

On Improving the Cohesiveness of Graphs by Merging Nodes: Supplementary Materials

[If a preview does not appear properly, please download the file]

1. Proofs

In this sections, we provide the proofs that are not included in the main text due to the space limit. For the sake of completeness, those theorems, lemmas, etc., whose proofs have been provided in the main text, are also listed here.

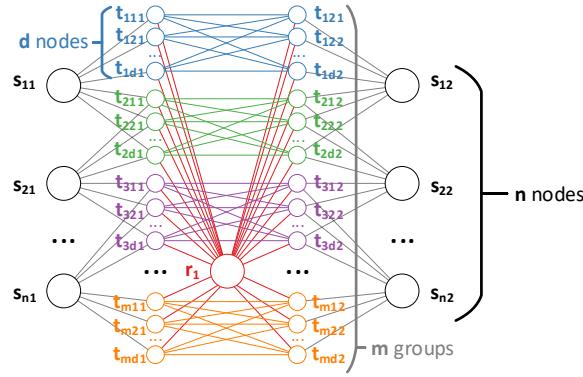


Fig. 1. The constructed instance of the TIMBER problem corresponding to the maximum cover problem with $k = 4$, where $S_1 = \{t_1, t_2\}$, $S_2 = \{t_2, t_3\}$, and $S_n = \{t_3, t_m\}$.

Theorem 1. *The TIMBER problem is NP-hard for all $k \geq 3$.*

Proof. We show the NP-hardness by reducing the NP-hard maximum coverage (MC) problem to the TIMBER problem. Consider the MC problem with the collection of n sets $\mathcal{S} = \{S_1, S_2, \dots, S_n\}$ and budget b . Let $T = \{t_1, t_2, \dots, t_m\} = \bigcup_{i=1}^n S_i$. Consider the decision version where we shall answer whether there is a subset $\mathcal{S}' \subseteq \mathcal{S}$ with $|\mathcal{S}'| \leq b$ such that at least X elements in T are covered by \mathcal{S}' . We shall construct an corresponding instance of the TIMBER problem. We construct the graph G as follows. For each $t_j \in T$, we create $2d$ nodes t_{jp1} and $t_{jp2}, \forall 1 \leq p \leq d$, where d is sufficiently large ($d > 10kmn$), and add edges $(t_{jp1}, t_{jp'2})$ for all $p \neq p'$. For each $S_i \in \mathcal{S}$, we create two nodes s_{i1} and s_{i2} , and for each $t_j \in S_i$, we add edges (s_{i1}, t_{jp1}) and $(s_{i2}, t_{jp2}), \forall 1 \leq p \leq d$. Fix any $k \geq 3$, we create $k - 3$ nodes r_1, r_2, \dots, r_{k-3} , each of which is connected with all t -nodes (i.e., t_{jp1} and $t_{jp2}, \forall j, p$). See Figure 1 for an example of the construction. We also consider the decision version of the TIMBER problem where we shall answer whether there is a set P' of pairs of nodes with $|P'| \leq b$ such that $f(P') \geq Xd^2$.
 $\Rightarrow)$ Given a YES-instance $\mathcal{S}' = \{S_{i_1}, S_{i_2}, \dots, S_{i_{b'}}\}$ with $|\mathcal{S}'| = b' \leq b$ for the MC problem, we claim that $P' = \{(s_{i_11}, s_{i_12})\}_{i=1}^{b'}$ is a YES-instance P' for the TIMBER problem. By our construction and $|\bigcup_{S_i \in \mathcal{S}'} S_i| \geq X$, merging all pairs in P' makes all the edges among the at least X corresponding groups of t -nodes enter the k -truss, and the total number is at least Xd^2 .

$\Leftarrow)$ Given a YES-instance P' with $|P'| = b' \leq b$ for the TIMBER problem, we claim that (1) those edges entering the k -truss are distributed in at least X groups of t -nodes corresponding to the elements in T , and (2) there exists $P'' \subseteq \{(s_{i1}, s_{i2})\}_{i=1}^n$ with $|P''| = b'$ that is also a YES-instance of the TIMBER problem. For (1), assume the opposite, i.e., less than X groups are involved, then the size of the new k -truss is at most $(X-1)d^2 + 2(k-3)md + 2mnd < Xd^2$, which contradicts the fact that P' is a YES-instance. For (2), we shall show that each non- (s_{i1}, s_{i2}) -type pair can be replaced an (s_{i1}, s_{i2}) -type pair without decreasing the size of the k -truss. For (s_{i1}, s_{j1}) or (s_{i2}, s_{j2}) or (t_{ip1}, s_{j1}) with $i \neq j$, or a pair containing any r -node, there are no edges between two t -nodes entering the k -truss when we merge such a pair. For (s_{i1}, s_{j2}) with $i \neq j$, merging such a pair is no better than merging (s_{i1}, s_{i2}) or (s_{j1}, s_{j2}) . For a pair consisting of an s -node and a t -node, it is no better than merging any (s_{i1}, s_{i2}) benefiting the same part. Hence we can replace each element in P' by an (s_{i1}, s_{i2}) -type pair without decreasing the number

of groups of edges among t -nodes entering the k -truss. Therefore, we can find $P'' \subseteq \{(s_{i1}, s_{i2})\}_{i=1}^n$ with $|P''| = b'$ such that $f(P'') \geq Xd^2$, completing the proof. \square

Theorem 2. *The function $f(P)$ is not submodular.*

Algorithm 1: Naive greedy algorithm

```

Input : graph  $G = (V, E)$ ; trussness  $k$ ; budget  $b$ 
Output:  $P$ : the pairs of nodes to be merged
1  $P \leftarrow \emptyset$ 
2 while  $|P| < b$  do
3    $f(\{p\}) \leftarrow |E(T_k(PM(p; G)))|, \forall p \in \binom{V'}{2}$ 
4    $p^* \leftarrow \arg \max_p f(\{p\}); P \leftarrow P \cup \{p^*\}$ 
5   if  $|P| < b$  then  $G = (V, E) \leftarrow PM(p^*; G)$ 
6 return  $P$ 

```

Theorem 3. *Given an input graph $G = (V, E)$ and budget b , Algorithm 1 takes $O(b|V|^2|E|^{1.5})$ time and $O(|E|)$ space for any k .*

Proof. Truss decomposition algorithm takes $O(|E|^{1.5})$ time and $O(|V| + |E|)$ space [5]. Since we only consider connected graphs, $|E| = O(|V|)$ and thus $O(|V| + |E|) = O(|E|)$. Computing the size of the k -truss after each merger takes $O(|E|^{1.5})$ time. Because there are $O(|V|^2)$ pairs and b iterations, the total time complexity is $O(b|V|^2|E|^{1.5})$. The space complexity is determined by that of storing the graphs and truss decomposition, which is $O(|E|)$. \square

Lemma 1. *Given any G , v_1 , and v_2 , for any $e \in E(G)$, if $v_1, v_2 \notin e$, then $|t(e; PM(v_1, v_2)) - t(e; G)| \leq 1$.*

Proof. Let G' denote $PM(v_1, v_2; G)$. First, we show the decrease is limited. For each k , for each edge in the current k -truss, merging a pair of nodes can decrease the support by at most 1. Therefore, each current k -truss at least satisfies the condition of $(k-1)$ -truss after the merger, completing the proof of the limited decrease. Regarding the increase, consider the inverse operation of merging two nodes, and we shall show the decrease is limited. Formally, we split v_1 in G' back into two nodes v_1 and v_2 in G , with $N(v_1; G') = N(v_1; G) \cup N(v_2; G)$. With regard to the trussness of each edge, this operation is no worse than deleting the node. Similar to merging a pair, when we delete a node, for each k , for each edge in the current k -truss, the support decreases by at most 1, completing the proof. \square

Corollary 1. *Given any G , k , and $v_1, v_2 \in V(G)$, $T_k(PM(v_1, v_2; G)) = T_k(G')$, where $V(G') = V(G)$ and $E(G') = E(T_{k-1}(G) \setminus \{v_1, v_2\}) \cup \{(v_1, x) : x \in (N(v_1) \cup N(v_2) \setminus \{v_1, v_2\}) \cap V(T_{k-1})\}$.*

Proof. Recall that $T_{k-1}(G) \setminus \{v_1, v_2\}$ is defined as the subgraph obtained by removing v_1 , v_2 , and all their incident edges from $T_{k-1}(G)$. Since $G' \subseteq PM(v_1, v_2)$, $T_k(G') \subseteq T_k(PM(v_1, v_2))$. Hence, it suffices to show that $T_k(PM(v_1, v_2)) \subseteq T_k(G')$. First, by Lemma 1, for $e \in E(G \setminus \{v_1, v_2\})$, if $t(e; G) < k-1$, then $t(e; PM(v_1, v_2)) < k$ and thus $e \notin E(T_k(PM(v_1, v_2)))$, completing the proof for the first part ($T_{k-1}(G) \setminus \{v_1, v_2\}$). Second, for an edge (v_1, x) , such an edge exists iff $x \in N(v_1) \cup N(v_2) \setminus \{v_1, v_2\}$; if $x \notin V(T_{k-1})$, then v_1 will be the only neighbor of x and thus (v_1, x) cannot be in the k -truss after the merger, completing the proof. \square

Lemma 2. *Given any G and $v_1, v_2 \in V(G)$, we assume $t(v_1) \geq t(v_2)$, without loss of generalization. For any $e \in E(G)$, if $t(e) > t(v_2)$, then $t(e; PM(v_1, v_2)) \geq t(e; G)$.*

Proof. If $t(v_2) < t(e)$, then $v_2 \notin V(T_{t(e)}(G))$. Therefore, merging v_1 and v_2 can only bring new edges into the $t(e)$ -truss, and thus the trussness of e cannot decrease, completing the proof. \square

Lemma 3. *Given any G , k , and $v_1, v_2 \in V(G)$, let N^* denote $N(v_1) \cup N(v_2) \setminus \{v_1, v_2\}$. For any $x \in N^*$, (v_1, x) is in $T'_k := T_k(PM(v_1, v_2))$ if and only if x is in the $(k-2)$ -core of $T'_k[N^*]$.*

Proof. \Leftrightarrow Put $\{(v_1, x) : x \text{ is in the } (k-2)\text{-core of } T'_k[N^*]\}$ and $E(T'_k[N^*])$ together, each such (v_1, x) is in at least $k-2$ triangles $\Delta_{v_1, x, x'}$ with $x' \in N^*$, completing the proof.

\Rightarrow Let X denote $\{x : (v_1, x) \in T'_k\}$. For each $x \in X$, we have at least $k-2$ triangles $\Delta_{v_1, x, x'}$ with all three constituent edges in T'_k . Hence $d(x; T'_k[N]) \geq k-2, \forall x \in X$, completing the proof. \square

Lemma 4. *Given any G and k , for any $u_1, u_2 \notin V(T_{k-1})$, if $\tilde{N}_k(u_1) \subseteq \tilde{N}_k(u_2)$, then $T_k(PM(v, u_1; G)) \subseteq T_k(PM(v, u_2; G)), \forall v \in V(G)$.*

Proof. Given any G , by Lemma 1 and 2, if $u \notin V(T_{k-1})$, then $T_k \subseteq T_k(PM(v, u)) \subseteq \tilde{T}_k \subseteq PM(v, u)$, where $\tilde{T}_k = \tilde{T}_k(v, u) = T_{k-1} \cup \{(v, x) : x \in N(v) \cup N(u) \setminus \{u, v\}\}$, for any v . Furthermore, if $x \notin V(T_{k-1}) \cup \{v, u\}$, then $d(x; T_k(PM(v, u))) \leq d(x; \tilde{T}_k(v, u)) = 0$. Hence, by Lemma 3, $x \notin V(T_k(PM(v, u)))$, which gives that $T_k(PM(v, u)) = T_k(\tilde{T}_k(v, u)) = \hat{T}_k(v, u)$, where $\hat{T}_k(v, u) = T_{k-1} \cup \{(v, x) : x \in (N(v) \cup N(u) \setminus \{u, v\}) \cap V(T_{k-1})\}$. For $u_1, u_2 \notin V(T_{k-1})$, if $N(u_1) \cap V(T_{k-1}) \subseteq N(u_2) \cap V(T_{k-1})$, then clearly $\hat{T}_k(v, u_1) \subseteq \hat{T}_k(v, u_2)$, completing the proof. \square

Lemma 5. Given G and k , let $V_o = V(G) \setminus V(T_{k-1})$ denote the set of outside nodes, and let $\tilde{V}_o = \{u \in V_o : \#\text{neighbors}(u) \in V \setminus V(T_{k-1})\}$ denote the set of outside nodes with a maximal set of inside neighbors. Then, $\max\{|E(T_k(PM(v_1, v_2)))| : v_1, v_2 \in V(G)\} = \max\{|E(T_k(PM(v_1, v_2)))| : v_1, v_2 \in V(T_{k-1}) \cup \tilde{V}_o\}$.

Proof. It suffices to show that for any $u \in V_o \setminus \tilde{V}_o$, if a merger includes u , then there exists another merger consisting of two nodes in $V(T_{k-1}) \cup \tilde{V}_o$ with no worse performance. And this is an immediate corollary of Lemma 4. \square

Algorithm 2: Prune outside nodes (based on [3])

```

Input : outside nodes  $V_o$ ; inside neighbors  $\tilde{N}_k(v), \forall v \in V_o$ 
Output:  $V_o^*$ : the outside nodes with maximal set of inside neighbors
1  $S, V'_o \leftarrow \emptyset$ 
2 for  $v \in V_o$  do
3   if  $\tilde{N}_k(v) \notin S$  then  $\{S \leftarrow S \cup \{\tilde{N}_k(v)\}; V'_o \leftarrow V'_o \cup \{v\}\}$ 
4    $i \leftarrow 0; m(v) \leftarrow 0, \forall v \in V_o; V_o^* \leftarrow \emptyset$ 
5   for  $v \in V'_o$  do
6     for  $u \in \tilde{N}_k(v)$  do  $m(u) \leftarrow \text{BitwiseOr}(m(u), 2^i)$ 
7      $i \leftarrow i + 1$ 
8    $r(v) \leftarrow \text{BitwiseAnd}(\{m(u) : u \in \tilde{N}_k(v)\}), \forall v \in V'_o$ 
9    $V_o^* \leftarrow \{v : r(v) \text{ is a power of } 2\}$ 
10  return  $V_o^*$ 

```

Lemma 6. Given the set of outside nodes V_o and the sets of their inside neighbors $\tilde{N}_k(v), \forall v \in V_o$. Algorithm 2 correctly finds the set of nodes $v' \in V_o$ with maximal $\tilde{N}_k(v')$ in $O(\sum_{v \in V_o} |\tilde{N}_k(v)| |V_o|) = O(|V||E|)$ time and $O(|E|)$ space.

Proof. Lines 1 to 3 remove the outside nodes with duplicate inside neighborhood and take $O(|V_o|)$ times. Lines 4 to 7 build the membership function m where for a inside node u , the i -th bit of $m(u)$ indicates the membership relation between u and the i -th element of V'_o , which takes $O(\sum_{v \in V_o} |\tilde{N}_k(v)|)$ time. Lines 8 to 9 use m to check the maximality of each unique inside neighborhood, and take $O(\sum_{v \in V_o} |\tilde{N}_k(v)| |V_o|)$. For the correctness, $r(v)$ consists of the nodes v' with $\tilde{N}_k(v') \supseteq \tilde{N}_k(v)$. If the final r is a power of 2, i.e., exactly a single bit of r is 1, then this bit represents v itself, which means that no other v' satisfies that $\tilde{N}_k(v') \supseteq \tilde{N}_k(v)$. Regarding the space complexity, the inputs and all the variables (S , V'_o , and V_o^*) take $O(|E|)$ space, $m(v)$ for all $v \in V_o^*$ takes $O(\sum_{v \in V_o^*} |\tilde{N}_k(v)|) = O(|E|)$ space if we represent the binary arrays in a sparse way [1]. \square

Proposition 1. Given any $G = (V, E)$, k , and $v_1, v_2 \notin T_{k-1}$, for any $x \in N(v_1) \cup N(v_2) \setminus \{v_1, v_2\}$, $T_k(G) = T_k(G')$, where $V(G') = V(G)$ and $E(G') = E(G) \cup \{(v_1, x)\}$.

Proof. If an edge e_0 is inserted into a graph G such that the trussness of e_0 after the insertion is l , then all edges with original trussness at least l will not gain any trussness, and the remaining edges can gain at most 1 trussness [4]. Hence, it suffices to show that for each considered x , after inserting (v_1, x) into G , the trussness of (v_1, x) is at most $k-1$. Indeed, since $v_1 \notin T_{k-1}$, all edges incident to v_1 have original trussness at most $k-2$ and thus have trussness at most $k-1$ after the insertion. Therefore, all triangles containing (v_1, x) will not be in T_k and thus neither will (v_1, x) . \square

Algorithm 3: Find IOM candidates

```

Input : pruned outside nodes  $V_o^*$ ; inside nodes  $V_i$ ; inside neighbors  $\tilde{N}_k(v), \forall v \in V_o^* \cup V_i$ ; shell edges  $\hat{E}_k$ ;  $k$ -truss  $T_k$ ;
       number of inside nodes to check  $n_i$ ; number of outside nodes to check  $n_o$ ; number of pairs to choose  $n_c$ 
Output:  $C_{IOM}$ : the chosen IOM candidates
1  $\hat{V}_i \leftarrow$  the  $n_i$  inside nodes  $v_i$  in  $V_i$  with most incident prospects (i.e., largest  $|\tilde{N}_k(v_i) \setminus N(v_i; T_k)|$ )
2  $\hat{V}_o \leftarrow$  the  $n_o$  outside nodes  $v_o$  in  $V_o^*$  with most inside neighbors (i.e., largest  $|\tilde{N}_k(v_o)|$ )
3 for  $v_i \in \hat{V}_i$  do
4    $H(t_i) \leftarrow \tilde{N}_k(t_i) \cup \tilde{N}_k(v_i), \forall t_i \in V_i \setminus \tilde{N}_k(v_i) \setminus \{v_i\}$ 
5   for  $v_o \in \hat{V}_o$  do
6      $Z = Z(v_i, v_o) \leftarrow (\tilde{N}_k(v_i) \cup \tilde{N}_k(v_o)) \setminus (N(v_i; T_k) \cup \{v_i\})$ 
7      $H_i \leftarrow \bigcup_{z \in Z} H(z)$ 
8      $H_n \leftarrow \{(x, y) \in \hat{E}_k : (x \in Z \vee y \in Z) \wedge x \in Z \cup \tilde{N}_k(v_i) \wedge y \in Z \cup \tilde{N}_k(v_i)\}$ 
9      $\hat{H}_k(v_i, v_o) \leftarrow H_i \cup H_n$ 
10   $C_{IOM} \leftarrow$  the  $n_c$  IOMs  $(v_i, v_o) \in \hat{V}_i \times \hat{V}_o$  with largest  $|\hat{H}_k(v_i, v_o)|$  (tie broken by  $|Z(v_i, v_o)|$ )
11  return  $C_{IOM}$ 

```

Lemma 7. Given pruned outside nodes V_o^* , inside nodes V_i , inside neighbors \tilde{N}_k , shell edges \hat{E}_k , and k -truss T_k , Algorithm 3 takes $O(|V_o^*| \log n_o + n_i n_o (|V_i| + |\hat{E}_k| + \log n_c))$ time to find n_c IOM candidates from n_i and n_o promising inside and outside nodes, respectively.

Proof. Finding the top- n_i inside nodes and top- n_o outside nodes (Lines 1 and 2) takes $O(|V_i| \log n_i + |V_o^*| \log n_o)$. For all inside nodes and all “new” neighbors, computing the incident PHSEs (Lines 3 to 4) takes $O(n_i |V(T_{k-1})|)$ time; and computing PHSEs for all pairs (Lines 5 to 9) takes $O(n_i n_o (|V(T_{k-1})| + |\hat{E}_k|))$ time. Maintaining the candidate set takes $O(n_i n_o \log n_c)$ time. Hence, the total time complexity is $O(|V_o^*| \log n_o + n_i n_o (|V_{k-1}| + |\hat{E}_k| + \log n_c))$. \square

Algorithm 4: Find IIM candidates

<p>Input : inside nodes V_i; inside neighbors $\tilde{N}_k(v), \forall v \in V_i$; shell edges \hat{E}_k; k-truss T_k; number of inside nodes to check n_i; number of pairs to choose n_c</p> <p>Output: C_{IIM}: the chosen IIM candidates</p> <p>1 $\hat{V}_i \leftarrow$ the n_i inside nodes v_i in V_i with most incident prospects</p> <p>2 for $(v_1, v_2) \in \binom{\hat{V}_i}{2}$ do</p> <p>3 $h(v_1, v_2) \leftarrow - \{u \in V(T_k) : \{(v_1, u), (v_2, u)\} \subseteq E(T_k)\}$</p> <p>4 for $(x, y) \in \hat{E}_k$ with $x, y \notin \{v_1, v_2\}$ and $\{x, y\} \subseteq \tilde{N}_k(v_1) \cup \tilde{N}_k(v_2)$ do</p> <p>5 if $x, y \notin \tilde{N}_k(v_1) \cap \tilde{N}_k(v_2)$ then</p> <p>6 $h(v_1, v_2) \leftarrow h(v_1, v_2) + 1$</p> <p>7 else if $\{x, y\} \subseteq \tilde{N}_k(v_1) \cap \tilde{N}_k(v_2)$ then</p> <p>8 $h(v_1, v_2) \leftarrow h(v_1, v_2) - 1$</p> <p>9 $C_{IIM} \leftarrow$ the n_c IIMs $(v_1, v_2) \in \binom{\hat{V}_i}{2}$ with largest $h(v_1, v_2)$</p> <p>10 return C_{IIM}</p>

Lemma 8. Given inside nodes V_i , inside neighbors \tilde{N}_k , shell edges \hat{E}_k , and the k -truss T_k , Algorithm 4 takes $O(|V_i| \log n_i + n_i^2 (|\hat{E}_k| + \log n_c))$ time to find n_c IIM candidates from n_i promising inside nodes.

Proof. Finding the top- n_i inside nodes (Line 1) takes $O(|V_i| \log n_i)$ time. For all pairs among the chosen inside nodes, computing the scores (Lines 2 to 8) takes $O(n_i^2 |\hat{E}_k|)$ time. Maintaining the set of candidates IOMs takes $O(n_i^2 \log n_c)$ time. Therefore, the total time complexity is $O(|V_i| \log n_i + n_i^2 (|\hat{E}_k| + \log n_c))$. \square

Algorithm 5: BATMAN: final proposed algorithm

<p>Input : graph $G = (V, E)$; trussness k; budget b; number of inside nodes to check n_i; number of outside nodes to check n_o; number of pairs to choose n_c</p> <p>Output: P: the pairs of nodes to be merged</p> <p>1 $P \leftarrow \emptyset; n_{io} \leftarrow \lfloor n_c / 2 \rfloor$</p> <p>2 while $P < b$ do</p> <p>3 compute or update $t(e)$ using truss decomposition</p> <p>4 $\hat{E}_k \leftarrow \{e \in E : t(e) = k - 1\}$</p> <p>5 $t(v) \leftarrow \max_{e \ni v} t(e), \forall v \in V$</p> <p>6 $V_i \leftarrow \{v \in V : t(v) \geq k - 1\}; V_o \leftarrow \{V\} \setminus V_i$</p> <p>7 $\tilde{N}_k(v) \leftarrow N(v) \cap V(T_{k-1}(G)), \forall v \in V$</p> <p>8 $V_o^* \leftarrow$ Alg. 2 with inputs V_o and \tilde{N}_k</p> <p>9 $C_{IOM} \leftarrow$ Alg. 3 with inputs $V_o^*, V_i, \tilde{N}_k, \hat{E}_k, T_k(G), n_i, n_o, n_{io}$</p> <p>10 $C_{IIM} \leftarrow$ Alg. 4 w/ inputs $V_i, \tilde{N}_k, \hat{E}_k, T_k(G), n_i, n_c - n_{io}$</p> <p>11 $p^* \leftarrow \arg \max_{c=(v_1, v_2) \in C_{IOM} \cup C_{IIM}} T_k(PM(v_1, v_2)) P \leftarrow P \cup \{p^*\}$</p> <p>12 if $P < b$ then</p> <p>13 $G = (V, E) \leftarrow PM(p^*; G)$</p> <p>14 if $p^* \in C_{IOM}$ then</p> <p>15 $n_{io} \leftarrow \min(n_{io} + \lfloor n_c / b \rfloor, \lceil n_c(b-1) / b \rceil)$</p> <p>16 else</p> <p>17 $n_{io} \leftarrow \max(n_{io} - \lfloor n_c / b \rfloor, \lceil n_c / b \rceil)$</p> <p>18 return P</p>

Theorem 4. Given an input graph G , trussness k , a budget b , and the parameters n_i , n_o , and n_c , Algorithm 5 takes $O(b(|E|^{1.5} + n_c |E(T_{k-1})|^{1.5} + |V_o^*| \log n_o + n_i n_o (|V_i| + |\hat{E}_k| + \log n_c) + n_i^2 (|\hat{E}_k| + \log n_c)))$ time and $O(|E| + n_c)$

space to find b pairs to be merged.

Proof. In each round, truss decomposition (Line 3) takes $O(|E|^{1.5})$ time. Collecting all the information (Lines 4 to 8) takes $O(|E|)$ time. By Lemmas 7 and 8, obtaining the candidate mergers (Lines 9 and 10) takes $O(|V_o^*| \log n_o + n_i n_o (|V_i| + |\hat{E}_k| + \log n_c) + n_i^2 (|\hat{E}_k| + \log n_c))$ time. Checking the results after all candidates (Line 11) takes $O(n_c |E(T_{k-1})|^{1.5})$ time. Updating the graph (Line 13) takes $O(|E|)$ time. Hence, it takes $O(b(|E|^{1.5} + n_c |E(T_{k-1})|^{1.5} + |V_o^*| \log n_o + n_i n_o (|V_i| + |\hat{E}_k| + \log n_c) + n_i^2 (|\hat{E}_k| + \log n_c)))$ time in total. All the inputs and variables take $O(|E| + n_c)$ space, including the intermediate ones in Algorithms 3 and 4 (note that we only maintain the set of best candidate nodes and pairs). By Lemma 6, Algorithm 2 takes $O(|E|)$ space. Hence, the total space complexity is $O(|E| + n_c)$. \square

2. Full experimental results

In this section, we show the full results of our experiments which we cannot put all in the main text due to the space limit.

2.1. Main experiments

Experimental settings. For each dataset, we conduct experiments for each $k \in \{5, 10, 15, 20\}$. We use $b = 10$, check 100 inside nodes and 50 outside nodes, and n_c , the number of pairs to check in each round, takes a value in $\{1, 2, 5, 10, 15, 20\}$. We conduct all the experiments on a machine with i9-10900K CPU and 64GB RAM. All algorithms are implemented in C++, and complied by G++ with O3 optimization.

In Tables 3 to 16, we report the full results of each dataset for all the considered parameters.

2.2. Sampling experiments

Experimental settings. For each dataset and each $k \in \{5, 10, 15, 20\}$, we randomly sample 10,000 **inside-inside (II)/inside-outside (IO)/outside-outside (OO)** mergers. For each experimental setting (dataset and k) and each case (II/IO/OO), we do five independent trials. We do this for one round (i.e., the budget $b = 1$).

In Figures 3 to 16, we report the full results of each dataset. In each plot, the x -axis represents the sampling size, and for each sampling size $1 \leq x \leq 10000$, the corresponding y value represents the best performance among the first x sampled mergers. We report the mean value and the standard deviation of five independent trials.

2.3. Heuristics experiments

Experimental settings. We study IOMs and IIMs separately. For each dataset and each $k \in \{5, 10, 15, 20\}$, we report the best performance among the mergers using the 100 inside nodes chosen by each node-heuristic (heuristic that chooses inside nodes), and report the best performance among the 10 mergers chosen by each pair-heuristic (heuristic that chooses pairs to be merged). The candidate mergers that each pair-heuristic chooses among are those using the 100 inside nodes chosen by the node-heuristic IP which performs best among all the considered node-heuristics.

In Tables 17 to 30, we report the full results of each dataset.

2.4. Effectiveness studies

Merging nodes is much more effective than adding edges in enhancing graph cohesiveness and robustness. For each measure, we report the change of it when we do 10 times of merging nodes or adding edges, over five independent trials, with the original value below the measure name. For each measure, the first result of merging nodes that is better than adding 10 edges is marked in bold and underlined.

Experimental settings.

- the Erdős-Rényi model: `networkx.gnp_random_graph(n=50, p=0.1)`.
- the Watts–Strogatz small-world model: `networkx.connected_watts_strogatz_graph(n=50, k=7, p=0.1)`.
- the Holme-Kim powerlaw-cluster model: `networkx.powerlaw_cluster_graph(n=50, m=3, p=0.1, seed=42)`.

In Tables 1 and 2, we provide the results using the Watts-Strogatz small-world model and the Holme-Kim powerlaw-cluster model.

Table 1. Results of the effectiveness study using the Watts-Strogatz small-world model.

measure	# operations	1	2	3	4	5	6	7	8	9	10
VB 72.58	merging	70.1	67.7	65.5	63.5	61.7	60.0	58.5	56.9	55.3	53.7
	adding	72.3	72.1	71.9	71.7	71.4	71.3	71.1	70.9	70.7	70.5
EB 10.8	merging	10.2	9.6	9.1	8.6	8.1	7.6	7.2	6.8	6.4	6.0
	adding	10.6	10.6	10.5	10.4	10.3	10.2	10.1	10.0	9.9	9.9
ER 369.0	merging	343.1	319.2	296.3	274.3	253.4	233.9	215.3	198.2	182.1	167.2
	adding	364.6	360.7	356.8	353.1	349.6	346.1	342.8	339.7	336.8	333.9
NC 7.5	merging	8.0	8.4	8.8	9.2	9.5	9.8	10.1	10.4	10.7	11.0
	adding	7.6	7.8	7.9	8.0	8.2	8.3	8.4	8.5	8.6	8.7
SG 2.3	merging	3.1	3.7	4.3	4.7	5.2	5.5	5.9	6.2	6.5	6.8
	adding	2.5	2.7	2.9	3.1	3.2	3.4	3.6	3.7	3.9	4.0

Table 2. Results of the effectiveness study using the Holme-Kim powerlaw-cluster model.

measure	# operations	1	2	3	4	5	6	7	8	9	10
VB 77.5	merging	73.4	69.5	65.8	63.0	60.8	59.1	57.4	55.8	54.2	52.6
	adding	76.9	76.4	76.0	75.6	75.2	74.9	74.5	74.2	73.8	73.5
EB 10.6	merging	9.7	8.8	8.1	7.5	7.0	6.6	6.3	5.9	5.6	5.3
	adding	10.4	10.3	10.2	10.1	10.0	9.8	9.7	9.6	9.5	9.4
ER 300.2	merging	276.1	254.7	236.3	219.8	204.4	190.1	176.7	164.0	152.0	140.7
	adding	296.4	293.1	289.9	287.1	284.3	281.8	279.3	277.0	274.7	272.6
NC 6.5	merging	7.0	7.7	8.3	8.7	9.3	9.7	10.1	10.5	10.9	11.2
	adding	6.6	6.6	6.7	6.8	6.9	6.9	7.0	7.1	7.2	7.3
SG 1.7	merging	2.8	3.6	4.3	4.8	5.6	6.1	6.6	7.1	7.6	8.1
	adding	1.9	2.0	2.1	2.3	2.4	2.5	2.6	2.7	2.9	3.0

2.5. A case study on *relato*

We conduct a case study on *relato*, in order to check which nodes are merged together when we apply BATMAN, the proposed algorithm. In the *relato* dataset, each node represents a company (mainly in the IT field) and each edge represents some business-partner relationship between two companies.

We use BATMAN on *relato* with $(k, b, n_i, n_o, n_c) = (10, 100, 100, 50, 10)$. After $b = 100$ rounds, the size of $(k = 10)$ -truss increases from 89041 to 94944.

- Only 110 nodes participate in the 100 mergers.
- There are 7 groups of companies consisting of more than two companies are merged together:
 - (size = 28) Apple Inc., Experian, Ameriprise, Peavey, REC Solar, Salesforce, Cubic, Kirin, RSA, Hanold Associates, Novatek, SKS, Interbrand, Hewlett Packard, Cemex, Beijing Enterprises, space150, NuGen, InSite, Wesco, Thomas & Betts, Bloom Energy, Ashland, Oshkosh Corporation, Azul Systems, ADC, BTG, Palantir; This group consists of a giant company (Apple Inc.) and 27 relatively small companies in various fields; This kind of mergers usually happen in real-world situations.
 - (size = 22) SAP, CloudBees, DragonWave, Klocwork, SunTrust, Basho, Merry Maids, Signal, Xcerra, SGI, Veeva, SWIFT, Mitsui & Co, Hologic, Comdata, Martin Agency, Spectra Energy, Zensar Technologies, United Rentals, ThreatMetrix, IMG College, NAVTEQ; Similarly, this group consists of a giant company SAP and 21 relatively small companies in various fields.

- (size = 19) Oracle, Airwatch, Amylin Pharmaceuticals, E2open, BMO Financial Group, Cyber-Ark Software, UC Berkeley, MedImmune, Petco, Piper Aircraft, Wheel Pros, Aker Solutions, Swiss Life, Torch, Brooks Brothers, RWE Group, Bell Mobility, Calabrio, Compal Electronics; Similar to the previous two groups, where the giant company is Oracle.
 - (size = 12) Google, Databricks, SimpliVity, Azul, Henry Schein, Apple, Newport News, HCL Technologies America, HP, AES, Hewlett Packard Enterprise, Marshall Aerospace; Similarly, the giant company is Google.
 - (size = 11) IBM, Nine Entertainment, Gores, OneSpot, TALX, Kaiser Aluminum, Coty, JC Penney, Scivantage, Ch2m Hill, State bank of India; Similarly, the giant company is IBM; It is interesting to see State bank of India here.
 - (size = 8) Facebook, VCE, SDL, Reval, MAXIM INTEGRATED, NEC, ThyssenKrupp, Commonwealth Bank of Australia; Similarly, the giant company is Facebook; Again, we see a foreign bank here (Commonwealth Bank of Australia).
 - (size = 4) Amazon Web Services, Hewlett-Packard, Xignite, Gainsight; This group is a bit different, both Amazon Web Services and Hewlett-Packard giant companies, while Xignite and Gainsight are two relatively small data and market companies.
 - (size = 2) Cisco, YourEncore; This is a combination between Cisco which corresponds to the node with highest node-degree in the dataset and a fairly small company YourEncore.
 - (size = 2) Intel, Mimecast; This is also a combination between a large company and a small company.
 - (size = 2) Amazon, Purdue University; In this dataset, Amazon Web Services and Amazon are two separate nodes; It is interesting to see that Purdue University can help Amazon through a merger between these two entities.
- Conclusion: the main case is that a giant company gets merged with a large number of companies in various fields, which is also the most common case in real-world situations; it is fairly uncommon for two relatively large companies to be merged together, but not totally impossible.

3. The counterpart problem using k -cores

In this section, we discuss the counterpart problem using k -cores and analyze the technical similarity between this problem and the anchored k -core problem [2].

Recall the problem that we are studying in this work.

Problem 1. (TIMBER: Truss-sIze Maximization By mERgers)

- **Given:** a graph $G = (V, E)$, $k \in \mathbb{N}$, and $b \in \mathbb{N}$,
- **Find:** a set P of up to b node mergers in G , i.e., $P \subseteq \binom{V}{2}$ and $|P| \leq b$,
- **to Maximize:** the size of the k -truss after the mergers, i.e.,

$$f(P) = f(P; G, k) = |E(T_k(PM(P; G)))|.$$

It is possible to consider the counterpart problem using k -cores. Note that the size of a k -core is usually defined as the number of nodes in the k -core.

Problem 2. (The counterpart problem of TIMBER using k -cores)

- **Given:** a graph $G = (V, E)$, $k \in \mathbb{N}$, and $b \in \mathbb{N}$,
- **Find:** a set P of up to b node mergers in G , i.e., $P \subseteq \binom{V}{2}$ and $|P| \leq b$,
- **to Maximize:** the size of the k -core after the mergers, i.e.,

$$f(P) = f(P; G, k) = |V(C_k(PM(P; G)))|,$$

where $C_k(G_0)$ denote the k -core of a graph G_0 .

We also provide the problem statement of the anchored k -core problem here for the sake of completeness. We first define the anchored k -core.

Definition 1. $G = (V, E)$, $k \in \mathbb{N}$ and a set $A \subseteq V$ of anchors, the anchored k -core of G w.r.t the anchor set A is the maximum subgraph $\tilde{C}_k(G; A) = (V', E')$ of G where $A \subseteq V'$ and $d(v'; \tilde{C}_k(G; A)) \geq k, \forall v' \in V' \setminus A$.

Problem 3. (The anchored k -core problem)

Given: a graph $G = (V, E)$, $k \in \mathbb{N}$, and $b \in \mathbb{N}$,

Find: a set A of up to b nodes in G , i.e., $A \subseteq V$ and $|A| \leq b$,

to Maximize: the size of the k -core after anchoring the chosen nodes in A , i.e.,

$$f(A) = f(A; G, k) = |V(\tilde{C}_k(G; A))|.$$

We claim the technical similarity between the counterpart problem of TIMBER using k -cores and the anchored k -core problem, stated as follows.

Claim 1. Problem 2 and Problem 3 are technically similar. Specifically, merging two nodes in Problem 2 is similar to anchoring both of the nodes in Problem 3.

Formally, given $G = (V, E)$ and $k \in \mathbb{N}$, if two nodes v_1 and v_2 are not in the current k -core and have no common neighbor in the current $(k-1)$ - and $(k-2)$ -shell,¹ and after the merger between them, v_1 is the new k -core, then $|V(\tilde{C}_k(G; \{v_1, v_2\}))| = |V(C_k(PM(\{(v_1, v_2)\}; G)))| + 1$, where the difference of one node comes from the merger itself which reduces the number of nodes by one.

See the following example (Figure 2). Let $k = 4$, the current k -core contains the five nodes 1, 2, 3, 4, 5. Both merging 6 and 7 and anchoring 6 and 7 brings 8 and 9 into the k -core.

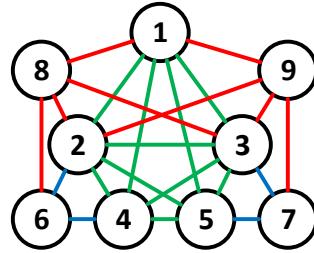


Fig. 2. An example.

¹A weaker but sufficient condition is that $|V(\tilde{C}_k(PM(\{(v_1, v_2)\}; G); \{v_1\}))| = |V(\tilde{C}_k(PM(\{(v_1, v_2)\}; G); \{v_1\}))| - 1$, i.e., no node other than v_1 and v_2 in the anchored k -core after anchoring v_1 and v_2 has exactly degree k and are adjacent to both v_1 and v_2 .

algorithm	n_c	$k = 5$	$k = 10$	$k = 15$	$k = 20$
BM	1	(190, 0.163258)	(588, 0.395745)	(1303, 0.452645)	(1527, 0.373819)
	2	(194, 0.297094)	(844, 0.630798)	(1376, 0.682457)	(1528, 0.434685)
	5	(200, 0.433535)	(953, 0.704848)	(1344, 0.748737)	(1445, 0.441133)
	10	(212, 0.536766)	(974, 0.868098)	(1343, 0.780103)	(1634, 0.503709)
	15	(215, 0.753264)	(947, 1.10923)	(1366, 1.040943)	(1634, 0.580716)
	20	(215, 0.939869)	(947, 1.321407)	(1278, 1.090379)	(1201, 0.571081)
EQ	1	N/A	N/A	N/A	N/A
	2	(194, 0.282179)	(844, 0.611814)	(1376, 0.671509)	(1528, 0.423497)
	5	(206, 0.349339)	(895, 0.661047)	(1304, 0.698516)	(1487, 0.456046)
	10	(213, 0.552619)	(896, 0.864929)	(1458, 0.778773)	(1124, 0.480327)
	15	(207, 0.691299)	(911, 1.08249)	(1406, 0.950659)	(1159, 0.512248)
	20	(221, 0.916641)	(974, 1.288419)	(1379, 1.12371)	(1159, 0.565624)
II	1	(190, 0.138759)	(908, 0.306687)	(1303, 0.411716)	(774, 0.333101)
	2	(204, 0.210995)	(908, 0.383291)	(1408, 0.472175)	(757, 0.343574)
	5	(211, 0.315223)	(896, 0.516913)	(1348, 0.546718)	(1178, 0.374554)
	10	(214, 0.484388)	(978, 0.681726)	(1435, 0.634548)	(754, 0.400293)
	15	(213, 0.687604)	(947, 0.908359)	(1448, 0.813922)	(820, 0.470702)
	20	(225, 0.839121)	(947, 1.11379)	(1256, 0.883392)	(820, 0.499459)
IO	1	(139, 0.145697)	(588, 0.35929)	(1417, 0.416889)	(1527, 0.36234)
	2	(138, 0.210198)	(636, 0.430234)	(1290, 0.491398)	(1238, 0.391185)
	5	(138, 0.303721)	(588, 0.563956)	(1411, 0.578495)	(1099, 0.407051)
	10	(145, 0.45026)	(697, 0.731267)	(1320, 0.722222)	(1634, 0.463949)
	15	(145, 0.620213)	(641, 0.958933)	(1452, 0.844707)	(1657, 0.520014)
	20	(145, 0.799318)	(643, 1.167234)	(1452, 0.991405)	(1608, 0.574232)
NT	1	(73, 1.316854)	(428, 1.131434)	(833, 0.762351)	(626, 0.377389)
	2	(72, 2.450766)	(504, 2.046731)	(1072, 1.327413)	(796, 0.54811)
	5	(81, 4.92864)	(465, 4.243704)	(1135, 2.765242)	(1140, 1.070902)
	10	(101, 7.167055)	(587, 6.50248)	(1089, 4.260347)	(1153, 1.559173)
	15	(109, 7.344824)	(590, 6.496875)	(1114, 4.242718)	(1129, 1.541246)
	20	(112, 7.488949)	(595, 6.70923)	(1287, 4.406364)	(1148, 1.600867)
NE	1	(93, 0.074646)	(263, 0.130554)	(394, 0.190378)	(1137, 0.209669)
	2	(93, 0.104544)	(263, 0.168751)	(394, 0.221188)	(1137, 0.21616)
	5	(93, 0.201608)	(263, 0.289639)	(394, 0.31141)	(1137, 0.249993)
	10	(129, 0.353582)	(433, 0.479871)	(888, 0.464709)	(1084, 0.300897)
	15	(93, 0.511208)	(263, 0.682291)	(394, 0.580377)	(1137, 0.359938)
	20	(93, 0.660565)	(263, 0.875819)	(394, 0.736546)	(1137, 0.39993)
RD	1	(35, 0.09364)	(42, 0.202609)	(174, 0.277664)	(351, 0.30549)
	2	(23, 0.124586)	(219, 0.251621)	(313, 0.308926)	(343, 0.307641)
	5	(39, 0.194363)	(264, 0.309078)	(619, 0.360495)	(376, 0.324811)
	10	(66, 0.391954)	(261, 0.557491)	(652, 0.526545)	(654, 0.404832)
	15	(56, 0.514945)	(479, 0.710561)	(660, 0.631788)	(749, 0.446687)
	20	(66, 0.695103)	(401, 0.935773)	(817, 0.815195)	(662, 0.491332)

Table 3. The full results of the main experiments on *email*. For each algorithm, each considered k value, and each n_c , we report the performance (left) and the running time (right).

algorithm	n_c	$k = 5$	$k = 10$	$k = 15$	$k = 20$
BM	1	(149, 0.506361)	(462, 0.948327)	(505, 1.133406)	(675, 1.171536)
	2	(152, 1.02818)	(620, 1.508909)	(505, 1.773869)	(1095, 1.66875)
	5	(158, 1.483856)	(640, 1.972026)	(631, 2.177783)	(1029, 2.040044)
	10	(163, 2.351635)	(675, 2.764291)	(678, 2.927482)	(1093, 2.70812)
	15	(177, 3.252112)	(675, 3.850927)	(636, 3.978673)	(1124, 3.711568)
	20	(172, 4.169596)	(678, 4.697119)	(678, 4.983967)	(1099, 4.534922)
EQ	1	N/A	N/A	N/A	N/A
	2	(152, 0.987369)	(620, 1.519664)	(505, 1.732861)	(1095, 1.669056)
	5	(158, 1.337278)	(652, 1.808965)	(513, 2.116939)	(1076, 1.996077)
	10	(164, 2.316492)	(675, 2.789305)	(617, 2.940854)	(1176, 2.733471)
	15	(164, 3.114176)	(682, 3.624242)	(617, 3.789719)	(1135, 3.48443)
	20	(171, 4.126044)	(678, 4.729749)	(678, 4.77951)	(1075, 4.421955)
II	1	(149, 0.463815)	(490, 0.796277)	(505, 1.034633)	(675, 1.115816)
	2	(149, 0.820292)	(556, 1.177575)	(612, 1.378685)	(662, 1.40776)
	5	(154, 1.353022)	(550, 1.731343)	(617, 1.878777)	(797, 1.890962)
	10	(171, 2.127139)	(627, 2.483068)	(678, 2.662917)	(877, 2.489292)
	15	(185, 3.103649)	(633, 3.549826)	(678, 3.586211)	(847, 3.418032)
	20	(185, 4.020618)	(616, 4.406482)	(678, 4.429359)	(896, 4.202753)
IO	1	(70, 0.485909)	(462, 0.868455)	(393, 1.137245)	(981, 1.218973)
	2	(84, 0.825116)	(531, 1.240481)	(393, 1.477159)	(1141, 1.487601)
	5	(89, 1.337836)	(653, 1.739939)	(387, 1.996417)	(1266, 1.920456)
	10	(89, 2.119162)	(654, 2.572274)	(352, 2.759679)	(1158, 2.568547)
	15	(90, 3.014986)	(672, 3.503828)	(411, 3.686824)	(1226, 3.380297)
	20	(90, 3.88141)	(657, 4.368629)	(349, 4.635049)	(1200, 4.090064)
NT	1	(25, 4.802132)	(185, 4.553131)	(165, 4.410222)	(212, 4.128859)
	2	(25, 8.323137)	(265, 8.190111)	(175, 7.638757)	(241, 6.939943)
	5	(20, 17.131463)	(276, 16.749262)	(232, 15.494895)	(264, 14.106341)
	10	(20, 27.410854)	(283, 27.03053)	(264, 24.976688)	(289, 22.699999)
	15	(24, 27.212796)	(273, 26.827285)	(296, 24.811599)	(301, 22.458058)
	20	(27, 27.993103)	(219, 27.642417)	(292, 25.626299)	(310, 23.035773)
NE	1	(9, 0.483263)	(0, 0.610785)	(0, 0.757779)	(0, 0.890101)
	2	(9, 0.629466)	(0, 0.787201)	(0, 0.907253)	(0, 1.020575)
	5	(9, 1.168563)	(0, 1.28736)	(0, 1.409836)	(0, 1.496966)
	10	(16, 1.890344)	(0, 2.065769)	(0, 2.246718)	(0, 2.158495)
	15	(9, 2.793643)	(0, 2.996425)	(0, 3.136047)	(0, 3.003932)
	20	(9, 3.632236)	(0, 3.903284)	(0, 3.904875)	(0, 3.791944)
RD	1	(-7, 0.478493)	(-1, 0.722488)	(-14, 0.951511)	(-157, 1.147531)
	2	(1, 0.645246)	(10, 0.931899)	(11, 1.160903)	(5, 1.293247)
	5	(1, 1.021822)	(23, 1.284559)	(9, 1.480335)	(38, 1.562286)
	10	(14, 1.992733)	(32, 2.313069)	(77, 2.51362)	(86, 2.488989)
	15	(12, 2.675058)	(34, 3.037993)	(36, 3.234321)	(46, 3.125762)
	20	(10, 3.640068)	(117, 4.074742)	(115, 4.248889)	(49, 4.021556)

Table 4. The full results of the main experiments on *facebook*. For each algorithm, each considered k value, and each n_c , we report the performance (left) and the running time (right).

algorithm	n_c	$k = 5$	$k = 10$	$k = 15$	$k = 20$
BM	1	(2660, 7.633889)	(759, 4.289924)	(606, 3.520721)	(738, 3.435266)
	2	(2660, 11.775407)	(759, 5.206878)	(635, 3.837289)	(753, 3.84938)
	5	(2601, 13.85089)	(941, 5.995754)	(749, 4.323002)	(923, 3.913824)
	10	(2606, 17.86887)	(974, 7.244179)	(674, 4.795776)	(967, 4.370866)
	15	(2606, 22.462996)	(940, 8.762238)	(677, 5.658468)	(870, 5.10412)
	20	(2606, 26.806823)	(960, 10.224163)	(705, 6.411012)	(888, 5.76321)
EQ	1	N/A	N/A	N/A	N/A
	2	(2660, 11.641451)	(759, 5.143468)	(635, 3.952877)	(753, 3.644825)
	5	(2644, 13.210472)	(866, 5.820045)	(617, 4.187215)	(818, 3.821646)
	10	(2601, 17.397328)	(937, 7.049637)	(762, 4.711021)	(867, 4.349421)
	15	(2606, 21.439289)	(983, 8.432824)	(705, 5.630066)	(867, 5.113627)
	20	(2606, 26.201712)	(951, 10.179697)	(719, 6.563192)	(870, 5.757685)
II	1	(2660, 7.014586)	(759, 4.099205)	(507, 3.402992)	(535, 3.265395)
	2	(2644, 8.570758)	(866, 4.560648)	(518, 3.426621)	(538, 3.325384)
	5	(2601, 11.002977)	(906, 5.279612)	(617, 3.9874)	(564, 3.80108)
	10	(2606, 15.256073)	(936, 6.663428)	(682, 4.563828)	(571, 4.192416)
	15	(2606, 19.08951)	(954, 7.858194)	(655, 5.383557)	(651, 4.826672)
	20	(2606, 23.448812)	(944, 9.089351)	(682, 6.010336)	(622, 5.58813)
IO	1	(563, 7.180937)	(666, 4.328697)	(606, 3.496552)	(738, 3.371479)
	2	(618, 8.639106)	(414, 4.809814)	(689, 3.638419)	(912, 3.561971)
	5	(598, 10.839214)	(610, 5.62101)	(772, 4.184578)	(921, 3.808747)
	10	(604, 14.174811)	(595, 6.497019)	(796, 4.620337)	(923, 4.280902)
	15	(618, 18.288144)	(594, 7.977383)	(807, 5.632297)	(837, 5.012554)
	20	(612, 22.374368)	(640, 9.567872)	(807, 6.256049)	(837, 5.788372)
NT	1	(532, 7.518926)	(371, 4.91902)	(409, 4.087247)	(380, 3.841569)
	2	(530, 12.03291)	(287, 6.96289)	(443, 5.47965)	(419, 4.904233)
	5	(577, 22.764435)	(300, 12.170004)	(470, 8.886947)	(416, 7.767748)
	10	(613, 39.233378)	(332, 21.191422)	(523, 14.484679)	(445, 12.271197)
	15	(613, 38.239648)	(359, 18.641235)	(590, 13.312159)	(515, 11.42225)
	20	(613, 41.894058)	(411, 19.597006)	(629, 13.746571)	(542, 11.971981)
NE	1	(219, 2.906677)	(78, 2.720494)	(116, 2.747374)	(184, 2.789192)
	2	(219, 3.663202)	(78, 2.963913)	(116, 2.88292)	(184, 2.912347)
	5	(219, 5.929757)	(78, 3.733847)	(116, 3.341918)	(184, 3.293982)
	10	(316, 9.966511)	(170, 5.009166)	(191, 4.191981)	(346, 3.908425)
	15	(219, 13.353948)	(78, 6.313105)	(116, 4.734477)	(184, 4.500818)
	20	(219, 17.166411)	(78, 7.551934)	(116, 5.43375)	(184, 5.182752)
RD	1	(3, 4.93581)	(50, 3.678218)	(-68, 3.118525)	(-2, 3.084485)
	2	(9, 5.627936)	(2, 3.963403)	(115, 3.250154)	(54, 3.154718)
	5	(6, 7.074868)	(77, 4.426632)	(181, 3.55516)	(271, 3.391911)
	10	(27, 11.565817)	(111, 6.226378)	(165, 4.524875)	(335, 4.239357)
	15	(17, 14.382752)	(167, 6.908416)	(112, 5.006554)	(282, 4.594821)
	20	(52, 19.584597)	(129, 8.378082)	(238, 5.881316)	(348, 5.450063)

Table 5. The full results of the main experiments on *brightkite*. For each algorithm, each considered k value, and each n_c , we report the performance (left) and the running time (right).

algorithm	n_c	$k = 5$	$k = 10$	$k = 15$	$k = 20$
BM	1	(511, 4.331406)	(2251, 5.445484)	(2293, 5.092611)	(4206, 5.190955)
	2	(511, 7.368159)	(2251, 7.866471)	(2486, 6.35433)	(4054, 6.097935)
	5	(544, 9.032235)	(2371, 8.981611)	(2590, 7.032122)	(4067, 6.437749)
	10	(526, 11.510036)	(2419, 11.134309)	(2668, 8.266657)	(3971, 6.609456)
	15	(552, 15.222338)	(2419, 14.188718)	(2738, 9.63729)	(4320, 7.399298)
	20	(556, 18.698971)	(2464, 16.68068)	(2738, 11.13879)	(4326, 7.999017)
EQ	1	N/A	N/A	N/A	N/A
	2	(511, 7.321111)	(2251, 7.676253)	(2486, 6.339604)	(4054, 6.03925)
	5	(554, 8.473394)	(2260, 8.626599)	(2509, 7.061166)	(4270, 6.04146)
	10	(561, 11.800697)	(2391, 11.205999)	(2673, 8.185404)	(3982, 6.583055)
	15	(526, 14.552206)	(2419, 13.813283)	(2668, 9.529306)	(4116, 7.424883)
	20	(526, 18.264272)	(2419, 16.406695)	(2738, 11.096055)	(4220, 7.607183)
II	1	(511, 3.870919)	(2251, 4.976404)	(2293, 4.810573)	(4206, 4.784768)
	2	(554, 5.19664)	(2260, 5.952932)	(2587, 5.369132)	(4178, 4.922209)
	5	(561, 7.048542)	(2391, 7.489798)	(2736, 5.913927)	(3951, 5.258277)
	10	(526, 10.603894)	(2419, 10.044706)	(2696, 7.635753)	(4324, 5.678987)
	15	(542, 13.509703)	(2419, 12.478366)	(2696, 8.871025)	(4297, 6.356354)
	20	(557, 17.138216)	(2464, 14.813504)	(2803, 10.09049)	(4297, 7.013217)
IO	1	(253, 3.62462)	(807, 5.110506)	(1941, 5.200724)	(2661, 5.386959)
	2	(267, 4.718587)	(838, 5.855962)	(1810, 5.676982)	(3195, 5.39356)
	5	(303, 6.34697)	(919, 7.50673)	(1756, 6.367354)	(3077, 5.783836)
	10	(298, 8.802689)	(946, 9.613448)	(1975, 7.534384)	(3732, 6.110118)
	15	(288, 11.671551)	(953, 11.961914)	(2002, 9.285292)	(3706, 6.872089)
	20	(278, 14.307012)	(933, 14.2551)	(2009, 10.585216)	(3873, 7.553795)
NT	1	(134, 10.738631)	(783, 7.442617)	(1648, 5.438749)	(3330, 4.277926)
	2	(142, 18.263571)	(826, 11.940534)	(1749, 7.689251)	(3470, 5.097733)
	5	(238, 36.935501)	(895, 21.992599)	(1924, 12.950219)	(3465, 7.417933)
	10	(242, 53.261851)	(875, 35.932222)	(1949, 21.180753)	(3888, 11.740368)
	15	(242, 58.864717)	(927, 34.930516)	(1959, 19.943574)	(3457, 10.411915)
	20	(244, 61.634726)	(928, 37.404548)	(1888, 21.231685)	(3629, 10.944137)
NE	1	(96, 1.883449)	(333, 2.670745)	(369, 3.156782)	(1273, 3.440137)
	2	(96, 2.50555)	(333, 3.098938)	(369, 3.420798)	(1273, 3.596383)
	5	(96, 3.918953)	(333, 4.518043)	(369, 4.203173)	(1273, 4.062471)
	10	(150, 6.508428)	(473, 6.744301)	(677, 5.571919)	(1337, 4.780549)
	15	(96, 9.349192)	(333, 9.112854)	(369, 6.814711)	(1273, 5.572274)
	20	(96, 11.92908)	(333, 11.537116)	(369, 8.080567)	(1273, 6.342468)
RD	1	(2, 2.086758)	(16, 3.947758)	(73, 4.294525)	(218, 4.13741)
	2	(7, 2.612672)	(103, 4.312337)	(215, 4.549018)	(1276, 4.31771)
	5	(2, 3.625463)	(131, 5.261591)	(594, 5.061123)	(1770, 4.634283)
	10	(10, 6.822703)	(300, 8.060247)	(772, 6.506863)	(1994, 5.512082)
	15	(12, 9.075867)	(284, 10.132303)	(825, 7.534221)	(2504, 5.927042)
	20	(23, 12.33712)	(360, 12.98275)	(845, 9.166356)	(2724, 6.702388)

Table 6. The full results of the main experiments on *enron*. For each algorithm, each considered k value, and each n_c , we report the performance (left) and the running time (right).

algorithm	n_c	$k = 5$	$k = 10$	$k = 15$	$k = 20$
BM	1	(1880, 10.71228)	(3239, 15.911818)	(1202, 13.304726)	(1309, 12.044654)
	2	(1880, 19.355977)	(3239, 21.000184)	(1423, 13.881173)	(1154, 12.016041)
	5	(1914, 25.084593)	(3210, 24.484485)	(1487, 14.438804)	(1230, 11.795518)
	10	(1897, 34.753535)	(3305, 31.267398)	(1668, 14.691768)	(1282, 11.975049)
	15	(1897, 46.433482)	(3305, 38.903798)	(1668, 15.861955)	(1419, 12.384224)
	20	(1897, 57.769216)	(3305, 45.976823)	(1735, 17.265859)	(1327, 12.78748)
EQ	1	N/A	N/A	N/A	N/A
	2	(1880, 18.920002)	(3239, 20.863257)	(1423, 13.529899)	(1154, 11.746036)
	5	(1865, 23.131213)	(3239, 23.511837)	(1727, 13.829663)	(1225, 11.902334)
	10	(1914, 34.562731)	(3305, 30.660947)	(1670, 14.639725)	(1289, 11.906666)
	15	(1897, 43.864536)	(3305, 37.108482)	(1573, 15.868421)	(1247, 12.38159)
	20	(1897, 55.831186)	(3305, 45.19937)	(1716, 17.017798)	(1377, 13.189475)
II	1	(1880, 9.928412)	(3239, 15.159316)	(1494, 12.704985)	(974, 11.709136)
	2	(1865, 14.008636)	(3239, 17.550303)	(1670, 13.081662)	(969, 11.524561)
	5	(1914, 20.544462)	(3305, 21.620116)	(1779, 13.34531)	(993, 12.081781)
	10	(1897, 31.228379)	(3305, 27.702994)	(1579, 14.490075)	(1037, 11.943175)
	15	(1897, 41.566679)	(3305, 34.459385)	(1591, 15.280399)	(1037, 12.185434)
	20	(1897, 51.697639)	(3305, 41.698888)	(1678, 16.12399)	(986, 12.690062)
IO	1	(446, 10.507681)	(1486, 15.723185)	(1202, 13.027482)	(1309, 11.839805)
	2	(487, 14.628238)	(1884, 18.08194)	(1472, 13.024111)	(1384, 11.741507)
	5	(464, 21.155257)	(1663, 22.202272)	(1597, 13.652119)	(1239, 11.755369)
	10	(486, 30.477748)	(1694, 27.723429)	(1651, 14.424961)	(1440, 11.875024)
	15	(500, 40.967156)	(2122, 34.057724)	(1651, 15.465994)	(1494, 12.399112)
	20	(500, 52.151216)	(1935, 42.542172)	(1797, 16.509463)	(1431, 12.686913)
NT	1	(185, 15.613714)	(1459, 14.178798)	(1011, 12.249921)	(773, 11.548451)
	2	(263, 25.216267)	(1498, 18.081384)	(838, 12.964268)	(776, 11.626199)
	5	(374, 49.21995)	(1889, 28.206763)	(1070, 14.966518)	(717, 12.372918)
	10	(491, 86.139788)	(2015, 51.823022)	(902, 23.426422)	(967, 17.74904)
	15	(463, 88.918728)	(2016, 47.755671)	(1401, 19.107009)	(996, 13.495021)
	20	(477, 99.358816)	(2015, 54.490456)	(1352, 19.638155)	(828, 13.64916)
NE	1	(12, 7.222833)	(0, 10.950282)	(20, 11.108081)	(428, 11.147636)
	2	(12, 9.055707)	(0, 12.183232)	(20, 11.29506)	(428, 11.223747)
	5	(12, 15.460855)	(0, 15.839832)	(20, 11.986463)	(428, 11.414039)
	10	(148, 25.873818)	(138, 22.346785)	(16, 12.837359)	(90, 11.690283)
	15	(12, 35.600186)	(0, 29.10255)	(20, 13.885689)	(428, 12.032483)
	20	(12, 46.373334)	(0, 34.820893)	(20, 14.854479)	(428, 12.373706)
RD	1	(0, 8.070257)	(0, 13.770937)	(0, 12.127693)	(88, 11.294168)
	2	(7, 9.89358)	(1, 15.024687)	(8, 12.293329)	(96, 11.355414)
	5	(1, 13.864795)	(0, 17.633792)	(3, 12.70848)	(273, 11.566043)
	10	(13, 26.739019)	(27, 25.426077)	(74, 13.92805)	(174, 11.872816)
	15	(25, 34.082305)	(204, 31.451282)	(138, 14.873115)	(401, 12.145065)
	20	(22, 46.099643)	(190, 38.863589)	(260, 16.012712)	(440, 12.447638)

Table 7. The full results of the main experiments on *hepph*. For each algorithm, each considered k value, and each n_c , we report the performance (left) and the running time (right).

algorithm	n_c	$k = 5$	$k = 10$	$k = 15$	$k = 20$
BM	1	(6502, 14.009076)	(7422, 14.679457)	(5780, 16.213886)	(4647, 15.751298)
	2	(6502, 22.344013)	(7422, 20.710244)	(6210, 19.447721)	(4934, 16.959438)
	5	(6637, 29.08989)	(7533, 25.647605)	(6681, 23.093492)	(5281, 17.980626)
	10	(6637, 40.696907)	(7533, 34.454681)	(6437, 26.957407)	(4942, 20.196656)
	15	(6637, 52.941491)	(7598, 44.065532)	(6437, 31.977536)	(4901, 22.260134)
	20	(6637, 64.841984)	(7598, 53.258305)	(6424, 37.207439)	(4818, 24.122128)
EQ	1	N/A	N/A	N/A	N/A
	2	(6502, 22.395535)	(7422, 20.669226)	(6210, 19.259234)	(4934, 17.382814)
	5	(6566, 26.95458)	(7383, 24.252107)	(6296, 21.941935)	(4760, 17.675723)
	10	(6637, 40.199188)	(7533, 34.247148)	(6258, 26.508954)	(5099, 20.104714)
	15	(6637, 50.061666)	(7533, 42.551266)	(6437, 31.300332)	(4868, 22.052029)
	20	(6637, 64.309491)	(7598, 53.074237)	(6437, 37.134823)	(5091, 24.256497)
II	1	(6502, 13.020298)	(7422, 14.011352)	(5780, 15.102904)	(4647, 15.371281)
	2	(6566, 17.572612)	(7383, 17.345369)	(6198, 16.74011)	(4505, 15.681111)
	5	(6637, 24.936549)	(7533, 22.787584)	(6498, 20.076558)	(4522, 16.746233)
	10	(6637, 36.842822)	(7598, 32.665774)	(6444, 24.675284)	(4522, 18.867458)
	15	(6637, 48.663534)	(7598, 41.064545)	(6601, 29.358617)	(4573, 20.916193)
	20	(6637, 60.973164)	(7598, 50.015291)	(6512, 34.012869)	(4567, 22.750986)
IO	1	(724, 12.581297)	(3232, 14.817602)	(5554, 16.286631)	(4633, 16.595315)
	2	(724, 16.798537)	(3302, 18.140384)	(5114, 17.774026)	(4654, 16.344556)
	5	(731, 23.663116)	(3363, 23.349389)	(5266, 20.962841)	(4906, 17.199864)
	10	(733, 33.785853)	(3429, 31.778832)	(5325, 25.200098)	(5058, 19.132696)
	15	(739, 46.322793)	(3509, 41.170955)	(5029, 30.604151)	(5198, 22.107354)
	20	(730, 56.169985)	(3338, 50.081576)	(5029, 35.782734)	(5165, 23.562279)
NT	1	(675, 24.167564)	(3003, 20.321986)	(3953, 17.597147)	(4306, 15.468346)
	2	(687, 39.750607)	(3061, 30.566673)	(4127, 23.683506)	(4380, 18.519992)
	5	(751, 78.414224)	(2945, 55.958911)	(4683, 38.628292)	(4697, 26.570887)
	10	(757, 127.379362)	(3214, 93.788406)	(4968, 65.970313)	(4836, 43.972665)
	15	(781, 131.775808)	(3350, 93.01329)	(4982, 60.001404)	(4954, 37.727108)
	20	(781, 142.780931)	(3180, 102.161783)	(5155, 64.922102)	(4925, 39.824714)
NE	1	(275, 7.370404)	(874, 10.173047)	(1324, 11.814216)	(491, 12.521565)
	2	(275, 9.37843)	(874, 11.923304)	(1324, 12.848376)	(491, 12.910815)
	5	(275, 15.794254)	(874, 17.237137)	(1324, 15.893406)	(491, 14.346997)
	10	(357, 26.582149)	(1279, 26.279711)	(1653, 21.400361)	(774, 16.745987)
	15	(275, 37.006772)	(874, 34.932669)	(1324, 25.826337)	(491, 19.091083)
	20	(275, 47.663125)	(874, 43.770436)	(1324, 30.826765)	(491, 21.424672)
RD	1	(15, 9.700132)	(53, 13.060758)	(251, 14.402305)	(333, 14.10091)
	2	(40, 11.891144)	(204, 14.965532)	(870, 15.397589)	(1703, 14.681986)
	5	(117, 16.139847)	(850, 18.510415)	(1505, 17.313076)	(2159, 15.575501)
	10	(118, 29.474276)	(908, 29.621664)	(1907, 23.615062)	(2917, 18.531446)
	15	(139, 37.421587)	(829, 36.361822)	(2366, 27.304857)	(2919, 19.847579)
	20	(135, 50.370877)	(1083, 46.770155)	(2524, 32.542717)	(3014, 22.616209)

Table 8. The full results of the main experiments on *epinions*. For each algorithm, each considered k value, and each n_c , we report the performance (left) and the running time (right).

algorithm	n_c	$k = 5$	$k = 10$	$k = 15$	$k = 20$
BM	1	(1399, 7.953749)	(1806, 7.376449)	(1302, 8.720494)	(1193, 8.159371)
	2	(1399, 13.250584)	(1806, 11.222614)	(1859, 10.938343)	(1332, 9.812224)
	5	(1404, 16.606493)	(1821, 13.930346)	(1920, 13.012133)	(1400, 11.523038)
	10	(1435, 21.827349)	(1872, 18.522814)	(1766, 15.586085)	(1303, 13.396541)
	15	(1467, 28.570891)	(1872, 24.503237)	(1574, 20.184689)	(1312, 16.084518)
	20	(1467, 34.881025)	(1876, 29.810441)	(1662, 23.744555)	(1326, 18.67953)
EQ	1	N/A	N/A	N/A	N/A
	2	(1399, 13.108872)	(1806, 10.868075)	(1859, 10.784598)	(1332, 10.09833)
	5	(1407, 15.511006)	(1821, 12.975058)	(1905, 12.289557)	(1279, 11.266874)
	10	(1435, 22.817317)	(1834, 18.198366)	(1952, 15.547785)	(1329, 13.307694)
	15	(1435, 27.209416)	(1806, 23.174056)	(1820, 19.458249)	(1323, 16.130359)
	20	(1445, 35.29857)	(1872, 29.688204)	(1590, 23.624911)	(1336, 18.755269)
II	1	(1399, 7.347652)	(1806, 7.081155)	(1728, 7.402999)	(1193, 7.493956)
	2	(1407, 9.912281)	(1821, 9.027593)	(1649, 8.69315)	(1224, 8.236692)
	5	(1435, 13.420627)	(1821, 12.348087)	(1724, 10.95328)	(1272, 9.71036)
	10	(1445, 22.163684)	(1872, 17.916443)	(1645, 14.745402)	(1316, 12.522046)
	15	(1467, 25.681819)	(1876, 22.858826)	(1645, 18.432552)	(1324, 14.675866)
	20	(1467, 32.023161)	(1876, 28.102126)	(1709, 22.085486)	(1342, 17.1649)
IO	1	(344, 6.962134)	(734, 7.338649)	(1302, 8.383445)	(1078, 8.590261)
	2	(327, 9.15968)	(729, 9.38972)	(1293, 9.778422)	(1198, 9.346424)
	5	(373, 12.85268)	(811, 12.347115)	(1361, 11.731662)	(1247, 10.700964)
	10	(363, 17.719778)	(742, 16.525877)	(1436, 15.063044)	(1230, 12.823346)
	15	(352, 23.680394)	(809, 21.543639)	(1524, 19.290959)	(1133, 16.408843)
	20	(354, 29.439376)	(809, 26.545)	(1524, 22.326641)	(1295, 18.101346)
NT	1	(273, 17.075997)	(608, 12.542701)	(1186, 10.383663)	(974, 9.07537)
	2	(264, 29.446356)	(752, 20.999337)	(1090, 16.217407)	(1282, 13.211717)
	5	(278, 57.006561)	(774, 41.079849)	(1189, 30.793082)	(1438, 23.824083)
	10	(284, 95.389934)	(854, 69.297485)	(1335, 52.808828)	(1500, 41.780687)
	15	(284, 93.791758)	(879, 66.696617)	(1377, 50.005423)	(1513, 38.528761)
	20	(286, 97.925998)	(880, 71.977105)	(1389, 53.819828)	(1615, 40.939716)
NE	1	(166, 3.621131)	(533, 4.608468)	(656, 5.246678)	(878, 5.60472)
	2	(166, 4.709424)	(533, 5.584783)	(656, 5.87103)	(878, 6.110478)
	5	(166, 7.966682)	(533, 8.348632)	(656, 7.968597)	(878, 7.644592)
	10	(240, 13.274469)	(557, 13.109462)	(789, 11.400203)	(1073, 10.386018)
	15	(166, 18.819954)	(533, 18.035512)	(656, 14.98909)	(878, 12.661607)
	20	(166, 24.10867)	(533, 22.786093)	(656, 18.558893)	(878, 15.229757)
RD	1	(35, 4.760348)	(109, 6.44393)	(108, 7.065213)	(94, 7.287121)
	2	(42, 5.93591)	(147, 7.444798)	(305, 7.930402)	(347, 7.920304)
	5	(59, 7.972565)	(256, 9.458135)	(514, 9.439179)	(723, 8.825496)
	10	(82, 14.790045)	(261, 15.718018)	(653, 13.987663)	(807, 12.326806)
	15	(113, 18.800661)	(315, 18.947982)	(658, 16.484998)	(900, 13.760862)
	20	(108, 25.363641)	(340, 25.863805)	(566, 20.477926)	(806, 16.893236)

Table 9. The full results of the main experiments on *relato*. For each algorithm, each considered k value, and each n_c , we report the performance (left) and the running time (right).

algorithm	n_c	$k = 5$	$k = 10$	$k = 15$	$k = 20$
BM	1	(18200, 20.066584)	(1525, 10.278747)	(1093, 9.362024)	(732, 8.8609)
	2	(18200, 30.911228)	(1631, 10.966134)	(1081, 9.880414)	(601, 8.934576)
	5	(17886, 37.100711)	(1769, 11.868651)	(1170, 10.131934)	(727, 9.160244)
	10	(17886, 47.582482)	(1815, 12.89966)	(1228, 10.930069)	(724, 9.874507)
	15	(17886, 59.291739)	(1634, 14.067592)	(1221, 12.1711)	(737, 10.838254)
	20	(17886, 71.037556)	(1634, 15.437461)	(1228, 13.320627)	(756, 11.759433)
EQ	1	N/A	N/A	N/A	N/A
	2	(18200, 31.367987)	(1631, 10.950923)	(1081, 9.631465)	(601, 8.898312)
	5	(18200, 35.502089)	(1777, 11.500195)	(1111, 10.015313)	(675, 9.169323)
	10	(17886, 47.871221)	(1618, 12.671074)	(1259, 10.910955)	(753, 9.767921)
	15	(17886, 57.456869)	(1815, 14.061171)	(1236, 11.888506)	(727, 10.982649)
	20	(17886, 71.596376)	(1634, 15.462811)	(1236, 12.980841)	(748, 11.536748)
II	1	(18200, 18.671986)	(1525, 9.813701)	(860, 9.093311)	(510, 8.63311)
	2	(18200, 23.279586)	(1698, 10.157537)	(862, 9.126792)	(537, 8.703942)
	5	(17886, 29.692579)	(1514, 10.802643)	(1083, 9.729115)	(570, 9.060151)
	10	(17886, 40.454163)	(1508, 12.003224)	(979, 10.872554)	(571, 9.79806)
	15	(17886, 52.286336)	(1586, 13.291565)	(1210, 11.522062)	(573, 10.516353)
	20	(17886, 62.886783)	(1537, 15.036476)	(1187, 12.597883)	(553, 11.15737)
IO	1	(3932, 19.492647)	(1398, 10.281061)	(1093, 9.361074)	(732, 8.828502)
	2	(3731, 23.300827)	(1554, 10.593149)	(1080, 9.357446)	(770, 9.018518)
	5	(3725, 29.477057)	(1542, 11.187701)	(1155, 9.99313)	(798, 9.323371)
	10	(3725, 39.646281)	(1567, 12.319004)	(1170, 10.702775)	(738, 9.72672)
	15	(3725, 50.968981)	(1443, 13.853482)	(1170, 11.932157)	(788, 10.766915)
	20	(3725, 61.487066)	(1499, 15.024706)	(1173, 12.932639)	(802, 11.435084)
NT	1	(3713, 15.530225)	(1048, 9.655758)	(777, 8.969255)	(495, 8.575624)
	2	(3838, 22.892191)	(1259, 11.657735)	(759, 10.429413)	(554, 9.588718)
	5	(3906, 42.422152)	(1374, 16.689715)	(717, 13.836441)	(652, 12.155182)
	10	(3751, 77.338054)	(1407, 25.30496)	(694, 20.404779)	(697, 17.628668)
	15	(3792, 77.208547)	(1445, 23.562442)	(815, 18.741732)	(736, 16.094562)
	20	(3792, 88.151785)	(1566, 24.759263)	(746, 19.567629)	(744, 16.827505)
NE	1	(719, 8.593711)	(610, 7.798539)	(375, 7.781)	(657, 7.841317)
	2	(719, 10.628516)	(610, 8.030336)	(375, 7.939821)	(657, 7.975527)
	5	(719, 16.820136)	(610, 8.773347)	(375, 8.54328)	(657, 8.386603)
	10	(1565, 27.174709)	(823, 9.991018)	(539, 9.470157)	(755, 9.209895)
	15	(719, 37.641159)	(610, 11.284551)	(375, 10.396356)	(657, 9.836579)
	20	(719, 47.937585)	(610, 12.481733)	(375, 11.305846)	(657, 10.579446)
RD	1	(26, 13.311316)	(53, 9.054355)	(45, 8.633299)	(56, 8.333059)
	2	(133, 15.341061)	(203, 9.317372)	(202, 8.856714)	(109, 8.478147)
	5	(1028, 19.566863)	(348, 9.954583)	(347, 9.187858)	(207, 8.818307)
	10	(1123, 32.759762)	(403, 11.688949)	(537, 10.80347)	(229, 9.698891)
	15	(1417, 40.345749)	(503, 12.404703)	(482, 11.102026)	(282, 10.363468)
	20	(879, 52.582941)	(518, 13.748626)	(502, 12.081631)	(336, 11.073083)

Table 10. The full results of the main experiments on *slashdot*. For each algorithm, each considered k value, and each n_c , we report the performance (left) and the running time (right).

algorithm	n_c	$k = 5$	$k = 10$	$k = 15$	$k = 20$
BM	1	(3078, 9.137355)	(6872, 23.077852)	(3216, 28.016744)	(1601, 31.364135)
	2	(3078, 15.931743)	(6872, 35.356373)	(3216, 34.519191)	(2532, 34.329742)
	5	(3078, 22.583234)	(7438, 46.274978)	(3717, 41.788776)	(2658, 39.501804)
	10	(2942, 33.817354)	(7410, 67.306994)	(3689, 52.481098)	(3066, 47.082249)
	15	(2942, 46.665795)	(7376, 89.841317)	(3760, 66.716082)	(3237, 55.769771)
	20	(2942, 57.968247)	(7487, 111.159931)	(3786, 79.026608)	(3260, 66.239228)
EQ	1	N/A	N/A	N/A	N/A
	2	(3078, 16.044073)	(6872, 35.108201)	(3216, 33.769681)	(2532, 33.472693)
	5	(3078, 20.728486)	(6977, 43.846302)	(3393, 39.830286)	(2466, 37.913488)
	10	(2942, 33.712189)	(7387, 65.986137)	(3705, 52.399195)	(3076, 47.011571)
	15	(2942, 43.736657)	(7410, 83.202126)	(3877, 64.562998)	(2991, 55.601181)
	20	(2942, 57.613948)	(7376, 109.244064)	(3694, 78.403743)	(3278, 66.61477)
II	1	(3078, 8.383145)	(6872, 21.465917)	(3216, 26.426679)	(2381, 29.018141)
	2	(3078, 13.202961)	(6977, 29.534145)	(3393, 30.959716)	(2445, 31.939913)
	5	(2942, 20.100729)	(7387, 41.521061)	(3705, 38.231511)	(2989, 36.817633)
	10	(2942, 31.696554)	(7376, 61.768423)	(3694, 51.451934)	(3278, 45.83766)
	15	(2942, 44.12425)	(7487, 82.986386)	(3786, 62.135343)	(3260, 53.732327)
	20	(2942, 56.538565)	(7487, 104.331364)	(3819, 75.139627)	(3260, 63.18732)
IO	1	(419, 9.144208)	(2292, 23.211475)	(2594, 27.894258)	(1601, 30.808521)
	2	(425, 13.140243)	(2464, 30.368479)	(2583, 31.953489)	(2105, 33.214502)
	5	(439, 20.094935)	(2403, 43.179821)	(2345, 38.853809)	(2286, 37.464285)
	10	(447, 30.193815)	(2458, 60.519335)	(2342, 50.122045)	(2339, 45.529253)
	15	(409, 41.46253)	(2458, 82.493371)	(2373, 64.779021)	(2129, 57.230257)
	20	(409, 52.13128)	(2435, 99.477884)	(2252, 76.79444)	(2127, 65.92331)
NT	1	(365, 25.020149)	(2017, 32.740586)	(2035, 32.208022)	(1695, 32.031095)
	2	(380, 41.080853)	(2017, 46.1374)	(2170, 41.072028)	(1874, 38.400952)
	5	(391, 81.016286)	(2240, 81.933398)	(2385, 63.984136)	(2047, 55.264581)
	10	(391, 133.656234)	(2378, 138.864884)	(2562, 105.211061)	(1881, 88.877944)
	15	(412, 136.512992)	(2381, 145.23193)	(2699, 103.561808)	(1920, 84.221371)
	20	(415, 147.788968)	(2519, 163.972721)	(2715, 115.110821)	(1935, 92.756394)
NE	1	(146, 8.032294)	(116, 20.242908)	(142, 23.902179)	(196, 25.865214)
	2	(146, 10.182026)	(116, 23.973655)	(142, 26.298077)	(196, 27.51254)
	5	(146, 16.575301)	(116, 35.209148)	(142, 33.098032)	(196, 32.672331)
	10	(241, 27.0287)	(492, 54.028916)	(581, 45.354465)	(388, 41.016239)
	15	(146, 38.067553)	(116, 72.680811)	(142, 55.833599)	(196, 49.720338)
	20	(146, 48.803032)	(116, 91.74155)	(142, 67.307069)	(196, 58.03318)
RD	1	(66, 8.209677)	(99, 21.610461)	(11, 26.46422)	(2, 28.758133)
	2	(56, 10.330515)	(121, 25.326023)	(122, 28.75007)	(67, 30.611359)
	5	(113, 14.586695)	(243, 32.846758)	(275, 33.366299)	(79, 33.651221)
	10	(174, 28.085976)	(332, 57.08309)	(297, 47.721802)	(137, 44.519811)
	15	(176, 36.432143)	(385, 70.733631)	(278, 56.186387)	(369, 50.485354)
	20	(185, 49.585751)	(625, 94.054384)	(429, 69.665654)	(338, 60.714386)

Table 11. The full results of the main experiments on *syracuse*. For each algorithm, each considered k value, and each n_c , we report the performance (left) and the running time (right).

algorithm	n_c	$k = 5$	$k = 10$	$k = 15$	$k = 20$
BM	1	(13584, 42.918833)	(6208, 37.637487)	(4041, 33.792637)	(3162, 31.89478)
	2	(13584, 67.972448)	(6208, 46.788955)	(4041, 37.013729)	(3455, 30.918941)
	5	(13575, 86.737187)	(6752, 57.790389)	(3823, 39.597373)	(3831, 32.481303)
	10	(13599, 119.925492)	(6726, 73.331638)	(4003, 45.031304)	(3831, 34.853393)
	15	(13599, 157.43262)	(6609, 92.880868)	(4032, 53.166402)	(3883, 37.619268)
	20	(13599, 194.824569)	(6768, 108.651844)	(3854, 59.337779)	(3883, 39.708514)
EQ	1	N/A	N/A	N/A	N/A
	2	(13584, 68.083202)	(6208, 46.390997)	(4041, 37.020529)	(3455, 30.987662)
	5	(13534, 81.61071)	(6677, 54.475581)	(3832, 39.988916)	(3885, 32.167532)
	10	(13575, 119.566966)	(6752, 73.701732)	(3896, 44.986285)	(3831, 34.600187)
	15	(13599, 152.357478)	(6707, 87.71731)	(4003, 52.026007)	(4122, 37.404323)
	20	(13599, 194.678042)	(6609, 111.009044)	(4032, 58.400001)	(3885, 40.207563)
II	1	(13584, 39.784097)	(6208, 35.406014)	(4041, 33.207643)	(3155, 30.838721)
	2	(13534, 53.167858)	(6677, 40.995739)	(3832, 33.814285)	(3050, 29.701283)
	5	(13575, 73.246415)	(6752, 51.249537)	(3896, 37.390047)	(3634, 31.497672)
	10	(13599, 106.95152)	(6609, 68.252545)	(4032, 44.07337)	(3231, 34.835858)
	15	(13599, 141.721769)	(6823, 85.316382)	(4032, 49.657822)	(3667, 35.776236)
	20	(13599, 177.902717)	(6823, 102.361751)	(3837, 55.366453)	(3667, 38.565606)
IO	1	(1180, 36.660868)	(1394, 34.937324)	(2062, 34.445082)	(3162, 32.699253)
	2	(1475, 49.889538)	(1401, 41.541774)	(2236, 34.817455)	(2604, 31.520299)
	5	(1475, 69.707858)	(1732, 51.103882)	(2536, 39.362832)	(3156, 32.904191)
	10	(1579, 99.048102)	(1743, 67.193724)	(2516, 43.292258)	(3219, 33.990909)
	15	(1556, 137.172782)	(1855, 87.183607)	(2375, 50.947088)	(3754, 37.311674)
	20	(1556, 172.371989)	(1698, 104.317272)	(2593, 56.394751)	(3859, 39.280838)
NT	1	(1577, 47.474689)	(2267, 35.795039)	(2200, 31.486294)	(2080, 28.850227)
	2	(2078, 74.812402)	(2283, 47.830792)	(2509, 36.376688)	(2133, 30.553379)
	5	(2188, 141.600142)	(2510, 76.865257)	(2699, 48.753152)	(2611, 35.919703)
	10	(2188, 230.624679)	(2515, 122.091206)	(2866, 72.79768)	(2667, 50.070531)
	15	(2035, 248.787257)	(2583, 127.339392)	(2809, 69.564209)	(2794, 44.51512)
	20	(2038, 280.394172)	(2566, 143.537395)	(2907, 74.808112)	(2757, 47.333103)
NE	1	(329, 21.047036)	(438, 24.928693)	(300, 26.296863)	(176, 26.673974)
	2	(329, 28.007259)	(438, 28.143183)	(300, 27.413802)	(176, 27.1633)
	5	(329, 45.821058)	(438, 37.908263)	(300, 30.91087)	(176, 28.71001)
	10	(574, 78.649986)	(702, 54.212184)	(917, 37.518702)	(439, 31.280486)
	15	(329, 110.359272)	(438, 70.787691)	(300, 42.592056)	(176, 34.128857)
	20	(329, 139.094946)	(438, 88.008542)	(300, 48.424284)	(176, 36.65451)
RD	1	(0, 28.390049)	(1, 31.537561)	(116, 30.250711)	(72, 28.421338)
	2	(6, 34.359303)	(75, 34.768408)	(9, 31.355581)	(493, 28.907215)
	5	(7, 46.523486)	(82, 41.281639)	(557, 33.869331)	(983, 29.929439)
	10	(21, 86.319679)	(158, 62.431811)	(428, 40.812047)	(989, 33.312353)
	15	(22, 108.426765)	(197, 73.398591)	(418, 44.921136)	(1245, 35.22558)
	20	(37, 146.327001)	(333, 92.227997)	(849, 51.733232)	(1628, 37.525779)

Table 12. The full results of the main experiments on *gowalla*. For each algorithm, each considered k value, and each n_c , we report the performance (left) and the running time (right).

algorithm	n_c	$k = 5$	$k = 10$	$k = 15$	$k = 20$
BM	1	(2156, 17.250765)	(4639, 34.457268)	(4558, 50.228279)	(3348, 62.148935)
	2	(2156, 28.167689)	(4639, 51.946555)	(4558, 68.217324)	(3348, 79.537184)
	5	(2169, 39.767643)	(4828, 70.161341)	(4815, 88.415418)	(3600, 95.969509)
	10	(2209, 59.279109)	(4991, 104.108203)	(5175, 122.547026)	(4051, 127.31719)
	15	(2169, 80.004062)	(4991, 136.618916)	(5372, 159.781998)	(4617, 160.744555)
	20	(2181, 101.828541)	(4991, 172.50932)	(5372, 199.099672)	(4652, 189.724944)
EQ	1	N/A	N/A	N/A	N/A
	2	(2156, 28.096701)	(4639, 52.097043)	(4558, 68.635538)	(3348, 78.514117)
	5	(2169, 36.565866)	(4639, 64.364222)	(4720, 81.717093)	(3480, 90.34128)
	10	(2169, 59.696621)	(4656, 102.948816)	(5221, 121.257137)	(3851, 125.697294)
	15	(2209, 76.146773)	(4991, 129.479459)	(5175, 152.444814)	(3853, 152.075571)
	20	(2241, 99.555031)	(4991, 168.191196)	(5372, 196.499618)	(4051, 188.770842)
II	1	(2156, 15.817059)	(4639, 33.14413)	(4558, 48.953266)	(3348, 61.198515)
	2	(2169, 23.972167)	(4639, 45.983909)	(4720, 63.230449)	(3480, 73.074145)
	5	(2169, 36.35377)	(4656, 65.563888)	(5221, 84.586214)	(3851, 91.057811)
	10	(2241, 60.956302)	(4991, 98.907459)	(5372, 121.011317)	(4051, 122.64463)
	15	(2173, 77.744099)	(4991, 132.748716)	(5372, 158.346635)	(4652, 154.625164)
	20	(2340, 100.499021)	(4991, 168.338879)	(5372, 195.343929)	(4599, 185.53489)
IO	1	(585, 15.390641)	(1665, 33.078106)	(2011, 49.502759)	(2408, 62.065986)
	2	(588, 23.13957)	(1653, 44.773951)	(1850, 62.257377)	(2217, 73.81874)
	5	(584, 33.783655)	(1524, 62.245573)	(2022, 82.289333)	(2352, 91.868419)
	10	(574, 51.673385)	(1516, 90.121998)	(2173, 113.223071)	(2593, 119.825747)
	15	(580, 70.769903)	(1516, 121.838574)	(2169, 145.921236)	(2342, 150.819693)
	20	(582, 88.914154)	(1517, 149.250357)	(2095, 177.999262)	(2400, 180.99605)
NT	1	(476, 58.926643)	(1558, 64.954823)	(1915, 71.927896)	(1748, 77.397144)
	2	(545, 99.766209)	(1596, 101.376652)	(2067, 102.452668)	(2105, 100.385736)
	5	(589, 200.149661)	(1748, 191.729642)	(2353, 177.370222)	(2209, 159.370979)
	10	(589, 334.970778)	(1870, 319.254124)	(2590, 288.175274)	(2651, 250.22854)
	15	(603, 325.665102)	(1940, 317.799222)	(2678, 293.884366)	(2481, 256.016475)
	20	(607, 346.781807)	(1940, 349.985538)	(2790, 324.063543)	(2600, 285.047393)
NE	1	(309, 13.788904)	(216, 28.110017)	(190, 43.50338)	(113, 55.991149)
	2	(309, 17.40175)	(216, 33.555561)	(190, 49.712142)	(113, 62.696089)
	5	(309, 28.33458)	(216, 50.846547)	(190, 68.710448)	(113, 79.404135)
	10	(329, 47.057335)	(695, 79.058022)	(434, 102.175082)	(392, 108.591515)
	15	(309, 65.575881)	(216, 108.238793)	(190, 132.052858)	(113, 137.83236)
	20	(309, 83.175236)	(216, 137.192202)	(190, 163.539437)	(113, 166.78048)
RD	1	(0, 14.388134)	(0, 31.767857)	(0, 48.771893)	(20, 62.0023)
	2	(1, 18.149702)	(5, 37.393978)	(55, 55.114615)	(116, 67.78141)
	5	(2, 25.468295)	(12, 48.794362)	(66, 67.796522)	(26, 79.191418)
	10	(12, 47.65298)	(19, 85.499047)	(100, 108.456509)	(81, 115.707457)
	15	(13, 61.772505)	(46, 105.917868)	(104, 130.881632)	(270, 137.866356)
	20	(17, 84.348169)	(32, 140.406237)	(201, 168.625494)	(217, 172.471614)

Table 13. The full results of the main experiments on *twitter*. For each algorithm, each considered k value, and each n_c , we report the performance (left) and the running time (right).

algorithm	n_c	$k = 5$	$k = 10$	$k = 15$	$k = 20$
BM	1	(5792, 32.22977)	(25273, 32.191346)	(12588, 38.239932)	(1068, 44.567476)
	2	(5406, 51.697749)	(25523, 48.436832)	(14172, 52.23859)	(993, 54.257068)
	5	(4919, 69.780089)	(25445, 66.888133)	(14820, 68.372353)	(1085, 66.340954)
	10	(6309, 105.836748)	(25574, 100.419997)	(14715, 101.620759)	(149189, 100.941726)
	15	(7288, 135.667083)	(25574, 132.941585)	(15129, 130.15164)	(149188, 124.15587)
	20	(7494, 170.204321)	(25672, 168.079383)	(17087, 165.087614)	(149176, 156.316675)
EQ	1	N/A	N/A	N/A	N/A
	2	(5406, 51.869004)	(25523, 48.432708)	(14172, 52.378278)	(993, 54.443817)
	5	(6741, 64.559927)	(25445, 60.918173)	(15350, 63.883068)	(1507, 63.765601)
	10	(6986, 101.530793)	(26344, 98.349682)	(14347, 101.317042)	(148768, 99.605697)
	15	(6992, 129.077426)	(25586, 126.146423)	(14669, 129.259442)	(1929, 107.28004)
	20	(7047, 168.380577)	(25586, 166.89998)	(18161, 161.833963)	(2362, 134.152945)
II	1	(5792, 30.174098)	(25273, 31.20066)	(12588, 37.185525)	(1887, 43.346764)
	2	(5792, 43.317874)	(25453, 43.40582)	(14225, 48.705107)	(2014, 50.856149)
	5	(5948, 63.137128)	(25465, 64.157894)	(19593, 65.183179)	(1495, 65.033025)
	10	(6385, 96.344019)	(25398, 97.407013)	(22378, 99.228458)	(119139, 88.479309)
	15	(6380, 129.943815)	(25692, 133.076064)	(17087, 127.554944)	(1930, 110.292199)
	20	(7090, 162.720907)	(25684, 167.108386)	(14767, 158.833008)	(119139, 135.438184)
IO	1	(4675, 29.207645)	(8406, 31.45901)	(13057, 36.980751)	(1068, 43.652551)
	2	(3658, 41.505399)	(20216, 42.844049)	(13337, 47.190616)	(1611, 51.012466)
	5	(5096, 59.139864)	(20619, 61.069498)	(14106, 63.702171)	(148768, 69.591456)
	10	(5091, 88.221983)	(8406, 91.471204)	(15410, 90.407044)	(149176, 94.918306)
	15	(5087, 119.665234)	(20720, 121.399374)	(17017, 117.710842)	(149188, 121.505219)
	20	(5264, 150.64538)	(8406, 155.302002)	(16280, 146.199353)	(149190, 147.688692)
NT	1	(1347, 85.938826)	(2766, 75.619618)	(11628, 66.656098)	(0, 59.299755)
	2	(1347, 121.679605)	(1690, 86.804609)	(8219, 82.54612)	(930, 81.934731)
	5	(1447, 206.327432)	(3680, 135.998975)	(4050, 110.855094)	(743, 124.472368)
	10	(1706, 314.501682)	(6224, 243.396519)	(10790, 230.891864)	(710, 190.639052)
	15	(1992, 390.721497)	(6225, 302.550387)	(27415, 267.379108)	(1697, 203.172245)
	20	(2121, 417.767729)	(6225, 342.265757)	(10872, 291.925606)	(847, 224.827101)
NE	1	(18, 23.140345)	(1605, 30.113673)	(15, 35.068699)	(0, 41.998658)
	2	(18, 29.351086)	(1605, 36.695096)	(15, 40.527794)	(0, 47.790536)
	5	(18, 48.526995)	(1605, 54.255724)	(15, 56.555583)	(0, 60.634051)
	10	(649, 80.425189)	(2740, 84.403829)	(15, 82.86777)	(0, 83.096467)
	15	(18, 109.869827)	(1605, 114.536891)	(15, 109.623321)	(0, 105.489152)
	20	(18, 140.707342)	(1605, 148.581678)	(15, 137.350974)	(0, 127.577672)
RD	1	(0, 24.450804)	(1, 31.233218)	(-11, 36.223551)	(-48, 41.869068)
	2	(0, 30.485499)	(2, 37.26326)	(0, 41.262597)	(25, 45.953401)
	5	(0, 42.50117)	(2, 49.479786)	(0, 51.695204)	(0, 54.720054)
	10	(1, 80.653146)	(1, 85.758497)	(17, 84.920984)	(9, 82.029572)
	15	(0, 102.999965)	(4, 108.338868)	(111, 104.065065)	(62, 98.417199)
	20	(1, 139.453087)	(10, 146.111188)	(3, 135.508874)	(25, 124.279489)

Table 14. The full results of the main experiments on *stanford*. For each algorithm, each considered k value, and each n_c , we report the performance (left) and the running time (right).

algorithm	n_c	$k = 5$	$k = 10$	$k = 15$	$k = 20$
BM	1	(34727, 96.815317)	(13903, 88.077645)	(7313, 79.695829)	(7933, 74.58187)
	2	(34727, 163.800204)	(13903, 101.660277)	(7358, 84.292301)	(8619, 75.905248)
	5	(35472, 210.667127)	(13712, 116.792159)	(7474, 90.294164)	(8364, 79.933056)
	10	(35483, 296.104172)	(13549, 141.735323)	(6773, 101.146874)	(9058, 85.75348)
	15	(35483, 379.843322)	(13549, 167.357328)	(6773, 112.453282)	(8655, 92.784557)
	20	(35483, 470.990498)	(13549, 193.362098)	(6773, 123.598105)	(8801, 99.734185)
EQ	1	N/A	N/A	N/A	N/A
	2	(34727, 162.052522)	(13903, 101.409627)	(7358, 84.475508)	(8619, 75.585538)
	5	(35057, 196.236969)	(13650, 112.538271)	(6727, 89.331761)	(8552, 79.23621)
	10	(35472, 291.866031)	(13549, 141.026136)	(6823, 100.507107)	(8891, 85.741432)
	15	(35483, 363.928129)	(13549, 163.431182)	(6761, 110.469261)	(8861, 91.665476)
	20	(35483, 467.948006)	(13549, 193.633128)	(6773, 123.979598)	(8967, 99.959984)
II	1	(34727, 91.237944)	(13903, 86.955482)	(7313, 79.52332)	(7933, 74.978634)
	2	(35057, 126.056803)	(13650, 96.646623)	(7361, 82.315159)	(8332, 75.345899)
	5	(35472, 175.673164)	(13549, 111.462079)	(7773, 89.368702)	(8364, 78.324265)
	10	(35483, 259.633478)	(13549, 135.378938)	(7078, 100.353824)	(8260, 86.502816)
	15	(35483, 347.251763)	(13549, 164.680759)	(7212, 112.436771)	(8294, 92.507716)
	20	(35442, 437.978777)	(13549, 188.161939)	(7212, 123.091461)	(8625, 99.140762)
IO	1	(5661, 89.014214)	(7077, 84.894401)	(5199, 83.422277)	(8145, 75.072201)
	2	(5479, 121.469296)	(7999, 92.596306)	(5880, 82.015747)	(8581, 73.922073)
	5	(5502, 167.262149)	(8450, 107.182301)	(5533, 91.749191)	(8682, 78.988132)
	10	(5520, 246.015041)	(8261, 129.768289)	(5921, 98.238124)	(8921, 84.525209)
	15	(5796, 333.021418)	(8261, 154.97954)	(5878, 113.489638)	(9052, 91.156537)
	20	(5796, 413.023137)	(7483, 177.147368)	(6062, 121.723597)	(9059, 98.88832)
NT	1	(3382, 103.389162)	(5724, 79.779424)	(2916, 74.370836)	(5361, 71.278303)
	2	(3859, 151.221716)	(6139, 92.829653)	(3099, 79.956918)	(5771, 72.274644)
	5	(4147, 270.213349)	(7012, 123.380309)	(3480, 93.147245)	(5908, 79.698591)
	10	(4179, 466.206248)	(7186, 185.257056)	(4242, 127.623758)	(6223, 97.864621)
	15	(4418, 517.675057)	(7995, 189.778014)	(4095, 122.447309)	(6103, 93.907214)
	20	(4498, 597.433512)	(7995, 216.309984)	(4110, 133.193601)	(6092, 100.494656)
NE	1	(139, 63.555624)	(595, 70.558657)	(371, 69.325438)	(3312, 68.733193)
	2	(139, 79.795067)	(595, 73.237299)	(371, 71.77277)	(3312, 71.158174)
	5	(139, 127.806795)	(595, 87.703684)	(371, 78.094574)	(3312, 75.459431)
	10	(506, 208.08281)	(1191, 111.561699)	(814, 90.293125)	(4510, 81.541043)
	15	(139, 290.510849)	(595, 136.452374)	(371, 99.434331)	(3312, 86.7421)
	20	(139, 371.255455)	(595, 161.463131)	(371, 110.222559)	(3312, 96.512952)
RD	1	(0, 64.169277)	(31, 81.413712)	(11, 76.234492)	(0, 70.665266)
	2	(121, 79.942868)	(250, 85.861006)	(545, 78.40747)	(3264, 72.485616)
	5	(140, 112.099574)	(462, 95.675977)	(635, 82.484578)	(4441, 75.22764)
	10	(37, 210.442689)	(697, 126.084332)	(1648, 95.920044)	(4859, 86.439338)
	15	(208, 271.602123)	(727, 141.739601)	(1807, 103.595016)	(4414, 88.147885)
	20	(197, 367.440253)	(1038, 172.267636)	(1989, 116.029053)	(4467, 95.818715)

Table 15. The full results of the main experiments on *youtube*. For each algorithm, each considered k value, and each n_c , we report the performance (left) and the running time (right).

algorithm	n_c	$k = 5$	$k = 10$	$k = 15$	$k = 20$
BM	1	(69841, 184.947758)	(15865, 109.131924)	(6154, 125.102625)	(1973, 116.184614)
	2	(69841, 269.715721)	(16639, 156.3468)	(6487, 148.578884)	(2187, 136.397296)
	5	(70392, 333.232194)	(17250, 188.865752)	(6246, 172.212999)	(2336, 159.929409)
	10	(70184, 447.916909)	(17482, 263.394664)	(6246, 217.438621)	(2347, 198.744257)
	15	(70184, 559.750126)	(17482, 321.388279)	(5906, 267.584617)	(2299, 226.794706)
	20	(70184, 681.211728)	(17482, 392.373696)	(4467, 312.21477)	(2357, 269.380681)
EQ	1	N/A	N/A	N/A	N/A
	2	(69841, 270.361965)	(16639, 156.262437)	(6487, 149.014505)	(2187, 135.776025)
	5	(70289, 314.912242)	(17348, 175.188496)	(6508, 164.977351)	(2258, 150.627091)
	10	(69737, 444.372591)	(17482, 260.021884)	(6246, 215.380874)	(2342, 196.503726)
	15	(70184, 534.436413)	(17482, 310.851462)	(6246, 259.94217)	(2269, 222.622928)
	20	(70184, 670.27082)	(17482, 388.571692)	(5906, 317.5184)	(2257, 270.485292)
II	1	(69841, 179.602117)	(15865, 108.033626)	(6154, 124.044298)	(1973, 117.409596)
	2	(70289, 225.902993)	(16368, 134.849478)	(6237, 140.792145)	(1983, 132.427966)
	5	(69737, 285.287187)	(16158, 176.135094)	(6246, 169.299593)	(2217, 152.173485)
	10	(70184, 399.478906)	(16168, 246.115413)	(5906, 213.597636)	(2274, 193.611218)
	15	(70184, 526.861574)	(16216, 314.135171)	(4467, 258.704611)	(2329, 226.436015)
	20	(70184, 642.020926)	(16455, 375.499729)	(4620, 308.995176)	(2280, 262.455593)
IO	1	(2295, 115.656188)	(3453, 119.008855)	(3767, 112.720193)	(2021, 122.897098)
	2	(2208, 156.583749)	(3866, 141.172058)	(3597, 130.649717)	(2239, 140.72643)
	5	(1885, 217.510045)	(3806, 176.122573)	(3686, 156.575334)	(2248, 162.098473)
	10	(1710, 316.557355)	(3614, 232.498359)	(3711, 198.373934)	(2441, 194.604057)
	15	(818, 420.451756)	(3561, 293.285089)	(3590, 242.467404)	(2391, 232.632324)
	20	(710, 522.844322)	(3934, 349.380345)	(3640, 285.66923)	(2419, 267.734644)
NT	1	(3361, 154.290558)	(3616, 144.460126)	(2800, 137.186695)	(3539, 142.928956)
	2	(3271, 233.801483)	(3625, 188.470627)	(2784, 169.520057)	(3677, 168.023174)
	5	(3220, 439.065302)	(3811, 298.813281)	(3030, 251.15891)	(3874, 233.807214)
	10	(3494, 705.594448)	(3906, 473.593645)	(3109, 375.332806)	(3990, 342.674057)
	15	(3783, 804.524135)	(3967, 495.260585)	(3123, 389.246175)	(4078, 351.200492)
	20	(4008, 915.755914)	(4093, 554.369119)	(3147, 429.889279)	(4118, 386.540142)
NE	1	(682, 86.673368)	(648, 101.997978)	(1405, 109.180708)	(1452, 118.312682)
	2	(682, 106.525254)	(648, 118.811623)	(1405, 117.111967)	(1452, 125.247142)
	5	(682, 167.174618)	(648, 152.96458)	(1405, 142.058964)	(1452, 146.397903)
	10	(1344, 267.953063)	(947, 215.08867)	(1510, 181.730074)	(1819, 179.622152)
	15	(682, 371.214326)	(648, 279.089291)	(1405, 224.449483)	(1452, 216.560952)
	20	(682, 470.687674)	(648, 343.055558)	(1405, 265.112105)	(1452, 250.082739)
RD	1	(23, 89.965633)	(16, 102.005447)	(121, 112.442735)	(155, 122.04761)
	2	(51, 109.182972)	(366, 116.9455)	(966, 124.456227)	(779, 130.313734)
	5	(119, 150.46222)	(453, 142.383985)	(936, 139.941693)	(1387, 145.472471)
	10	(105, 275.956563)	(971, 226.873622)	(1564, 196.010391)	(1854, 196.772464)
	15	(159, 353.856702)	(996, 262.244178)	(1770, 232.126078)	(2292, 219.906269)
	20	(137, 469.818807)	(1264, 337.926391)	(2056, 290.098063)	(2632, 265.957037)

Table 16. The full results of the main experiments on *wikitalk*. For each algorithm, each considered k value, and each n_c , we report the performance (left) and the running time (right).

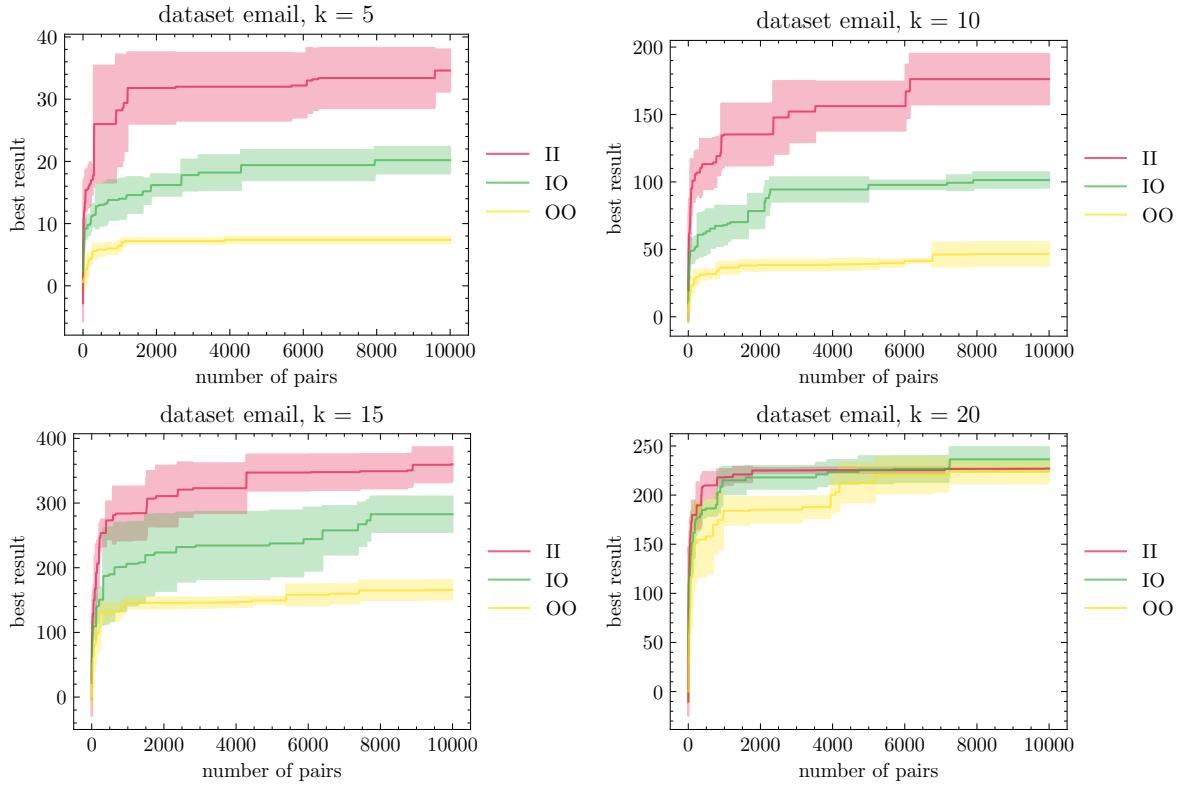


Fig. 3. The full results of the sampling experiments on *email*. For each considered k value and each case, we report the best performance among the first x sampled mergers.

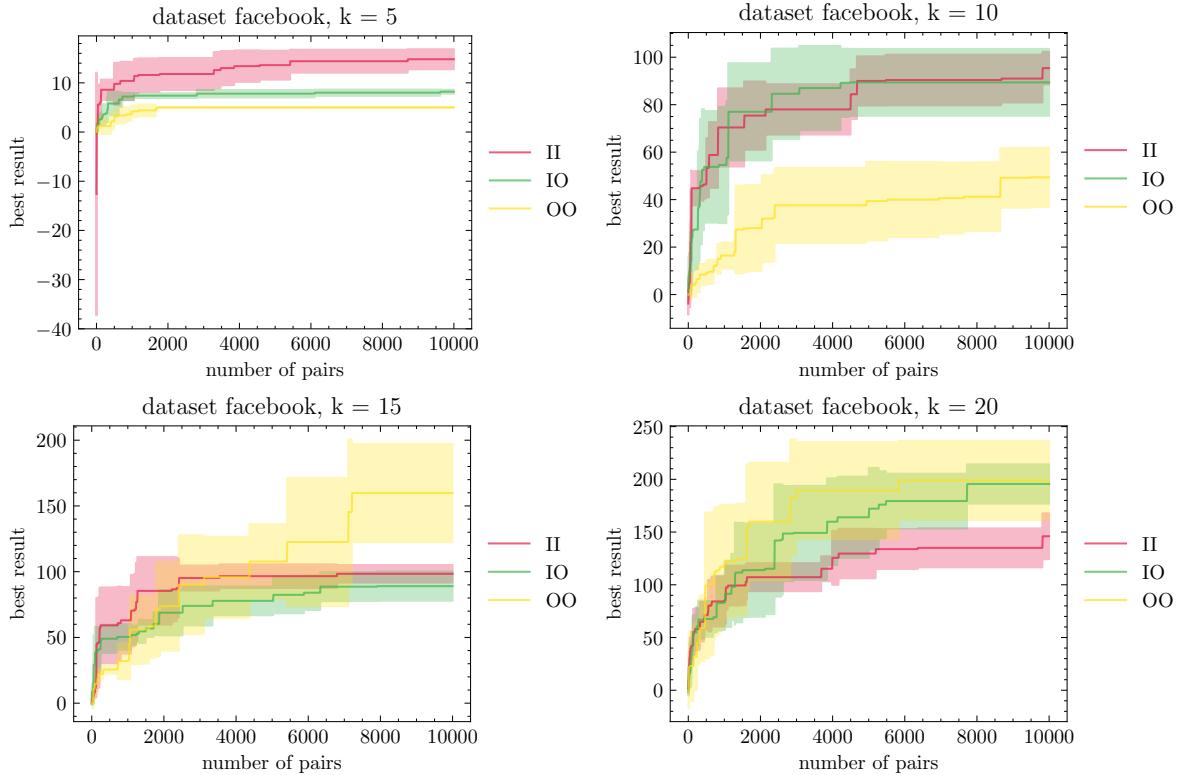


Fig. 4. The full results of the sampling experiments on *facebook*. For each considered k value and each case, we report the best performance among the first x sampled mergers.

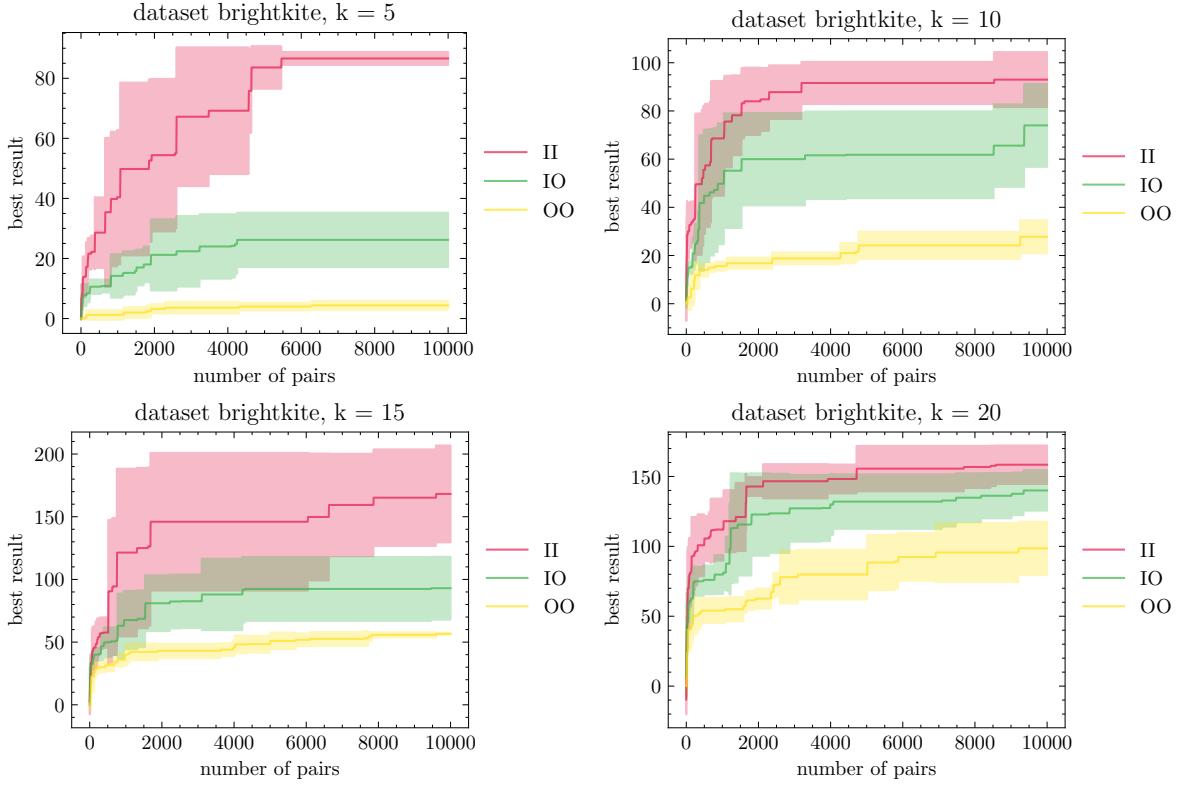


Fig. 5. The full results of the sampling experiments on *brightkite*. For each considered k value and each case, we report the best performance among the first x sampled mergers.

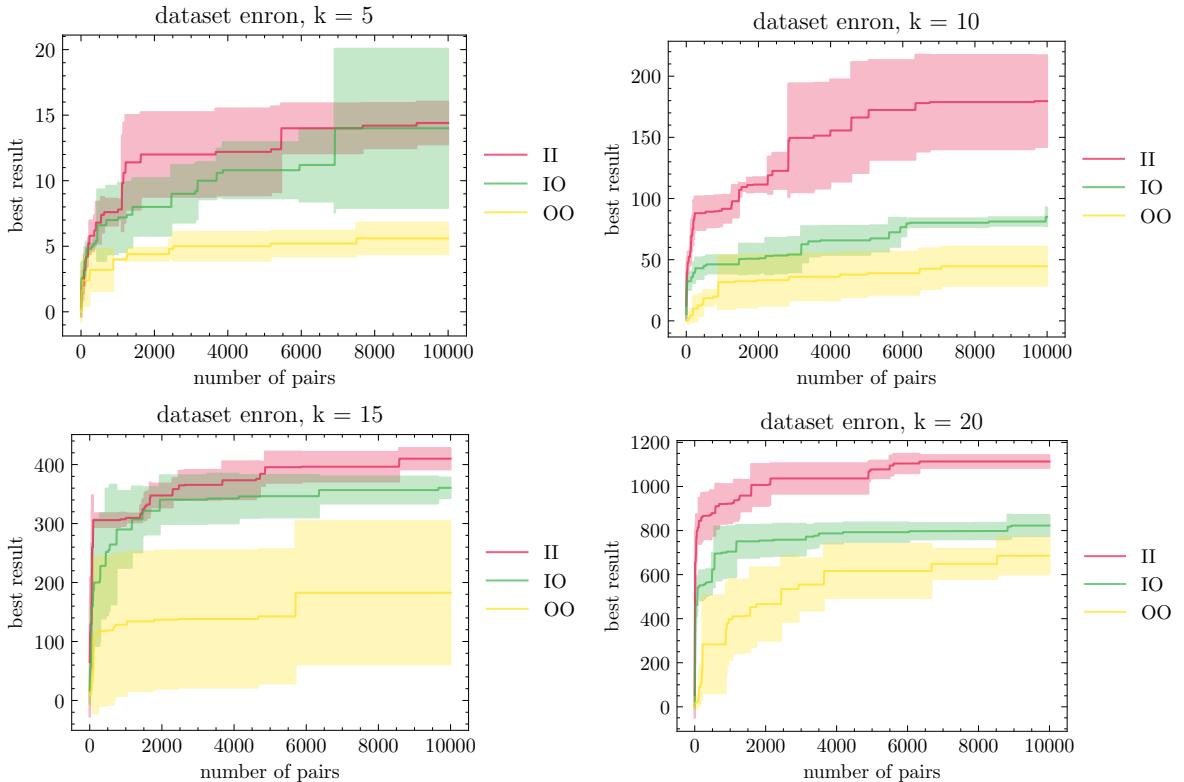


Fig. 6. The full results of the sampling experiments on *enron*. For each considered k value and each case, we report the best performance among the first x sampled mergers.

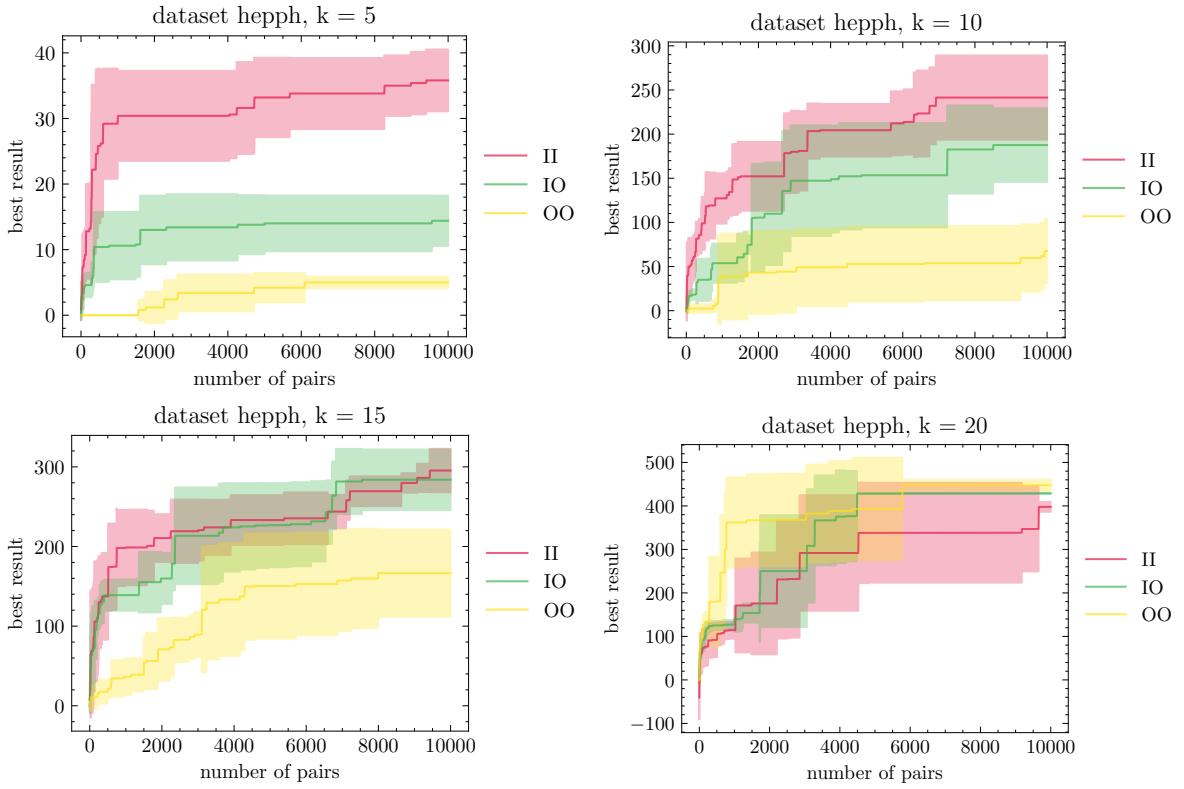


Fig. 7. The full results of the sampling experiments on *hepph*. For each considered k value and each case, we report the best performance among the first x sampled mergers.

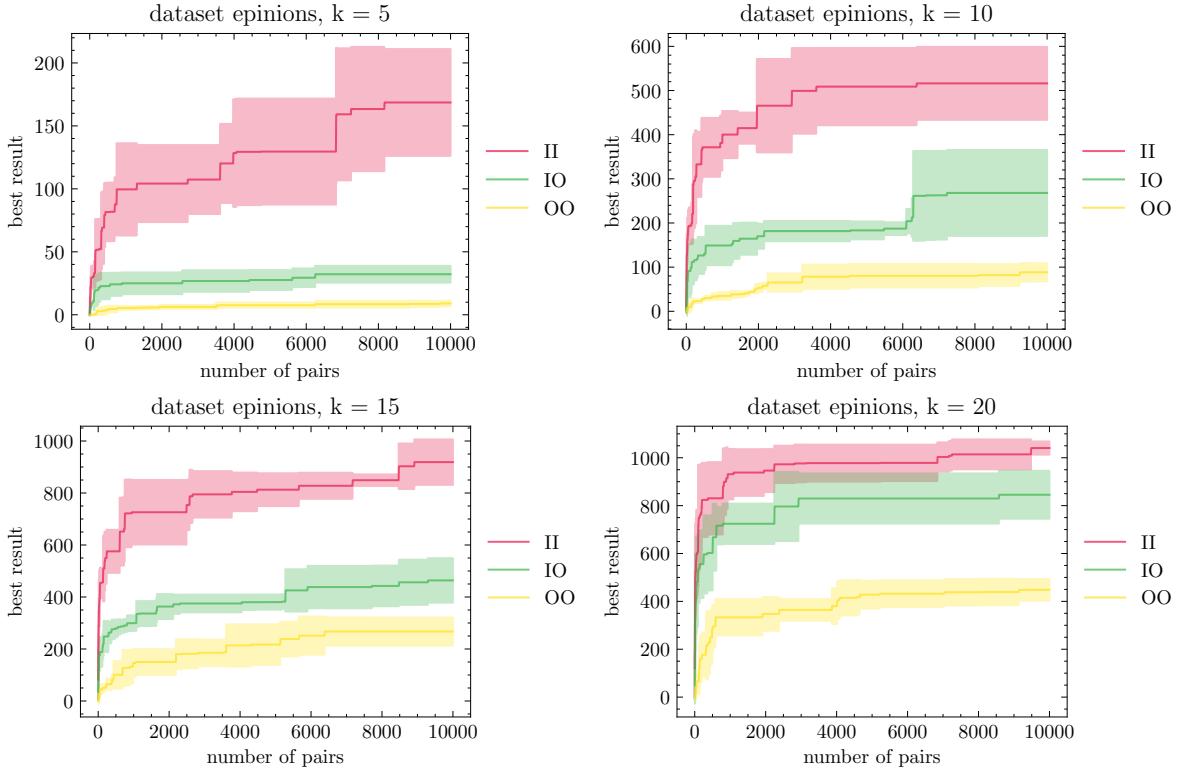


Fig. 8. The full results of the sampling experiments on *opinions*. For each considered k value and each case, we report the best performance among the first x sampled mergers.

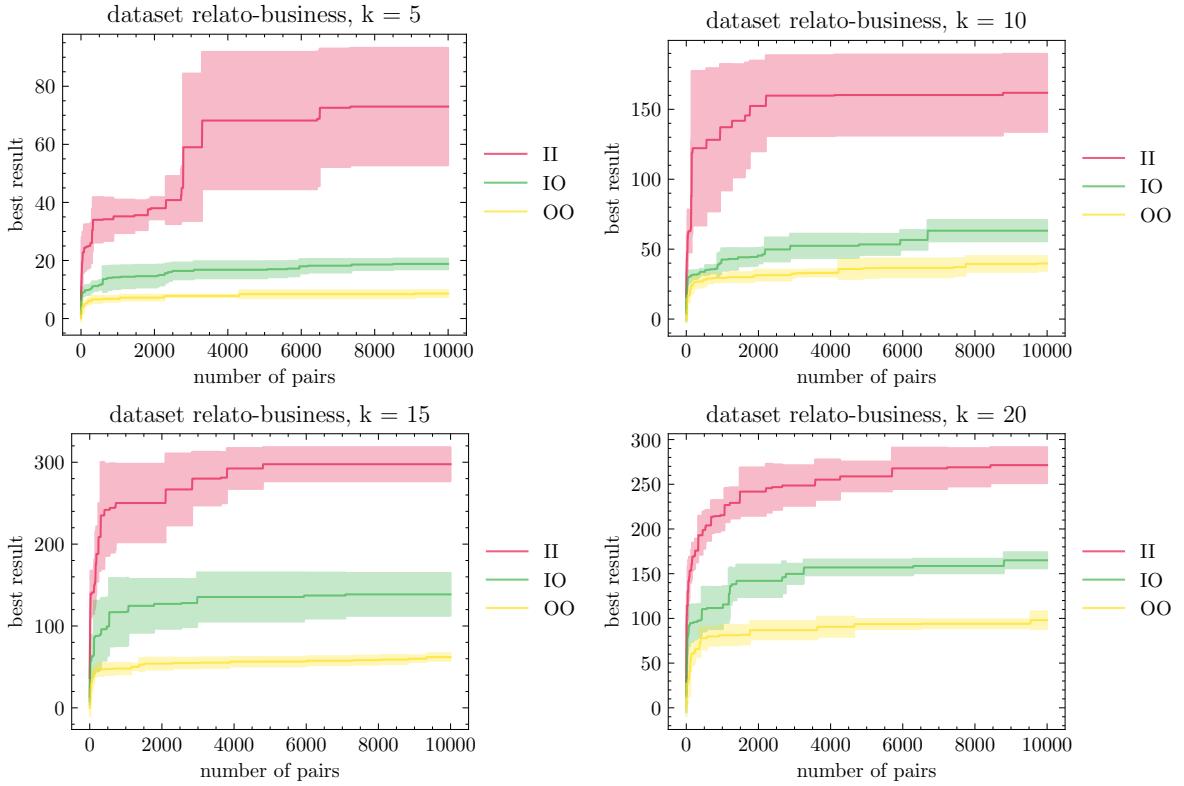


Fig. 9. The full results of the sampling experiments on *relato*. For each considered k value and each case, we report the best performance among the first x sampled mergers.

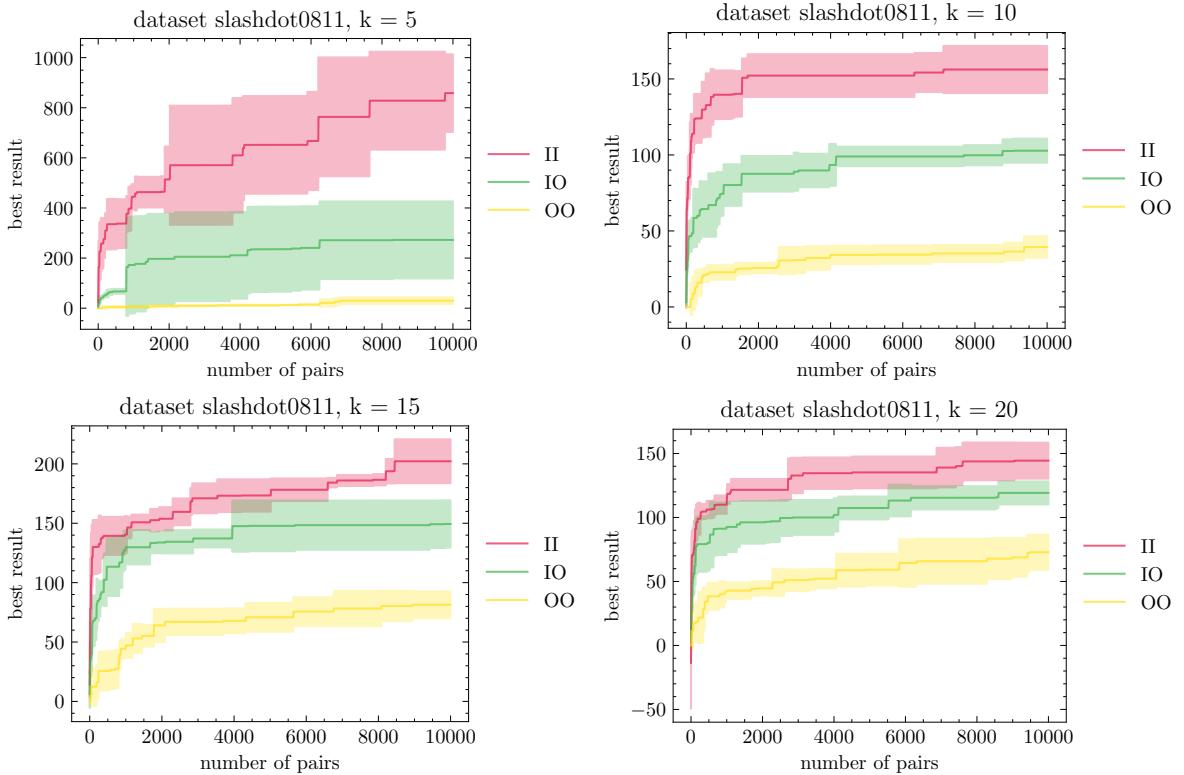


Fig. 10. The full results of the sampling experiments on *slashdot*. For each considered k value and each case, we report the best performance among the first x sampled mergers.

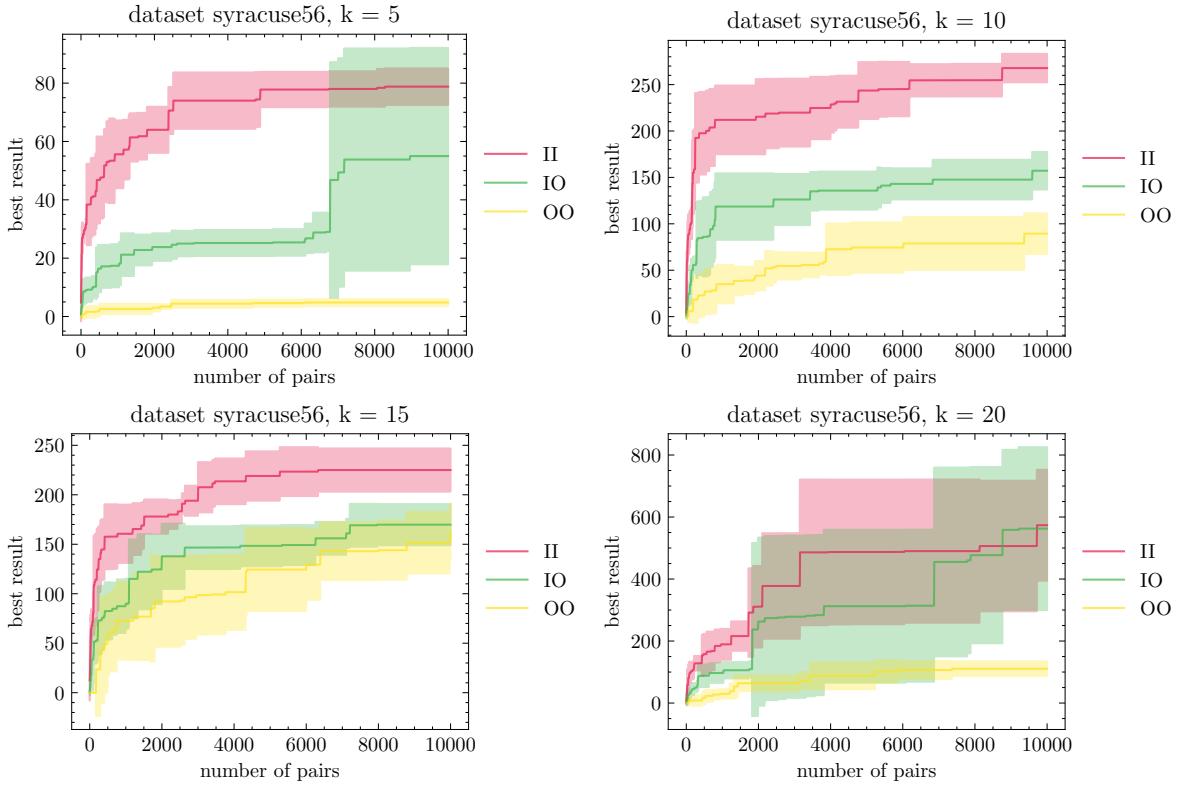


Fig. 11. The full results of the sampling experiments on *syracuse*. For each considered k value and each case, we report the best performance among the first x sampled mergers.

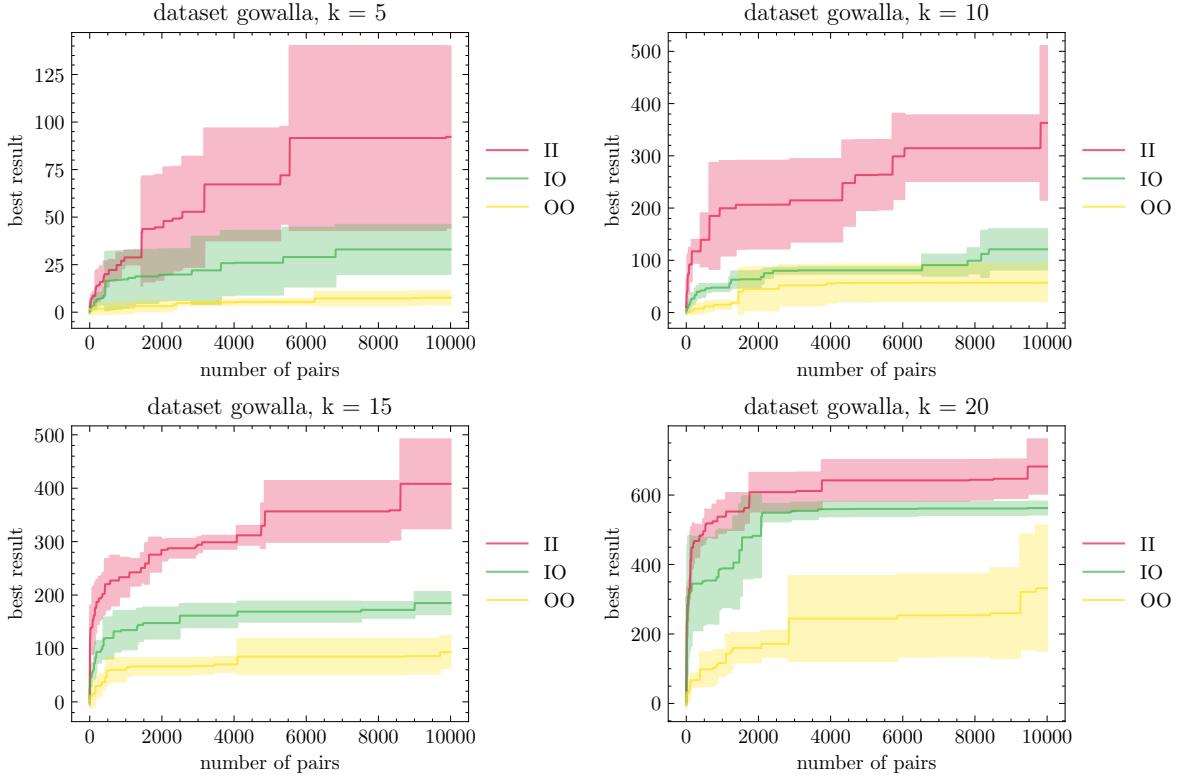


Fig. 12. The full results of the sampling experiments on *gowalla*. For each considered k value and each case, we report the best performance among the first x sampled mergers.

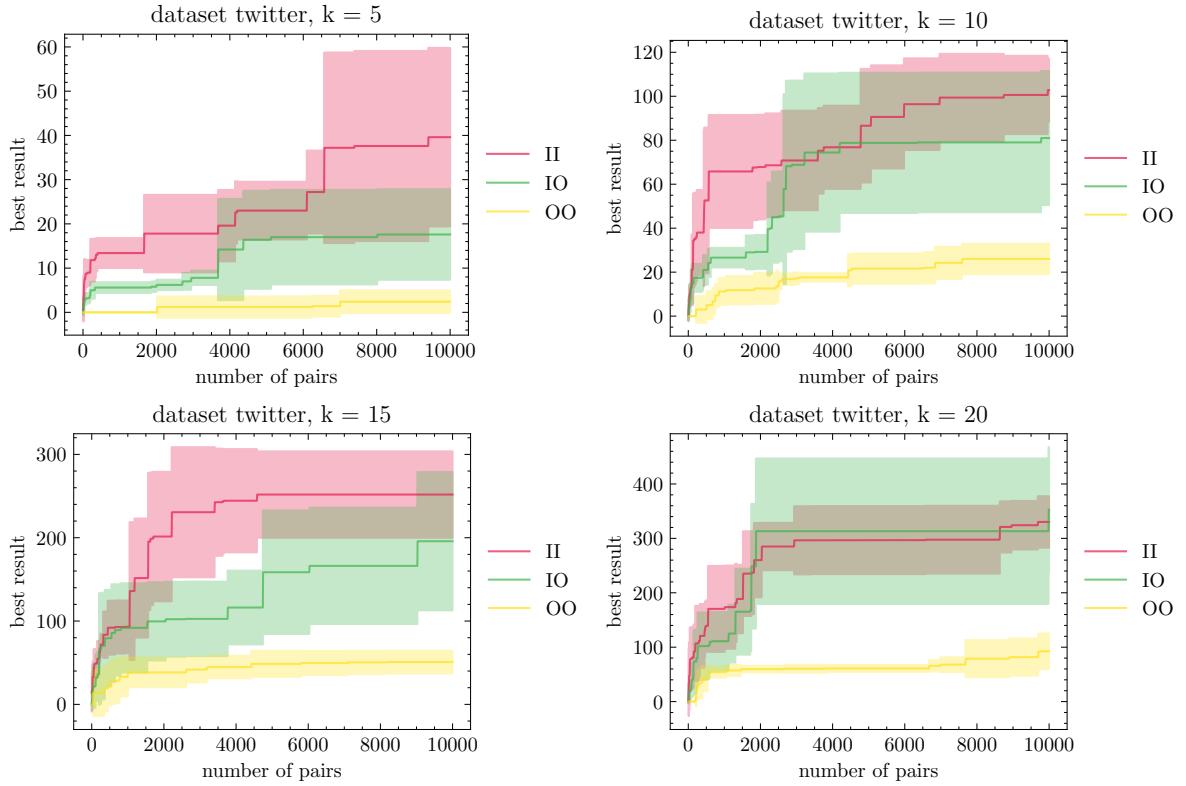


Fig. 13. The full results of the sampling experiments on *twitter*. For each considered k value and each case, we report the best performance among the first x sampled mergers.

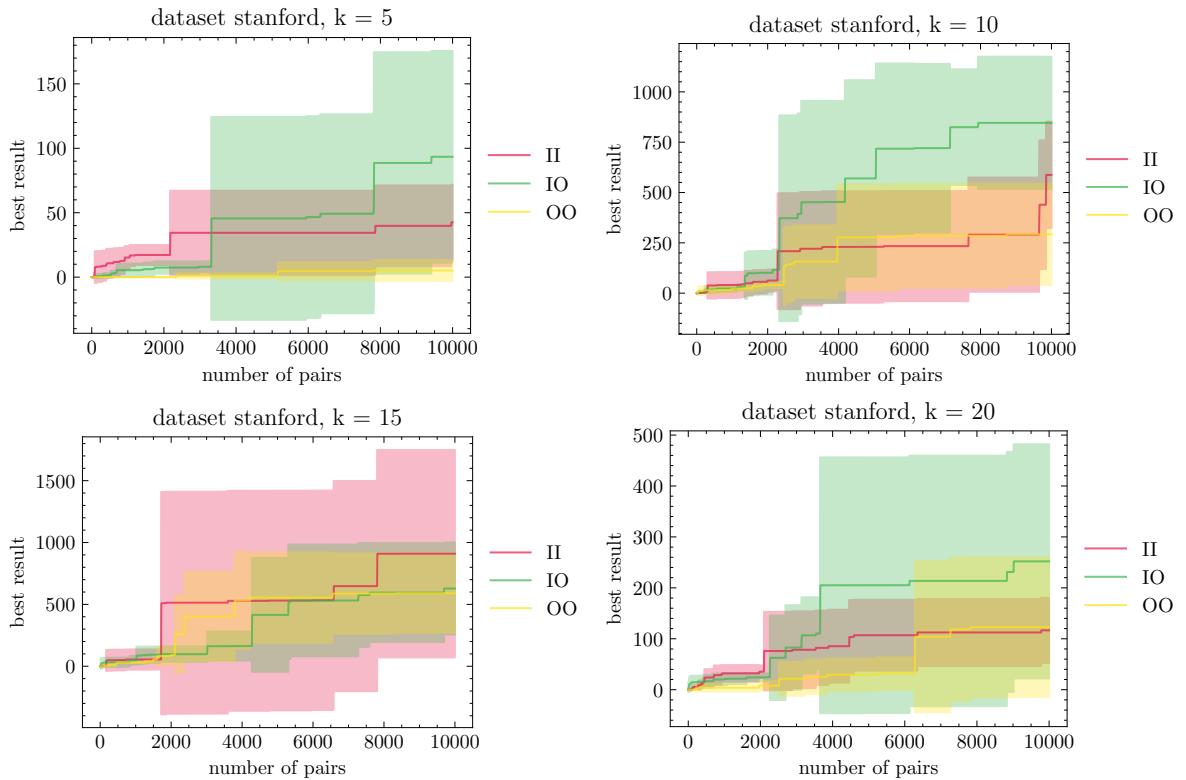


Fig. 14. The full results of the sampling experiments on *stanford*. For each considered k value and each case, we report the best performance among the first x sampled mergers.

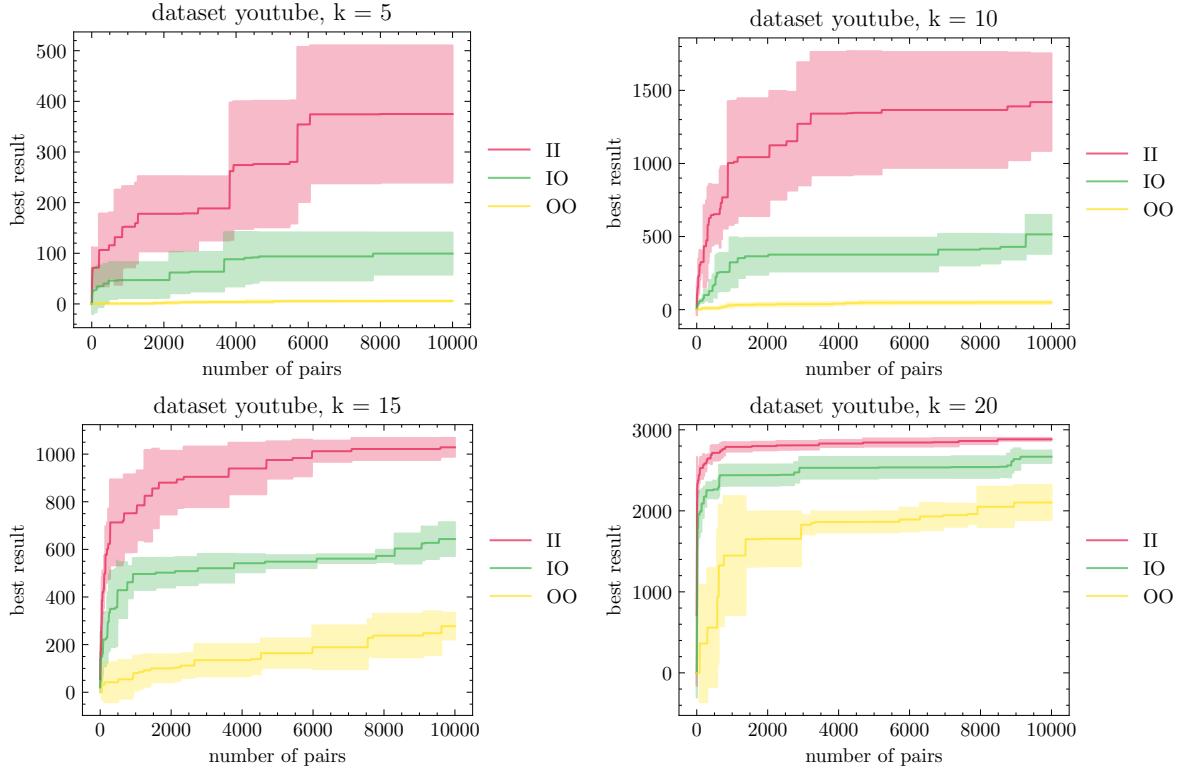


Fig. 15. The full results of the sampling experiments on *youtube*. For each considered k value and each case, we report the best performance among the first x sampled mergers.

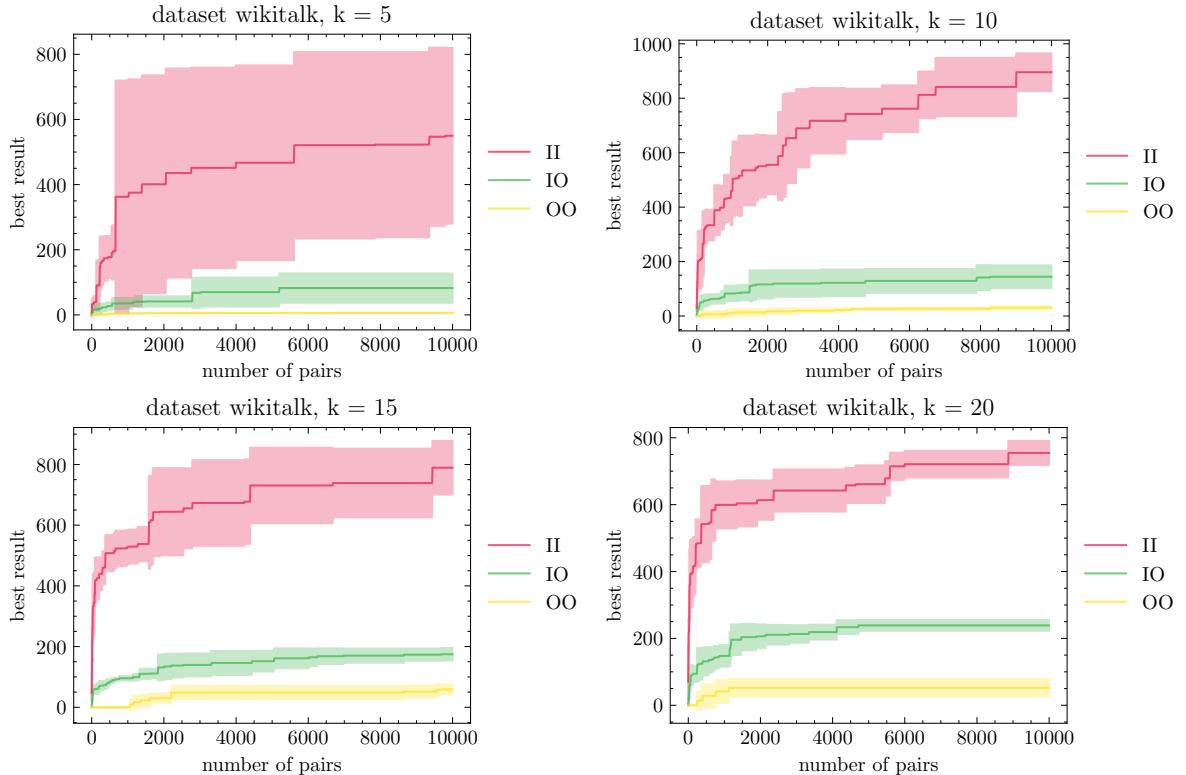


Fig. 16. The full results of the sampling experiments on *wikitalk*. For each considered k value and each case, we report the best performance among the first x sampled mergers.

IOMs/IIMs	nodes/pairs	heuristic	$k = 5$	$k = 10$	$k = 15$	$k = 20$
IOMs	node-heuristics	IP	21	150	331	255
		IN	21	150	331	255
		RD	18.7	97.0	289.3	255.0
	pair-heuristics	SE	21	150	196	255
		NN	21	27	195	0
		RD	7.0	39.3	124.0	133.0
IIMs	node-heuristics	IP	46	192	385	227
		IN	47	200	381	227
		RD	27.7	127.3	320.7	227.0
	pair-heuristics	SE	30	175	255	227
		AE	18	150	291	206
		RD	14.0	78.0	181.7	129.0

Table 17. The full results of the heuristics experiments on *email*. For each algorithm, each considered k value, we report the performance of each considered node-heuristic and pair-heuristic.

IOMs/IIMs	nodes/pairs	heuristic	$k = 5$	$k = 10$	$k = 15$	$k = 20$
IOMs	node-heuristics	IP	12	128	142	227
		IN	5	93	54	61
		RD	8.3	100.0	105.0	188.7
	pair-heuristics	SE	12	128	128	165
		NN	0	16	29	151
		RD	3.0	7.0	48.7	85.7
IIMs	node-heuristics	IP	21	100	151	171
		IN	7	17	24	18
		RD	12.3	73.7	92.3	116.7
	pair-heuristics	SE	17	46	151	169
		AE	15	74	50	72
		RD	7.0	22.3	36.0	14.3

Table 18. The full results of the heuristics experiments on *facebook*. For each algorithm, each considered k value, we report the performance of each considered node-heuristic and pair-heuristic.

IOMs/IIMs	nodes/pairs	heuristic	$k = 5$	$k = 10$	$k = 15$	$k = 20$
IOMs	node-heuristics	IP	79	100	204	195
		IN	79	100	126	151
		RD	34.0	77.0	181.7	150.7
	pair-heuristics	SE	79	72	204	150
		NN	62	24	76	88
		RD	38.7	34.7	36.3	72.3
IIMs	node-heuristics	IP	452	161	238	181
		IN	452	161	72	37
		RD	54.0	81.7	159.3	113.7
	pair-heuristics	SE	452	161	136	71
		AE	452	161	136	58
		RD	130.3	51.3	36.3	85.0

Table 19. The full results of the heuristics experiments on *brightkite*. For each algorithm, each considered k value, we report the performance of each considered node-heuristic and pair-heuristic.

IOMs/IIMs	nodes/pairs	heuristic	$k = 5$	$k = 10$	$k = 15$	$k = 20$
IOMs	node-heuristics	IP	104	145	461	1058
		IN	104	149	456	1058
		RD	13.3	126.0	413.0	971.0
	pair-heuristics	SE	104	122	364	806
		NN	10	82	101	666
		RD	10.7	53.3	162.7	659.7
IIMs	node-heuristics	IP	139	315	445	1224
		IN	97	315	429	1224
		RD	10.3	131.0	348.7	992.0
	pair-heuristics	SE	139	315	330	1115
		AE	57	315	330	1115
		RD	59.0	128.7	215.0	606.3

Table 20. The full results of the heuristics experiments on *enron*. For each algorithm, each considered k value, we report the performance of each considered node-heuristic and pair-heuristic.

IOMs/IIMs	nodes/pairs	heuristic	$k = 5$	$k = 10$	$k = 15$	$k = 20$
IOMs	node-heuristics	IP	71	441	409	430
		IN	73	441	409	430
		RD	30.0	272.0	321.3	428.7
	pair-heuristics	SE	71	441	409	430
		NN	19	61	23	0
		RD	10.7	182.0	15.7	198.7
IIMs	node-heuristics	IP	267	531	328	407
		IN	227	556	231	115
		RD	34.0	156.7	219.7	399.3
	pair-heuristics	SE	267	531	312	108
		AE	267	531	328	115
		RD	22.3	108.0	22.3	21.0

Table 21. The full results of the heuristics experiments on *hepph*. For each algorithm, each considered k value, we report the performance of each considered node-heuristic and pair-heuristic.

IOMs/IIMs	nodes/pairs	heuristic	$k = 5$	$k = 10$	$k = 15$	$k = 20$
IOMs	node-heuristics	IP	102	550	770	1069
		IN	102	550	770	1205
		RD	45.0	385.3	705.7	1081.3
	pair-heuristics	SE	102	550	770	1054
		NN	49	243	457	445
		RD	39.3	237.3	417.0	487.7
IIMs	node-heuristics	IP	1177	1113	1105	1067
		IN	1177	1113	1129	914
		RD	117.7	543.3	725.7	858.3
	pair-heuristics	SE	1177	1113	1105	958
		AE	1093	1113	1105	841
		RD	333.0	585.7	590.7	778.0

Table 22. The full results of the heuristics experiments on *epinions*. For each algorithm, each considered k value, we report the performance of each considered node-heuristic and pair-heuristic.

IOMs/IIMs	nodes/pairs	heuristic	$k = 5$	$k = 10$	$k = 15$	$k = 20$
IOMs	node-heuristics	IP	62	115	246	260
		IN	62	115	246	311
		RD	28.3	82.0	185.3	264.0
	pair-heuristics	SE	59	89	246	186
		NN	20	57	90	165
		RD	33.3	76.0	81.0	113.3
IIMs	node-heuristics	IP	265	259	255	236
		IN	265	248	410	287
		RD	29.0	123.3	228.7	241.7
	pair-heuristics	SE	265	259	244	236
		AE	224	259	196	236
		RD	79.7	68.7	107.3	83.0

Table 23. The full results of the heuristics experiments on *relato*. For each algorithm, each considered k value, we report the performance of each considered node-heuristic and pair-heuristic.

IOMs/IIMs	nodes/pairs	heuristic	$k = 5$	$k = 10$	$k = 15$	$k = 20$
IOMs	node-heuristics	IP	621	171	192	154
		IN	621	179	189	154
		RD	329.3	166.0	176.3	142.0
	pair-heuristics	SE	621	150	185	135
		NN	237	89	171	83
		RD	201.0	64.0	81.3	81.7
IIMs	node-heuristics	IP	2737	186	233	136
		IN	2737	177	233	151
		RD	495.7	136.3	173.3	124.7
	pair-heuristics	SE	2737	186	136	124
		AE	2737	153	233	136
		RD	918.3	65.7	120.3	68.7

Table 24. The full results of the heuristics experiments on *slashdot*. For each algorithm, each considered k value, we report the performance of each considered node-heuristic and pair-heuristic.

IOMs/IIMs	nodes/pairs	heuristic	$k = 5$	$k = 10$	$k = 15$	$k = 20$
IOMs	node-heuristics	IP	67	259	287	859
		IN	67	259	287	722
		RD	32.7	171.3	212.0	790.3
	pair-heuristics	SE	67	240	249	859
		NN	57	259	249	216
		RD	11.3	65.3	72.7	72.0
IIMs	node-heuristics	IP	525	973	634	809
		IN	525	973	634	414
		RD	60.0	226.0	231.7	400.7
	pair-heuristics	SE	525	973	463	709
		AE	525	973	634	414
		RD	98.3	382.3	129.0	231.7

Table 25. The full results of the heuristics experiments on *syracuse*. For each algorithm, each considered k value, we report the performance of each considered node-heuristic and pair-heuristic.

IOMs/IIMs	nodes/pairs	heuristic	$k = 5$	$k = 10$	$k = 15$	$k = 20$
IOMs	node-heuristics	IP	334	496	376	757
		IN	334	496	470	757
		RD	28.0	147.0	297.3	735.0
	pair-heuristics	SE	334	427	376	757
		NN	63	161	270	593
		RD	42.7	133.3	219.7	233.7
IIMs	node-heuristics	IP	2802	853	601	779
		IN	2802	853	601	676
		RD	28.3	144.0	319.3	574.3
	pair-heuristics	SE	2802	810	601	529
		AE	2802	853	437	529
		RD	460.7	399.0	207.0	273.7

Table 26. The full results of the heuristics experiments on *gowalla*. For each algorithm, each considered k value, we report the performance of each considered node-heuristic and pair-heuristic.

IOMs/IIMs	nodes/pairs	heuristic	$k = 5$	$k = 10$	$k = 15$	$k = 20$
IOMs	node-heuristics	IP	214	345	443	540
		IN	214	345	520	483
		RD	12.0	84.7	193.0	340.0
	pair-heuristics	SE	214	345	306	327
		NN	147	251	197	167
		RD	18.3	84.0	147.7	113.7
IIMs	node-heuristics	IP	632	955	815	787
		IN	632	955	815	787
		RD	12.0	62.7	146.7	280.3
	pair-heuristics	SE	632	955	815	414
		AE	632	955	815	414
		RD	62.0	332.3	355.3	315.7

Table 27. The full results of the heuristics experiments on *twitter*. For each algorithm, each considered k value, we report the performance of each considered node-heuristic and pair-heuristic.

IOMs/IIMs	nodes/pairs	heuristic	$k = 5$	$k = 10$	$k = 15$	$k = 20$
IOMs	node-heuristics	IP	1212	1853	4036	704
		IN	423	1853	4036	676
		RD	680.3	1363.7	2435.3	260.3
	pair-heuristics	SE	1212	1853	4036	704
		NN	0	1165	0	0
		RD	344.3	215.7	462.7	215.7
IIMs	node-heuristics	IP	2407	4879	4054	648
		IN	1454	2868	4054	144
		RD	244.7	896.0	607.7	55.0
	pair-heuristics	SE	2407	4879	4054	59
		AE	1826	2868	4054	14
		RD	317.3	1355.0	40.7	0.0

Table 28. The full results of the heuristics experiments on *stanford*. For each algorithm, each considered k value, we report the performance of each considered node-heuristic and pair-heuristic.

IOMs/IIMs	nodes/pairs	heuristic	$k = 5$	$k = 10$	$k = 15$	$k = 20$
IOMs	node-heuristics	IP	854	995	973	2964
		IN	854	995	887	2964
		RD	394.7	669.0	942.7	2929.3
	pair-heuristics	SE	854	995	973	2809
		NN	54	512	724	1902
		RD	185.3	395.7	430.0	2151.3
IIMs	node-heuristics	IP	5363	2145	952	2853
		IN	5363	2145	821	2853
		RD	239.0	688.0	808.7	2771.0
	pair-heuristics	SE	5363	2145	952	2813
		AE	4447	2137	949	2813
		RD	923.7	814.3	458.7	1677.0

Table 29. The full results of the heuristics experiments on *youtube*. For each algorithm, each considered k value, we report the performance of each considered node-heuristic and pair-heuristic.

IOMs/IIMs	nodes/pairs	heuristic	$k = 5$	$k = 10$	$k = 15$	$k = 20$
IOMs	node-heuristics	IP	778	1595	930	344
		IN	778	1595	930	687
		RD	84.0	701.7	553.0	551.7
	pair-heuristics	SE	117	1595	930	317
		NN	73	118	194	287
		RD	207.3	193.0	166.3	221.7
IIMs	node-heuristics	IP	30577	2687	1025	287
		IN	30577	2121	1144	954
		RD	121.0	687.3	555.0	615.3
	pair-heuristics	SE	30577	2687	1025	214
		AE	30577	1570	1025	210
		RD	2892.0	1123.0	204.3	204.7

Table 30. The full results of the heuristics experiments on *wikitalk*. For each algorithm, each considered k value, we report the performance of each considered node-heuristic and pair-heuristic.

References

1. BARRETT, R., BERRY, M., CHAN, T. F., DEMMEL, J., DONATO, J., DONGARRA, J., EIJKHOUT, V., POZO, R., ROMINE, C., AND VAN DER VORST, H. *Templates for the solution of linear systems: building blocks for iterative methods*. SIAM, 1994.
2. BHAWALKAR, K., KLEINBERG, J., LEWI, K., ROUGHGARDEN, T., AND SHARMA, A. Preventing unraveling in social networks: the anchored k-core problem. *SIAM Journal on Discrete Mathematics* 29, 3 (2015), 1452–1475.
3. GENE. Efficient algorithm for finding all maximal subsets, 2013.
4. HUANG, X., CHENG, H., QIN, L., TIAN, W., AND YU, J. X. Querying k-truss community in large and dynamic graphs. In *SIGMOD* (2014).
5. WANG, J., AND CHENG, J. Truss decomposition in massive networks. *PVLDB* 5, 9 (2012), 812–823.