertex sets rather than unordered pairs $\{A, B\}$. Having explored every possible solution with $v \in A$, the search then considers $v \notin A$. But there is nothing to stop it from then considering a new $v' \in A$, and later placing $v \in B$. This is wasted effort, since if such a solution existed we would already have considered an equivalent with A and B reversed.

We may break this symmetry as follows: if, at the top of search, we have considered every possibility with $v \in A$ then we may eliminate v from P_b to avoid considering $v \in B$. The modified **expand** function in Algorithm 2 includes this rule: lines 38 to 39 remove symmetric solutions.

This technique may be seen as a special case of the standard lex symmetry breaking technique used in constraint programming [4,5]. A constraint programmer would view A and B as binary strings, and impose the constraint $B \leq A$

Algorithm 2. An improved alternating branch and bound algorithm for the maximum balanced induced biclique problem.

1 improvedBiclique :: (Graph G) \rightarrow (Set of Integer, Set of Integer) 2 begin $(A_{max}, B_{max}) \leftarrow (\emptyset, \emptyset)$ // Initially our best solution is empty 3 permute G so that the vertices are in non-increasing degree order $\mathbf{4}$ $expand(G, \emptyset, \emptyset, V(G), V(G), A_{max}, B_{max})$ $\mathbf{5}$ return (A_{max}, B_{max}) (unpermuted) 6 7 cliqueSort :: (Graph G, Set P) \rightarrow (Array of Integer, Array of Integer) 8 begin 9 $bounds \leftarrow an Array of Integer$ 10 $order \leftarrow an Array of Integer$ $P' \leftarrow P$ // vertices yet to be allocated 11 $k \leftarrow 1$ // current clique number 12 while $P' \neq \emptyset$ do 13 $Q \leftarrow P'$ // vertices to consider for the current clique 14 while $Q \neq \emptyset$ do 15 $v \leftarrow \text{the first element of } Q$ // get next vertex to allocate 16 $P' \leftarrow P' \setminus \{v\}$ 17 $Q \leftarrow Q \cap \mathcal{N}(G, v)$ // remove non-adjacent vertices 18 append k to bounds 19 20 append v to order $k \leftarrow k+1$ 21 // start a new clique return (bounds, order) 22

```
23 expand :: (Graph G, Set A, Set B, Set P_a, Set P_b, Set A_{max}, Set B_{max})

24 begin

25 \downarrow (beyond a order) ( alignee Cart(C, B))
```

 $(bounds, order) \leftarrow \texttt{cliqueSort}(G, P_a)$ $\mathbf{25}$ for $i \leftarrow |P_a|$ downto 1 do 26 if $bounds[i] + |A| > |A_{max}|$ and $|P_b| + |B| > |B_{max}|$ then $\mathbf{27}$ $v \leftarrow order[i]$ $\mathbf{28}$ $A \leftarrow A \cup \{v\}$ // Consider $v \in A$ 29 $P_a \leftarrow P_a \setminus \{v\}$ 30 $P'_a \leftarrow P_a \cap \overline{\mathrm{N}_{\mathrm{G}}(v)}$ 31 // Remove vertices adjacent to v $P'_b \leftarrow P_b \cap \mathcal{N}_{\mathcal{G}}(v)$ // Remove vertices not adjacent to v32 if |A| = |B| and $|A| > |A_{max}|$ then 33 $(A_{max}, B_{max}) \leftarrow (A, B)$ // We've found a better solution 34 if $P'_{h} \neq \emptyset$ then 35 $expand(G, B, A, P'_b, P'_a, B_{max}, A_{max})$ // Swap and recurse 36 $A \leftarrow A \setminus \{v\}$ // Now consider $v \notin A$ 37 if $B = \emptyset$ then 38 $P_b \leftarrow P_b \setminus \{v\}$ // Avoid symmetric solutions 39

(or the other way around—after all, the order of A and B is arbitrary). We are doing the same thing, by saying that if the first n bits of A are 0 then the first n bits of B must also be 0. Unlike adding a lex constraint, this approach does not interfere with the search order and does not introduce the risk of disrupting ordering heuristics [6]. Additionally, this constraint always removes symmetric solutions from the search tree as early as possible [7].

Bounding. We know that A and B must be independent sets. Finding a maximum independent set is a well studied NP-hard problem (although the literature usually discusses finding a maximum clique, which is a maximum independent set in the complement graph), and the main inspiration for our algorithm comes from a series of maximum clique algorithms due to Tomita [8,9,10]. These are branch and bound algorithms which use graph colouring (i.e. a clique cover in the complement graph) both as a bound and ordering heuristic.

If we can cover a graph G using k cliques, we know that G cannot contain an independent set of size greater than k (each element in an independent set must be in a different clique). Finding an optimal clique cover is NP-hard, but a greedy clique cover may be found in polynomial time. This gives us a bound on P_a which can be much better than simply considering $|P_a|$: we construct a greedy clique cover of the subgraph induced by P_a , and consider its size instead.

Constructing a clique cover gives us more information than just a bound on the size of an independent set in all of P_a . This is the main benefit of Tomita's approach: a constructive greedy clique cover gives us an ordering heuristic and a way of reducing the number of clique covers which must be computed.

Tomita has considered ways of producing and using greedy colourings; we refer to a computational study by Prosser [11] for a detailed comparison. Our greedy clique cover bound and ordering routine is presented in Algorithm 2. The approach we have taken is a variation by San Segundo [2,3] which allows a bitset encoding to be used.

The cliqueSort function in Algorithm 2 produces two arrays. The *bounds* array contains bounds on the size of a maximum independent set: the subgraph induced by vertices 1 to n of *order* cannot have a maximum independent set of size greater than bounds[n]. The *order* array contains the vertices of P in some order, and is to be traversed from right to left, repeatedly removing the rightmost value for the choice branching vertex v.

These arrays are constructed in the cliqueSort function as follows: the variable P' tracks which vertices have yet to be allocated to a clique, and initially (line 11) it contains every vertex in the parameter P. While there are unallocated vertices (line 13), we greedily construct a new clique. The variable Q (line 14) tracks which vertices may legally be added to this growing clique. On line 16 we select a vertex v from Q, add it to the clique, and on line 18 we remove from Q any vertices which are not adjacent to v (so every vertex remaining in Q is adjacent to every vertex in the growing clique). We continue adding vertices to the growing clique until Q is empty (line 15), indicating we can go no further. We then start a new clique (line 21, looping back to line 13) if some vertices remain unallocated.

To integrate this bound, we make the following changes: we begin by using **cliqueSort** to obtain the *bounds* and *order* variables (line 25). We explicitly iterate over *order* from right to left (lines 26 and 28), rather than drawing v from P_a arbitrarily. And we make use of the bound on P_a , rather than using $|P_a|$ (line 27).

Search Order. We use a static ordering for constructing clique covers, so the initial order of vertices must also be considered—experiments show that, as for the maximum clique problem, a static non-increasing degree order fixed at the top of search is a good choice. We achieve this ordering by permuting the graph (again, to allow the possibility of a bitset encoding).

Detecting when the Bound is Useless. Our bound considers how far A can grow, based upon what is in P_a , and how far B can grow based upon what is in P_b . If both P_a and P_b are independent sets, this does not help, and constructing the clique cover ordering is a substantial overhead. This situation occurs in particular if the input is a bipartite graph, or close to one. We can at least detect when P_a is an independent set: this happens precisely if bounds[i] = i (assuming bounds is 1-indexed), since if the graph contains at least two non-adjacent vertices then at least one such pair will be placed in the same clique [12, Proposition 2].

Ideally we would be able to switch to a better bound in the case that both P_a and P_b are (potentially overlapping) independent sets. However the authors have been unable to find a better bound which is sufficiently cheap to compute to provide a benefit—approaches which reduce the search space but increase runtime include the use of degrees, indirect colouring, or the fact that finding an (unbalanced) induced biclique in a bipartite graph can be done in polynomial time via a matching algorithm. However, we may still decay to a version of the algorithm which includes symmetry breaking and uses cardinality bounds as in Algorithm 1. We do not demonstrate this technique in Algorithm 2, but it is simple to incorporate.

3 Computational Experiments

We now present experimental results on a range of standard benchmark problems. The algorithm was implemented using C++, with a bitset encoding. The experiments were run on a machine with four AMD Opteron 6366 HE processors, and single-threaded runtimes are given. The implementation does include detection for independent sets, and falls back to a simple algorithm when this happens. Timing results include pre-processing and the initial sorting step, but do not include the time taken to read a graph in from a file. For the maximum clique problem, a sequential implementation previously described by the authors [13] was used.

In Table 1 we present results from four datasets. First is all the graphs from the Second DIMACS Implementation Challenge¹. Many of these graphs are dense,

¹ http://dimacs.rutgers.edu/Challenges/

and designed to be computationally challenging for maximum clique algorithms. The second dataset is the smallest family of graphs for BHOSLIB². These graphs contain a hidden clique of known size; again, these are challenging for maximum clique algorithms. Thirdly, we look at some large sparse graphs from BioGRID [14]. Finally, we include some large sparse graphs from a collection by Mark Newman³. For each instance we show results for both maximum clique and maximum balanced induced biclique: we show the size of the result, the time taken, and the number of search nodes (recursive calls made). Longer-running problems were aborted after one day; such results are shown in parentheses.

Sometimes $\ddot{\omega} = \omega$, sometimes it is larger, and sometimes it is smaller. Often finding $\ddot{\omega}$ was easier than finding ω (and there are no problems where the biclique search was aborted after a day but where the clique succeeded), but not always.

Further experiments show that the symmetry breaking technique is successful in reducing both runtimes and the size of the search space. In many instances the gain approaches 50% (this is expected: halving the number of solutions will not halve the size of the search space). In other cases the interaction of the bound and symmetry breaking reduces the benefit (sometimes to zero, when the bound can already eliminate symmetric solutions), but it is never a penalty.

Detecting when the bound is useless and decaying to a simpler algorithm provides a measurable benefit for several of the "p_hat" family of graphs and for "san1000", but does not generally make a substantial difference. On the other hand, for random bipartite graphs, this technique avoids a factor of five slowdown from the overhead of calculating a useless bound.

4 Conclusion and Future Work

We have shown that max clique techniques generalise to other graph-related problems, although not always in the most obvious way—despite the name, finding a biclique involves finding independent sets, not cliques. Unlike the maximum clique problem, symmetry is an issue, but we provided a very simple and effective way of avoiding this problem. We do not have a good bound for the case where both sides are already independent sets, although we can detect this and fall back to a faster algorithm; this limitation is this work's main weakness.

More detailed computational experiments would be beneficial, particularly with random and (once the weakness is addressed) random bipartite graphs. We intend to look in more detail at "where the hard problems are" for this problem [15]: there is a conflict between wanting to create two independent sets, and requiring those independent sets be interconnected, which means it is not obvious how the density of a random graph would affect the difficulty.

Finally, this approach can likely be extended to exploit multi-core parallelism the sequential algorithms upon which this work is based have been threaded successfully [13,16].

 $^{^2 \ \}texttt{http://www.nlsde.buaa.edu.cn/~kexu/benchmarks/graph-benchmarks.htm}$

³ http://www-personal.umich.edu/~mejn/netdata/

For each we show the size of a maximum clique, the time taken to obtain this result, and the number of search nodes (recursive calls Table 1. Results for the balanced biclique problem in DIMACS, BHOSLIB and large sparse graphs from BioGRID and Mark Newman. made). We then give the same information for maximum balanced induced bicliques. Besults in parentheses were aborted after one day.

$\mathbf{Problem}$		3	а		:3		Problem		3			:3		Problem		3			:3	
	Size	e Time	e Nodes	Size	Time	e Nodes		Size	Time	Nodes S	Size T	$_{\rm Time}$	Nodes		Size 7	Time No	Nodes S	Size Ti	Time 1	Nodes
C125.9	ά	4 91ms	s 50240	80	1 ms		gen400_p0.9_75	(53)	1 day 2.	2.0×10^{10}	12 3.	35 ms	16388	san400_0.7_2	30	$4.0s \ 8.9 \times 10^5$	10^{5}		33 ms	7973
C250.9	4	4 3043s	3043s 1.1×10 ⁹	80	12ms		hamming6-2	32	0 ms	32	4	0 ms	4	san400_0.7_3	22	$2.3s$ 5.2×10^{5}	10^{5}	38 38	38ms	10361
C500.9	(53)) 1 day	$1 \text{ day } 2.0 \times 10^{10}$	10	174ms		hamming6-4	4	0 ms	82	14	1 ms	1896	san400_0.9_1	100 5	$52.3s 4.5 \times 10^{6}$	106	10 38	38ms	19054
C1000.9	(58)		$ day 1.3 \times 10^{10}$	10	13.9s	7.4×10^{6}	hamming8-2	128	2 ms	128	4	1 ms	4	san1000	15	$3.5s 1.5 \times 10^5$	105	134 167ms	sm	10778
C2000.5	(16)		1 day 1.4×10^{10}	(16)	1 day		hamming8-4	16	80 ms	36452	32	2 ms	303	sanr200_0.7	18 23	$235ms 1.5 \times 10^{5}$	10^{5}	10 96	96ms 1.3	1.3×10^{5}
C2000.9	(62)		75.5×10^{9}	12	1478s		hamming10-2	512	56 ms	512	4 2	21 ms	4	sanr200_0.9	42 4	$45.2s \ 1.5 \times 10^7$	107	8	4 ms	4095
C4000.5	(17)) 1 day		(18)	1 day		hamming 10-4	(38)	1 day 1.	1.0×10^{10}	40 3	390s 4.5	4.5×10^{7}	sanr400_0.5		$543ms \ 3.2 \times 10^{5}$	10^{5}	14 14	$14.1s \ 1.4 \times 10^{7}$	$\times 10^{7}$
DSJC500-5	Ŀ.	3 1.8s		14	63.4s		johnson8-2-4	4	0 ms	24	9	0 ms	460	sanr400_0.7	21	$159s \ 6.4 \times 10^7$	107	14 4	4.3s 3.4	3.4×10^{6}
DSJC1000_5	Ŀ.	5 222s	7.7×1	16	12996s	8.9×10^{9}	johnson8-4-4	14		126	10		211_{1}				(
MANN_a9	÷	6 0ms	s 71	9	0 ms		johnson16-2-4	80	97ms 2	2.6×10^{5}	14 40:	402ms 2.2	2.2×10^{6}	frb30-15-1		$1165s 2.9 \times 10^8$	10^{8}	30 58	58ms	15361
MANN_a27	12,	6 533ms		9	4 ms	1407	johnson32-2-4	(16)	$1 \text{ day } 1.4 \times 10^{11}$	~	(30) 1	1 day 4.2)	4.2×10^{11}	frb30-15-2	30 2	2187s 5.6×10 ⁸	10^{8}	30 63	63ms	16071
MANN_a45	345	5 383s		9	56ms	9852	keller4	11	17ms	13725	18 6	69 ms	82646	frb30-15-3		655s 1.7×10 ⁸	10^{8}	30 59	59 ms	16120
MANN_a81	(1100)	(1100) 1 day		9	974ms	53902	keller5	(27)	1 day 1.	l day 1.8×10 ¹⁰	32 72	7294s 3.6	3.6×10^{9}	frb30-15-4	••	3575s 9.9×10 ⁸	10^{8}	30 61	61 ms	16694
brock200_1	7	21 868ms		10	45 ms		keller6	(53)	1 day 2	2.6×10^{9} ((62) 1	1 day 6.0	6.0×10^{9}	fr b30-15-5		$1056s \ 2.8 \times 10^8$	10^{8}	30 55	55ms	14850
brock200_2	Т.	2 5ms	s 3826	12	111ms		p_hat300-1	x	4 ms	1480	12 19.	195ms 2.8	2.8×10^{5}							
brock200-3	Ļ.	5 23ms	s 14565	12	92 ms		p-hat300-2	25	18ms	4256	12 26	268ms 2.8	2.8×10^{5}	fission-yeast	12 5	50 ms	208	$12 110 \mathrm{ms}$		33253
brock200-4	1	7 85ms		12	76ms		-	36	2.0s = 6	6.2×10^{5}	12 26	265ms 2.3	2.3×10^{5}	fruitfly	7 51	518ms	47	16 584ms	sm	11538
brock400_1	27			12	2.3s	-	p_hat500-1	6	18ms	2779	12		3.9×10^{6}	human	13 89	897ms	13		1.0s	10300
brock400_2	29	9 362s		12	2.0s		p_hat500-2	36	461ms 1	1.1×10^{5}	14	6.4s 5.9	5.9×10^{6}	mouse		21 ms	4	10 22	22 ms	1267
brock400_3	31	$1 287_{8}$	1.2×10^{8}	12	2.1s		-	50	201s 3	3.9×10^{7}	12		6.4×10^{6}	plant	9	29 ms	6	10 31	31 ms	1578
brock400_4	33	3 140s		12	2.0s		-	11		26649	12 3.		4.3×10^{7}	worm	7 122ms	2ms	1-	12 130	.30ms	3778
brock800_1	23	3 7725s		14	1424s		p_hat700-2	44	5.0s 7	7.5×10^{5}	14 5.		3.5×10^{7}	yeast	33 37	375ms	68	14 13	13.4s 2.5	5×10^{6}
brock800_2	24			14			-			2.8×10^{8}	14 6		3.1×10^7							
brock800-3	25	5 7138s	2.1×1	14	1448s		p-hat1000-1	10	454ms 1	1.8×10^{3}	14 2	295s 2.5	2.5×10^{8}	adjnoun	ŋ	0ms	17	9	0 ms	207
brock800_4	26	6 2705s	6.4×1	14	1401s		p_hat1000-2	46	251s 3	3.4×10^7	16	546s 3.6	3.6×10^{8}	astro	57	2.7s	57	9 9	3.5s	28143
c-fat 200-1	12	2 0ms		7	0 ms			(63)		8.9×10^{9}	14 15		5.6×10^{8}	celegens	80	$1 \mathrm{ms}$	32	80	2 ms	1853
$c-fat_{200-2}$	24	4 0ms		0	1 ms		p-hat1500-1			1.2×10^{6}	16 11859s		5.2×10^{9}	condmat	30 1	l7.2s	30	6 20	20.2s	33980
c-fat200-5	ú	8 1ms	-	0	3ms		p_hat1500-2			2.0×10^{9}	$16 \ 23677s$		6.8×10^{9}	dolphins	ъ	0ms	10	4	0 ms	66
c-fat500-1	÷	4 3ms		7	3 ms		p_hat1500-3	(4)		3.2×10^{9}	$16 \ 25745s$		5.5×10^{9}	football	6	0ms	6	4 0	0 ms	422
c-fat500-2	0			7			san200_0.7_1	30	31 ms	13399		6ms	4330	internet	17	5.1s	50	10		24477
c-fat500-5	64	4 4ms	s 64				san200_0.7_2	18	3ms	464	24	3 ms	1939	karate	n S	0 ms	n N	4	0 ms	31
c-fat500-10		6 4m	126 4ms 126		4		san200_0.9_1	20	206ms	87329		3ms	1850	lesmis		0 ms	10	4	0 ms	77
gen200-p0.9-44		4 4.8	$3 1.8 \times 10^{9}$	10			$san 200_{-0.9_{-2}}$	09		2.3×10^{3}	× x	4ms	3540	netscience		24 ms	20	4 26	26 ms	1184
gen200_p0.9_55	55 5.	5 461ms	6 1.7×10 ⁶	x	4ms		san200_0.9_3	44		6.8×10^{0}	10	3ms	2085	polblogs	20	23 ms	60	12 83	83ms	36693
gen400_p0.9_55 (50) 1 day 2.2×10^{10}	55 (50) 1 day	$^{\prime}$ 2.2×10 ¹⁰	16	21 ms		$san400_{-0.5_{-1}}$	13	15 ms	2453	62	9 ms	1315	polbooks	9	0 ms	11	4 0	0 ms	168
gen400_p0.9_65 (49) 1 day 2.3×10 ¹⁰	35 (49) 1 day	2.3×10 ¹⁰	14	26ms	11709	$san400_0.7_1$	40	459ms 1	1.2×10^{3}	20 5	54ms	16229	power	6 23	235ms	9	$4 \ 252 ms$	ms	4623

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