

On the Hardness of Partially Dynamic Graph Problems and Connections to Diameter

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Abstract

Conditional lower bounds for dynamic graph problems has received a great deal of attention in recent years. While many results are now known for the fully-dynamic case and such bounds often imply worst-case bounds for the partially dynamic setting, it seems much more difficult to prove amortized bounds for incremental and decremental algorithms. In this paper we consider partially dynamic versions of three classic problems in graph theory. Based on popular conjectures we show that:

- No algorithm with amortized update time $O(n^{1-\varepsilon})$ exists for incremental or decremental maximum cardinality bipartite matching. This significantly improves on the $O(m^{1/2-\varepsilon})$ bound for sparse graphs of Henzinger et al. [STOC'15] and $O(n^{1/3-\varepsilon})$ bound of Kopelowitz, Pettie and Porat¹. Our linear bound also appears more natural. In addition, the result we present separates the node-addition model from the edge insertion model, as an algorithm with total update time $O(m\sqrt{n})$ exists for the former by Bosek et al. [FOCS'14].
- No algorithm with amortized update time $O(m^{1-\varepsilon})$ exists for incremental or decremental maximum flow in directed and weighted sparse graphs. No such lower bound was known for partially dynamic maximum flow previously. Furthermore no algorithm with amortized update time $O(n^{1-\varepsilon})$ exists for directed and unweighted graphs or undirected and weighted graphs.
- No algorithm with amortized update time $O(n^{1/2-\varepsilon})$ exists for incremental or decremental $(4/3 - \varepsilon')$ -approximating the diameter of an unweighted graph. We also show a slightly stronger bound if node additions are allowed. The result is then extended to the static case, where we show that no $O((n\sqrt{m})^{1-\varepsilon})$ algorithm exists. We also extend the result to the case when an additive error is allowed in the approximation. While our bounds are weaker than the already known bounds of Roditty and Vassilevska Williams [STOC'13], it is based on a weaker conjecture of Abboud et al. [STOC'15] and is the first known reduction from the 3SUM and APSP problems to diameter. Showing an equivalence between APSP and diameter is a major open problem in this area (Abboud et al. [SODA'15]), and thus showing even a weak connection in this direction is of interest.

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¹ Kopelowitz et al. showed this result at SODA'16, and after posting their result online it was improved in an online version of the paper by Henzinger et al. Kopelowitz et al. also showed a slightly stronger bound of $O(n^{0.39-\varepsilon})$ if node insertions are allowed.



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1 Introduction

Arguably one of the most important goals of computer science is to understand the complexity of natural computational problems. For many such problems we know of polynomial time algorithms, but getting matching unconditional lower bounds seem far beyond the scope of our current techniques. Therefore a recent and very active line of research at top-level conferences concerns itself with hardness results in the class \mathbf{P} [26, 6, 8, 17, 21, 3, 14, 4, 13, 12, 10, 2, 1]. Such results are obtained by reducing from classic problems like 3SUM, APSP and CNF-SAT, for which there exist very popular conjectures about the running time. We call such a hardness result a *conditional lower bound (CLB)* as it is based (conditioned) on the truthfulness of some popular conjecture. The main goal of CLBs is to explain barriers in algorithm development and provide “warning signs” that improving an algorithm for some problem has major and surprising consequences for a classic problem like the ones mentioned above, which researchers have worked on for decades, and trying to do so may be ill-advised.

One particular area that has received a lot of attention from this perspective is dynamic graph problems [29, 26, 6, 8, 17, 21]. In dynamic graph problems we are asked to maintain some property about a graph such as reachability or shortest paths distances as the graph undergoes changes (typically edge insertions and deletions). One may also consider the partially dynamic cases where only edge insertions are allowed (incremental) or edge deletions (decremental) or cases where node insertion and deletion is allowed. Several conditional lower bounds are known for both partially and fully dynamic problems such as shortest paths [29, 17], maximum bipartite matching [6, 17, 21], maximum flow [8], reachability [26, 6, 17], and many more.

1.1 Difficulties of partially dynamic

Most of the research on CLBs for dynamic graph problems has been focused on the fully dynamic case, however such results do not translate well into CLBs for incremental or decremental algorithms. A typical reduction works by 1) building a structured base graph, 2) for each element in some subset of the input perform a series of insertions and queries to decide whether this element is in a possible solution, 3) perform a series of deletions returning the graph to its base state. From a partially dynamic perspective we may use the above procedure to get similar *worst-case* bounds, by keeping track of the data structure state and simulating step 3 by *rolling back* the insertions, however this kills any hope of good amortized bounds. As noted in [6, 17, 21] it seems more difficult to obtain good bounds in this case, and specialized reductions are often needed.

1.2 Bounds under weaker assumptions

While proving higher lower bounds is the main goal of CLBs, a simultaneous goal is to prove similar CLBs under weaker assumptions, thus lending more credibility to the belief that a problem is difficult or even impossible. Several recent papers concerns themselves with this be either replacing a conjecture with a weaker version as done by Abboud et al. in [4] or by showing similar reductions under several conjectures [32, 5, 7, 8, 17]. As an example Abboud, Vassilevska Williams, and Yu [8] showed that 3SUM, APSP and CNF-SAT can all be reduced to the same problem of finding triangles in a node-colored graph and showed several interesting results based on the following conjecture:

► **Conjecture 1** ([8]). *At least one of the following is true:*

1. *There is no algorithm for the 3-SUM problem running in $O(n^{2-\varepsilon})$ for any $\varepsilon > 0$.*

2. *There is no algorithm for the APSP problem on weighted graphs running in $O(n^{3-\varepsilon})$ for any $\varepsilon > 0$.*
3. *For every $\delta > 0$ there is an integer $k \geq 3$ such that k -SAT on n variables and $O(n)$ clauses cannot be solved in $2^{(1-\delta)n} \text{poly}(n)$ time.*

The third item in Conjecture 1 is what is known as the strong exponential time hypothesis (SETH) [18] and the $O(n)$ bound on the number of clauses follows from the sparsification lemma of Impagliazzo, Paturi, and Zane [19].

1.3 Our results

In this paper we consider three of the perhaps most classic problems in graph theory, namely maximum flow, maximum bipartite matching and diameter in the partially dynamic setting. For maximum flow and maximum bipartite matching we show new, stronger, and more natural conditional lower bounds. For diameter we show a new reduction from Conjecture 1 to both the partially dynamic version of diameter and, perhaps more interestingly, the static case. This is the first known connection from APSP and 3SUM to diameter in graphs and addresses one of the main open problems in the area as stated in [3].

Maximum bipartite matching. In dynamic maximum cardinality bipartite matching we wish to maintain the size of a maximum matching in a dynamic graph G . One can trivially do this in $O(m)$ time by finding an augmenting path. Sankowski [30] gave a fully dynamic algorithm with update time $O(n^{1.495})$ by using fast matrix multiplication. In the incremental setting, one may consider a node-addition version in which the right-hand side of the bipartite graph is given and the left-hand side arrives one node at a time with all its incident edges. In this model Bosek et al. [11] gave an algorithm with total running time of $O(m\sqrt{n})$. From a hardness perspective, Abboud and Vassilevska Williams [6] gave reductions from 3SUM, triangle detection and boolean matrix multiplication to fully-dynamic maximum cardinality bipartite matching. In particular, they showed that a $O(n^{2-\varepsilon})$ algorithm would imply a faster *combinatorial* boolean matrix multiplication algorithm. Their reductions, however, only imply worst-case bounds in the case of partially dynamic algorithms. This was addressed by Kopelowitz, Pettie and Porat [21] who revisited Pătraşcu's reductions from [26] and showed that any $O(n^{1/3-\varepsilon})$ algorithm for incremental MCM would imply a truly subquadratic algorithm for 3SUM. They also showed the same result for $O(n^{0.39-\varepsilon})$ algorithms when node insertions are allowed. Subsequently, in an online version of [17], it was shown how to obtain a CLB of $O(m^{1/2-\varepsilon})$ in sparse graphs by reducing from the online matrix-vector multiplication (OMv) problem.

In this paper we show the following theorem:

► **Theorem 2.** *There is no algorithm for solving incremental (or decremental) maximum cardinality bipartite matching with amortized time $O(n^{1-\varepsilon})$ per insertion (or deletion) and $O(n^{2-\varepsilon})$ time per query unless the OMv conjecture of [17] is false.*

One thing to note about Theorem 2 is that it separates the node-addition model from the edge-insertion model as it implies a total running time of $O(mn^{1-o(1)})$ in contrast to the $O(m\sqrt{n})$ running time of the algorithm from [11]. Furthermore, the reduction used to prove Theorem 2 also rules out any efficient incremental (or decremental) approximation algorithm that works by ruling out the existence of short augmenting paths. Ruling out such paths is a popular way of ensuring a good approximation ratio [25].

Maximum flow. Single-source single-sink maximum flow (*st* Max-Flow) is one of the most classic problems in graph theory. In recent years there have been several breakthrough results for *st* maximum flow using the powerful tools of Laplacian system solvers and interior point methods [24, 31, 20, 22]. These algorithms seem to take near-line time in practice, and the limits of our current analysis might be the bottleneck in proving such upper bounds. Proving super-linear conditional lower bounds for this problem may thus be difficult if not impossible. Therefore, Abboud et al. [8] considered different variants of the problem such as single-source maximum flow and *ST* maximum flow. They also showed that any algorithm solving the fully-dynamic version of *st* maximum flow with amortized update and query time $O(n^{1-\varepsilon})$ for any $\varepsilon > 0$ would refute Conjecture 1. Finally, we note that it is possible to modify the $m^{1-o(1)}$ CLB for fully dynamic #SSR of Abboud and Vassilevska Williams [6] to obtain a $m^{1-o(1)}$ CLB for fully-dynamic *st* max-flow in sparse graphs.

In this paper we show that even in the incremental and decremental case *st* maximum flow exhibit the same kind of CLB, but based solely on SETH. This is summarized in the following theorem:

► **Theorem 3.** *There is no algorithm for solving incremental (or decremental) max st flow on a weighted and directed graph with n nodes and $\tilde{O}(n)$ edges with amortized time $O(m^{1-\varepsilon})$ per operation for any $\varepsilon > 0$ unless SETH is false.*

Our bound shows that we cannot hope to get incremental maximum flow in offline time as is the case for other problems. We note that the above result only holds for directed and weighted graphs. We show similar results for other types of graphs:

► **Theorem 4.** *There is no algorithm for solving incremental (or decremental) max st flow on unweighted directed graphs or weighted undirected graphs on n nodes with amortized time $O(n^{1-\varepsilon})$ per operation for any $\varepsilon > 0$ unless the OMv conjecture is false.*

This result follows directly from Theorem 2 by using textbook reductions from maximum bipartite matching to directed flow (see e.g. [15]) and from directed flow to undirected flow (see e.g. [23]).

Diameter. The diameter problem asks us to compute the longest shortest-path distance in a graph G . Efficiently computing or approximating the diameter is a basic problem in graphs [3, 9, 14, 16, 28]. One can trivially compute the diameter in the same time as computing APSP, however in general no better algorithm is known. It remains a major open problem whether a reduction exists in the other direction [3] – that is, can we compute all distances in the same time as the longest? One can, however, approximate the diameter faster. Roditty and Vassilevska Williams [28] showed how to compute a $3/2$ -approximation in time $\tilde{O}(m\sqrt{n})$ randomized, and Chechik et al. [14] showed how to obtain the same guarantee deterministically in time $\tilde{O}(\min(m^{3/2}, mn^{2/3}))$. More recently, it was shown by Cairo, Grossi and Rizzi [13] how to obtain a $(2 - \frac{1}{2^k})$ -approximation in time $\tilde{O}(mn^{\frac{1}{k+1}})$. From a hardness perspective it is known that any algorithm able to distinguish between diameter 3 and 2 in time $O(m^{2-\varepsilon})$ for sparse graphs would refute SETH [28]. Chechik et al. [14] showed that approximating within a $4/3 - \varepsilon$ factor with additive error $\beta = O(m^\delta)$ in time $O(m^{2-2\delta-\varepsilon'})$ for sparse graphs would also refute SETH, and this bound was improved in [13] to rule out any $3/2 - \varepsilon$ approximation with the same additive error and time bounds based on SETH (also for sparse graphs). From the perspective of dynamic algorithms Abboud and Vassilevska Williams [6] showed that any algorithm for $4/3 - \varepsilon$ -approximating the diameter in a fully dynamic graph with amortized update time $O(m^{2-\varepsilon'})$ would refute SETH. We also

note, that the above static reductions rules out any $O(m^{1-\varepsilon'})$ amortized update time for incremental algorithms.

We note that all the reductions mentioned above are based on SETH. Similar to the work of [8, 4] we seek to replace this assumption by a weaker one. In this paper we show the first reduction from 3SUM and APSP to the diameter problem. That is, we show that a fast algorithm for approximating the diameter implies a faster algorithm for the APSP and 3SUM problems. The bounds we achieve are not as strong as the known bounds based on SETH [28, 14, 13], however they are based on a weaker conjecture and hold even if SETH turns out to be false, thus giving more credibility to the difficulty of the problem. For the partially dynamic case we show the following theorem:

► **Theorem 5.** *There exists no incremental (or decremental) algorithm that approximates the diameter of an unweighted graph within a factor of $4/3 - \varepsilon$ running in amortized time $O(n^{1/2-\varepsilon'})$ for any $\varepsilon, \varepsilon' > 0$ unless Conjecture 1 is false. Furthermore, if we allow node insertions in the incremental case the bound is $O(n^{0.618-\varepsilon'})$.*

In order to achieve the result for node insertions, we use the technique of Kopelowitz et al. [21] leveraging rollback with our standard incremental bound. By doing this we obtain a graph with fewer nodes and thus a better bound. More interestingly, we are able to generalize our results from the incremental case to the following result for static graphs:

► **Theorem 6.** *There exists no static $4/3 - \varepsilon$ approximation to the diameter on unweighted graphs running in $O((n\sqrt{m})^{1-\varepsilon'})$ time for any $\varepsilon, \varepsilon' > 0$ and any number of edges m unless Conjecture 1 is false.*

As mentioned, this is the first known reduction from APSP to diameter and shows at least some weak connection in this direction. An interesting property of Theorem 6 is that it holds for any m as a function of n and thus an algorithm need not exist for all m . As a corollary of Theorem 6 we see that no algorithm can $(4/3 - \varepsilon)$ -approximate the diameter of static unweighted graph in time $O(n^{2-\varepsilon'})$ for any $\varepsilon, \varepsilon'$ unless Conjecture 1 is false. This is reminiscent of the bounds from [28, 14, 13], however not quite as strong as it does not hold for sparse graphs, for which we get a bound of $O(m^{3/2-\varepsilon'})$.

Similar to [14, 13] we also extend the above bound to the case of $(4/3 - \varepsilon)$ -approximations with additive error $O(m^\delta)$. We show the following

► **Corollary 7.** *There exists no static $4/3 - \varepsilon$ approximation with additive error $O(m^\delta)$ with running time $O(m^{\frac{3}{2}(1-\delta)-\varepsilon'})$ or incremental/decremental algorithm with amortized time $O(m^{\frac{1}{2}-\frac{3\delta}{2}-\varepsilon'})$ for any $\varepsilon, \varepsilon' > 0$ unless Conjecture 1 is false.*

1.4 A note on the decremental results and preprocessing

We will in general only describe the reductions in the incremental case and note that the decremental results are obtained by removing the edges in the reverse order of insertions. This requires an assumption on the beginning graph, and we will thus assume any suitable graph on $\tilde{O}(n)$ edges in the sparse case and the complete graph in the dense case.

Furthermore, we do not assume that any of the algorithms are allowed to preprocess the graph. It is often an assumption in the design of amortized partially dynamic algorithms that one starts with the empty (or complete) graph in order for the analysis to work. Thus, our results hold for this case.

2 Preliminaries

Notation. Throughout the paper we assume that matrices are boolean. Thus the output of a vector-matrix-vector multiplication will always be a single bit. We use $[n]$ to denote the set $\{0, \dots, n-1\}$.

Online vector-matrix-vector multiplication. We will consider the online vector-matrix-vector multiplication problem of [17]:

► **Definition 8** (Oumv problem [17]). Let M be a binary $n \times n$ matrix that can be preprocessed. After preprocessing n vector pairs $(u^1, v^1), \dots, (u^n, v^n)$ arrive one at a time and the task is to compute $(u^i)^T M v^i$ before being presented with the $i+1$ th vector pair for every i .

In [17] they showed that the OMv problem can be reduced to the Oumv problem. They also came up with the following conjecture:

► **Conjecture 9** ([17]). *There is no algorithm for the OMv problem (and thus the Oumv problem) running in time $O(n^{3-\varepsilon})$ for any $\varepsilon > 0$.*

Triangle collection. We will also consider the triangle collection problem of [8]:

► **Definition 10** (Triangle collection [8]). Given a node-colored graph G , is it true that for every triplet of colors a, b, c there exists a triangle (u, v, w) in G where u has color a , v has color b and w has color c ?

In fact, we will consider the more structured triangle collection* (TC*) problem which they also used in [8]

► **Definition 11** (Triangle collection* [8]). Let n, Δ, p be parameters and let G be an undirected node-colored tripartite graph with partitions A, B, C . Let G be any graph with the following structure:

- Each partition has its own n colors and we denote these by the numbers of $[n]$ for each partition.
- A contains nodes of the form a_j^i , where $i \in [n]$ is the color of the node and $j \in [\Delta]$.
- B and C contains nodes of the form $b_{j,x}^i$ and $c_{j,x}^i$ where $i \in [n]$ is the color of the node and $j \in [\Delta], x \in [p]$.

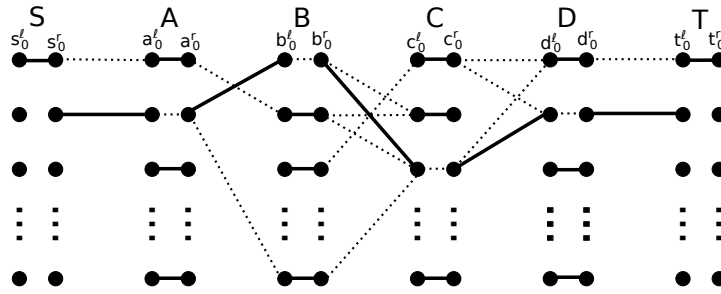
And the edges of G are as follows:

- For each $i, i' \in [n]$ and $j \in [\Delta]$ there is an edge from a_j^i to $b_{j,x}^{i'}$ for *exactly one* x . Similarly there is an edge from a_j^i to $c_{j,y}^{i'}$ for exactly one y (note that y and x need not be the same for the same j and i').
- There may be an edge between nodes $b_{j,x}^i$ and $c_{j',y}^{i'}$ *only if* $j = j'$.

We ask the following question: Does there exist a triple of colors (one color per partition) such that G does not contain a triangle with these colors?

In [8] it was shown that this problem does not have a truly subcubic algorithm unless Conjecture 1 is false.

It will be important that the reductions from these problems to TC* hold even when Δ and p are bounded by $\text{polylog}(n)$.



■ **Figure 1** Reduction to incremental maximum matching.

3 Incremental maximum matching

We will reduce from the OuMv problem of Definition 8. Observe that the OuMv problem is equivalent to the following statement: For each vector pair u^i, v^i determine whether indices j, k exist, such that $u_j^i = v_k^i = M_{jk} = 1$. In order to model this as an incremental maximum matching problem we construct the following graph: Create 6 copies of $2n$ nodes and name these S, A, B, C, D, T . Partition A into n pairs of nodes $a_1^l, a_1^r, \dots, a_n^l, a_n^r$. Do the same for S, B, C, D, T . Add the edges (a_i^l, a_i^r) for each i and do the same for B, C, D . Now for each i, j add the edge (b_i^r, c_j^l) if $M_{ij} = 1$. Observe that this graph has a unique maximum matching each (l, r) pair. Observe also that the graph is bipartite. Now we do the following n phases – one for each u^i, v^i vector pair.

1. For each j such that $u_j^i = 1$ add the edge (a_i^r, b_j^l) .
2. For each j such that $v_j^i = 1$ add the edge (c_j^r, d_i^l) .
3. Add the edges (s_i^r, a_i^l) and (d_i^r, t_i^l) .
4. Query the size of a maximum matching.
5. Add the edges (s_i^l, s_i^r) and (t_i^l, t_i^r) .

This is illustrated in Figure 1.

► **Lemma 12.** *Let the setting be as above and let the phases be numbered $0, 1, \dots, n - 1$. Then the size of the maximum matching during the i th phase is exactly $4n + 2i + 1$ if the resulting vector-matrix-vector product is 1 and $4n + 2i$ otherwise.*

Proof. Note that prior to any of the i phases the size of the maximum matching is exactly $4n + 2i$, which is also a perfect matching of the graph induced by the edges. To see this observe that each s_0^l, \dots, s_{i-1}^l must be matched to its corresponding s_0^r, \dots, s_{i-1}^r , and this is the only edge incident to the l -nodes. As a consequence of this, each a_j^l must be matched with a_j^r , and so on.

Now consider the i th phase. Adding any edge (a_i^r, b_j^l) or (c_j^r, d_i^l) cannot increase the size of the maximum matching, as the size of the subgraph induced by the edges of the graph does not increase – i.e. all nodes with edges incident to them are already matched.

Assume that adding the edges (s_i^r, a_i^l) and (t_i^r, d_i^l) increases the matching. The matching can increase by at most 1, as only two more nodes can be matched. Furthermore the matching must now contain edges as follows

$$(s_i^r, a_i^l), (a_i^r, b_j^l), (b_j^r, c_k^l), (c_k^r, d_x^l), (d_x^r, t_y^l) .$$

Now observe that each t_y^l for $y < i$ must be matched to t_y^r , as the right nodes have no other incident edges and all nodes have to be matched for the size of the matching to increase.

Thus we must have $y = i$ in the list above, but this means that we have exactly found a pair j, k such that $u_j^i = v_k^i = M_{jk} = 1$ and the vector-matrix-vector product is thus 1.

Conversely, assume that the vector-matrix-vector product is 1, then such an index pair j, k must exist and we can find the following matching of size $4n + 2i + 1$: Match the edges

$$(s_i^r, a_i^\ell), (a_i^r, b_j^\ell), (b_j^r, c_k^\ell), (c_k^r, d_i^\ell), (d_i^r, t_i^\ell).$$

For all $x < i$ add the edges (s_x^ℓ, s_x^r) and (t_x^ℓ, t_x^r) to the matching. For all $x \neq i$ add the edges (a_x^ℓ, a_x^r) and (d_x^ℓ, d_x^r) to the matching. And for all $x \neq j$ and $y \neq k$ add the edges (b_x^ℓ, b_x^r) and (c_y^ℓ, c_y^r) to the matching. This matches all nodes incident to an edge and has size $4n + 2i + 1$. This is also exactly the matching illustrated in Figure 1 for $i = 1$. ◀

It follows from Lemma 12 that we can solve the OuMv problem correctly via this reduction. The reduction creates a graph with $O(n)$ nodes and $O(n^2)$ edges. We perform $O(n^2)$ insertions and $O(n)$ queries giving the result in Theorem 2

4 Maximum flow

In order to show Theorem 3 we will use a similar graph construction as have been used numerous times before [27, 28, 14, 6]: First partition the variables of the SAT problem into two groups A and B of $n/2$ variables each. For each possible assignment to the variables in A we create a node in our graph G (and likewise for B). Furthermore, for each clause of the SAT formula, we create a node as well. We denote the corresponding sets of nodes by A, B, C . Set $N = 2^{n/2} = |A| = |B|$. For each pair of nodes $a \in A, c \in C$ we add the directed edge (a, c) with capacity N if the partial assignment a does not satisfy the clause c . Similarly, for each pair of nodes $b \in B, c \in C$ we add the directed edge (c, b) with capacity 1 if b does not satisfy c . Finally we add two nodes s, t and add edges (b, t) with capacity 1 for each $b \in B$.

We now continue in phases with a phase for each $a \in A$. Denote these nodes by a_1, a_2, \dots, a_N :

1. Add the edge (s, a_i) with capacity N .
2. Query the maximum flow between s and t .
3. Add the edge (“shortcut”) (a_i, t) with capacity N .

► **Lemma 13.** *Let the setup be as described above. If the st flow returned during any of the i phases is $< i \cdot N$, then the SAT formula is satisfiable. Otherwise the formula is not satisfiable.*

Proof. Observe, that prior to the i th phase, the flow is exactly $(i - 1) \cdot N$, as we can use the paths $(s, a_j), (a_j, t)$ for each $j < i$, which has capacity N and exactly $(i - 1) \cdot N$ flow leaves s .

Now assume that the partial formula corresponding to a_i can be completed to a satisfying assignment. In this case, there must be some node $b \in B$, for which there is no path from a_i to b . This follows because such a path has to go through a node $c \in C$, but then both a_i and b do not satisfy the clause c , which is a contradiction. However, the only way to send flow from a_i to t is through the nodes $b \in B$ and thus it is not possible to send all N units of flow from a_i to t .

Now assume that the flow is $< i \cdot N$, then there must be some $b \in B$ such that there is no path from a_i to b . Otherwise, we could route N units of flow from a_i to t via the nodes of B and the remaining $(i - 1) \cdot N$ units through the “shortcuts”. It now follows that a_i and b together satisfy all clauses (otherwise there would be a path) and thus the CNF formula is satisfiable.

Since this is true for all of the i phases, the statement of the lemma follows. ◀

As a consequence of Lemma 13 we may use the above procedure to solve the given SAT problem. By the sparsification lemma of [19] it follows that we can assume the graph has $O(N)$ nodes and $\tilde{O}(N)$ edges and we perform a total of $\tilde{O}(N)$ insertions and queries. The result of Theorem 3 thus follows directly.

5 Diameter

In this section we show how to obtain conditional lower bounds for the problem of approximating the diameter of an unweighted graph within a factor of $4/3 - \varepsilon$.

5.1 A graph construction

We will first describe the graph structure we use.

► **Definition 14.** Let G be an instance of the TC* problem as defined above. We will define the graph $H_{\gamma,k}(G)$. The idea is that $H_{\gamma,k}(G)$ “corresponds” to the colors $\{kn^\gamma, \dots, (k+1)n^\gamma - 1\}$ of A . Thus k is a number in $[n^{1-\gamma}]$. The nodes of this graph are as follows:

- The nodes B and C of G .
- For each color $i \in \{kn^\gamma, (k+1)n^\gamma - 1\}$ of A we add the nodes a_0^i, \dots, a_{n-1}^i and t_0^i, \dots, t_{n-1}^i .
- We also add several special nodes: A “master node” u , n^γ “skip nodes” v_i and three “connector nodes” w_1, w_2, w_3 .

For a color $i \in \{kn^\gamma, (k+1)n^\gamma - 1\}$ we denote the nodes a_0^i, \dots, a_{n-1}^i by A_i and the collection of all A_i s by A . We do the same for T_i and T .

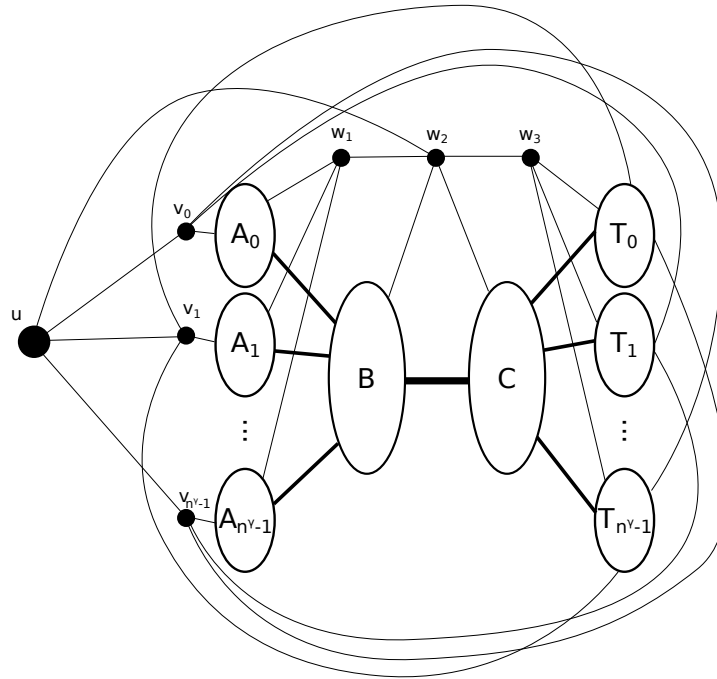
The edges of $H_{\gamma,k}(G)$ are as follows:

- Add the edges between B and C in G .
- Connect the node w_1 to each node of A and w_2 .
- Connect w_2 to each node of B and C as well as w_3 and the master node u .
- Connect w_3 to each node of T .
- Connect u to all nodes v_i .
- For each $i \in \{kn^\gamma, (k+1)n^\gamma - 1\}$ do as follows:
 - Connect v_i to all nodes of $T \setminus T_i$ and to all nodes of A_i .
 - For each $i' \in [n]$ and each edge $(a_j^i, b_{j,x}^{i'}) \in G$ add the edge $(a_{i'}^i, b_{j,x}^{i'})$.
 - For each $i' \in [n]$ and each edge $(a_j^i, c_{j,x}^{i'}) \in G$ add the edge $(c_{j,x}^{i'}, t_{i'}^i)$.

An overview of the graph $H_{\gamma,k}(G)$ is illustrated in Figure 2 and a more detailed view in Figure 3.

The idea is that length three paths between A_i and T_i correspond to triangles in G containing the color i of A . Each of the n nodes in A_i thus correspond to picking a color from B and each of the n nodes in T_i correspond to picking a color from C . If two such nodes don’t have a length three path there is no triangle in G of the corresponding triplet of colors. In this case the connector nodes ensure that there is a length four path between the nodes. The master and skip nodes ensure that all other nodes have distance at most 3. This is captured by the following lemma:

► **Lemma 15.** *Let G be an instance to the TC* problem and let $H_{\gamma,k}(G)$ be as defined above. Let $i \in \{kn^\gamma, (k+1)n^\gamma - 1\}$ be a color of A and let $\alpha, \beta \in [n]$ be colors of B and C respectively. Then the distance from a_α^i to t_β^i in $H_{\gamma,k}(G)$ is 3 if the colors i, α, β have a triangle in G and 4 otherwise.*



■ **Figure 2** Diameter structure.

Proof. Assume first that there is a triangle $a_j^i, b_{j,x}^\alpha, c_{j,y}^\beta$ for some j in G (note that such a triangle can only occur if j is the same for all the three nodes). In this case there is a path $a_\alpha^i, b_{j,x}^\alpha, c_{j,y}^\beta, t_\beta^i$ in $H_{\gamma,k}(G)$ and thus the distance is at most 3. Observe also, that no node is connected to both A_i and T_i and thus the distance is strictly greater than 2.

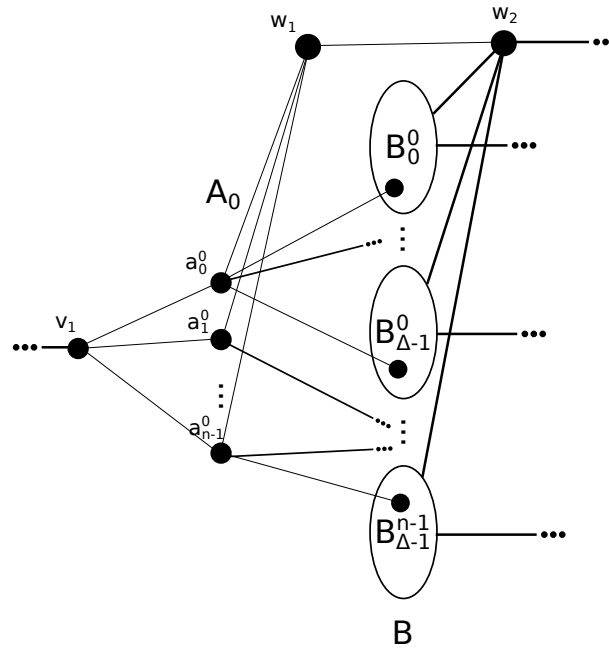
Now assume that the distance from a_α^i to t_β^i is 3. Such a path has to go from A_i to B to C to T_i as any node w_ℓ, v_ℓ or u either has distance 3 to one of a_α^i or t_β^i or it has distance 2 to both of them. Now consider a shortest path $a_\alpha^i, b, c, t_\beta^i$, where b and c are the nodes of B and C on this path. Clearly the node b must have color α in G as it would not have an edge to a_α^i otherwise, and similarly c must have color β in G . Thus the path consists of nodes $a_\alpha^i, b_{j,x}^\alpha, c_{j',y}^\beta, t_\beta^i$. Since no edge in G goes between nodes with different j -values we must have $j' = j$. It is now clear that the edge $(a_\alpha^i, b_{j,x}^\alpha)$ corresponds to the edge $(a_j^i, b_{j,x}^\alpha)$ in G and the edge $(c_{j,y}^\beta, t_\beta^i)$ corresponds to the edge $(a_j^i, c_{j,y}^\beta)$ in G . Thus, these three nodes form a triangle of the correct color triple in G . ◀

Furthermore it is easy to see that the longest distance in $H_{\gamma,k}(G)$ is at most 4, thus the diameter is 4 exactly when one of the corresponding color triplets do not have a triangle in G and 3 otherwise.

5.2 Dynamic

We will first consider the problem without node additions. For simplicity we only consider the incremental case and note that the decremental case follows by deleting edges until we obtain the same graph².

² Under the assumption that the algorithm starts with some suitable graph



■ **Figure 3** Diameter structure.

Given an instance to the TC^* problem we create the graph $H_{1,0}(G)$ (that is, the graph representing all colors of A). This graph is created by adding edges incrementally and has $\tilde{O}(n^2)$ nodes and edges. It follows that an edge insertion must take $n^{1/2-o(1)}$ time unless Conjecture 1 is false.

Next, we consider the problem with node additions. It was shown in [21] that if we allow node additions in the problem of incremental maximum matching, it is possible to show stronger lower bounds by leveraging the amortized running time with the widely used rollback technique. We here apply the same argument to the problem of incremental diameter approximation.

The goal is again to construct (a subgraph of) $H_{1,0}(G)$ but we do not start with all nodes in the graph. We will assume that the amortized running time of an insert operation is n^α for some α . The goal is to get a bound on α by expressing the total running time in terms of α and using the assumption on running time for TC^* . We let \hat{n} denote the current number of nodes in the graph G . We continue as follows:

1. Insert all nodes of B and C into the dynamic graph. Also insert the nodes w_1, w_2, w_3 and u . We also insert all the edges induced by these nodes in $H_{1,0}(G)$ into the graph.
2. For each color $i \in [n]$ of A we do a phase:
 - We insert the nodes of A_i, T_i, v_i into the dynamic graph and all the edges induced by these nodes and the current state of the dynamic graph in $H_{1,0}(G)$.
 - Query the diameter of the graph.
 - Assume we inserted k edges+nodes in this phase. If the total running time of all these insertions was greater than $2k\hat{n}^\alpha$ we keep the nodes in the graph. Otherwise we rollback all operations of this phase.

We answer the question of the TC^* problem according to whether the diameter was 3 all the time or not similar to the proof of the case without node additions.

The goal is now to bound α by using the method of [21]. We will do this by carefully

counting the number of “amortized credit units” the data structure has and using this to bound the total number of nodes added to the graph (i.e. not rolled back).

Observe that after the first step, we have added $\tilde{O}(n^2)$ edges to the graph and $\tilde{O}(n)$ nodes. Thus the data structure has at most $\tilde{O}(n^{2+\alpha})$ credit at this point (this happens if almost all operations were $O(1)$). Now consider the total time spent by the algorithm. This can be bounded by $\tilde{O}(n^2 \cdot N^\alpha)$ where N is the number of nodes at the end of all phases. This is the case since $N \geq N_0$, where $N_0 = \tilde{O}(n)$ is the number of nodes after the first step and there are at most $\tilde{O}(n^2)$ total operations. Note that this would not be the case if we did not have a bound on the cost of the rolled back operations, but we only rollback the cheap operations, so this is okay. We wish to express N in terms of n and α in order to express the total running time in terms of these.

Observe, that every time we keep the added nodes in the graph, the data structure spent at least twice the amortized cost. Since we started out with $\tilde{O}(n^{2+\alpha})$ credit it must be true that

$$\sum_{i=N_0}^N i^\alpha \leq \text{cost of non-rolled-back operations} = \tilde{O}(n^{2+\alpha}) .$$

The worst case is if N is polynomially larger than N_0 , and thus $\sum_{i=N_0}^N i^\alpha = \Omega(N^{1+\alpha})$. It follows that $N = \tilde{O}(n^{\frac{2+\alpha}{1+\alpha}})$. Thus the total running time is $\tilde{O}(n^2 \cdot n^{\frac{2+\alpha}{1+\alpha}\alpha})$. Now, by Conjecture 1 we must have $\frac{2+\alpha}{1+\alpha}\alpha = 1 - o(1)$. Solving this for α gives $\alpha = \frac{\sqrt{5}-1}{2} < 0.618$.

5.3 Static

Proof of Theorem 6. Let G be an instance of the TC* problem with parameters n, Δ, p with Δ and p bounded by $\tilde{O}(1)$ and $m = \tilde{O}(n^2)$ as in [8].

For a parameter $0 < \gamma \leq 1$ we create the graphs $H_{\gamma,0}(G), \dots, H_{\gamma,n^{1-\gamma}-1}(G)$ and solve the diameter problem on these graphs up to a $4/3 - \varepsilon$ approximation. This is sufficient to distinguish between diameters 4 and 3 in all of the graphs. Now, if the diameter is 4 in just one of the graph we answer that there exists a triplet of colors such that there is no triangle in G . This follows from Lemma 15.

We note that the graphs $H_{\gamma,k}(G)$ each have $N = \tilde{O}(n^{1+\gamma})$ nodes and $M = \tilde{O}(n^2)$ edges. Assume now that that any algorithm approximating the diameter within a factor of $4/3 - \varepsilon$ in time $O(N\sqrt{M}^{1-\varepsilon'}) = O(n^{2+\gamma-\varepsilon'})$ for any $\varepsilon, \varepsilon' > 0$ exists. Since we create $n^{1-\gamma}$ instances of the problem this would imply an $O(n^{3-\varepsilon''})$ algorithm for the TC* problem for some $\varepsilon'' > 0$. ◀

5.4 Additive error

To see Corollary 7 we fix m^α and consider TC* on a graph G with N nodes and $M = \tilde{O}(N^2)$ edges such that $M = m^{1-\alpha}$. We then create $H_{1,0}(G)$ and subdivide each edge into m^α nodes. This graph now has m nodes and edges and any algorithm solving $4/3 - \varepsilon$ diameter with additive error $O(m^\alpha)$ in time $M^{3/2-\varepsilon'} = m^{\frac{3}{2}(1-\alpha)-\varepsilon''}$ time thus violates Conjecture 1.

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