

Near-Optimal Massively Parallel Graph Connectivity*

Soheil Behnezhad[†]
University of Maryland
soheil@cs.umd.edu

Laxman Dhulipala
Carnegie Mellon University
ldhulipa@cs.cmu.edu

Hossein Esfandiari
Google Research
esfandiari@google.com

Jakub Lacki
Google Research
jlacki@google.com

Vahab Mirrokni
Google Research
mirrokni@google.com

Abstract

Identifying the connected components of a graph, apart from being a fundamental problem with countless applications, is a key primitive for many other algorithms. In this paper, we consider this problem in parallel settings. Particularly, we focus on the *Massively Parallel Computations* (MPC) model, which is the standard theoretical model for modern parallel frameworks such as MapReduce, Hadoop, or Spark. We consider the *truly sublinear* regime of MPC for graph problems where the space per machine is n^δ for some desirably small constant $\delta \in (0, 1)$.

We present an algorithm that for graphs with diameter D in the wide range $[\log^\epsilon n, n]$, takes $O(\log D)$ rounds to identify the connected components and takes $O(\log \log n)$ rounds for all other graphs. The algorithm is *randomized*, succeeds with high probability¹, does not require prior knowledge of D , and uses an optimal total space of $O(m)$. We complement this by showing a conditional lower-bound based on the widely believed 2-CYCLE conjecture that $\Omega(\log D)$ rounds are indeed necessary in this setting.

Studying parallel connectivity algorithms received a resurgence of interest after the pioneering work of Andoni *et al.* [FOCS 2018] who presented an algorithm with $O(\log D \cdot \log \log n)$ round-complexity. Our algorithm improves this result for the whole range of values of D and almost settles the problem due to the conditional lower-bound.

Additionally, we show that with minimal adjustments, our algorithm can also be implemented in a variant of the (CRCW) PRAM in asymptotically the same number of rounds.

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¹We use the term *with high probability* to refer to probability at least $1 - n^{-c}$ for arbitrarily large constant $c > 1$.

1 Introduction

Identifying the connected components of a graph is a fundamental problem that has been studied in a variety of settings (see e.g. [2, 33, 28, 61, 65, 57] and the references therein). This problem is also of great practical importance [60] with a wide range of applications, e.g. in clustering [57]. The main challenge is to compute connected components in graphs with over hundreds of billions or even trillions of nodes and edges [60, 64]. The related theory question is:

What is the true complexity of finding connected components in massive graphs?

We consider this problem in parallel settings which are a common way of handling massive graphs. Our main focus is specifically on the *Massively Parallel Computations* (MPC) model [12, 45, 38]; however, we show that our techniques are general enough to be seamlessly implemented in other parallel models such as (CRCW) PRAM. The MPC model is arguably the most popular theoretical model for modern parallel frameworks such as MapReduce [30], Hadoop [5], or Spark [67] and has received significant attention over the past few years (see Section 1.1). We consider the strictest regime of MPC for graph problems where the space per machine is strongly sublinear in n .

The MPC model. The input, which in our case is the edge-set of a graph $G(V, E)$ with n vertices and m edges, is initially distributed across M machines. Each machine has a space of size $S = n^\delta$ words where constant $\delta \in (0, 1)$ can be made arbitrarily small. Furthermore, $M \cdot S = O(m)$ so that there is only enough total space to store the input. Computation proceeds in rounds. Within a round, each machine can perform arbitrary computation on its local data and send messages to each of the other machines. Messages are delivered at the beginning of the following round. An important restriction is that the total size of messages sent and received by each machine in a round should be $O(S)$. The main objective is to minimize the number of rounds that are executed.

What we know. Multiple algorithms for computing connected components in $O(\log n)$ MPC rounds have been shown [45, 64, 57, 48]. On the negative side, a popular 2-CYCLE conjecture [66, 59, 48, 7] implies that $\Omega(\log n)$ rounds are necessary. Namely, the conjecture states that in this regime of MPC, distinguishing between a cycle on n vertices and two cycles on $n/2$ vertices each requires $\Omega(\log n)$ rounds. However, the 2-CYCLE conjecture and the matching upper bound are far from explaining the true complexity of the problem. First, the hard example used in the conjecture is very different from what most graphs look like. Second, the empirical performance of the existing algorithms (in terms of the number of rounds) is much lower than what the upper bound of $O(\log n)$ suggests [47, 48, 64, 57, 52].

This disconnect between theory and practice has motivated the study of graph connectivity as a function of diameter D of the graph. The reason is that the vast majority of real-world graphs, indeed have very low diameter [50, 27]. This is reflected in multiple theoretical models designed to capture real-world graphs, which yield graphs with polylogarithmic diameter [19, 39, 51, 20].

Our contribution. Our main contribution is the following algorithm:

Theorem 1 (main result). *There is a strongly sublinear MPC algorithm with $O(m)$ total space that given a graph with diameter D , identifies its connected components in $O(\log D)$ rounds if $D \geq \log^\epsilon n$ for any constant $\epsilon > 0$, and takes $O(\log \log_{m/n} n)$ rounds otherwise. The algorithm is randomized, succeeds with high probability, and does not require prior knowledge of D .*

The 2-CYCLE conjecture mentioned above directly implies that $o(\log D)$ round algorithms do not exist in this setting for $D = \Theta(n)$. However, it does not rule out the possibility of achieving an

$O(1)$ round algorithm if e.g. $D = O(\sqrt{n})$. We refute this possibility and show that indeed for any choice of $D \in [\log^{1+\Omega(1)}, n]$, there are family of graphs with diameter D on which $\Omega(\log D)$ rounds are necessary in this regime of MPC, if the 2-CYCLE conjecture holds.

Theorem 2. *Fix some $D' \geq \log^{1+\rho} n$ for a desirably small constant $\rho \in (0, 1)$. Any MPC algorithm with $n^{1-\Omega(1)}$ space per machine that w.h.p. identifies each connected component of any given n -vertex graph with diameter D' requires $\Omega(\log D')$ rounds, unless the 2-CYCLE conjecture is wrong.*

We note that proving any unconditional super constant lower bound for any problem in P , in this regime of MPC, would imply $\mathsf{NC}^1 \subsetneq \mathsf{P}$ which seems out of the reach of current techniques [59].

Extention to PRAM. As a side result, we provide an implementation of our connectivity algorithm in $O(\log D + \log \log_{m/n} n)$ depth in the multiprefix CRCW PRAM model, a parallel computation model that permits concurrent reads and concurrent writes. This implementation of our algorithm performs $O((m+n)(\log D + \log \log_{m/n} n))$ work and is therefore *nearly* work-efficient. The following theorem states our result. We defer further elaborations on this result to Appendix B.3.

Theorem 3. *There is a multiprefix CRCW PRAM algorithm that given a graph with diameter D , identifies its connected components in $O(\log D + \log \log_{m/n} n)$ depth and $O((m+n)(\log D + \log \log_{m/n} n))$ work. The algorithm is randomized, succeeds with high probability and does not require prior knowledge of D .*

Comparison with the state-of-the-art. The round complexity of our algorithm improves over that of the state-of-the-art algorithm by Andoni *et al.* [4] that takes $O(\log D \cdot \log \log_{m/n} n)$ rounds. Note that the algorithm of [4] matches the $\Omega(\log D)$ lower bound for a very specific case: if the graph is extremely dense, i.e., $m = n^{1+\Omega(1)}$. In practice, this is usually not the case [24, 50, 32]. In fact, it is worth noting that the main motivation behind the MPC model with sublinear in n space per machine is the case of sparse graphs [45]. We also note that for the particularly important case when $D = \text{poly log } n$, our algorithm requires only $O(\log \log n)$ rounds. This improves quadratically over a bound of $O(\log^2 \log n)$ rounds, which follows from the result of [4].

Our result also provides a number of other qualitative advantages. For instance it succeeds with high probability as opposed to the constant success probability of [4]. Furthermore, the running time required for identifying each connected component depends on its own diameter only. The diameter D in the result of [4] is crucially the largest diameter in the graph.

1.1 Further Related work

The MPC model has been extensively studied over the past few years especially for graph problems. See for instance [45, 38, 49, 11, 3, 1, 59, 42, 9, 29, 35, 13, 14, 10, 6, 15, 36, 22, 4, 7, 21] and the references therein.

More relevant to our work on graph connectivity, a recent result by Assadi *et al.* [7] implies an $O(\log \frac{1}{\lambda} + \log \log n)$ round algorithm for graphs with $\tilde{O}(n)$ edges that have *spectral gap* at least λ . By a well-known bound, $D = O(\frac{\log n}{\lambda})$. Therefore, our algorithm requires $O(\log D + \log \log n) = O(\log(\frac{\log n}{\lambda}) + \log \log n) = O(\log \frac{1}{\lambda} + \log \log n)$ rounds for graphs with spectral gap at least λ . As a result, the running time bound of our algorithm is never worse than the bound due to Assadi *et al.* However, as shown in [4], there are graphs with $\frac{1}{\lambda} \geq D \cdot n^{\Omega(1)}$ making our algorithm more general.

Finally, we remark that a preprint claiming a deterministic MPC connectivity algorithm requiring only $O(\log D)$ rounds has been published recently [23]. However, the key claim of the paper is fundamentally incorrect. Specifically, the paper first shows that the algorithm requires $O(\log k)$

rounds for a graph that is a path of length k and directly concludes that this implies round complexity of $O(\log D)$ (see Lemma 3 in [23]). This kind of reasoning is not valid. In particular, the HashToMin algorithm [57] works in $O(\log k)$ rounds for graphs consisting of disjoint paths of length at most k , but has been shown to require $\omega(\log D)$ rounds for certain graphs [4]. Apart from the fact that the proof is incorrect, we believe that the counterexample of [4] also shows that the algorithm of [23] on a family of graphs with diameter $O(\log n)$, has round complexity $\Omega(\log n) = \Omega(D)$.

1.2 Paper Organization

Section 2 gives a high-level overview of our techniques. Sections 3 and 4 are devoted to our algorithm, its correctness and performance. Then, in Section 5 we give a new lower bound for the problem of solving connectivity in the MPC model. In Appendix A we describe the implementation details of the algorithm in the MPC model. We remark that the implementation follows from standard techniques, but we provide it for completeness.

2 High-Level Overview of Techniques

Recall that we assume the regime of MPC with strictly sublinear space of n^δ with δ being a constant in $(0, 1)$. This local space, roughly speaking, is usually not sufficient for computing any meaningful global property of the graph within a machine. As such, most algorithms in this regime proceed by performing *local operations* such as contracting edges/vertices, adding edges, etc. Note that even the direct neighbors of a high-degree vertex may not fit in the memory of a single machine, however, using standard techniques most of basic local operations can be implemented in $O(1/\delta) = O(1)$ rounds of MPC. The details are given in Appendix A. For the purpose of this section, we do not get into technicalities of how this can be done.

We start with a brief overview of some of the relevant techniques and results, then proceed to describe the new ingredients of our algorithm and its analysis.

Graph exponentiation. Consider a simple and well-known algorithm that connects every vertex to vertices within its 2-hop (i.e., vertices of distance 2) by adding edges. It is not hard to see that the distance between any two vertices shrinks by a factor of 2. By repeating this procedure, each connected component becomes a clique within $O(\log D)$ steps. The problem with this approach, however, is that the total space required can be up to $\Omega(n^2)$, which for sparse graphs is much larger than $O(m)$.

Andoni *et al.* [4] manage to improve the total space to the optimal bound of $O(m)$, at the cost of increasing the round complexity to $O(\log D \cdot \log \log_{m/n} n)$. We briefly overview this result below.

Overview of Andoni *et al.*'s algorithm. Suppose that every vertex in the graph has degree at least $d \gg \log n$. Select each vertex as a *leader* independently with probability $\Theta(\log n/d)$. Then contract every non-leader vertex to a leader in its 1-hop (which w.h.p. exists). This shrinks the number of vertices from n to $\tilde{O}(n/d)$. As a result, the amount of space available per remaining vertex increases to $\tilde{\Omega}(\frac{m}{n/d}) = \tilde{\Omega}(\frac{nd}{n/d}) \approx d^2$. At this point, a variant of the aforementioned graph exponentiation technique can be used to increase vertex degrees to d^2 (but not more), which implies that another application of leader contraction decreases the number of vertices by a factor of $\Omega(d^2)$. Since the available space per remaining vertex increases doubly exponentially, $O(\log \log n)$ phases of leader contraction suffice to increase it to n per remaining vertex. Moreover, each phase requires $O(\log D)$ iterations of graph exponentiation, thus the overall round complexity is $O(\log D \log \log n)$.

2.1 Our Connectivity Algorithm: The Roadmap

The main shortcoming of Andoni *et al.*'s algorithm is that within a phase, where the goal is to increase the degree of every vertex to d , those vertices that have already reached degree d are *stalled* (i.e., do not connect to their 2-hops) until all other vertices reach this degree. Because of the stalled vertices, the only guaranteed outcome of the graph exponentiation operation is increasing vertex degrees. In particular, the diameter of the graph may remain unchanged. This is precisely why their algorithm may require up to $O(\log D \cdot \log \log n)$ applications of graph exponentiation. We note that this is not a shortcoming of their analysis. Indeed, we remark that there are family of graphs on which Andoni *et al.*'s algorithm takes $\Theta(\log D \cdot \log \log n)$ rounds.

Instead of describing our algorithm, we focus in this section on some of the properties that we expect it to satisfy, and how they suffice to get our desired round complexity. This overview should be helpful when reading the description of the algorithm in Section 3.1.

Our algorithm assigns *budgets* to vertices. Intuitively, a budget controls how much space a vertex can use, i.e., how much it can increase its degree. To bound the space complexity, we will bound the sum of all vertex budgets. In our algorithm vertices may have different budgets (differently from the algorithm of Andoni *et al.*). This allows us to prevent the vertices from getting stalled behind each other. Overall, we have $L = \Theta(\log \log n)$ possible budgets $\beta_0, \beta_1, \dots, \beta_L$ where $\beta_0 = O(1)$, $\beta_L = \Omega(n)$, and $\beta_i = (\beta_{i-1})^{1.25}$. We say a vertex v is at *level* $\ell(v) = i$, if its budget $b(v)$ equals β_i . The algorithm executes a single loop until each connected component becomes a clique. We call a single execution of this loop an *iteration* which can be implemented in $O(1)$ rounds of MPC.

Property 1 (see Lemma 3.8 for a formal statement). For any two vertices u and v at distance exactly 2 at the beginning of an iteration of the algorithm, after the next 4 iterations, either their distance decreases to 1, or the level of both vertices increases by at least one.

We call every 4 iterations of the algorithm a *super-iteration*. Property 1 guarantees that if a vertex does not get connected to every vertex in its 2-hop within a super-iteration, its level must increase. Recall, on the other hand, that the maximum level of any vertex is at most $O(\log \log n)$. As such, every vertex resists getting connected to those in its 2-hop for at most $O(\log \log n)$ super-iterations. However, somewhat counter-intuitively, this observation is (provably) not sufficient to guarantee an upper bound of $O(\log D + \log \log n)$ rounds. Our main tool in resolving this, is maintaining another property.

Property 2 (see Observation 3.6 for a formal statement). If a vertex v is neighbor of a vertex u with $\ell(u) > \ell(v)$, then by the end of the next iteration, the level of v becomes at least $\ell(u)$.

The precise proof of sufficiency of Properties 1 and 2 is out of the scope of this section. Nonetheless, we provide a proof sketch with the hope to make the actual arguments easier to understand. See Lemma 3.11 for the formal statement and its proof.

Proof sketch of round complexity. Fix two vertices u and v in one connected component of the original graph and let P_1 be the shortest path between them. As the vertices connect to their 2-hops and get closer to each other, we drop some of the vertices of P_1 while ensuring that the result is also a valid path from u to v . More precisely, we maintain a path P_i by the end of each super-iteration i which is obtained by replacing some subpaths of P_{i-1} of length at least two by single edges. We say that the interior vertices of the replaced subpaths are dropped.

Our goal is to show that for $R := O(\log D + \log \log n)$, path P_R has length 2; it is not hard to see that this means each connected component becomes a clique by iteration R . To show this, we require a potential-based argument. Suppose that we initially put one coin on every vertex of P_1 , thus we have at most $D + 1$ coins. As we construct P_{i+1} from P_i , every vertex that gets dropped

from P_i , passes its coins to any of its two neighbors in P_i that survives to P_{i+1} (if they both survive, it divides them equally and if none of them survive the coins are discarded). Moreover, we construct P_{i+1} from P_i such that it satisfies the following property, which we call invariant 1: If the level of a vertex $w \in P_i$ within super-iteration $i + 1$ does not increase, either w , or one of its two neighbors in P_i are dropped. This is guaranteed to be possible due to Property 1.

Finally, we use Property 2 to prove invariant 2: In any path P_i , every vertex of level j has at least $(1.5)^{i-j}$ coins. That is, we have *more* coins on the vertices that have *lower* levels. Note that this is sufficient to prove the round complexity. For, otherwise, if $|P_R| > 2$, due to the fact that the level of every vertex is at most $O(\log \log n)$, there should remain a vertex in P_R with at least

$$(1.5)^{R-j} \geq (1.5)^{\Theta(\log D + \log \log n) - O(\log \log n)} \geq (1.5)^{2 \log D} \gg D + 1$$

coins, while we had only $D + 1$ coins in total. Property 2 is useful in the proof of invariant 2 in the following sense: If a low-level vertex $w \in P_i$ survives to P_{i+1} without increasing its level, its dropped neighbor (which exists by invariant 1) cannot have a higher level than w , and thus has a lot of coins to pass to w . \square

3 Main Algorithm: Connectivity with $O(m+n \text{ poly } \log n)$ Total Space

In this section, we describe an $O(\log D + \log \log_{T/n} n)$ round connectivity algorithm assuming that the total available space is $T \geq m + n \log^\alpha n$ where α is some desirably large constant. We later show how to improve the total space to the optimal bound of $O(m)$ in Section 4. We start with description of the algorithm in Section 3.1 and proceed to its analysis in Sections 3.2, 3.3, and 3.4.

Remark 3.1. *For simplicity, we describe an algorithm that succeeds with probability $1 - 1/n^{\Omega(1)}$. One can boost the success probability to $1 - 1/n^c$ by changing some parameters in the algorithm or by simply running $O(c)$ independent copies of it in parallel.*

3.1 The Algorithm

The algorithm consists of a number of *iterations*, each of which calls **three subroutines** named **Connect2Hops**, **RelabelInterLevel**, and **RelabelIntraLevel**.² Each iteration will be implemented in $O(1)$ rounds of MPC and we later show that $O(\log D + \log \log_{T/n} n)$ iterations are sufficient. We first formalize the overall structure of the algorithm as Algorithm 1, then continue to describe the subroutines of each iteration one by one.

Within the **Connect2Hops** subroutine, **every active vertex v attempts to connect itself to a subset of the vertices in its 2-hop**. If there are more candidates than the budget of v allows, we discard some of them arbitrarily. To formalize this, we use $N(u)$ to denote the neighbors of a vertex u .

Next, in the **RelabelInterLevel** subroutine, **every vertex v that sees a vertex u of a higher level in its neighborhood, is “reabeled” to that vertex**. That is, any occurrence of v in the edges is replaced with u . As a technical point, it might happen that we end up with a chain $v_1 \rightarrow v_2 \rightarrow v_3 \rightarrow \dots$ of relabelings where vertex v_1 has to be relabeled to v_2 , v_2 has to be relabeled to v_3 , and so on. In each iteration of the algorithm, we *only apply the direct relabeling of every vertex*, that is v_1 ends up with label v_2 , v_2 ends up with label v_3 , etc. An example of this is illustrated in Figure 1.

Finally, the last subroutine **RelabelIntraLevel**, is where we increase the budgets/levels.

²We note that the relabeling subroutines are close to the leader contraction operation we discussed in Section 2. However, we use a different terminology to emphasize the difference in handling *chains*. See Figure 1.

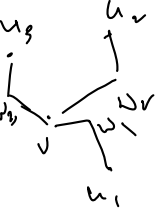
Algorithm 1. `FindConnectedComponents`($G(V, E)$)

1. To any vertex v , we assign a *level* $\ell(v) \leftarrow 0$, a *budget* $b(v) \leftarrow (\frac{T}{n})^{1/2}$, and a set $C(v) \leftarrow \{v\}$ which throughout the algorithm, denotes the set of vertices that v *corresponds to*. Moreover, every vertex is initially marked as *active* and we set $\text{next}(v) \leftarrow v$ for every vertex v .
2. Repeat the following steps until each remaining connected components becomes a clique:
 - (a) `Connect2Hops`(G, b, ℓ)
 - (b) `RelabelInterLevel`($G, b, \ell, C, \text{next}$)
 - (c) `RelabelIntraLevel`(G, b, ℓ, C)
3. For every remaining connected component \mathcal{C} corresponds to one of the connected components of the original graph whose vertex set is $\cup_{v \in \mathcal{C}} C(v)$.

`Connect2Hops`(G, b, ℓ)

For every active vertex v :

1. Define $H(v) := \{u \mid \exists w \text{ s.t. } w \in N(u) \cap N(v), \ell(u) = \ell(w) = \ell(v)\}$.
2. Let d_v be the number of vertices currently connected to v that have level at least $\ell(v)$. Pick $\min\{b(v) - d_v, |H(v)|\}$ arbitrary vertices in $H(v)$ and connect them to v .



3.2 Analysis of Algorithm 1 – Correctness

Correctness. We first show that the algorithm indeed computes the connected components of the given graph. The following lemma follows directly from the fact that Algorithm 1 does not split or merge connected components.

Lemma 3.2. *Let $\mathcal{S}_1, \dots, \mathcal{S}_k$ be the connected components of G at the end of Algorithm 1. Then, the family of sets $\{\cup_{v \in \mathcal{S}_i} C(v) \mid i \in [k]\}$ is equal to the family of vertex sets of connected components of the original graph.*

Proof. We use induction to show that the claim is true at the end of each iteration r of Algorithm 1. Before we start the algorithm, i.e., when $r = 0$, for every vertex v we have $C(v) = \{v\}$. Therefore, clearly the base case holds. For the rest of the proof, it suffices to show that the three steps of `Connect2Hops`, `RelabelInterLevel`, and `RelabelIntraLevel` maintain this property.

Within the `Connect2Hops` subroutine, we only add edges to the graph. The only way that this operation may hurt our desired property, is if the added edges connect two different connected components of the previous iteration. However, every added edge is between two vertices of distance at most 2 (and thus in the same component) implying that this cannot happen.

For the `RelabelInterLevel` subroutine, we first have to argue that the relabelings do not change the connectivity structure of the graph. It is clear that two disconnected components cannot become connected since each vertex is relabeled to another vertex of the same connected component. Moreover, we have to argue that one connected component does not become disconnected. For this, consider a path between two vertices u and v of the same component. After relabeling vertices, there is still a walk between the corresponding vertices to u and v , thus they remain connected. Finally, observe that once a vertex v is relabeled to some vertex u , in Line 5 of the `RelabelInterLevel` subroutine, we add every vertex of $C(v)$ to $C(u)$. This ensures that for every component \mathcal{S} , the set $\cup_{v \in \mathcal{S}} C(v)$ does not lose any vertex and thus remains unchanged.

RelabelInterLevel($G, b, \ell, C, \text{next}$)

1. For every (active or inactive) vertex v :
 - (a) Let $h(v)$ be the neighbor of v with the highest level with ties broken arbitrarily.
 - (b) If $\ell(h(v)) > \ell(v)$, mark v as *inactive* and set $\text{next}(v) \leftarrow h(v)$.
2. Replace every edge $\{u, v\}$ in the graph with $\{\text{next}(u), \text{next}(v)\}$.
3. Remove duplicate edges and self-loops.
4. For every vertex v , set $I(v) \leftarrow \cup_{u: \text{next}(u)=v} C(u)$.
5. For every vertex v , if v is active, set $C(v) \leftarrow C(v) \cup I(v)$ and if v is inactive set $C(v) \leftarrow I(v)$.
6. If an inactive vertex has become isolated, remove it from the graph.

RelabelIntraLevel(G, b, ℓ, C)

1. Mark an active vertex v as “saturated” if it has more than $b(v)$ active neighbors that have the same level as v .
2. If an active vertex v has a neighbor u with $\ell(u) = \ell(v)$ that is marked as saturated, v is also marked as saturated.
3. Mark every saturated vertex v as a “leader” independently with probability $\min\{\frac{3 \log n}{b(v)}, 1\}$.
4. For every leader vertex v , set $\ell(v) \leftarrow \ell(v) + 1$ and $b(v) \leftarrow b(v)^{1.25}$.
5. Every non-leader saturated vertex v that sees a leader vertex u of the same level (i.e., $\ell(u) = \ell(v)$) in its 2-hop (i.e., $\text{dist}(v, u) \leq 2$), chooses one as its leader arbitrarily.
6. Every vertex is contracted to its leader. That is, for any vertex v with leader u , every edge $\{v, w\}$ will be replaced with an edge $\{u, w\}$ and all vertices in set $C(v)$ will be removed and added to set $C(u)$. We then remove vertex v from the graph.
7. Remove duplicate edges or self-loops and remove saturated/leader flags from the vertices.

Similarly, in the **RelabelIntraLevel** step, the vertices only get contracted to the leaders in their 2-hop and once removed from the graph, a vertex v passes every element in $C(v)$ to $C(u)$ of another vertex u in its component, thus the property is maintained, concluding the proof. \square

3.3 Analysis of Algorithm 1 – Round Complexity

In order to pave the way for future discussions, we start with some definitions. We use $G_r = (V_r, E_r)$ to denote the resulting graph by the end of iteration r of Algorithm 1. Therefore, we have $V = V_0 \supseteq V_1 \supseteq V_2 \supseteq \dots$ as we do not add any vertices to the graph. Moreover, for any vertex $v \in V$ and any iteration $r \geq 0$, we define $\text{next}_r(v)$ to be the vertex $w \in V_r$ such that $v \in C(w)$ by the end of iteration r . That is, $\text{next}_r(v)$ is the vertex that *corresponds* to v by the end of iteration r .

Observation 3.3. *Let $v \in V_r$ be an active vertex. Then for any $r' \leq r$, we have $\text{next}_{r'}(v) = v$.*

For any iteration $r \geq 0$ and any vertex $v \in V$, we respectively use $\ell_r(v)$, $b_r(v)$ and $C_r(v)$ to denote the value of $\ell(\text{next}_r(v))$, $b(\text{next}_r(v))$ and $C(\text{next}_r(v))$ by the end of iteration r . Furthermore, for any two vertices $v, u \in V$, we use $\text{dist}_r(u, v)$ to denote the length of the shortest path between $\text{next}_r(u)$ and $\text{next}_r(v)$ in graph G_r .

The following claim implies that the corresponding level of a vertex is non-decreasing over time.

active in $\pi \Rightarrow$ active in $\pi' \subset \pi$

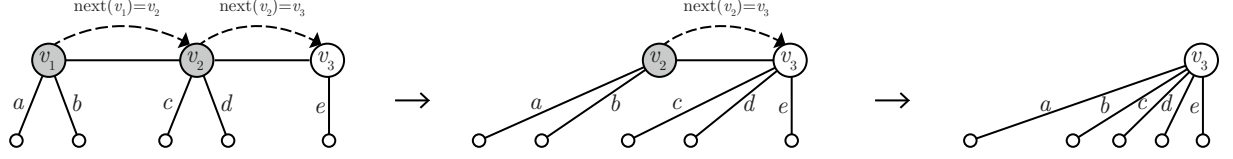


Figure 1: Algorithm 1 does not traverse “relabeling chains”. In the first iteration, vertex v_1 is relabeled to v_2 and v_2 is relabeled to v_3 . After two iterations, both v_1 and v_2 are contracted to v_3 . Note that the edge $\{v_2, v_3\}$ of iteration 1 will become a self-loop after applying the relabeling $v_2 \rightarrow v_3$ and thus will be removed. However, the edge $\{v_2, v_3\}$ that still remains in the second iteration is the result of applying relabelings $v_1 \rightarrow v_2$ and $v_2 \rightarrow v_3$ on edge $\{v_1, v_2\}$.

Claim 3.4. *For any vertex $v \in V$ and any $r \geq r'$, we have $\ell_r(v) \geq \ell_{r'}(v)$.*

Proof. We use induction on r . For the base case with $r = r'$, we clearly have $\ell_r(v) = \ell_{r'}(v)$. Suppose, by the induction hypothesis, that $\ell_{r-1}(v) \geq \ell_{r'}(v)$. If in iteration r of the algorithm, vertex $\text{next}_{r-1}(v)$ is not relabeled, i.e., if we have $\text{next}_r(v) = \text{next}_{r-1}(v)$, then $\ell_r(v) = \ell_{r-1}(v)$ by definition and the fact that the level of a particular vertex cannot decrease in one iteration. Therefore, by the induction hypothesis, we have $\ell_r(v) = \ell_{r-1}(v) \geq \ell_{r'}(v)$. On the other hand, if vertex v is relabeled in iteration r , i.e., if $\text{next}_r(v) \neq \text{next}_{r-1}(v)$, then it suffices to show that it is relabeled to a vertex whose level is higher. This is clear from description of the algorithm. A vertex that gets relabeled within the **RelabelInterLevel** subroutine, does so if and only if the new vertex has a higher level. Similarly, in within the **RelabelIntraLevel** subroutine of Algorithm 1, any vertex v that is contracted to another vertex does so if it is a marked saturated vertex of the same level, whose level increases by the end of the iteration. \square

The next claim shows, in a similar way, that the distance between the corresponding vertices of two vertices u and v is non-increasing over time.

Claim 3.5. *For any two vertices $v, u \in V$ and any $r \geq r'$, we have $\text{dist}_r(u, v) \leq \text{dist}_{r'}(u, v)$.*

Proof. Similar to the proof of Claim 3.4, we can show this by induction on r and, thus, the problem reduces to showing that in one iteration the corresponding distance between two vertices cannot increase. To show this, fix a shortest path p between two vertices v and u at any iteration. Within the next iteration, the **Connect2Hops** subroutine does not affect this path as it only adds some edges to the graph. Moreover, the only effect of the relabeling steps on this path is that it may shrink it as one vertex of the path can be relabeled to one of its neighbors in the path. However, relabeling can in no way destroy or increase the length of this path. Thus, the lemma follows. \square

Our next observation follows directly from the description of the algorithm.

Observation 3.6. *For any $r \geq 0$ and any vertices $u, v \in V$ with $\text{dist}_r(u, v) \leq 1$, we have $\ell_{r+1}(u) \geq \ell_r(v)$ and $\ell_{r+1}(v) \geq \ell_r(u)$.*

Proof. This comes from the fact that any vertex who sees a neighbor of a higher level, is relabeled to its neighbor with the highest level in subroutine **RelabelInterLevel** of Algorithm 1. \square

Claim 3.7. *With high probability for any iteration r and any vertex $v \in V_r$, if v becomes saturated in the next iteration $r + 1$, then there is at least one leader of the same level in its 2-hop, thus $\ell_{r+1}(v) \geq \ell_r(v) + 1$.*

Proof. If v is saturated, then by definition, it has at least $b(v)$ vertices in its inclusive 2-hop (i.e., the set $v \cup N(v) \cup N(N(v))$) that have the same level as that of v and are also saturated. To see this, note that if v is marked as saturated in Line 1 of `RelabelIntraLevel`, then it has at least $b(v)$ other active direct neighbors with level at least $b(v)$ all of which will be marked as saturated in Line 2. Furthermore, if a vertex v is marked as saturated in Line 2, then it has a saturated neighbor which has $b(v)$ direct saturated neighbors as just described. Thus v 's 2-hop will include $b(v)$ saturated vertices as desired.

It suffices to show that one of these $b(v)$ saturated vertices will be marked as a leader with high probability. Recall that we mark each vertex independently with probability $\frac{3 \log n}{b(v)}$, thus

$$\Pr \left[\ell_{r+1}(v) = \ell_r(v) \right] \leq \left(1 - \frac{3 \log n}{b(v)} \right)^{b(v)} \leq \exp(-3 \log n) \leq 1/n^3.$$

By a union bound over all vertices, and over the total number of iterations of the algorithm which is clearly less than n^2 , we get that with probability at least $1 - 1/n$ every vertex that gets saturated sees a marked vertex in its 2-hop and its corresponding level will thus be increased in the next iteration. \square

The next lemma highlights a key property of the algorithm and will be our main tool in analyzing the round complexity. Intuitively, it shows that with high probability, after every 4 iterations of Algorithm 1, every vertex v is either connected to its 2-hop, or its corresponding level increases by at least 1.

Lemma 3.8. *Let $u, v \in V$ be two vertices with $\text{dist}_r(u, v) = 2$ for some iteration r . If $\text{dist}_{r+4}(u, v) \geq 2$, then $\ell_{r+4}(v) \geq \ell_r(v) + 1$ and $\ell_{r+4}(u) \geq \ell_r(u) + 1$. This holds for all vertices u and v and over all iterations of the algorithm with high probability.*

Proof. By Claim 3.5, we have $\text{dist}_{r+4}(u, v) \leq \text{dist}_r(u, v) = 2$. As such, to prove the lemma, it suffices to obtain a contradiction by assuming that $\text{dist}_{r+4}(u, v) = 2$ and (w.l.o.g.) $\ell_{r+4}(u) = \ell_r(u)$.

Recall that the lemma assumes that $\text{dist}_r(u, v) = 2$. Therefore, there must exist a vertex w with $\text{dist}_r(u, w) = \text{dist}_r(w, v) = 1$. By an application of Observation 3.6, we have

$$\ell_{r+4}(u) \geq \ell_{r+3}(w) \geq \ell_{r+2}(v) \geq \ell_{r+1}(w) \geq \ell_r(u).$$

Combining this with our assumption that $\ell_{r+4}(u) = \ell_r(u)$, we get

$$\ell_{r+4}(u) = \ell_{r+3}(w) = \ell_{r+2}(v) = \ell_{r+1}(w) = \ell_r(u). \quad (1)$$

Moreover, by Claim 3.4 which states the levels are non-decreasing over time, we have

$$\ell_{r+4}(u) \geq \ell_{r+2}(u) \geq \ell_r(u) \quad \text{and} \quad \ell_{r+3}(w) \geq \ell_{r+2}(w) \geq \ell_{r+1}(w). \quad (2)$$

Combination of (1) and (2) directly implies the following two useful inequalities.

Observation 3.9. $\ell_{r+2}(u) = \ell_{r+2}(w) = \ell_{r+2}(v)$.

Proof. Inequality $\ell_{r+4}(u) \geq \ell_{r+2}(u) \geq \ell_r(u)$ of (2) combined with equality $\ell_{r+4}(u) = \ell_r(u)$ of (1) implies $\ell_{r+2}(u) = \ell_r(u)$. This combined with $\ell_r(u) = \ell_{r+2}(v)$ of (1), gives $\ell_{r+2}(u) = \ell_{r+2}(v)$.

Inequality $\ell_{r+3}(w) \geq \ell_{r+2}(w) \geq \ell_{r+1}(w)$ of (2) combined with equality $\ell_{r+3}(w) = \ell_{r+1}(w)$ of (1) implies $\ell_{r+2}(w) = \ell_{r+1}(w)$. Combined with $\ell_{r+1}(w) = \ell_{r+2}(v)$ of (1), it gives $\ell_{r+2}(w) = \ell_{r+2}(v)$. \square

Observation 3.10. $\ell_{r+4}(u) = \ell_{r+2}(u)$.

Proof. Inequality $\ell_{r+4}(u) = \ell_r(u)$ due to (1) combined with inequality $\ell_{r+4}(u) \geq \ell_{r+2}(u) \geq \ell_r(u)$ of (2) implies $\ell_{r+4}(u) = \ell_{r+2}(u) = \ell_r(u)$. \square

Observation 3.9 implies that the corresponding levels of all three vertices u , w and v should be the same at the end of iteration $r + 2$. Thus, within the **Connect2Hops** subroutine of iteration $r + 3$, we have $\text{next}_{r+2}(v) \in H(\text{next}_{r+2}(u))$; now either we connect $\text{next}_{r+2}(u)$ and $\text{next}_{r+2}(v)$ which reduces their distance to 1 contradicting our assumption that $\text{dist}_{r+4}(u, v) = 2$, or otherwise vertex $\text{next}_{r+2}(u)$ spends its budget to get connected to at least $b_{r+2}(u)$ other vertices of level at least $\ell_{r+2}(u)$. Let N be the set of these neighbors of $\text{next}_{r+2}(u)$. There are three scenarios and each leads to a contradiction:

- If for a vertex $x \in N$, $\ell_{r+2}(x) > \ell_{r+2}(u)$, then by Observation 3.6, the level of the corresponding vertex of u increases in the next iteration and we have $\ell_{r+4}(u) \geq \ell_{r+3}(u) > \ell_{r+2}(u)$ which contradicts equality $\ell_{r+4}(u) = \ell_{r+2}(u)$ of Observation 3.10.
- If a vertex $x \in N$ is inactive, then x is in a chain by definition of inactive vertices. Every vertex in a chain has a vertex of higher level next to it, thus $\ell_{r+3}(x) > \ell_{r+2}(x)$ by Observation 3.6. Furthermore, since $x \in N$, we know $\ell_{r+2}(x) \geq \ell_{r+2}(u)$. This means that $\text{next}_{r+3}(u)$ has a neighbor of strictly higher level, thus by Observation 3.6, we have to have $\ell_{r+4}(u) > \ell_{r+2}(u)$ which contradicts equality $\ell_{r+4}(u) = \ell_{r+2}(u)$ of Observation 3.10.
- If the two cases above do not hold, then after applying **Connect2Hops** in iteration $r + 2$, $\text{next}_{r+2}(u)$ has at least $b_{r+2}(u)$ active neighbors of level exactly $\ell_{r+2}(u)$. Furthermore, vertex $\text{next}_{r+2}(u)$ itself has to be active, or otherwise its corresponding level has to increase in the next iteration which is a contradiction. This means by definition that $\text{next}_{r+2}(u)$ is saturated during iteration 3. By Claim 3.7, with high probability the corresponding level of every saturated vertex increases by at least one in the next iteration, and thus we get $\ell_{r+3}(u) > \ell_{r+2}(u)$ which, again, would imply $\ell_{r+4}(u) \neq \ell_{r+2}(u)$ contradicting Observation 3.10.

To wrap up, we showed that if the distance between the corresponding vertices to u and v after the next 4 iterations is not decreased to at most 1, then the corresponding level of u and v has to go up by one with high probability. \square

As discussed before, Lemma 3.8 implies that after every $O(1)$ consecutive iterations of Algorithm 1, each vertex either is (roughly speaking) connected to the vertices in its 2-hop or sees a level increase. It is easy to show that if *every* vertex is connected to the vertices in its 2-hop, the diameter of the graph is reduced by a constant factor, and thus after $O(\log D)$ iterations every connected component becomes a clique. Notice, however, that Lemma 3.8 does not guarantee this, as for some vertices, we may only have a level increase instead of connecting them to their 2-hop. Let L be an upper bound on the level of the vertices throughout the algorithm. (We later show in Lemma 3.15 that $L = O(\log \log_{T/n} n)$.) Since the maximum possible level is L , each vertex does not connect 2-hops for at most L iterations. Therefore, if for instance, within each of the first L iterations of the algorithm, the corresponding level of *every* vertex increases, we cannot have any level-increases afterwards. Therefore within the next $O(\log D)$ iterations, each vertex connects 2-hops and every connected component becomes a clique. Overall, this takes $O(L + \log D)$ iterations. In reality, however, the level increases do not necessarily occur in bulk within the first L iterations of the algorithm. In fact, Lemma 3.8 alone is not enough to show a guarantee of $O(L + \log D)$. To get around this problem, we need to use another crucial property of the algorithm highlighted in Observation 3.6. A proof of sketch of how we combine these two properties to get our desired bound was already given in Section 2. The following lemma formalizes this.

Lemma 3.11. *Let L be an upper bound on the number of times that the corresponding level of a vertex may increase throughout the algorithm. Only $O(L + \log D)$ iterations of the for loop in Algorithm 1 suffices to make sure that with high probability, every remaining connected component becomes a clique.*

Proof. It will be convenient for the analysis to call every 4 consecutive iterations of the for-loop in Algorithm 1 a *super-iteration*. That is, for any $i \geq 1$, we define the i th super-iteration to be the combination of performing iterations $4i - 3, 4i - 2, \dots, 4i$ of Algorithm 1.

Fix two arbitrary vertices u and v in a connected component of the original graph G . It suffices to show that after running the algorithm for $R := O(L + \log D)$ super-iterations, the corresponding vertices to u and v , are at distance at most 1. To show this, we maintain a path between u and v and update it over time. We use P_r to denote the maintained path by the end of super-iteration r , i.e., the path is updated every four iterations. The initial path, P_0 , is any arbitrary shortest path between u and v in the original graph G ; notice that P_0 has at most $D + 1$ vertices, as the diameter of G is D . As we move forward, u and v may be relabeled; nonetheless, the path P_r will be a path from vertex $\text{next}_{4r}(u)$ (which is the corresponding vertex to u by the end of iteration $4r$ or equivalently super-iteration r) to vertex $\text{next}_{4r}(v)$. Crucially, the path P_r is not necessarily the shortest path between $\text{next}_{4r}(v)$ and $\text{next}_{4r}(u)$ in G_r . The reason is that the naive shortest paths may “radically” change from one iteration to another. Instead, we carefully construct P_r to ensure that it passes only through the corresponding vertices of the vertices in P_{r-1} , which also inductively indicates that every vertex in P_r is in set $\{\text{next}_{4r}(w) \mid w \in P_0\}$.

To use these gradual updates, for every r , we define a potential function $\Phi_r : V(P_r) \rightarrow \mathbb{N}$ that maps every vertex of path P_r to a positive integer. The definition of function Φ_r and construction of path P_r are recursively based on Φ_{r-1} and P_{r-1} . As for the base case, we have $\Phi_0(v) = 1$ for every vertex $v \in P_0$. For the rest of the iterations, we follow the following steps.

To construct P_r from P_{r-1} , we first apply the relabelings of iterations $4r - 3, \dots, 4r$, on the vertices in P_{r-1} . That is, the sequence $P_{r-1} = (w_1, \dots, w_s)$ becomes $Q = (q_1, \dots, q_s)$ where $q_i = \text{next}_{4r}(w_i)$. Note that multiple vertices in P_{r-1} may have been relabeled to the same vertex throughout these four iterations, and thus the elements in Q are not necessarily unique. Next, we use an s -bit *mask* vector $K \in \{0, 1\}^s$ to denote a subsequence³ of Q that corresponds to the vertices in P_r . That is, P_r contains the i th element of Q if and only if $K_i = 1$. To guarantee that P_r is indeed a path and that it has some other useful properties, our mask vector K should satisfy the following properties:

- (P1) $K_1 = K_s = 1$.
- (P2) If for some $i, j \in [s]$ with $i \neq j$, we have $q_i = q_j$, then at most one of K_i and K_j is 1.
- (P3) If for some $1 \leq i < j \leq s$ with $K_i = K_j = 1$, there is no k with $i < k < j$ for which $K_k = 1$, then q_i and q_j should have a direct edge in graph G_{4r} .
- (P4) If for some $i \in [s]$, we have $\ell_{4r}(q_i) = \ell_{4(r-1)}(w_i)$ (i.e., the level of the corresponding vertex to w_i is not increased) and $K_i = 1$, then at least one of K_{i-1} or K_{i+1} should be 0.⁴

Property P1 guarantees that the path of the next iteration remains to be between the corresponding vertices to u and v . Property P2 ensures that we do not revisit any vertex in P_r which is necessary if we want P_r to be a path. Moreover, Property P3 ensures that every two consecutive vertices in

³A *subsequence* is a derived from another sequence by deleting some or no elements of it without changing the order of the remaining elements.

⁴ K is an s -bit vector, but assume for preciseness of definition that $K_0 = K_{s+1} = 1$.

P_r are neighbors in G_{4r} , which again, is necessary if we want P_r to denote a path in G_{4r} . Finally, Property P4 guarantees that if the corresponding level of a vertex $w_i \in V_{4(r-1)}$ does not increase in iterations $4r - 3, \dots, 4r$, and that q_i (which is the corresponding vertex to w_i after these four iterations) is included in path P_r , the successor and/or predecessor vertices of w_i in P_{r-1} should not be included in P_r . Note that we have to be careful that by satisfying Property P4, we do not violate Property P3. In other words, we have to make sure that once we drop the neighboring vertices of w_i in P_{r-1} from P_r , P_r remains to be a connected path. However, this can be guaranteed by Lemma 3.8 which says if the corresponding level of a vertex does not increase in 4 iterations, its distance to the vertices in its 2-hop decreases to at most 1. Overall, we get the following result.

Claim 3.12. *If $q_1 \neq q_s$ and if $|P_{r-1}| > 3$, then with high probability there exists a mask vector K satisfying Properties P1-P4.*

Construction of function Φ_r is also based on the mask vector K that we construct P_r with. Recall that Φ_r is a function from the vertices in P_r to \mathbb{N} . Therefore, in order to describe Φ_r , it suffices to define the value of Φ_r on vertex q_i iff $K_i = 1$. Assuming that $K_i = 1$, define l_i to be the smallest number in $[1, i]$ where for all $j \in [l_i, i - 1]$, we have $K_j = 0$. In a similar way, define r_i to be the largest number in $[i, s]$ where for all $j \in [i + 1, r_i]$, we have $K_j = 0$. Having these, we define $\Phi_r(q_i)$ in the following way:

$$\Phi_r(q_i) := \Phi_{r-1}(w_i) + \frac{1}{2} \sum_{j=l_i}^{i-1} \Phi_{r-1}(w_j) + \frac{1}{2} \sum_{j=i+1}^{r_i} \Phi_{r-1}(w_j). \quad (3)$$

The next two claims are the main properties of function Φ_r that we use in proving Lemma 3.11.

Claim 3.13. *For any $r \geq 0$ and any vertex $w \in P_r$ with level $\ell = \ell_{4r}(w)$, we have $\Phi_r(w) \geq (3/2)^{r-\ell}$.*

Proof. We use induction on r . For the base case with $r = 0$, we have $\Phi_0(w) = 1$ and since it is before the first iteration, we have $\ell = 0$. Thus, we have $\Phi_0(w) \geq (3/2)^{0-0} = 1$. The induction hypothesis guarantees for every vertex w' of path P_{r-1} with level ℓ' , that $\Phi_{r-1}(w') \geq (3/2)^{r-1-\ell'}$. We show that this carries over to the vertices of P_r as well.

We would like to prove that for every vertex $w \in P_r$, we have $\Phi_r(w) \geq (3/2)^{r-\ell_{4r}(w)}$. We know by construction of P_r from P_{r-1} that vertex w of P_r is the corresponding vertex of some vertex $w'_i \in P_{r-1}$ with $K_i = 1$ where K denotes the mask vector that we use to construct P_r from P_{r-1} , i.e., $w = \text{next}_{4(r-1)}^4(w'_i)$. By the induction hypothesis, we have

$$\Phi_{r-1}(w'_i) \geq (3/2)^{r-1-\ell_{4(r-1)}(w'_i)}. \quad (4)$$

Therefore, if during super-iteration r , the corresponding level of w_i increases, i.e., if we have $\ell_{4r}(w) \geq \ell_{4(r-1)}(w'_i) + 1$, then we have

$$\Phi_r(w) \geq \Phi_{r-1}(w'_i) \stackrel{\text{By (4)}}{\geq} (3/2)^{r-1-\ell_{4(r-1)}(w'_i)} \geq (3/2)^{r-\ell_{4r}(w)},$$

where the first inequality comes from the fact that $\Phi_r(w_i) > \Phi_{r-1}(w'_i)$ which itself is directly followed by (3). This means that if the corresponding level of w'_i remains unchanged within super-iteration r , we have our desired bound on $\Phi_r(w)$. The only scenario that is left is if the corresponding level of w'_i remains unchanged, i.e., $\ell_{4r}(w) = \ell_{4(r-1)}(w'_i)$.

If the corresponding level of w'_i remains unchanged during super-iteration r , then by Property P4 of the mask vector K , either $K_{i-1} = 0$ or $K_{i+1} = 0$ (or both). Suppose without loss of generality that $K_{i-1} = 0$. First, observe that we have to have

$$\ell_{4(r-1)}(w'_{i-1}) \leq \ell_{4(r-1)}(w'_i). \quad (5)$$

The reason is that if level of w'_{i-1} , which is a neighbor of w'_i in graph $G_{4(r-1)}$, has a higher level than w'_i , then by Observation 3.6, the corresponding level of w'_i in the next iteration should increase to at least $\ell_{4(r-1)}(w'_{i-1})$ which would contradict the assumption that the corresponding level of w'_i remains unchanged for 4 iterations. This means that by the induction hypothesis, now on vertex w'_{i-1} of path P_{r-1} , we have

$$\Phi_{r-1}(w'_{i-1}) \geq (3/2)^{r-1-\ell_{4(r-1)}(w'_{i-1})} \stackrel{\text{By (5)}}{\geq} (3/2)^{r-1-\ell_{4(r-1)}(w'_i)}. \quad (6)$$

Now, recall that we assumed $K_{i-1} = 0$. This means, by construction of Φ_r using (3), that we have to have

$$\Phi_r(w) \geq \Phi_{r-1}(w'_i) + \frac{1}{2}\Phi_{r-1}(w'_{i-1}) \quad (7)$$

Therefore, we have

$$\begin{aligned} \Phi_r(w) &\geq \Phi_{r-1}(w'_i) + \frac{1}{2}\Phi_{r-1}(w'_{i-1}) && \text{By (7).} \\ &\geq \left((3/2)^{r-1-\ell_{4(r-1)}(w'_i)}\right) + \frac{1}{2}\left((3/2)^{r-1-\ell_{4(r-1)}(w'_i)}\right) && \text{By induction hypothesis and (6).} \\ &= \frac{3}{2}\left((3/2)^{r-1-\ell_{4(r-1)}(w'_i)}\right) = (3/2)^{r-\ell_{4(r-1)}(w'_i)} \\ &\geq (3/2)^{r-\ell_{4r}(w)}. && \text{Since } \ell_{4r}(w) \geq \ell_{4(r-1)}(w'_i). \end{aligned}$$

Concluding the proof of Claim 3.13. \square

Claim 3.14. *For any $r \geq 0$ with $|P_r| > 3$, we have $\sum_{w \in P_r} \Phi_r(w) = \sum_{w \in P_0} \Phi_r(w) \leq D + 1$.*

Proof. The inequality $\sum_{v \in P_0} \Phi_r(v) \leq D + 1$ is followed by the fact that P_0 , which is a shortest path between u and v in the original graph has at most $D + 1$ vertices and that $\Phi_0(w) = 1$ for any vertex $w \in P_0$. Moreover, one can easily show that for any $r > 0$, we have $\sum_{w \in P_r} \Phi_r(w) = \sum_{w \in P_{r-1}} \Phi_{r-1}(w)$ directly by the definition of Φ_r from Φ_{r-1} and Property P1 of the mask vectors used. Combining these two facts via a simple induction on r proves the claim. \square

We are now ready to prove Lemma 3.11. Run the algorithm for $R := L + 2 \log D$ super-iterations. If path P_R has at most 3 vertices, we are done since our goal is to show that the distance between the corresponding vertices of u and v in graph G_R is at most 2 — which itself would imply that every connected component in G_R has diameter at most 2. In fact, we show that this should always be the case.⁵ Suppose for the sake of contradiction that we can continue to super-iteration R in constructing P_R and Φ_R and still have $|P_R| > 3$. Let $u_R := \text{next}_{4R}(u)$ be the corresponding vertex to vertex u by the end of super-iteration R . Property P1 of our mask vectors in constructing paths P_1, \dots, P_R ensures that path P_R should start with vertex u_R . By Claim 3.13, we have

$$\Phi_R(u_R) \geq (3/2)^{R-\ell_R(u_R)} \geq (3/2)^{R-L}, \quad (8)$$

where the latter inequality comes from the assumption that L is an upper bound on the level of every vertex. Now, since $R = L + 2 \log D$, we have

$$R - L \geq 2 \log D. \quad (9)$$

⁵More precisely, the “always” here is conditional on the assumption that our high probability events hold. This is not a problem since otherwise we say the algorithm fails and this happens with probability at most $1/n$.

Combining (8) with (9) we get

$$\Phi_R(u_R) \geq (3/2)^{2 \log D} > D + 1.$$

However, this contradicts with Claim 3.14 which guarantees $\Phi_R(u_R)$ should be less than $D + 1$. Therefore, our initial assumption that R can be as large as $L + 2 \log D$ cannot hold; meaning that in $O(L + \log D)$ iterations, the remaining graph will be a collection of connected components of diameter $O(1)$.

Once the diameter of every remaining connected component gets below $O(1)$, it is easy to confirm that in the next $O(L)$ iterations of the algorithm, the diameter reduces to 1 (i.e., every connected component becomes a clique). To see this, note that since the diameter is $O(1)$, the maximum level within each component propagates to all the vertices in $O(1)$ iterations. If this budget is not enough for a vertex to connect 2-hop, its level increases by Lemma 3.8. This level, again, propagates to all other vertices. Eventually, after the next $O(L)$ iterations, the vertices will reach the maximum possible level and thus have enough budget to get connected to every remaining vertex in the component.

Overall, it takes $O(L + \log D)$ iterations until the diameter of every remaining connected component becomes $O(1)$ and after that, at most $O(L)$ other iterations for them to become cliques. \square

To continue, we give the following upper bound on the levels.

Lemma 3.15. *For any vertex v , the value of $\ell(v)$ never exceeds $O(\log \log_{T/n} n)$.*

Proof. Observe that the only place throughout Algorithm 1 that we increase the level of a vertex is in Line 4 of the **RelabelIntraLevel** procedure. Within this line, the budget of the vertex is also increased from $b(v)$ to $b(v)^{1.25}$. Now, given that the initial budget of every vertex is $\beta_0 = (T/n)^{1/2}$, throughout the algorithm, we have $b(v) = \beta_0^{1.25^{\ell(v)}}$. On the other hand, observe that if a vertex reaches a budget of n , it will not be marked as saturated, and thus, we do not update its level/budget anymore. Therefore, we have $b(v) = \beta_0^{(1.25)^{\ell(v)}} \leq n$ which means $\ell(v) \leq \log_{1.25} \log_{\beta_0} n = O(\log \log_{T/n} n)$. \square

Combining the two lemmas above, we can prove the following bound on the round complexity.

Lemma 3.16. *With high probability the number of rounds executed by Algorithm 1 is $O(\log D + \log \log_{T/n} n)$.*

Proof. By Lemma 3.11, it takes only $O(L + \log D)$ iterations for Algorithm 1 to halt where L is an upper bound on the level of the vertices. Lemma 3.15 shows that $L = O(\log \log_{T/n} n)$. Therefore, the round complexity of Algorithm 1 is $O(\log D + \log \log_{T/n} n)$. \square

3.4 Analysis of Algorithm 1 – Implementation Details & Space

Lemma 3.17. *The total space used by Algorithm 1 is $O(T)$.*

Proof. To bound the total space used by Algorithm 1, we have to bound the number of edges that may exist in the graph. More specifically, we have to show that within the **Connect2Hops** subroutine, we do not add too many edges to the graph. Recall that we control this with the budgets. It is not hard to argue that sum of budgets of remaining vertices in each round of the algorithm does not exceed T . However, there is a subtle problem that prevents this property to be sufficient for bounding the number of edges in the graph. The reason is that throughout the algorithm, the degree of a vertex may be much larger than its budget. For instance in the first iteration, a vertex may have a degree of up to $\Omega(n)$ while the budgets are much smaller.

For the analysis, we require a few definitions. For every iteration r and any vertex $v \in V_r$, we define $d_r(v)$ to be the number of neighbors of v in G_r with level at least $\ell_r(v)$. Moreover, we define the *remaining budget* $s_r(v)$ of v to be $\max\{0, b_r(v) - d_r(v)\}$ if v is active and 0 otherwise. To clarify the definition, note that within the **Connect2Hops** subroutine, each vertex v connects to at most $s_r(v)$ new vertices. We further define

$$y_r := |E_r| + \sum_{v \in V_r} s_r$$

to be the *potential space* by the end of iteration r . It is clear by definition that y_r is an upper bound on the total number of edges in the graph after iteration r . Therefore it suffices to show that $y_r = O(T)$ for any r . The base case follows immediately:

Observation 3.18. $y_0 = O(T)$.

Proof. We have $y_0 = |E_0| + \sum_{v \in V_0} s_r \leq m + n \cdot (\frac{T}{n})^{1/2} < m + T \leq O(T)$ where the last inequality comes from the fact that $T = \Omega(m)$. \square

In what follows, we argue that for any r , we have $y_r \leq y_0 + O(T) = O(T) + O(T) = O(T)$ as desired. To do this, we consider the effect of each of the three subroutines of Algorithm 1 in any iteration $r + 1$ on the value of y_{r+1} compared to y_r . We first show that the two procedures **Connect2Hops** and **RelabelInterLevel** cannot increase the potential space. We then give an upper bound of $O(T)$ on the increase in the potential space due to procedure **RelabelIntraLevel** over the course of the algorithm (i.e., not just one round).

Connect2Hops procedure. In the **Connect2Hops** procedure, each vertex v connects itself to at most $s_r(v)$ other vertices of level at least $\ell(v)$ in its 2-hop as described above. These added edges, will then decrease the remaining budget of v by definition. Therefore, for any edge that is added to the graph, the remaining budget of at least one vertex is decreased by 1. Thus, the total potential space cannot increase.

RelabelInterLevel procedure. Next, within the **RelabelInterLevel** procedure, we do not add any edges to the graph. Therefore, the only way that we may increase the potential space is by increasing the remaining budget of the vertices. If a vertex gets relabeled to a higher level neighbor, the algorithm marks it as inactive; this by definition decreases its remaining budget to 0. As such, it only suffices to consider the remaining budget of the vertices that are not relabeled; take one such vertex v . Recall that the remaining budget of v depends on the level of the neighbors of v as well. The crucial property here is that whenever a vertex is relabeled to a neighbor, its corresponding level is increased. This implies that the change in the corresponding level of v 's neighbors cannot increase the remaining budget of v .

There is still one way that v 's remaining budget may increase: if an edge $\{v, u\}$ with $\ell_r(u) \geq \ell_r(v)$ is removed from the graph. Recall that an edge may be removed from the graph within Line 3 of **RelabelInterLevel** where we remove duplicate edges or self-loops. Note that if removal of an edge increases the remaining budget of one of its endpoints only, then the potential space y_{r+1} does not change as the increase in $\sum_v s_{r+1}(v)$ is canceled out by the decrease in $|E_{r+1}|$. However, we have to argue that removal of an edge cannot increase the remaining budget of its both end-points. To see this, observe that the graph, before the **RelabelInterLevel** procedure cannot have any duplicate edges or self-loops (as we must have removed them before) and all these edges have been created within this iteration. Take an edge $\{u, v\}$ and suppose that there are multiple duplicates of it. All, but at most one, of duplicates of $\{u, v\}$ are the result of the relabelings. Call these the *reabeled* edges and suppose due to symmetry that any removed edge is relabeled. Consider an edge e' that

is relabeled to $\{u, v\}$ and is then removed. At least one of endpoints of e' must be some vertex w which is relabeled to either u or v , say u w.l.o.g. An equivalent procedure is to remove e' before w is relabeled to u and the outcome would be the same. Since $u \notin e'$, there is no way that removing e' would change the remaining budget of u . On the other hand, since w is relabeled and does not survive to V_{r+1} it does not have any effect on s_{r+1} . This means that removing any duplicate edge increases sum of remaining budgets by at most 1 thus the potential space cannot increase.

RelabelIntraLevel procedure. We showed that subroutines **Connect2Hops** and **RelabelInterLevel** cannot increase the potential space of the previous round. Here, we consider the effect of the last subroutine **RelabelIntraLevel**. Similar to **RelabelInterLevel**, we do not add any edges to the graph. Therefore, we only have to analyze the remaining budgets after this procedure.

First take a vertex v that is not marked as saturated. The remaining budget of v may increase if some of its edges are removed because of duplicates which are caused by contracting saturated vertices to their leaders. However, precisely for the same argument that we had for the **RelabelInterLevel** procedure, removal of an edge can only increase the remaining budget of at most one of its end-points thus this does not increase the potential space.

Next, if a vertex v is marked as saturated but is not marked as a leader, by Claim 3.7 it is, w.h.p., going to get contracted to a leader and removed from the graph. Therefore, the only case for which the remaining budget of a vertex may increase is for saturated vertices that are marked as leaders. We assume the worst case. That is, we assume that if a vertex v is saturated and is marked as a leader within iteration $r + 1$, then the potential space is increased by its new budget $b_{r+1}(v)$ (note, by definition, that remaining budget can never be larger than budget). Instead of analyzing the effect of this increase within one iteration, we show that the total sum of such increases over all iterations of the algorithm is bounded by $O(T)$.

Let us use β_i to denote the budget of vertices with level i and use n_i to denote the number of vertices that have been selected as a leader over the course of algorithm for at least i times. In other words, n_i denotes the total number of vertices that reach a level of at least i throughout the algorithm. We can bound sum of increases in potential space due to the **RelabelIntraLevel** procedure over all iterations of the algorithm by:

$$\sum_{i=1}^{\infty} \beta_i \cdot n_i. \quad (10)$$

Thus it suffices to bound this quantity by $O(T)$.

Claim 3.19. *For any $i \geq 1$, we have $\beta_i = (\beta_{i-1})^{1.25}$ and have $\beta_0 = (T/n)^{1/2}$.*

Proof. We have $\beta_0 = (T/n)^{1/2}$ for Line 1 of Algorithm 1. Furthermore, we have $\beta_i = (\beta_{i-1})^{1.25}$ due to Line 4 of **RelabelIntraLevel** which is the only place we increase the level of a vertex and at the same time increase its budget from b to $b^{1.25}$. \square

We also have the following bound on n_i :

Claim 3.20. *For any $i \geq 1$ we have $n_i < n_{i-1} \cdot (\beta_{i-1})^{-0.25}$.*

Before describing the proof of Claim 3.20, let us first see we can get an upper bound of $O(T)$ for the value of (10). For any $i \geq 1$, we have

$$\beta_i \cdot n_i \stackrel{\text{Claim 3.19}}{=} (\beta_{i-1})^{1.25} \cdot n_i \stackrel{\text{Claim 3.20}}{<} (\beta_{i-1})^{1.25} \cdot (\beta_{i-1})^{-0.25} \cdot n_{i-1} = \beta_{i-1} \cdot n_{i-1}. \quad (11)$$

On the other hand, recall by Lemma 3.15 that the maximum possible level for a vertex is $L = O(\log \log_{T/n} n)$, meaning that for any $i > L$ we have $n_i = 0$; thus:

$$\sum_{i=1}^{\infty} \beta_i \cdot n_i = \sum_{i=1}^L \beta_i \cdot n_i \stackrel{(11)}{<} L(\beta_0 \cdot n_0) \leq O(\log \log n) \cdot (T/n)^{1/2} \cdot n,$$

where the last inequality comes from the fact that $\beta_0 = (T/n)^{1/2}$ due to Claim 3.19 and $n_0 = n$ by definition. Moreover, recall that $T \geq m + n \log^\alpha n$ for some large enough constant α , therefore $(T/n)^{1/2} \geq \log^{\alpha/2} n \gg O(\log \log n)$. This means that

$$O(\log \log n) \cdot (T/n)^{1/2} \cdot n \ll (T/n)^{1/2} \cdot (T/n)^{1/2} \cdot n = T.$$

Therefore, the total increase over the potential space over the course of the algorithm is at most T , meaning that indeed for any r , $y_r = O(T)$ and thus in any iteration we have at most $O(T)$ edges. It is only left to prove Claim 3.20.

Proof of Claim 3.20. To prove the claim, we show that for every vertex of level $i - 1$ that gets saturated and is marked as a leader, there are $(\beta_{i-1})^{0.5}$ other unique vertices of level $i - 1$ that are not marked as a leader and are removed from the graph. This is clearly sufficient to show $n_i \leq n_{i-1} \cdot (\beta_{i-1})^{-0.5} \ll n_{i-1} \cdot (\beta_{i-1})^{-0.25}$.

Consider some arbitrary iteration of the algorithm, and denote the set of saturated vertices and leaders with budget β_{i-1} by S and L respectively. Since each saturated vertex of budget β_{i-1} is chosen to be a leader independently with probability $\Theta(\frac{\log n}{\beta_{i-1}})$, we have $\mathbb{E}[|L|] = \Theta(\frac{\log n}{\beta_{i-1}}|S|)$. On the other hand, note that if $S \neq \emptyset$, we have $|S| \geq \beta_{i-1}$ since a vertex of budget β_{i-1} is marked as saturated in Line 1 of `RelabelIntraLevel` if it has at least β_{i-1} active neighbors with budget β_{i-1} , all of which will also get marked as saturated in Line 2 and thus join S . Therefore, $|S| \geq \beta_{i-1}$, meaning that $\mathbb{E}[|L|] = \Theta(\frac{\log n}{\beta_{i-1}}|S|) = \Omega(\log n)$. Thus, by a standard Chernoff bound argument, we get $|L| = \Theta(\frac{\log n}{\beta_{i-1}}|S|)$ with high probability. On the other hand, recall that by Claim 3.7, every non-leader saturated vertex will be contracted to a leader in its 2-hop. That is, all vertices in $S \setminus L$ will be removed from the graph. This, averaged over the vertices in L , we get

$$\frac{|S \setminus L|}{|L|} \geq \frac{|S| - |L|}{|L|} \geq \frac{|S|}{|L|} - 1 \geq \frac{|S|}{\Theta(\frac{\log n}{\beta_{i-1}}|S|)} - 1 \geq \Theta\left(\frac{\beta_{i-1}}{\log n}\right)$$

unique vertices that are removed from the graph per leader. Thus, it suffices to show that $\frac{\beta_{i-1}}{\log n} \gg (\beta_{i-1})^{0.5}$. For this, observe from Claim 3.19 and $T \geq m + n \log^\alpha n$ that $\beta_{i-1} \geq (T/n)^{1/2} \geq \log^{\alpha/2} n$ where α is some sufficiently large constant. It suffices to set $\alpha > 4$, say $\alpha = 5$, to get $\beta_{i-1} \gg \log^2 n$ and thus $\log n \ll (\beta_{i-1})^{0.5}$. This indeed means $\Theta(\frac{\beta_{i-1}}{\log n}) \gg \frac{\beta_{i-1}}{(\beta_{i-1})^{0.5}} = (\beta_{i-1})^{0.5}$ as desired. \square

We already showed how proving Claim 3.20 gives an upper bound of $O(T)$ on the potential space of all iterations, which by definition, is also an upper bound on the number of edges in the graph, concluding the proof of Lemma 3.17. \square

The next lemma is important for implementing the algorithm.

Lemma 3.21. *For any r , we have $\sum_{v \in V_r} (b_r(v))^2 \leq T$.*

Proof. We use induction on r . For the base case with $r = 0$, we have

$$\sum_{v \in V_0} (b_0(v))^2 = \sum_{v \in V_0} ((T/n)^{1/2})^2 = T.$$

Suppose by the induction hypothesis that $\sum_{v \in V_{r-1}} (b_{r-1}(v))^2 \leq T$, we prove that $\sum_{v \in V_r} (b_r(v))^2 \leq T$. For this, it suffices to show that $\sum_{v \in V_r} (b_r(v))^2 \leq \sum_{v \in V_{r-1}} (b_{r-1}(v))^2$. Recall that we only increase the budgets in the `RelabelIntraLevel` procedure, thus we only have to consider the effect of this procedure. Take a vertex $v \in V_r$ and with $b_r(v) > b_{r-1}(v)$ (otherwise the sum remains unchanged clearly). Note that v must have been marked as a leader in iteration r and thus $b_r(v) = b_{r-1}(v)^{1.25}$. Recall from the proof of Claim 3.20 above that there are at least $b_{r-1}(v)^{0.5}$ unique vertices for v with budget $b_{r-1}(v)$ that get removed from the graph in iteration r . Denote the set of these vertices by U . Removing these vertices decreases sum of budgets' square by

$$\sum_{u \in U} b_{r-1}(u)^2 = |U|(b_{r-1}(v))^2 \geq b_{r-1}(v)^{2.5}. \quad (12)$$

On the other hand, increasing the budget of v from $b_{r-1}(v)$ to $b_{r-1}(v)^{1.25}$ increases the sum of budgets' square by $(b_{r-1}(v)^{1.25})^2 - b_{r-1}(v)^2 = b_{r-1}(v)^{2.5} - b_{r-1}(v)^2$ which is not more than the decrease due to (12). Thus, we have $\sum_{v \in V_r} (b_r(v))^2 \leq \sum_{v \in V_{r-1}} (b_{r-1}(v))^2$ as desired. \square

Finally, we have to argue that each iteration of Algorithm 1 can be implemented in $O(1)$ rounds of MPC using $O(n^\delta)$ space per machine and with $O(T)$ total space. Since the proof is straightforward by known primitives, we defer it to Appendix A.

4 Improving Total Space to $O(m)$

In the previous section, we showed how it is possible to find connected components of an input graph in $O(\log D + \log \log_{T/n} n)$ rounds so long as $T \geq m + n \log^\alpha n$. In this section, we improve the total space to $O(m)$. The key to the prove is an algorithm that shrinks the number of vertices by a constant factor with high probability. More formally:

Lemma 4.1. *There exists an MPC algorithm using $O(n^\delta)$ space per machine and $O(m)$ total space that with high probability, converts any graph $G(V, E)$ with n vertices and m edges to a graph $G'(V', E')$ and outputs a function $f : V \rightarrow V'$ such that:*

1. $|V'| \leq \gamma n$ for some absolute constant $\gamma < 1$.
2. $|E'| \leq |E|$.
3. For any two vertices u and v in V , vertices $f(u)$ and $f(v)$ in V' are in the same component of G' if and only if u and v are in the same component of G .

We emphasize that Lemma 4.1 shrinks the number of vertices by a constant factor *with high probability*. This is crucial for our analysis. An algorithm that shrinks the number of vertices by a constant factor in expectation was already known [45] but cannot be used for our purpose.

Let us first show how Lemma 4.1 can be used to improve total space to $O(m)$ proving Theorem 1.

Proof of Theorem 1. First, observe that if $m \geq n \log^\alpha n$ or if $T \geq m + n \log^\alpha n$, then the algorithm of Section 3 already satisfies the requirements of Theorem 1. Assuming that this is not the case,

Algorithm 2. Shrinks the number of vertices by a constant factor in $O(1)$ rounds w.h.p.

1. For each vertex v , draw a directed edge from v to its neighbor with the minimum id.
2. If for two vertices u and v , we drew two directed edges (u, v) and (v, u) , we remove one arbitrary.
3. If a vertex has more than one incoming edge, we remove its outgoing edge.
4. If a vertex v has more than one incoming edge, we merge it with all its neighbors pointing to v and remove the incoming directed edges of the neighbors of v .
5. We remove each edge with probability $2/3$.
6. We merge each directed isolated edge.

we first run the algorithm of Lemma 4.1 for $(\alpha \log_{1/\gamma} \log n)$ iterations. Let $G'(V', E')$ be the final graph and f be the function mapping the vertices of the original graph to those of G' . We have

$$|V'| \leq n \cdot \gamma^{\alpha \log_{1/\gamma} \log n} = n \cdot \log^{-\alpha} n.$$

Now, we can run the algorithm of Section 3 on graph G' to identify its connected components. The total space required for this is

$$O(|E'| + |V'| \cdot \log^\alpha |V'|) = O\left(m + (n \cdot \log^{-\alpha} n) \cdot \log^\alpha n\right) = O(m + n) = O(m).$$

We can then use function f to identify connected components of the original graph in $O(1)$ rounds.

Also, observe that the running time required is $O(\log \log n) + O(\log D + \log \log_{T/n} n)$. Given that $m \leq n \log^\alpha n$ and $T \leq m + n \log^\alpha n$ (as discussed above), we have $T/n = O(\text{poly } \log n)$, thus $\log \log_{T/n} n = \Omega(\log \frac{\log n}{\log \log n}) = \Omega(\log \log n)$; meaning that $O(\log \log n) + O(\log D + \log \log_{T/n} n) = O(\log D + \log \log_{T/n} n)$ and thus the running time also remains asymptotically unchanged. \square

We now turn to prove Lemma 4.1.

Proof of Lemma 4.1. In order to prove this lemma, we show that the following procedure reduces the number of vertices of the graph by a constant factor, with high probability. This procedure only merges some neighboring vertices and hence maintains the connected components. In this procedure, without loss of generality, we assume that there is no isolated vertices. One can simply label and remove all isolated vertices at the beginning. It is easy to implement this procedure in $\frac{1}{\delta}$ rounds using $O(n^\delta)$ space per machine and a total space of $O(m)$ (see Appendix A for implementation details).

Next we show that this procedure reduces the number of vertices by a constant factor. For readability, we do not optimize this constant. Note that in Line 1 we are adding n edges. It is easy to see that there is no cycle of length larger than 2 in the directed graph constructed in Line 1. Line 2 removes at most half of the edges. Moreover, it removes all cycles of length 2. Thus by the end of Line 2 we have a rooted forest with at least $n/2$ edges.

After Line 3 every vertex with indegree more than 1 has no outgoing edges. Recall that each vertex has at most one outgoing edge. Thus, after Line 3 we have a collection of rooted trees where only the root may have degree more than 2. We call such trees *long tail stars*. Note that if we remove the outgoing edge of a vertex v there are two incoming edges pointing to v (which uniquely correspond to v). Although the process of Line 3 may cascade and remove the incoming edges of v , the following simple double counting argument bounds the number of removed edges. Note that this argument is just to bound the number of the edges and we do not require to run it, in order to execute our algorithm.

We put a token on each directed edge of the forest (before running Line 3). Next we are going to move the tokens such that (a) we never have more than two tokens on each edge, and (b) at the end we move all tokens to the edges that survive after Line 3. This says that at least half of the edges (i.e., at least $n/4$ edges) survive Line 3.

We traverse over each rooted tree from the root to the leaves. At each step, if the outgoing edge of a vertex v is removed, by induction hypothesis there are at most two tokens on the edge. Also, v has at least two incoming edges. We move each of the tokens on the outgoing edge of v to one of its incoming edges. Note that this is the only time we move a token to the incoming edges of v and hence we do not have more than two tokens on each edge as desired.

If we merge a vertex v with r incoming edges in Line 4, we remove at most $2r$ directed edges (r incoming edges of v and at most one incoming edge per each neighbor of v). On the other hand, we decrease the number of vertices by r . Thus, if this stage removes more than $n/8$ edges the number of vertices drops to at most $n - \frac{n}{16} = \frac{15}{16}n$, as desired. To complete the proof, we assume that at most $n/8$ edges are removed in Line 4 and show that in this case Lines 5 and 6 decrease the number of vertices by a constant factor.

Note that Line 4 removes the root of all long tailed stars. Thus after Line 4 we have a collection of directed edges. The probability that an edge passed to Line 5 becomes an isolated edge after sampling is at least $\frac{2}{3} \cdot \frac{1}{3} \cdot \frac{2}{3} = \frac{4}{27}$. If we mark every third edge (starting from an end of each path), the chance that each marked edge becomes an isolated edge after sampling is independent of other marked edges. There are $\frac{1}{3} \cdot \frac{n}{8} = \frac{n}{24}$ marked edges. Let X be a random variable that indicates the number of marked edges that are isolated after sampling. Note that $\mathbb{E}[X] \geq \frac{4}{27} \frac{n}{24} = \frac{n}{162}$. By applying a simple Chernoff bound we have

$$\Pr \left[X \leq 0.5 \frac{n}{162} \right] \leq \exp \left(- \frac{0.5^2 \frac{n}{162}}{2} \right) = \exp \left(- \frac{n}{1296} \right).$$

Therefore, with high probability we merge at least $\frac{n}{324}$ edges in Line 6 as desired. \square

5 Lower Bound

In this section we show a conditional lower bound on the round complexity of finding connected components in the MPC model. We use the following conjecture to show our hardness result.

Conjecture 5.1 (2-CYCLE conjecture [66, 59, 48, 7]). *Any MPC algorithm that uses $n^{1-\Omega(1)}$ space per machine requires $\Omega(\log n)$ rounds to distinguish one cycle of size n from two cycles of size $n/2$ with high probability.*

The conjecture above implies that the round complexity of our algorithm is tight for graphs with diameter $\Omega(n)$. However, it leaves the possibility of having faster algorithms for graphs with smaller diameter. For instance, one may still wonder whether for the case of graphs with $D = n^{1-\Omega(1)}$, an $O(1)$ connectivity algorithm exists or not. In what follows, we refute this possibility and show that the round complexity of our algorithm is indeed conditionally tight as long as $D = \log^{1+\Omega(1)} n$.

Theorem 2. *Fix some $D' \geq \log^{1+\rho} n$ for a desirably small constant $\rho \in (0, 1)$. Any MPC algorithm with $n^{1-\Omega(1)}$ space per machine that w.h.p. identifies each connected component of any given n -vertex graph with diameter D' requires $\Omega(\log D')$ rounds, unless the 2-CYCLE conjecture is wrong.*

Proof. We prove this theorem by contradiction. Assume that there exists an algorithm ALG in the MPC model with $n^{1-\Omega(1)}$ space per machine that finds all connected components of any given graph with diameter D' w.h.p. in $o(\log D')$ rounds. Using this assumption we show that the following

Algorithm 3.**Input:** a graph G consisting of disjoint cycles.

1. Remove each edge of G with probability $\frac{2\log n}{D'}$, thus obtaining G' .
2. Find the connected components of G' using ALG.
3. Contract each connected component of G' to a single vertex and return the obtained graph.

procedure applied to a graph consisting of sufficiently long disjoint cycles, shrinks the length of each cycle by a factor of $\frac{4\log n}{D'}$ w.h.p.

We first prove two properties of Algorithm 2, then show how it helps in obtaining a contradiction.

Claim 5.2. *Algorithm 2 takes $o(\log D')$ rounds of MPC with $n^{1-\Omega(1)}$ space per machine w.h.p.*

Proof. Lines 1 and 3 of Algorithm 2 can be trivially implemented in $O(1)$ rounds of MPC. It suffices to show that the diameter of graph G' is at most D' so that running ALG takes $o(\log D')$ rounds.

Fix a path of length $D' + 1$ in G . The probability that all edges of this path survive Line 1 of Algorithm 2 is $(1 - \frac{2\log n}{D'})^{D'+1} \leq e^{-2\log n} = n^{-2}$. There are only n such paths in G , thus by a simple union bound, w.h.p., none of them survives to G' ; meaning that diameter of G' is $\leq D'$. \square

Claim 5.3. *If G has m edges and $D' \leq m$, Algorithm 2 removes at most $\frac{4m\log n}{D'}$ edges w.h.p.*

Proof. Let Z be the number of removed edges. We have $\mathbb{E}[Z] = \frac{2\log n}{D'} \cdot m$. Observe that Z is sum of independent Bernoulli random variables and hence by Chernoff bound we have

$$\Pr \left[Z \geq 2 \cdot \frac{2m\log n}{D'} \right] \leq \exp \left(- \frac{2m\log n}{3D'} \right) \leq \exp \left(- \frac{2\log n}{3} \right) = n^{-2/3},$$

as desired. \square

We iteratively run Algorithm 2 and shrink the graph until it fits the memory of a single machine. Observe that after each application of Algorithm 2, only those edges that were removed from the graph will remain as the rest of the edges are contracted to single vertices. This means by Claim 5.3 that if the current graph has m edges, after one application of Algorithm 2, the resulting graph will have at most $\frac{4m\log n}{D'}$ edges. We repeat Algorithm 2 for at most

$$\log_{\frac{D'}{4\log n}} n = \frac{\log n}{\log(\frac{D'}{4\log n})} \leq \frac{\log n}{\log(\frac{D'}{\log n}) - \log 4} \leq \frac{\log n}{\log(D' \frac{\rho}{1+\rho}) - \log 4} \leq \frac{\log n}{(\frac{\rho}{1+\rho}) \log D' - \log 4} = O\left(\frac{\log n}{\log D'}\right)$$

times until the number of edges in the graph drops to $n^{o(1)}$ where we can store the entire graph on a single machine and solve the problem. The overall round complexity would be $O\left(\frac{\log n}{\log D'}\right) \cdot o(\log D) = o(\log n)$ which is a contradiction. \square

A MPC Implementation

In this section we provide some details on the implementation of our algorithm in MPC. We start by reviewing some known computational primitives in the MPC model with strictly sublinear space per machine.

A.1 Primitives

The following primitives can be implemented in the MPC model using $O(n^\delta)$ space per machine. All of the algorithms here use space proportional to the input to the primitive (denoted by N).

- **Sorting.** Sorting N tuples can be solved in $O(1/\delta)$ rounds [38]. The input is a sequence of N tuples, and a comparison function f . The output is a sequence of N tuples that are in sorted order with respect to f .
- **Filtering.** Filtering N tuples can be solved in $O(1/\delta)$ rounds. The input is a sequence of N tuples, and a predicate function f . The output is a sequence of k tuples such that a tuple x is in the output if and only if $f(x) = \text{true}$.
- **Prefix Sums.** Computing the prefix sum of a sequence of N tuples can be solved in $O(1/\delta)$ rounds [38]. The input is a sequence of tuples $\{t_1, \dots, t_N\}$, an associative binary operator \oplus , and an identity element, \perp . The output is a sequence of tuples S , s.t. S_j is equal to t_j , with an extra entry containing $\perp \oplus_{i=1}^{j-1} t_j$. Note that reductions are a special case of prefix sums.
- **Predecessor.** The predecessor problem on a sequence of N tuples can be solved in $O(1/\delta)$ rounds [38, 4]. The input is a sequence of N tuples, where each tuple has an associated value in $\{0, 1\}$. The problem is to compute for each tuple x , the first tuple x' that appears before x in the sequence s.t. x' has an associated value of 1.
- **Duplicate Removal.** Given a sequence of N elements, we can remove duplicates in the sequence in $O(1/\delta)$ rounds by simply sorting the elements and removing any tuple that is identical to the one before it, using predecessor.

A.2 Algorithm Implementation

Here we show that each subroutine used in the algorithm can be implemented in $O(1)$ rounds of MPC. We start by describing the representation of the data structures maintained by the algorithm.

Data Representation. Here we specify the representation of several data structures that we maintain over the course of the algorithm. All of the data structures are collections of tuples, which have a natural distributed representation and can be stored on any machine. In addition to each tuple we store the round that the tuple was written. This simplifies the process of applying updates to the sets.

- $G = (V, E)$: The graph is represented as a set of vertex neighborhoods. Each vertex $u \in V$ stores its neighborhood, $N(u)$ as a set of tuples (u, v) , which can be located on any machine.
- b : budgets are represented as a collection of tuples $(u, b(u))$. The levels, and active flags for each vertex are stored similarly.
- C : The set of vertices that have been merged to some vertex, u , are stored as a collection of (u, x) tuples.
- We represent degrees implicitly by storing $O(\log \log_{T/n} n)$ entries for each vertex, v . The i 'th entry indicates the number of level i neighbors that v has. We refer to this per-vertex structure as its degree array.

Updating Budgets and Levels. We update the budgets and levels as follows. We emit a tuple $(v, b(v), r)$ where r is the current iteration of the algorithm. Updates can be processed by first sorting by decreasing lexicographic order. Next, we can use predecessor and a filter to eliminate any tuple $(v, b(v)', r')$ that is overwritten by a tuple $(v, b(v), r)$ where $r > r'$. This can be done in $O(1)$ rounds.

Merging and Updating Neighbor Sets and Degrees. As the algorithm proceeds we merge active vertices to other vertices (for example in `RelabelInterLevel`, when merging to our highest level neighbor, and in `RelabelIntraLevel`, when merging to a leader in our 2-hop). We assume that the output of each merge operation is a tuple (x, m) indicating that a currently active vertex x is merged to m .

Let $m(x)$ be the id that x is merging to. To merge vertices, we map over all tuples (u, v) representing the graph, to a set of tuples $(u, v, 0)$. We also add the tuples $(x, m, 1)$ for each merge input. Then we sort by the first entry in the tuple, and run predecessor, which associates each $(u, v, 0)$ tuple with $m(x)$, and lets us emit a collection of $(m(x), v, 0)$ tuples. We apply the same idea again on the output of the previous step, with the first and second entries swapped, which produces a collection of $(m(v), m(x), 0)$ tuples (the tuples with 1 can be filtered out). The graph on the merged vertices is produced by swapping the components, and removing any duplicate tuples that result from merges. We also remove self-loops by filtering all (u, v) tuples in G where $u = v$.

Lastly, we can update the degree arrays by recomputing them after each update and merge step. Updating is easily done by sorting, and applying a prefix sum to produce the number of level i neighbors incident to each vertex.

Since we apply a constant number of $O(1)$ round algorithms, the procedure to update all vertex sets and degrees in the graph takes $O(1)$ rounds in total.

Computing Degrees. Note that the degree of all vertices can be computed by sorting all (x, y) tuples in the graph and applying a prefix sum. Computing the degree of each vertex can therefore be done in $O(1)$ rounds. Alternately, we can prefix sum the degree array for the vertex.

Since we maintain the level i degree of each vertex explicitly in the degree arrays, we can easily compute the induced degree of a neighboring vertex when restricted to vertices with level $\geq i$. This is done by applying a prefix sum over the tuples with degree at least i .

A.3 Implementing Algorithm 1

Implementing Connect2Hops. In `Connect2Hops`, each *active* vertex, v , either fully connects itself to its 2-hop if the size of its 2-hop has size at most $b(v)$, or connects itself to $b(v) - d(v)$ neighbors arbitrarily. First for each vertex $u \in N(v)$ we compute its degree when restricted to vertices with level at least $\ell(v)$. This can be done in $O(1)$ rounds as described previously. Note that if the restricted degree of v is more than $b(v)$ we do not need to add any edges since $b(v) - d(v) \leq 0$. Thus, we assume $d(v) < b(v)$.

Case 1. If any of v 's neighbors has a restricted degree $\geq b(v)$, we take the first $b(v)$ vertices from this neighbors degree and union them with the vertices currently in $N(v)$. We mark each of our current neighbors with 0 and mark each new (incoming vertex) with 1 and remove duplicates (ignoring the $\{0, 1\}$ tag on the tuples). Next, we sort lexicographically. If this set contains more than $b(v)$ vertices, we pick the first $b(v)$ to include in $N(v)$ and drop the remaining tuples. Note that any neighbors of v are guaranteed to remain in this set, since $d(v)$ was initially less than $b(v)$, and the lexicographic sort will order our existing neighbors before any new neighbors. The total space used in this step is $O(b(v))$ per vertex, and the output is exactly $b(v)$ neighbors with level at least $\ell(v)$.

Case 2. If each of v 's neighbors has restricted degree $< b(v)$, since v has less than $b(v)$ neighbors of level at least $\ell(v)$, and each has restricted degree smaller than $b(v)$, we can copy each of these neighbor lists into the space available for v , which is at least $\Theta(b(v)^2)$. Finally, we can remove duplicates for these neighbors. By using a similar tagging idea as in the previous step, we tag each neighbor based on whether it was present in $N(v)$ originally. If more than $b(v)$ vertices are produced in this step, we pick the first $b(v)$ of them in the lexicographically ordered sequence.

As we use a constant number of primitive calls, each of which require $O(1)$ rounds, the overall round-complexity is $O(1)$. Furthermore, the maximum space a vertex uses is at most $O(b(v)^2)$, which by Lemma 3.21, is precisely the space we can use for each vertex while using only $O(T)$ total space. The output either fully connects v 's 2-hop, or updates $N(v)$ to have size at most $b(v)$, adding vertices chosen arbitrarily from v 's degree-restricted 2-hop.

Implementing RelabelInterLevel. In `RelabelInterLevel`, each *active* vertex, v , chooses the highest level vertex $h(v)$ in its direct neighborhood and merges itself to it.

We can implement this procedure by having each active vertex sort its direct neighbors by their level in descending order. If the first neighbor in this sequence has the same level as v , we do nothing, otherwise we have found $h(v)$ and merge v to $h(v)$ by emitting a tuple $(v, h(v))$. We then merge and update the neighbor sets of all vertices in G . Overall, the algorithm runs in $O(1)$ rounds.

Implementing RelabelIntraLevel. In `RelabelIntraLevel`, each active saturated vertex, v , first samples itself to be a leader. If it is chosen as a leader, it does nothing. Otherwise, each non-leader saturated vertex selects a leader in its 2-hop and merges with it. The sampling can easily be done in 1 round of computation, assuming that each machine has a source of randomness. For each sampled leader, we update the level and budget of the vertex by writing the tuple $(v, \ell(v) + 1)$ to the levels and $(v, b(v)^{1.25})$ to the budgets. These are updated as described earlier.

Next, we must check whether a vertex has a leader in its 2-hop, which can be implemented as follows. First, each active saturated vertex chooses a candidate leader in its neighborhood, breaking ties arbitrarily if multiple leaders are present. If no candidate exists, we mark this fact with a null value. This can be done by using mapping the graph to tuples (u, v, l) where $l \in \{0, 1\}$ indicates whether v is marked as a leader. Then, for each u we inject a tuple $(u, \infty, 0)$, perform a lexicographic sort, and compute predecessor. Each $(u, \infty, 0)$ tuple finds the first tuple before it that contains a 1—if this tuple's first entry starts with u , we use the second entry as the chosen candidate for u . Otherwise, the candidate is set to null. The candidates are a collection of (u, c) pairs, where c is the candidate for vertex u and null otherwise. Note that the algorithm just described computes a function f (in this case projecting a leader) which is aggregated over the neighbors of a vertex in $O(1)$ rounds.

Lastly, each non-leader saturated vertex performs another aggregation, identical to the one described in the previous step, which gives each active saturated vertex v a leader, $l(v)$, in its 2-hop w.h.p. We emit tuples $(v, l(v))$ indicating that v is merged with $l(v)$. Finally we merge and update the neighbor sets of all vertices in G . The algorithm runs in $O(1)$ rounds as it performs a constant number of steps, each of which take $O(1)$ rounds.

A.4 Implementing Algorithm 2

We now discuss how each subroutine used in Algorithm 2 can be implemented. Recall that this algorithm eliminates a constant factor of the vertices in the graph w.h.p. in $O(1)$ rounds of MPC.

Line 1 can be implemented by using a reduction (prefix sum with min) over the neighbors of each vertex. Line 2 can be implemented by sorting the chosen edges, and removing duplicates. Note that if both (u, v) and (v, u) are chosen (say $u < v$), only the (u, v) edge remains. To implement Line 3,

we first compute the in-degree of each vertex, which can be done by sorting. Next, we send the in-degrees of each vertex to its outgoing edge, which can be done via sorting and predecessor, and drop the outgoing edge if its in-degree is greater than 1. To implement Line 4, each v with incoming edge set $\{(v, u_1), \dots, (v, u_k)\}$, we generate the tuples $\{(u_1, v), \dots, (u_k, v)\}$ which indicates that u_1, \dots, u_k should be merged to v . Recall that we can use a previously described merging algorithm to merge these vertices to v in $O(1)$ rounds. Line 5 simply drops each tuple for a remaining edge with probability $2/3$. Lastly, in Line 6 we can detect isolated edges by computing the in-degree and out-degree of the vertices as previously described, summing them together, and choosing out edges of vertices whose in-degree and out-degree sum to 1, which can be done in $O(1)$ rounds in total. As each step takes $O(1)$ rounds of MPC, each call to Algorithm 2 takes $O(1)$ rounds in total.

B PRAM implementation

In this section we show that our connectivity algorithm can be simulated in $O(\log D + \log \log_{m/n} n)$ depth on the *multiprefix CRCW PRAM*, a strong model of parallel computation permitting concurrent reads and concurrent writes. The parallel algorithm we derive performs $O((m + n)(\log D + \log \log_{m/n} n))$ work and is therefore nearly work-efficient. We start by describing existing PRAM models, how the multiprefix CRCW PRAM compares to these models, and reviewing existing results on parallel graph connectivity algorithms from the literature.

B.1 Model

We state results in this section in the *work-depth model* where the *work* is equal to the number of operations required (equivalent to the processor-time product) and the *depth* is equal to the number of time steps taken by the computation. The related machine model used by our algorithms is the parallel random access machine (PRAM). Note that in work-depth models, we do not concern ourselves with how processors are mapped to tasks (see for example, Jaja [43] or Blelloch et al. [17, 18]). We now place our machine model, the multiprefix CRCW PRAM, in context by reviewing related PRAM models.

The *arbitrary* CRCW PRAM handles concurrent writes to the same memory cell by selecting an arbitrary write to the cell to succeed. The *scan* PRAM extends the arbitrary PRAM with a unit-depth scan (prefix-sum) operation [16] (note that in the original paper the extended model was the EREW PRAM). The inclusion of this primitive is justified based on the observation that a prefix-sum can be efficiently implemented in hardware as quickly as retrieving a reference to shared-memory. The *combining* CRCW PRAM combines concurrent writes to the same memory location based on an associative and commutative combining operator (e.g., sum, max). The multiprefix CRCW PRAM extends the arbitrary PRAM with a unit-depth *multiprefix operation* which is a generalization of the scan operation that performs multiple independent scans. The input to the multiprefix operation is a sequence of key-value pairs. The multiprefix performs an independent scan for each key, and outputs a sequence containing the result of each scan. The multiprefix CRCW PRAM was proposed by Ranade, who gave a routing algorithm for butterfly networks in which a multiprefix could be implemented as quickly as fetching a memory reference [56]. In all PRAM models considered in this paper we assume that each processor has its own random source. We refer the interested reader to the Karp and Ramachandran chapter on parallel algorithms for more details on PRAMs [46].

We observe that all of aforementioned PRAM models can be work-efficiently simulated in the MPC model with strictly sublinear space per machine, such that the number of rounds of the resulting MPC computation is asymptotically equal to the depth. To see this, note that the multiprefix CRCW PRAM can work-efficiently simulate all of the other PRAM variants, without an increase in

depth. Furthermore, a multiprefix operation on n key-value pairs can be implemented in the MPC with strictly sublinear space per machine in $O(n)$ space and $O(1)$ rounds by performing independent scan operations for each key independently in parallel (see Section E.6 (Multiple Tasks) in [4] for implementation details). Therefore, the MPC model with strictly sublinear space per machine is more powerful than the PRAM variants described above.

B.2 Parallel Connectivity Algorithms

Connectivity algorithms on the PRAM have a long history, and many algorithms have been developed over the past few decades [62, 8, 58, 54, 34, 44, 25, 40, 41, 55, 53, 63]. Classic parallel connectivity algorithms include the hook-and-contract algorithms of Shiloach and Vishkin [62] and Awerbuch and Shiloach [8], and the random-mate algorithms of Reif [58] and Phillips [54]. All of these algorithms reduce the number of vertices in each round by a constant fraction, but do not guarantee that the number of edges reduces by a constant fraction, and therefore perform $O(m \log n)$ work and run in $O(\log n)$ depth on the multiprefix CRCW PRAM. (The algorithms of Reif and Phillips are randomized, so the bounds hold w.h.p.)

Historically, obtaining a work-efficient parallel connectivity algorithm (an algorithm which performs asymptotically the same work as the most efficient sequential algorithm) was difficult, and progress was not made until the early 90s [34]. A number of work-efficient algorithms were subsequently discovered [25, 40, 41, 55, 53, 63]. Many of these work-efficient algorithms also achieve $O(\log n)$ depth, with the algorithm of Halperin and Zwick achieving this bound on the EREW PRAM [40].

Since a work bound of $O(m + n)$ is optimal, the remaining question is whether the depth can be improved. In terms of lower-bounds, the results of Cook *et al.* [26] and Dietzfelbinger *et al.* [31] imply a lower bound of $\Omega(\log n)$ depth for connectivity on randomized EREW PRAMs. Despite the lower-bound only holding for the EREW setting, to the best of our knowledge all existing connectivity algorithms in the PRAM literature run in least $\Omega(\log n)$ depth, even in models permitting concurrent reads and writes. A natural question therefore is whether we can solve connectivity on a stronger PRAM model in $o(\log n)$ depth.

If work-inefficiency is permitted, the answer is certainly yes. For example, on the CRCW PRAM, which permits unbounded fan-in writes, a folklore result for connectivity is to perform matrix squaring, stopping once each connected component becomes a clique. This algorithm has $O(\log D)$ depth, but requires $O(n^3)$ work using a combinatorial matrix multiplication algorithm and is therefore work-inefficient for sparse graphs. Note that $O(\log D)$ depth is a natural goal for the PRAM, and is in fact a lower bound if the 2-CYCLE conjecture is true, due to known simulations of the PRAM on MPC [45, 38]. Is there a more work-efficient parallel connectivity algorithm that runs in $O(\log D)$ depth? Our result shows that a nearly work-efficient PRAM algorithm with $O(\log D + \log \log_{m/n} n)$ depth w.h.p. exists in the multiprefix CRCW PRAM, resolving this question affirmatively for graphs with $D = \Omega(\text{polylog}(n))$.

B.3 Multiprefix CRCW Implementation of Algorithm 1

Data Representation. We represent *active* and *next* as dense arrays of length n . We represent C using an array for each vertex. We store the graph in a sparse format, storing each vertex's neighbors in an array.

Sequence Primitives.

- **Map** takes as input an array A and a function f and applies f to each element of A . Map

can be implemented in $O(n)$ work and $O(1)$ depth on all of the PRAM models considered in this paper.

- **Scan** takes as input an array A of length n , an associative binary operator \oplus , and an identity element \perp such that $\perp \oplus x = x$ for any x , and returns the array $(\perp, \perp \oplus A[0], \perp \oplus A[0] \oplus A[1], \dots, \perp \oplus_{i=0}^{n-2} A[i])$ as well as the overall sum, $\perp \oplus_{i=0}^{n-1} A[i]$. We use **plus-scan** to refer to the scan operation with $\oplus = +$ and $\perp = 0$. Scan can be implemented by simply dropping the keys (or making all keys equal) and applying a multiprefix.
- **Multiprefix** takes as input an array $A = [(k_0, v_0), \dots, (k_{n-1}, v_{n-1})]$ of length n , an associative binary operator \oplus and an identity element \perp (similarly to scan), and returns an array $[(k_0, v'_0), \dots, (k_{n-1}, v'_{n-1})]$ where the output values associated with each key are the result of applying an independent scan operation for the values with each key. We use a **plus-multiprefix** to refer to the multiprefix operation with $\oplus = +$ and $\perp = 0$.
- **Remove Duplicates** takes an array A of elements and returns a new array containing the distinct elements in A , in the same order as in A . Removing duplicates can be implemented by using a plus-multiprefix operation where the keys are elements, and the values are initially all 1s. Since the plus-multiprefix assigns the first instance of each key a 0 value, the keys corresponding to values greater than 0 are filtered out, leaving only a single copy of each distinct element in A .
- **Filter** takes an array A and a predicate f and returns a new array containing $a \in A$ for which $f(a)$ is true, in the same order as in A . Filter can be implemented by first mapping the array in parallel with the predicate f , and setting the key to 1 if $f(e)$ is true, and 0 otherwise. A plus-multiprefix is then used to assign each element with a 1 key contiguous and distinct indices. Finally, the elements where $f(e)$ is true are copied to the output array using the indices from the previous step.

The multiprefix operation on an array of length n costs $O(n)$ work and $O(1)$ depth on the multiprefix CRCW PRAM. Therefore, scan, filter and removing duplicates on arrays of length n can also be implemented in $O(n)$ work and $O(1)$ in this model.

We note that for convenience, the parallel algorithm we describe below often runs *multiple* multiprefix operations in parallel. These operations can usually be run using a single multiprefix. In particular, parallel multiprefix operations can be simulated using a single operation so long as each parallel operation is keyed by a unique key. The idea is to prepend the unique key to the keys within each multiprefix operation. In our implementation, this unique key is usually the vertex id.

Graph Primitives. **Symmetrize** takes as input a directed graph $G = (V, E)$ as a collection of tuples and outputs an undirected graph G_S in adjacency array form. The algorithm first computes a plus-scan over the array $S = [2d(i)|i \in [0, n]]$. Each vertex v then copies its incident out-edges into an array of size $2m$ at offset $S[v]$, and copies the edges with their direction reversed at offset $S[v] + d(v)$. Next, the algorithm removes duplicates from the array. Lastly, the algorithm collects the edges incident to a vertex contiguously. This is done by first running a plus-multiprefix, M , where the keys are the first component of each tuple and the value is 1. Next, the algorithm computes S , a plus-scan over the distinct keys, where the value is degree of the vertex, which is obtained from the result of the multiprefix within each key. The algorithm finally allocates an array proportional to the output of this scan, and copies edge i into the location $S[fst(i)] + M[i]$ where $fst(i)$ is the first component of edge i . The work of this operation is $O(|E| + |V|)$ and the depth is $O(1)$.

Contract takes as input an undirected graph $G = (V, E)$ in adjacency array form and a mapping $m : V \rightarrow V$ s.t. either $m(u) = u$ or $m(u) = v$ where $v \in N_G(u)$. The contraction algorithm

constructs the graph $G' = \{(m(u), m(v)) \mid (u, v) \in E(G)\}$ with duplicate edges and self-loops removed. The contraction algorithm is implemented as follows. The algorithm first uses a plus-scan to count the number of remaining vertices, n' . Next, it computes $d'(v)$, the degree of the v in G' using a plus-multiprefix (or a combining write, which can be work-efficiently simulated in $O(1)$ depth). It then maps each edge $(u, v) \in E(G)$ to $(m(u), m(v))$, and uses a multiprefix operation to remove duplicates, which takes $O(m)$ work and $O(1)$ depth. After this step, edges exist in both directions and all edges incident to a vertex $m(u)$ are stored contiguously. The work of this operation is $O(|E| + |V|)$ and the depth is $O(1)$.

Implementing Connect2Hops. Recall that in this step every active vertex either fully connects to its 2-hop if the size of its 2-hop is at most $b(v)$, or connects to $C = \min(b(v) - d(v), |H(v)|)$ neighbors arbitrarily. For ease of discussion we assume that we must connect to exactly $b(v)$ neighbors.

Case 1: $\forall u \in N(v), d(u) \leq b(v)$. In this case, the algorithm must set v 's neighbors to $N(v) \cup \cup_{u \in N(v)} N(u)$. One simple idea (implementable on the arbitrary PRAM) is to initialize a parallel hash-table and insert all neighbors into the table, which takes $O(b(v)^2)$ work and $O(\log^* n)$ depth [37]. After insertion, all elements in the table will be distinct. However, using parallel hashing increases the depth by a multiplicative factor of $O(\log^* n)$. Instead, our algorithm uses the multiprefix operation to copy the neighbor's neighbors into an array and remove duplicates from this array in $O(1)$ depth.

Concretely, the algorithm first writes the degree of each of its neighbors (including itself) into an array S , and computes a plus-scan over this array. Next, it allocates an array E_v with size proportional to the result of the scan, and copies the neighbors of the i th neighbor to the sub-array $E_v[S[i]]$. Note that the array E_v now contains $N(v) \cup \cup_{u \in N(v)} N(u)$, possibly with duplicates. We produce the new neighbors of v by removing duplicates from E_v .

We now address how to add edges discovered by a vertex u in the **Connect2Hops** procedure the endpoint, v . Note that v may already have degree at least $b(v)$, but still have edges added to it by vertices that discover v in this procedure. This operation is implemented by simply symmetrizing the graph.

Case 2: $\exists u \in N(v)$ s.t. $\ell(u) > \ell(v)$. This case can be checked in constant depth using a concurrent write. Note that if v has any higher-level neighbors it will become inactive on this round in **RelabelInterLevel** so we can quit.

Case 3: $\exists u \in N(v)$ s.t. $d(u) > b(v)$. This case can also be checked using an arbitrary write. In this case, the algorithm copies $b(v)$ neighbor ids from the neighbor v with degree $> b(u)$. It then removes duplicates, and adds edges from the chosen endpoints to itself by symmetrizing the graph, as before.

Implementing RelabelInterLevel. Recall that in **RelabelInterLevel**, each *active* vertex, v , chooses the highest level vertex $h(v)$ in its direct neighborhood and merges itself to it by updating *next*. The maximum value can be selected either using a scan with the max operation. An arbitrary neighbor with the maximum level in v 's direct neighborhood can then be selected using a concurrent write. We then contract the graph using the contraction primitive where $m = \text{next}$. Finally, we update C . Since each vertex is uniquely stored in $C(v)$, we do not need to remove duplicates in this step and simply flatten the sets $C(v) \forall m(v) = u$ to be contiguous, which can be done using a plus-scan and a parallel copy.

Implementing RelabelIntraLevel. Detecting whether an active vertex, v is saturated is done by computing a prefix sum over its neighbors, filtering out neighbors with degree less than $b(v)$. In a second synchronous step, each vertex v checks whether it has a neighbor u with $\ell(u) = \ell(v)$ that is marked as saturated, and if so marks itself as saturated by performing an arbitrary write. We then use the processor's internal randomness to sub-sample vertices as leaders. Vertices which

successfully become leaders do nothing. The non-leader saturated vertices select a leader in their 2-hop as follows.

First, each vertex checks if it has a leader in its direct neighborhood, which can be done by mapping over the neighbors and using a concurrent write. Vertices that successfully find a leader in their neighborhood indicate mark themselves with the selected neighbor. Each vertex that failed the previous step re-check their direct neighborhood, and pick an arbitrary leader chosen by some marked neighbor, again using a concurrent write (such a neighbor exists w.h.p.). Finally, we contract the graph using the contraction primitive, and update C using the same method as in `RelabelInterLevel`.

B.4 Parallel Implementation of Algorithm 2

Recall that this algorithm eliminates a constant factor of the vertices in the graph w.h.p. per round. We discuss how to implement each step of the algorithm on the arbitrary PRAM. Step 1 can be implemented work-efficiently using the minimum algorithm in $O(d(v))$ work and $O(1)$ depth w.h.p. Step 2 can be implemented in $O(n + m)$ work and $O(1)$ depth by checking each neighbor. Similarly, Step 3 can be implemented in two PRAM rounds by first arbitrarily writing any neighbor pointing to the vertex u , and in the second round writing another edge if it differs from the first one. The step also takes $O(m + n)$ work and $O(1)$ depth. Step 4 can be checked similarly. The merge is handled using the contraction primitive given above which costs $O(m + n)$ work and $O(1)$ depth. Step 5 can be done in $O(m + n)$ work and $O(1)$ depth using a random source within each processor. Finally, we can detect isolated edges in Step 6 similarly to Step 3 above, and merge these edges using graph contraction in $O(m + n)$ work and $O(1)$ depth using the contraction algorithm described above. In total, one round of Algorithm 2 costs $O(m + n)$ work and $O(1)$ depth.

B.5 Cost in the multiprefix CRCW PRAM Model

Theorem 3. *There is a multiprefix CRCW PRAM algorithm that given a graph with diameter D , identifies its connected components in $O(\log D + \log \log_{m/n} n)$ depth and $O((m + n)(\log D + \log \log_{m/n} n))$ work. The algorithm is randomized, succeeds with high probability and does not require prior knowledge of D .*

Proof. Observe that in our parallel implementation, in each iteration a vertex never performs more than $O(b(v)^2)$ work. By Lemma 3.21 the total work is therefore $O(T)$ per round. All other operations in an iteration such as contraction and symmetrization cost $O(m + n)$ work. As the algorithm performs $O(\log D + \log \log_{m/n} n)$ rounds w.h.p., the overall work is $O(T(\log D + \log \log_{m/n} n)) = O((m + n)(\log D + \log \log_{m/n} n))$ w.h.p. for $T = O(m + n)$.

By Lemma 3.16 the overall depth is $O(\log D + \log \log_{m/n} n)$ w.h.p. since each round of the algorithm is implemented in $O(1)$ depth. \square

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