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Amitath Trehan Candidate Computer science Depart This dissertation is approved, and it is acceptable in quality and form for publication: Approved by the Dissertation Committee: , Chairperson Dan

# **Algorithms for Self-Healing Networks**

by

## Amitabh Trehan

B.Sc., Biology, Punjab University, 1994M.C.A., Indira Gandhi National Open University, 2000M.Tech., Indian Institute of Technology Delhi, 2002

### DISSERTATION

Submitted in Partial Fulfillment of the Requirements for the Degree of

> Doctor of Philosophy Computer Science

The University of New Mexico

Albuquerque, New Mexico

May, 2010

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# Dedication

To the sun, the moon and the intrepid spirit, To my family who made this journey possible.

> The question walks the length of pages, rain drops on roof.

# Acknowledgments

If this were an Oscar awards ceremony, my list of thank yous would have had the music director going crazy trying to hound me off the stage. There are many many to thank for the journey responsible for this document. My foremost gratitude goes towards my advisor, Professor Jared Saia, for his constant enthusiastic guidance. He has patiently ironed out a multitude of rough edges that I, as a scientist, have presented, and has taught the virtues of discipline and mathematical rigour. My academic collaborator and committee member Professor Thomas Haves has been a source of constant inspiration. I am thankful to my dissertation committee (Professors Saia, Haves, Cris Moore and Tanya-Beger Wolf) who have provided me with much insight and guidance. I am thankful to all my close friends, who have been with me through good times and bad, especially Navin Rustagi and Vaibhav Madhok (their lively discussions have lit up many evenings!). I am thankful to the US educational system, for its support of quality graduate education and research. I owe a debt of gratitude to all my teachers and friends in India, and to the Art of Living foundation and it's founder Sri Sri Ravi Shankar, for Sudershan Kriya, the meditation and the satsangs. Finally, I have to thank my biggest inspiration: my mother, and my family: my late father, my step-father, my brothers, my sister-in-laws, my nieces and my nephew, without whose support and love I would never have been able to pursue the path around the world and in my academic world that I have.

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### Abstract

Many modern networks are *reconfigurable*, in the sense that the topology of the network can be changed by the nodes in the network. For example, peer-to-peer, wireless and ad-hoc networks are reconfigurable. More generally, many social networks, such as a company's organizational chart; infrastructure networks, such as an airline's transportation network; and biological networks, such as the human brain, are also reconfigurable. Modern reconfigurable networks have a complexity unprecedented in the history of engineering, resembling more a dynamic and evolving living animal rather than a structure of steel designed from a blueprint. Unfortunately, our mathematical and algorithmic tools have not yet developed enough to handle this complexity and fully exploit the flexibility of these networks.

We believe that it is no longer possible to build networks that are scalable and never have node failures. Instead, these networks should be able to admit small, and maybe, periodic failures and still recover like skin heals from a cut. This process, where the network can recover itself by maintaining key invariants in response to attack by a powerful adversary is what we call *self-healing*.

Here, we present several fast and provably good distributed algorithms for selfhealing in reconfigurable dynamic networks. Each of these algorithms have different properties, a different set of gaurantees and limitations. We also discuss future directions and theoretical questions we would like to answer.

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# Chapter 1

# Introduction

Begin at the beginning and go on till you come to the end: then stop. The king of hearts *Alice in Wonderland* 

Networks in the modern age have grown by leaps and bounds, both in size and complexity. The size of some networks spans nations and even the globe. Networks provide a multitude of services using a wide variety of protocols and components to the extent that they have now begun to resemble self-governed living entities. The Internet is the obvious example but there are others too like cellular phone networks. There are networks which have always been around but which only now have been scrutinized by tools of computer science, such as the social networks. Most networks are dynamic since nodes can enter the network or be removed by choice, failure or attack. We are also fortunate that we live in a time where we can observe and inuence the evolution of a dynamic network like the Internet. Due to the scale and nature of design of modern networks, it may simply not be practical to build robustness into the individual nodes or into the structure of the initial network itself.

#### Chapter 1. Introduction

Many important networks are also *reconfigurable* in the sense that they can change their topology. Often, individual nodes can initiate new connections or drop existing connections. For example, peer-to-peer, wireless and ad-hoc networks are reconfigurable. Looking beyond computer networks, many social networks, such as a company's organizational chart, or friendship networks on social networking sites are reconfigurable. Infrastructure networks, such as an airline's transportation network are reconfigurable. Many biological networks, including the human brain, which shows such capacity for learning and adaptability, are also reconfigurable. From an engineering aspect, modern reconfigurable networks have a complexity unprecedented in history. We are approaching scales of billions of components. Such systems are less akin to a traditional engineering enterprise built from a blueprint such as a bridge, and more akin to a dynamic and evolving living organism in terms of complexity. A bridge must be designed so that key components never fail, since there is no way for the bridge to automatically recover from system failure. In contrast, a living organism can not be designed so that no component ever fails: there are simply too many components. For example, skin can be cut and still heal. Designing skin that can heal is much more practical than designing skin that is completely impervious to attack. Unfortunately, current algorithms ensure robustness in computer networks through hardening individual components or, at best, adding lots of redundant components. Such an approach is increasingly unscalable.

Our mathematical and algorithmic tools have not yet developed enough to handle the complexity and fully exploit the flexibility of modern networks. As an example, on August 15, 2007 the Skype network crashed for about 48 hours, disrupting service to approximately 200 million users [17, 42, 46, 51, 55]. Skype attributed this outage to failures in their "self-healing mechanisms" [2]. We believe that this outage is indicative of the much broader problems outlined earlier.

#### Chapter 1. Introduction

In the following chapters, we will propose some algorithms for self-healing. Informally, we define self-healing to be maintenance of certain properties within desirable bounds by the nodes in a network suffering from failures or under attack. As the name implies, self-healing has to be initiated and executed by the nodes themselves. As such, the algorithms we have proposed here are fully distributed. Equivalenty we can say that a self-healing system, when starting from a correct state, can only be temporarily out of a correct state i.e. it recovers to a correct state, in presence of attacks. Self-healing is one of the so called 'Self-\*' properties which systems such as autonomic systems may be required to have. Section 1.5.1 has a brief discussion on these properties.

One approach towards self-healing is to add additional capacity or rerouting in anticipation of failures. There has been plenty of work which has followed this approach. However, there are obvious limitations including wastage of resources and limitations on additional capacity. In this Dissertation, we have adopted a *responsive* approach. Our approach is responsive in the sense that it responds to an attack (or component failure) by changing the topology of the network. This approach works irrespective of the initial state of the network, and is thus orthogonal and complementary to traditional non-responsive techniques.

Informally, the model we adopt in this work is as follows. We assume that the network is initially a connected graph over n nodes. An adversary repeatedly attacks the network. This adversary knows the network topology and our algorithm, and it has the ability to delete arbitrary nodes from the network or insert a new node in the system which it can connect to any subset of the nodes currently in the system. However, we assume the adversary is constrained in that in any time step it can only delete or insert a single node. Following that, the self-healing algorithm has a short time to reconfigure and heal the network by adding edges between remaining nodes before the next act of the adversary. Our model captures what can happen when a

worm or software error propagates through the population of nodes. This model is described in more detail Section 1.2.

## 1.1 Naive self-healing

Even in a very simple setting, we need to be smart about reconfiguring. Suppose we are trying to maintain a property such as connectivity of the network but our algorithm is not very sophisticated. Then, it may be very easy for the adversary to force the algorithm to cause high degree increase (which may lead to overload and eventual network breakdown) or increase in distances between nodes (which may lead to poor communication). Figure 1.1 shows a naive algorithm attempting to heal the network by using only a small number of edges at each timestep. However, node v in the figure ends up increasing its degree by 3 over a course of 3 deletions. Thus, a naive algorithm could yield a degree increase as high as  $\theta(n)$ .

## 1.2 Model of self-healing

Our general model of self-healing is shown in Figure 1.2. The specific models used in our algorithms are special cases of this model, differing mainly in the way the success metrics of the graph properties are presented. This model is very similar to the model described in Figure 3.2.1. Let  $G = G_0$  be an arbitrary graph on n nodes, which represent processors in a distributed network. In each step, the adversary either deletes or adds a node. After each deletion, the algorithm gets to add some new edges to the graph, as well as deleting old ones. At each insertion, the processors follow a protocol to update their information. The algorithm's goal is to maintain the chosen graph properties within the desired bounds. At the same time, the algorithm wants to minimize the resources spent on this task. Initially,



Figure 1.1: A sequence of 3 deletions and healings using a naive algorithm. A node marked red is deleted by the adversary. The neighbors of the deleted node reconnect (golden edges) to maintain connectivity. Notice node v increases its degree by 3.

each processor only knows its neighbors in  $G_0$ , and is unaware of the structure of the rest of  $G_0$ . After each deletion or insertion, only the neighbors of the deleted or inserted vertex are informed that the deletion or insertion has occured. After this, processors are allowed to communicate by sending a limited number of messages to

#### Chapter 1. Introduction

their direct neighbors. We assume that these messages are always sent and received successfully. The processors may also request new edges be added to the graph. The only synchronicity assumption we make is that no other vertex is deleted or inserted until the end of this round of computation and communication has concluded. To make this assumption more reasonable, the per-node communication cost should be very small in n (e.g. at most logarithmic).

We also allow a certain amount of pre-processing to be done before the first attack occurs. This may, for instance, be used by the processors to gather some topological information about  $G_0$ , or perhaps to coordinate a strategy. Another success metric is the amount of computation and communication needed during this preprocessing round. For our success metrics, we compare the graphs at time T: the actual graph  $G_T$  to the graph  $G'_T$  which is the graph with only the original nodes (those at  $G_0$ ) and insertions without regard to deletions and healing. This is the graph which would have been present if the adversary was not doing any deletions and (thus) no self-healing algorithm was active. This is the natural graph for comparing results. Figure 1.3 shows an example of  $G'_T$  and a corresponding  $G_T$ . The figure also shows, in  $G'_T$ , the nodes and edges inserted and deleted, and in  $G_T$ , the edges inserted by the healing algorithm, as the network evolved over time. Figure 1.2: The general distributed Node Insert, Delete and Network Repair Model.

Each node of  $G_0$  is a processor.

Each processor starts with a list of its neighbors in  $G_0$ .

Pre-processing: Processors may exchange messages with their neighbors.

#### for t := 1 to T do

Adversary deletes a node  $v_t$  from  $G_{t-1}$  or inserts a node  $v_t$  into  $G_{t-1}$ , forming  $H_t$ .

if node  $v_t$  is inserted then

The new neighbors of  $v_t$  may update their information and exchange messages with their neighbors.

#### end if

if node  $v_t$  is deleted then

All neighbors of  $v_t$  are informed of the deletion.

### Recovery phase:

Nodes of  $H_t$  may communicate (asynchronously, in parallel) with their immediate neighbors. These messages are never lost or corrupted, and may contain the names of other vertices.

During this phase, each node may add edges joining it to any other nodes as desired. Nodes may also drop edges from previous rounds if no longer required.

#### end if

At the end of this phase, we call the graph  $G_t$ .

### end for

Success metrics: Minimize the following "complexity" measures:

Consider the graph G' which is the graph consisting solely of the original nodes and insertions without regard to deletions and healings. Graph  $G'_t$  is G' at timestep t (i.e. after the  $t^{\text{th}}$  insertion or deletion).

### 1. Graph properties/invariants.

The graph properties/ invariants we are trying to preserve. e.g. Degree increase:  $\max_{v \in G} \text{degree}(v, G_T)/\text{degree}(v, G'_T)$ 

- 2. Communication per node. The maximum number of bits sent by a single node in a single recovery round.
- 3. **Recovery time.** The maximum total time for a recovery round, assuming it takes a message no more than 1 time unit to traverse any edge and we have unlimited local computational power at each node.





(a)  $G'_T$ : Nodes in red (dark gray in grayscale) deleted, and nodes in green (patterned) inserted, by the adversary.



(b)  $G_T$ : The actual graph. Edges added by the healing algorithm shown in gold (light shaded in grayscale) color.

Figure 1.3: Graphs at time T.  $G'_T$ : The graph of initial nodes and insertions over time,  $G_T$ : The actual healed graph.

## 1.3 Healing by Reconstruction Trees



Figure 1.4: Deleted node x (in red, crossed) replaced by a Reconstruction Tree, which is a structure formed by its neighbors (a, b, c, d, j).

Our algorithms (DASH, ForgivingTree, ForgivingGraph) use the same basic principle: when a node is deleted, replace it by a tree based structure formed from its neighbors, as shown in Figure 1.4. This structure we call the Reconstruction Tree (RT), and thus, we can also call these algorithms Reconstruction Tree healing algorithms. It turns out that trees are a natural choice for the graph properties we have tried to maintain. A balanced tree is a structure which has low distance between nodes (at most  $2 \log_2 n$  for a balanced binary tree) while each node has a small degree (at most 3 for a binary tree). At the same time, coming up with the suitable RTs and maintaining them over the run of the algorithm is quite a significant challenge.

### 1.4 Our Results

In our algorithms, we have focused on some fundamentally important properties: maintaining connectivity, ensuring low degree increase for all nodes, and simultaneously, in later algorithms, ensuring low increase of diameter (or a stronger property, the stretch) of the network. Figure 1.4 (repeated as Figure 2.9) shows a series of snapshots from a simulation of our algorithm called DASH (Chapter 2). Notice that the network stays connected, and no individual node gets a large number of extra edges during healing.

We have developed three different distributed self-healing algorithms, whose results are optimal (i.e. with a matching lower bound) for their particular objectives. All of them fulfill the objectives of maintaining connectivity in the network in face of adverserial attacks, and low degree increase for individual nodes. These algorithms were presented at reputed conferences and have been well received by the academic community. These algorithms are:

• DASH: Degree Assisted Self Healing: DASH guarantees network connectivity and degree increase of at most  $2 \log n$ , where n is the number of nodes initially in the network. DASH is locality-aware i.e. only the immediate neighbors of a



Figure 1.5: A timeline of deletions and self healing in a network with 100 nodes. The gray edges are the original edges and the red edges are the new edges added by our self-healing algorithm.

deleted node are involved in reconstruction. Also, the healing algorithm always adds in less edges than the adversary has removed from the system. Empirical results show that DASH performs well in practice on power-law networks. This is joint work with Jared Saia. An earlier version [53] was presented at the conference *IEEE International Parallel & Distributed Processing Symposium 2008*.

- FORGIVINGTREE: This algorithm efficiently maintains a special spanning tree which guarantees at worst a constant additive degree increase and diameter increase of only a log Δ factor, where Δ is the maximum degree of a node in the original network, by a system of inheritance and wills. This is work jointly done with Tom Hayes, Navin Rustagi and Jared Saia. An earlier version [24] was presented at the conference ACM Principles of Distributed Computing 2008.
- FORGIVINGGRAPH: This algorithm efficiently maintains a general graph of the network, handling both deletions and insertions, while guaranteeing at worst a constant multiplicative degree increase and the simultaneously challenging property of a low (log n) factor stretch (maximum distance increase between any two nodes). Also, we introduce a novel mergable data structure called half-full trees(haft) having a one-to-one correspondence with binary numbers, with the merge corresponding to binary addition. This is joint work with Tom Hayes and Jared Saia. An earlier version [23] was presented at the conference ACM Principles of Distributed Computing 2009.

Table 1.1 gives a comparison of these self-healing algorithms with regards to various criteria including methods of adverserial attack, properties maintained, and costs of the algorithm. Many important open questions remain and there are many promising directions towards which our work can be extended. Some of these are discussed in the last chapter (Chapter 5).

#### Chapter 1. Introduction

	Adversar	ial Attack	Property bounded			
	Deletion	Insertion	Connec-	Degree	Diameter	Stretch
			tivity	(orig: d)*	(orig: D)*	
DASH	$\checkmark$	$\checkmark$	$\checkmark$	$d + 2\log n$		
Forgiving Tree	$\checkmark$	×	$\checkmark$	d+3	$D\log\Delta$	
Forgiving Graph	$\checkmark$	$\checkmark$	$\checkmark$	3d	$D\log n$	$\log n$

\* 'orig:' the original value of the property in the graph (i.e. the value in the graph G' in our model)

		Costs			
	Repair time	# Msgs per dele-	Msg size	match	locality
		tion		lower	$(hops)^{\sharp}$
				bound <sup>‡</sup>	
DASH	$O(\log n)^{\dagger}$	$O(\delta \log n + \log^2 n)^{\dagger}$	$O(\log n)$	$\checkmark$	1
Forgiving Tree	O(1)	$O(\delta)$	$O(\log n)$	$\checkmark$	2
Forgiving Graph	$O(\log \delta \log n)$	$O(\delta \log n)$	$O(\log^2 n)$	$\checkmark$	$\log n$

<sup>†</sup> with high probability, and amortized over O(n) deletions.

<sup>‡</sup> The lower bounds differ according to the properties being bounded.

<sup>#</sup> Number of hops from the deleted node to nodes involved in repair.

Table 1.1: Comparison of our self-healing Algorithms. d is the degree of an individual node,  $\Delta$  is the maximum degree of a node in the graph, and  $\delta$  is the degree of the deleted node.

### 1.5 Related Work

There have been numerous papers that discuss strategies for adding additional capacity or rerouting in anticipation of failures [3, 15, 18, 29, 49, 58, 61]. Results that are responsive in some sense include the following. Médard, Finn, Barry, and Gallager [44] propose constructing redundant trees to make backup routes possible when an edge or node is deleted. Anderson, Balakrishnan, Kaashoek, and Morris [1] modify some existing nodes to be RON (Resilient Overlay Network) nodes to detect failures and reroute accordingly. Some networks have enough redundancy built in so that separate parts of the network can function on their own in case of an attack [20]. In all these past results, the network topology is fixed. In contrast, our algorithms add or deletes edges as node failures occur. Moreover, our algorithms do not dictate routing paths or specifically require redundant components to be placed in the network initially.

There has also been recent research in the physics community on preventing cascading failures. In the model used for these results, each vertex in the network starts with a fixed capacity. When a vertex is deleted, some of its "load" (typically defined as the number of shortest paths that go through the vertex) is diverted to the remaining vertices. The remaining vertices, in turn, can fail if the extra load exceeds their capacities. Motter, Lai, Holme, and Kim have shown empirically that even a single node deletion can cause a constant fraction of the nodes to fail in a powerlaw network due to cascading failures[25, 48]. Motter and Lai propose a strategy for addressing this problem by intentional removal of certain nodes in the network after a failure begins [47]. Hayashi and Miyazaki propose another strategy, called emergent rewirings, that adds edges to the network after a failure begins to prevent the failure from cascading[22]. Both of these approaches are shown to work well empirically on many networks. However, unfortunately, they perform very poorly under adversarial attack.

A responsive approach was followed by the authors in [9, 10], which proposed a simple line algorithm for self-healing to maintain network connectivity. This algorithm has obvious drawbacks with regard to properties such as diameter maintenance but has served as a useful starting point for our research.

### 1.5.1 Self-healing and Self-\* properties

The importance of self-healing in systems is worth mentioning. As an example, self-healing is one of the main components of IBM's autonomic systems initiative [27, 28].

#### Chapter 1. Introduction

Autonomic computing itself is one of the building blocks of pervasive computing, an anticipated future computing model in which tiny - even invisible - computers will be all around us, communicating through increasingly interconnected networks [60]. Self-healing forms one of the eight crucial elements in IBM's autonomic computing vision. Self-healing is one of the self-\* properties that a system can possess, where the '\*' in self-\* is a wildcard character that can take on many different forms. IBM's vision often refers to an autonomic computing system as a self-managing system that has the so-called self-CHOP properties: *self-configuring, self-healing, self-optimizing,* and *self-protecting.* Often, *self-management* is a generic term which implies the system has at least one of the other self-\* properties i.e. it has some desired autonomic behavior [8].

In the distributed systems world, perhaps the most well-known self-\* property is *self-stabilization* [12, 13, 14, 57]. Self-stabilization was introduced by Djikstra in 1974 [12]. A self-stabilizing system is a system which, starting from an arbitrary state and being affected by adversarial transient failures, can, in finite time, recover to a correct state. Often, self-stabilization does not take code corruption (byzantine behavior) or fail-stop failures (node crashes) into account. A self-healing system, when starting from a correct state, can only be temporarily out of a correct state i.e. it recovers to a correct state, in presence of some adversarial attacks including node removal. Other self-\* properties, often broadly defined, include *self-scaling*, *self-repairing* (similar to self-healing), *self-adjusting* (similar to self-managing), *selfaware/self-monitoring*, *self-immune*, *self-containing* [8].

## **1.6** Structure of the document

The next three chapters are self-contained presentations of the three algorithms with an occasional reference to the Introduction. Chapter 2 presents DASH, chapter 3 Chapter 1. Introduction

describes ForgivingTree, chapter 4 presents ForgivingGraph. Chapter 5 sketches some open problems and possible directions. For chapter 2 of this dissertation, we gratefully acknowledge the help of Iching Boman, Dr. Deepak Kapur and his class *Introduction to Proofs, Logic and Term-rewriting*, and the UNM Computer Science Theory Seminar.

# Chapter 2

# DASH

But he said what mattered most of all was the dash between those years The Dash Poem LINDA ELLIS

This chapter presents the first of our self-healing algorithms called DASH (short for *Degree Assisted Self-Healing*, which first appeared at *IEEE International Parallel* & *Distributed Processing Symposium 2008* [53] To recap, we consider the problem of self-healing in networks that are *reconfigurable* in the sense that they can change their topology during an attack. Our goal is to maintain connectivity in these networks, even in the presence of repeated adversarial node deletion, by carefully adding edges after each attack. We present a new algorithm, DASH which provably ensures that: 1) the network stays connected even if an adversary deletes up to all nodes in the network; and 2) no node ever increases its degree by more than  $2 \log n$ , where n is the number of nodes initially in the network. DASH is fully distributed; adds new edges only among neighbors of deleted nodes; and has average latency and bandwidth costs that are at most logarithmic in n. DASH has these properties irrespective of the topology of the initial network, and is thus orthogonal and complementary to traditional topology-based approaches to defending against attack. The detailed model used in DASH and its relation to the general model we described in Section 1.2 is given in Section 2.1.

We also prove lower-bounds showing that DASH is asymptotically optimal in terms of minimizing maximum degree increase over multiple attacks. Finally, we present empirical results on power-law graphs that show that DASH performs well in practice, and that it significantly outperforms naive algorithms in reducing maximum degree increase.

## 2.1 Introduction

Earlier in Chapter 1, we have made a case for better "self-healing mechanisms" and of the need for using *responsive* approaches for maintaining robust networks. There are many desirable invariants to maintain in the face of an attack. Here we focus only on the simplest and most fundamental invariants: maintaining network connectivity and ensuring low node degree increase.

**Our Model:** We now describe our model of attack and network response. We assume that the network is initially a connected graph over n nodes. We assume that every node knows not only its neighbors in the network but also the neighbors of its neighbors i.e. neighbor-of-neighbor (NoN) information. In particular, for all nodes x, y and z such that x is a neighbor of y and y is a neighbor of z, x knows z. There are many ways that such information can be efficiently maintained, see e.g. [43, 50].

We assume that there is an adversary that is attacking the network. This adversary knows the network topology and our algorithm, and it has the ability to delete carefully selected nodes from the network. However, we assume the adversary
is constrained in that in any time step it can only delete a small number of nodes from the network<sup>1</sup>. We further assume that after the adversary deletes some node x from the network, that the neighbors of x become aware of this deletion and that they have a small amount of time to react.

When a node x is deleted, we allow the neighbors of x to react to this deletion by adding some set of edges amongst themselves. We assume that these edges can only be between nodes which were previously neighbors of x. This is to ensure that, as much as possible, edges are added which respect locality information in the underlying network. We assume that there is very limited time to react to deletion of x before the adversary deletes another node. Thus, the algorithm for deciding which edges to add between the neighbors of x must be fast and localized.

This model can be seen as a special case of our general model (Section 1.2). We do not explicitly discuss node insertions in our further treatment but assume we begin with a connected graph of n vertices. DASH can easily handle insertions in a natural way, and thus, as long as the number of insertions are O(n), our bounds hold. Also, for the same reason, for our bounds, we need only compare our graph properties in the present graph at timestep  $t(G_t)$ , to the initial graph  $G_0$  which has n vertices (notice n is the maximum number of nodes the network will have in this model).

**Our Results:** We introduce an algorithm for self-healing of reconfigurable networks, called DASH (an acronym for *Degree Assisted Self-Healing*). DASH is *locality-aware* in that it uses only the neighbors of the deleted node for reconnection. We prove that DASH maintains connectivity in the network, and that it increases the degree of any node by no more than O(logn). During reconnection of nodes, our algorithm

<sup>&</sup>lt;sup>1</sup>Throughout this chapter, for ease of exposition, we will assume that the adversary deletes only one node from the network before the algorithm responds. However, our main algorithm, DASH, can easily handle the situation where any number of nodes are removed, so long as the neighbor-of-neighbor graph remains connected.

uses only local information, therefore, it is scalable and can be implemented in a completely distributed manner. Algorithm DASH is described as Algorithm 2.2.1 in Section 2.2. The main characteristics of DASH are summarized in the following theorem that is proved in Section 2.2.

**Theorem 2.1.** DASH guarantees the following properties even if up to all the nodes in the network are deleted:

- The degree of any vertex is increased by at most  $2 \log n$ .
- The number of messages any node of initial degree d sends out and receives is no more than  $2(d + 2\log n) \ln n$  with high probability<sup>2</sup> over all node deletions.
- The latency to reconnect is O(1) after attack; and the amortized latency to update the state of the network over θ(n) deletions is O(log n) with high probability.

We also prove (in Section 2.3) the following lower bound that shows that DASH is asymptotically optimal.

**Theorem 2.2.** Consider any locality-aware algorithm that increases the degree of any node after an attack by at most a fixed constant. Then there exists a graph and a strategy of deletions on that graph that will force the algorithm to increase the degree of some node by at least  $\log n$ .

We also present empirical results (in Section 2.4) showing that DASH performs well in practice and that it significantly outperforms naive algorithms in terms of reducing the maximum degree increase. Finally (in Section 2.4) we describe SDASH, a heuristic based on DASH that we show empirically both keeps node degrees small and also keeps shortest paths between nodes short.

<sup>&</sup>lt;sup>2</sup>Throughout this text, we use the phrase with high probability (w.h.p) to mean with probability at least  $1 - 1/n^C$  for any fixed constant C.

In this chapter, we build on earlier work done in [9, 10], which proposed a simple line algorithm for self-healing to maintain network connectivity.

Table of Contents: The rest of this chapter is organized as follows. Section 2.2 describes the algorithm DASH, and its theoretical properties. Section 2.3 gives a lower bound on locality-aware algorithms. Section 2.4 gives empirical results for DASH, and several other simple algorithms on random power-law networks. It also describes and gives results for SDASH. We conclude and give areas for future work in Section 2.5.

# 2.2 DASH: An Algorithm for Self-Healing

In this Section, we describe DASH and prove certain properties about it. In brief, when a deletion occurs, DASH asks the neighbors of the deleted node to reconnect themselves into a certain kind of complete binary tree. Then messages are propagated so that the nodes can keep track of which connected component they belong to.

Let the actual network at a particular time step be G(V, E). Let  $E_h$  be the edges (i.e. *healing edges*), that have been added by the algorithm up to that time step (note  $E_h \subseteq E$ ). Let  $G_h = (V, E_h)$ . We show that  $G_h$  is a forest in Lemma 2.1.

## 2.2.1 DASH: Degree Assisted Self-Healing

As the acronym suggests, DASH employs information of previous degree increase to control further degree increase for a node. When a deletion occurs, we assume the neighbors of the deleted node are able to detect the deletion. Then they employ DASH to heal. To maintain connectivity, DASH connects the neighbors of a deleted node as a binary tree. The tree is structured so that the vertices which

have incurred the maximum degree increase previously get to be leaves and thus not increase their degree in this round. Notice that at least half the vertices in a binary tree are leaves. The nodes maintain information about the virtual network and their connected component in this network. The algorithm tries to use only a single node from each component during reconnection and thus adds only a low number of new edges during healing.

To describe DASH we give some definitions. Let N(v, G) be the neighbors of vertex v in the graph G representing the real network. Let  $N(v, G_h)$  be the neighbors of vertex v in graph  $G_h$  consisting of the edges added by the healing algorithm. Let  $\delta(v)$  be the degree increase of the vertex v compared to its initial degree. Note that this is not the same as the degree of v in  $G_h$ .

When a node v is deleted, partition on the basis of their ID all the neighbors of v in G (not having the same ID as v). Let UN(v, G) (Unique Neighbors) be the set having one representative from each of the partitions. If there is more than one node as a possible representative from a partition, we include the one with the lowest initial ID.

Note that  $UN(v,G) \cap N(v,G_h) = \phi$  and  $UN(v,G) \cup N(v,G_h) \subseteq N(v,G)$ . The ID of a node allows us to keep track of which connected component in  $G_h$  it belongs to. The lowest ID of any node in that component is broadcast and all the nodes in the component take on this ID.

Our main results about DASH are stated in Theorem 2.1.

**Theorem 2.1.** DASH is a distributed algorithm with the following properties:

- The degree of any vertex is increased by at most  $2 \log n$ .
- The latency to reconnect is O(1).

1: Init: for given network G(V, E), Initialize each vertex with a random number ID between [0,1] selected uniformly at random.

2: while true do

- 3: If a vertex v is deleted, do
- 4: Nodes in  $UN(v, G) \cup N(v, G_h)$  are reconnected into a *complete binary tree*. To connect the tree, go left to right, top down, mapping nodes to the *complete binary tree* in increasing order of  $\delta$  value.
- 5: Let MINID be the minimum ID of any node in  $UN(v, G) \cup N(v, G_h)$ . Propagate MINID to all the nodes in the tree of  $UN(v, G) \cup N(v, G_h)$  in  $G_h$ . All these nodes now set their ID to MINID.

#### 6: end while

#### Algorithm 2.2.1: DASH: Degree-Based Self-Healing

- The number of messages any node of degree d sends out and receives is no more than  $(2d + 2\log n) \ln n$  with high probability over all node deletions.
- The amortized latency for ID propagation is O(logn) with high probability over all node deletions.

# 2.2.2 Towards the proof of Theorem 2.1

For analysis, we use the following definitions:

- Let T(x, y) be the tree in  $G_h y$  that contains x.
- Each vertex v will have a weight, w(v). The weight of a vertex will start at 1 and may increase during the algorithm. If v is deleted, w(v) is added to an arbitrarily chosen neighbor in  $G_h$ .
- Let  $W(S) = \sum_{v \in V} w(v)$ , for a graph S(V, E) i.e. the sum of the weights of all vertices in S.

• For vertex v, let rem(v) =

$$\sum_{u \in N(v,G_h)} W(T(u,v)) - \max_{u \in N(v,G_h)} W(T(u,v)) + w(v).$$

We will show that as the degree of a vertex increases in our algorithm, so will the rem value of that vertex. Intuitively rem(v) is large when removing v from its tree in  $G_h$  gives rise to many connected components with large weight.

**Lemma 2.1.** The edges added by the algorithm,  $E_h$ , form a forest.

*Proof.* We prove this by induction on the number of nodes deleted.

Base Case: Initially,  $G_h$  is a forest because  $E_h$  is empty.

We note that  $E_h$  and  $G_h$  change only when a deletion occurs. Consider the  $i^{th}$  deletion and let v be the node deleted.

Let v belong to tree  $T_v$  in  $G_h$  just prior to the deletion of v. Now, for all  $x, y \in N(v, G_h)$  x and y are not connected in  $E_h$  since that would have implied the existence of a cycle through v contradicting the Inductive Hypothesis. Note also that for all  $z \in UN(v, G), z \notin T_v$ . Since we select only 1 node from each tree  $T_i$  in which vhad a neighbor, no pair of nodes in  $UN(v, G) \cup N(v, G_h)$  are connected in  $G_h$ . We reconnect all the nodes in  $UN(v, G) \cup N(v, G_h)$  in a Binary Tree and propagate the minimum ID. Since we are adding edges between nodes which previously were in separate connected components in  $G_h$ , no cycles are introduced. Hence,  $G_h$  remains a forest.

**Lemma 2.2.** For any vertex v, rem(v) is non-decreasing over any vertex deletion where v has not been deleted.

*Proof.* By Lemma 2.1, every vertex v in  $G_h$  belongs to some tree, which we will call  $T_v$ . For every  $T_v$  in  $G_h$ ,  $W(T_v)$  is the sum of the weights of all vertices in  $T_v$ .

By definition, rem(v) =

$$\sum_{u \in N(v,G_h)} W(T(u,v)) - \max_{u \in N(v,G_h)} (W(T(u,v))) + w(v)$$

Therefore,

 $rem(v) = W(T_v) - \max_{u \in N(v,G_h)} W(T(u,v))$ 

Observe first that  $W(T_v)$  cannot decrease even when there is a deletion in  $T_v$  because the deleted vertex's weight is not "lost", but added to some member of  $T_v$ .

Since  $W(T_v)$  cannot decrease, rem(v) can only decrease if the maximum subtree weight increases more than  $W(T_v)$ . Since the maximum subtree is a subset of the tree,  $T_v$ , any increases or decreases in the maximum subtree is also counted in  $W(T_v)$ . Thus, rem(v) cannot decrease.

**Lemma 2.3.** For any node v, for all nodes  $q \in N(v, G_h)$ ,  $W(T(v, q)) \ge rem(v)$ .



Figure 2.1:  $W(T(v,m)) \ge rem(v)$ .

*Proof.* For all nodes q,

$$\begin{split} W(T(v,q)) &= \sum_{\substack{u \in N(v,G_h) \\ u \neq q}} W(T(u,v)) + w(v) \\ &\geq \sum_{\substack{u \in N(v,G_h) \\ - \max_{u \in N(v,G_h)}} W(T(u,v)) \\ &- \max_{u \in N(v,G_h)} W(T(u,v)) + w(v) \\ &= rem(v) \end{split}$$

For example, in figure 2.1,  $W(T(V, M)) = W(T(L, V)) + W(T(R, V)) + w(v) \ge rem(v)$ .

**Lemma 2.4.** For any node v,  $rem(v) \ge 2^{\delta(v)/2}$ , where  $\delta(v)$ , as defined earlier, is the degree increase of the vertex v in G.

*Proof.* Let t be the number of rounds of healing where a round is a single adversarial deletion followed by self-healing by DASH. We prove this lemma by induction on t. Let  $G_{ht}$ , rem<sub>t</sub>(v) and  $\delta_t(v)$  be  $G_h$ , rem(v) and  $\delta(v)$  respectively at time t.

Base Case: t = 0: In this case, all nodes v have  $\delta(v) = 0$ ; rem(v) = 1. Thus, rem $(v) \ge 2^0$ .

Inductive Step: Consider the network at round t. We assume by the inductive hypothesis that for all nodes v in  $G_h$ ,  $\operatorname{rem}_{t-1}(v) \ge 2^{\delta_{t-1}(v)/2}$ . Our goal is to show that  $\operatorname{rem}_t(v) \ge 2^{\delta_t(v)/2}$ .

Suppose node x was deleted at round t. According to our algorithm, some or all of the neighbors of x will be reconnected as a binary tree. Let us call this tree RT (short for *Reconstruction Tree*). Let T(x, y) be the tree in  $G_{h(t-1)} - y$  that contains x, and T'(x, y) be the tree in  $G_{ht} - y$  that contains x.

Consider a surviving vertex v. If v is not a part of RT, then by a simple application of lemma 2.2, our induction holds. If v is a part of RT, there are 3 possibilities:

1. v is a leaf node in RT

The degree of v did not change. Thus,  $\delta_t(v) = \delta_{t-1}(v)$ . By Lemma 2.2, rem<sub>t</sub>(v)  $\geq$  rem<sub>t-1</sub>(v). Thus, using the induction hypothesis, rem<sub>t</sub>(v)  $\geq 2^{\delta_t(v)/2}$ .

2. v is the root of RT

If v has only one child in RT, then this is the same as the previous case with the parent and child role reversed and the induction holds. Let us consider the case



Figure 2.2: node v is the root, with 2 children

when v has two children in RT. Now,  $\delta_t(v)$  has increased by 1. Let z be the neighbor of v such that W(T(z, v)) is the largest among all neighbors of v except x. Note that W(T'(z, v)) = W(T(z, v)), since this subtree was not involved in the reconstruction. Consider the possibly empty subtree of v rooted at z. Let the two children of v in RT be  $w_1$  and  $w_2$ , as illustrated in figure 2.2. By our algorithm, we know that  $\delta_{t-1}(w_1) \ge \delta_{t-1}(v)$  and  $\delta_{t-1}(w_2) \ge \delta_{t-1}(v)$ . Thus, using the inductive hypothesis and lemma 2.3, we have that  $W(T(w_1, x)) \ge$  $\operatorname{rem}_{t-1}(w_1) \ge 2^{\delta_{t-1}(w_1)/2}$  and  $W(T(w_2, x)) \ge \operatorname{rem}_{t-1}(w_2) \ge 2^{\delta_{t-1}(w_2)/2}$ . By lemma 2.2, this implies that in  $G_{ht}$ ,

$$W(T'(w_1, v)) \ge 2^{\delta_{t-1}(w_1)/2} \ge 2^{\delta_{t-1}(v)/2}$$
$$W(T'(w_2, v)) \ge 2^{\delta_{t-1}(w_2)/2} \ge 2^{\delta_{t-1}(v)/2}$$

Assume without loss of generality that  $W(T'(w_1, v)) \leq W(T'(w_2, v))$ . There are two cases:

(a)  $W(T(z, v)) < W(T'(w_1, v))$ 

In this case  $\operatorname{rem}_{t-1}(v)$  did not include W(T(x, v)). But  $\operatorname{rem}_t(v)$  will include  $W(T'(w_1, v))$  Hence,

$$\operatorname{rem}_{t}(v) \geq \operatorname{rem}_{t-1}(v) + W(T'(w_{1}, v))$$
$$\geq 2^{\delta_{t-1}(v)/2} + 2^{\delta_{t-1}(v)/2}$$
$$= 2^{(\delta_{t-1}(v)+2)/2}$$
$$= 2^{(\delta_{t}(v)+1)/2}$$

(b)  $W(T(z, v)) \ge W(T'(w_1, v))$ 

In this case  $\operatorname{rem}_t(v)$  will include  $W(T'(w_1, v))$  and the smaller of  $W(T'(w_2, v))$  and W(T'(z, v)). Note that by Lemmas 2.3 and 2.2, the inductive hypothesis, and the fact that  $\delta_{t-1}(w_1) \geq \delta_{t-1}(v)$ ,  $W(T'(w_1, v)) \geq \operatorname{rem}_t(w_1) \geq \operatorname{rem}_t(w_1) \geq 2^{\delta_{t-1}(w_1)/2} \geq 2^{\delta_{t-1}(v)/2}$ .

Also, since by assumption  $W(T'(w_2, v)) \ge W(T'(w_1, v))$ , we know that  $W(T'(w_2, v)) \ge 2^{\delta_{t-1}(v)/2}$ .

Further, since  $W(T'(z,v)) = W(T(z,v)) \ge W(T'(w_1,v))$  we know that  $W(T'(z,v)) \ge 2^{\delta_{t-1}(v)/2}$ .

Hence,

$$\operatorname{rem}_{t}(v) \geq 2^{\delta_{t-1}(v)/2} + 2^{\delta_{t-1}(v)/2}$$
$$= 2^{(\delta_{t-1}(v)+2)/2}$$
$$= 2^{(\delta_{t}(v)+1)/2}$$

3. v is an internal node in T'

For node v to become an internal node, the deleted neighbor x must have at least three other neighbors. Three neighbors of x are shown as C1, C2 and Pin the figures 2.3 and 2.4. Also, now v's degree can increase by 1, as illustrated in figure 2.3, or by 2, as illustrated in figure 2.4. Let us consider these cases separately:

(a) 
$$\delta_t(v) = \delta_{t-1}(v) + 1$$





Figure 2.3: Internal node v with 1 child



Figure 2.4: Internal node v with 2 children

This can only happen when v has a parent and a single child in RT as in figure 2.3. Let P be the parent of v and C1 the child of v. C1 has to be a leaf node since the tree is complete and v has only one child. Observe that there exists at least one leaf node besides  $C_1$  in the tree, accessible to v only via P. Let this node be C2 and let P2 be its parent. Note that P2 and P may even be the same node. In our algorithm, any leaf node in RT has a  $\delta$  value no less than the  $\delta$  value of any internal node. Thus,

$$\delta_{t-1}(C1) \geq \delta_{t-1}(v);$$
 and  
 $\delta_{t-1}(C2) \geq \delta_{t-1}(v)$ 

These inequalities, Lemmas 2.2 and 2.3, and the Inductive Hypothesis, imply that

$$W(T'(C1, v)) \geq \operatorname{rem}_{t}(C1)$$

$$\geq \operatorname{rem}_{t-1}(C1)$$

$$\geq 2^{\delta_{t-1}(v)/2};$$

$$W(T'(C2, P2)) \geq \operatorname{rem}_{t}(C2)$$

$$\geq 2^{\delta_{t-1}(v)/2};$$

$$W(T(v, x)) \geq \operatorname{rem}_{t}(v)$$

$$\geq \operatorname{rem}_{t-1}(v)$$

$$\geq 2^{\delta_{t-1}(v)/2}.$$

Since  $\operatorname{rem}_t(v)$  can exclude at most one of W(T'(C1, v)), W(T'(C2, P2))and W(T(v, x)),

$$\operatorname{rem}_t(v) \ge 2^{\delta_{t-1}(v)/2} + 2^{\delta_{t-1}(v)/2}$$
  
=  $2^{(\delta_t(v)+1)/2}$ 

(b)  $\delta_t(v) = \delta_{t-1}(v) + 2$ 

In this case v has two children in RT, C1 and C2, as illustrated in figure 2.4. The analysis is similar to the case above. The value  $\operatorname{rem}_t(v)$  can exclude at most one of W(T'(C1, v)), W(T'(C2, v)) and W(T(v, x)) and we can show that all three of these values are at least  $2^{\delta_{t-1}(v)/2}$ . Thus,  $\operatorname{rem}_t(v) \geq 2^{(\delta_t(v))/2}$ .

Hence, the induction holds.

**Lemma 2.5.** For all vertices v, rem(v) is always no more than n.

*Proof.* No vertex is counted twice in a *rem* value since the subtrees of a vertex are disjoint. Since the number of vertices in the subtrees cannot be more than the number of vertices remaining, the *rem* value is always no more than the sum of the weights of all undeleted vertices in  $G_h$ .

Define  $W^*$  to be the sum of weights of all undeleted vertices in  $G_h$ . After initialization,  $W^* = n$ , since there are *n* vertices. At each step of the algorithm,  $W^* = n$ , since the weight of the deleted vertex is added to one of the remaining vertices. Thus, for node v,  $rem(v) \leq n$ .

**Lemma 2.6.** DASH increases the degree of any vertex by at most  $O(\log n)$ .

*Proof.* Every vertex v starts with  $\operatorname{rem}(v) = w(v) = 1$ . We know that  $\operatorname{rem}(v) \ge 2^{\delta(v)/2}$  by Lemma 2.4. since  $\operatorname{rem}(v)$  is at most n,  $2^{\delta(v)/2} \le n$ . Taking log of both sides,  $\delta(v)/2 \le \log n$ . Solving for  $\delta(v)$  gives  $\delta(v) \le 2\log n$ .

**Lemma 2.7.** The latency to reconnect the network in DASH is O(1).

*Proof.* During the reconnection process, DASH requires communication only between nodes one hop away, thus, the latency is just O(1).

**Lemma 2.8.** The number of messages any node of initial degree d sends out and receives is no more than  $2(d + 2\log n) \ln n$  with high probability over all node deletions.

*Proof.* In DASH, after the reconnections have been made, messages are sent out by nodes when the minimum ID has to be propagated. With similarity to the *record breaking problem* [19](Section 2.2.3), it is easily shown that *w.h.p.*, a node has its ID reduced no more than 2 ln *n* times, where the record is the node's ID. These are the only messages the node needs to transmit or receive. Each time its ID changes, the node sends this message to all its neighbors, Thus, it sends or receives  $O((d + \log n) \ln n)$  messages, since the final degree of the node is at most  $d + 2 \log n$ .

**Lemma 2.9.** The amortized latency for ID propagation is  $O(\log n)$  with high probability over all node deletions.

*Proof.* Again, with similarity to the record breaking problem, a node sends messages to its neighbors (neighbors, by definition, are a single hop away) only  $O(\log n)$  times with high probability. Thus, messages are transmitted  $O(n \log n)$  times over all the nodes. Over O(n) deletions, this implies that the amortized latency for messages (involving *ID* propagation) is only  $O(\log n)$ .

## 2.2.3 The Record Breaking Problem

Here we recap the well known record breaking problem. Given a sequence of deleted vertices,  $v_1, v_2, ..., v_n$ , we define  $id(v_j)$   $(j \le n)$  to be a record value if  $id(v_j) < id(v_i)$  for all  $1 \ge i < j$ .

Let  $X_1, X_2, ..., X_n$  be indicator random variable:

$$X_j = \begin{array}{cc} 1 & \text{if } id(v_j) \text{ is a record} \\ 0 & \text{otherwise} \end{array}$$

The probability that  $v_j$  is a record is  $P_j = \frac{(j-1)!}{j!} = \frac{1}{j}$ . Therefore:  $E[X_j] = 1/j$ .

Let 
$$X = \sum_{j=1}^{n} X_j$$
.

By linearity of expectation:

$$E[X] = \sum_{j=1}^{n} E[X_j] = \sum_{j=1}^{n} 1/j = \theta(ln(n))$$

The variance for  $X_j$  is  $Var(X_j) = E[X_j^2] - E[X_j]^2$ . We calculate  $E[X_j^2]$  from the second derivative of the moment generating function for  $X_j$ .

$$M''(t) = E[X_j^2 e^{tX_j}]$$
  
=  $\sum_j X_j^2 e^{tX_j} P_j$   
=  $(1)(e^{t(1)})(1/j) + 0$   
=  $e^t/j$ 

$$Var(X_j) = E[X_j^2] - (E[X_j])^2$$
  
=  $M''(0) - (1/j)^2$   
=  $1/j - 1/j^2$   
=  $(j - 1)/j^2$ 

# 2.2.4 Proof of Theorem 2.1

The proof of Theorem 2.1 now follows immediately from Lemmas 2.6, 2.7, 2.8 and 2.9.

# 2.3 Lower bounds on Locality-aware algorithms

To begin with, we give an insight as to why a healing strategy might need to keep track of connected components.

## 2.3.1 Necessity of Component tracking for healing strategies

**Lemma 2.10.** For a tree, deletion of a node of degree d increases the sum total of degrees of its neighbors by d - 2 for a locality-aware acyclic healing strategy.

*Proof.* A *locality-aware acyclic healing strategy* will reconnect the neighbors of a deleted node without creating any cycles. If there were no cycles in the original graph involving the neighbors and not involving the deleted node, then such a strategy can only reconnect these neighbors as a tree to maintain their connectivity.

A node of degree d has d neighbors. Since it was part of a tree, this node and its neighbors also constitute a tree. Let us call this the *immediate subtree*. The *immediate subtree* had d edges and a total of 2d degrees. These d neighbors are now reconnected as a tree with d-1 edges and 2(d-1) degrees. Each of these neighbors lost a single degree due to the deletion of their edge to the deleted node. Thus, the total degrees gained on reconstruction are 2(d-1) - d = d - 2.

It is reasonable to assume that an efficient healing algorithm adds close to the minimum possible edges at each step to maintain connectivity of the neighbors of the deleted node. In  $G_h$ , if a deleted node v had two neighbors which had an alternate path between themselves not involving v, then the algorithm may need to use only one of them for reconnection to other nodes. By extension, if there were many neighbors which had alternate connections between them, the algorithm may need to use only one of these nodes. This is equivalent to stating that the algorithm may need to use only one node from a connected component. Knowing that certain nodes are in the same component would allow the algorithm to do this.  $G_h$  is comprised only of edges added by the healing algorithm, and is always a forest. If the adversary mainly deletes nodes with degree greater than 2 and the algorithm does not use the component information, the sum total of degrees of the neighbors of the deleted nodes will increase by (d-2) i.e. at least 1, at each step. After many (O(n)) deletions, only a few nodes will be left, and these will have O(n) degree increase.

# 2.3.2 A lower bound on healing by Degree-bounded localityaware healing algorithms

We prove a result regarding the lower bounds for degree-bounded locality-aware algorithms in Theorem 2.2. We also show a lower bound which shows that any locality-aware healing algorithm (not necessarily degree-bounded) will increase node degree by at least  $\log_2 \log_3 n$  in Section 2.3.3.

Our lower bound occurs on graphs that are originally trees. To state the proof, we need to prove some other lemmas.

First, we define the following operation that the adversary can perform on trees, where we assume self-healing is applied after every deletion:

**Prune**  $(\mathbf{r}, \mathbf{s})$ : For a node r and its subtree headed by node s, the *Prune* operation on s leads to deletion of all the nodes in that subtree including s. This operation can be accomplished by repeatedly deleting leaf nodes in the subtree till all the nodes including s are deleted.



Figure 2.5: Steps in Prune(v,x). Leaf nodes are deleted at each step.

**Lemma 2.11.** Deletion of a node with degree at least 3 increases the degree of at least one node by degree 1, no matter how the healing occurs.



Figure 2.6: An internal node in a 3-node line reconnection suffers a degree increase.

*Proof.* Any reconnection of more than two nodes has a 3-node line (as in figure 2.6) as a subgraph. Here the internal node has a degree increase of 1. Thus, at least one node increases it's degree by at least 1.

For further discussion, we define the following:

**Degree-bounded** / **M-degree-bounded** : A healing algorithm is *degree-bounded* or *M-degree-bounded* if any node can increase its degree by at most M in a single round of deletion and healing.

**Lemma 2.12.** Consider a M-degree-bounded locality-aware healing algorithm used on a tree. In such a situation, deletion of a node v with degree at least M+3 leads to degree increase for at least two neighbors of v.

*Proof.* Node v has M+3 neighbors. By Lemma 2.10, the sum total of degree increase of neighbors is M+1, when the graph is a tree. Since one node can get a maximum degree increase of M, at least one node has to incur the rest of the degree increase. Thus, at least two nodes have to increase their degrees.

 Consider an (M+2)-ary tree T of depth D with levels numbered 0 to D, the root being at level 0.

 $2: i \leftarrow D - 1$ 

- 3: while  $i \ge 0$  do
- 4: for each node v at level i do
- 5: if v has c > M + 2 children remove the excess c (M + 2) nodes by deleting those with least degree increases and their subtrees by using the *Prune* operation, so that v now has M + 2 children.
- 6: delete v.
- 7: end for
- 8:  $i \leftarrow i 1$
- 9: end while

Algorithm 2.3.1: LEVELATTACK: level-by-level attack on a (M+2)-ary tree

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Figure 2.7: M+2 -ary Tree

Here, we introduce a new attack strategy:

LEVELATTACK: This strategy is described in Algorithm 2.3.1. In brief, the adversary deletes nodes one level at a time beginning one level above the leaves of a M + 2-ary complete tree going up to the root. The reasoning behind the strategy is the following: If the adversary deletes a node of degree M + 3 in a tree, this ensures that a degree increase of at least 1 is passed to its children. What the adversary must do is to ensure that *logn* of these degree increases are credited to the same node.

**Lemma 2.13.** Assume a (M+2)-ary tree T, a degree-bounded locality-aware healing algorithm and the LEVELATTACK adversarial strategy. Then, when LEVELATTACK deleted a node at level i, 0 < i < D some leaf node of the original tree increases its degree by at least D - i.

*Proof.* The proof is by induction.

Base case: In the LEVELATTACK strategy, the nodes at level D - 1 are deleted first. Thus, a deletion of a node at D - 1 is our base case. A node at level D - 1has M + 3 neighbors. By lemma 2.12, there is at least one leaf node that increases its degree by 1 or more. Thus, the base case holds.

Inductive step: Assume the hypothesis holds for nodes at level i + 1. We now show that it holds for nodes at level i. Consider a node, say X at level  $i \ge 0$ . It had M+2 children at level i+1. By the inductive hypothesis, each of these deletions led to at least one node with degree D - (i+1). Moreover, X is not among these M+2nodes. Moreover, all of these are now neighbors of X, since X itself was involved in each of these deletions. The *Prune* algorithm in step 5 retains only these M+2as children of X. Each of these children has degree increase D - (i+1) and was originally a leaf node of T. The adversary now deletes X. By lemma 2.12, at least one of these children incurs a degree increase.

**Theorem 2.2.** Consider any locality-aware algorithm that increases the degree of any node after an attack by at most a fixed constant. Then there exists a graph and a strategy of deletions on that graph that will force the algorithm to increase the degree of some node by at least  $\log n$ .

*Proof.* It is sufficient to give a graph and an attack strategy such that any degreebounded locality-aware healing algorithm will have to increase a particular node's degree by  $\log n$ . Let M be the constant degree increase that is the maximum that the healing algorithm can impose on any one node in the graph. Then, for a graph which is a full (M+2)-ary tree (Figure 2.7), the adversary uses LEVELATTACK. Consider a (M+2)-ary tree T of depth D with levels numbered 0 to D. By lemma 2.13, after the last deletion in the adversary strategy, which is the deletion of the root of T i.e. the node at level 0 there is at least one node left which has a degree increase of D. Since D is O(logn), this adversary strategy achieves a degree increase of at least O(logn).

# 2.3.3 A general lower bound on healing by locality-aware algorithms

For the discussion that follows, consider the following structure: Let T be a top-level 3-level complete subtree, as illustrated in figure 2.8(a). Top-level subtree implies that the root node has no parent but each of the leaf node may themselves have other subtrees hanging off them. There are three levels labeled from 0 to 2. Let  $\delta(v)$  be the increase in degree experienced by node v.

We also define another operation called Graft, which uses the previously defined operation Prune.

**Graft**  $(\mathbf{r}, \mathbf{s})$ : Given a node r and another node s in a subtree of r, the Graft operation makes r and s neighbors without changing the degree increase of either of them. This can be accomplished as follows: Take a node x on the path between r and s. *Prune* all subtrees of x except those containing r and s, then delete x. Repeat this process for all nodes on the path between r and s.

**Lemma 2.14.** For a top-level 3-level complete ternary subtree, for any locality aware algorithm, the adversary strategy Algorithm 2.3.2 forces some node to increase it's degree by 2.

- 1: If, at any point, any node has its degree increased by 2, stop.
- 2: Delete all nodes at level 1.
- 3:
- 4: for Root Node r (Level 0) do
- 5: while there is a neighbor v' where  $\delta(v') = 0$  do

```
6: delete v'
```

- 7: end while
- 8: end for
- 9: delete the Root Node (level 0).

Algorithm 2.3.2: (ROOT NODE): Increase degree by 2 for a 3-level ternary subtree



Figure 2.8: Strategy-1

*Proof.* Let T be the top-level 3-level ternary subtree depicted in figure 2.8(a). There are 3 levels labeled 0 to 2. The adversary strategy Algorithm 2.3.2 consists of 3 possible rounds of deletions. As expected, a locality-aware self-healing algorithm does self-healing after every node deletion. In the following, the steps refer to the steps of the algorithm 2.3.2.

- <u>Round 1; step 2</u>: The adversary deletes all nodes at level 1. By lemma 2.11, at least one neighbor of the deleted node would get a degree increase of 1. Moreover, this node will now be a neighbor of the parent of the deleted node, at level 0. This is shown in figure 2.8(b).
- <u>Round 2</u>; step4: If no node got degree increase of 2 in the previous round, round 2 and 3 are initiated. In this round, the adversary will delete all neighbors v' of the root node (level 0), where  $\delta(v') = 0$ , if any. Now each neighbor of 0 has degree increase of 1.
- <u>Round 3</u>; step 9: After the previous round, the root node will have 3 neighbors, each with degree increase of 1. The adversary now deletes the root node at level 0. On Self-healing, one of the nodes will get a degree increase of 2.

- 1: Init: Let  $\delta(v)$  be the increase in degree experienced by node v. Let virgin subtrees be subtrees none of whose nodes have been involved in a deletion/self-healing process yet.
- 2: if i = 0 then

```
3: V' = Strategy - 1(V)
```

- 4: end if
- 5: for Each of the 3 virgin subtrees of V do
- 6:  $V' \leftarrow \text{root of virgin subtree.}$
- 7: while  $\delta(V') < i$  do
- 8:  $V' \leftarrow \text{DegreeUp}(V', \delta(V'))$

```
9: Graft(V, V')
```

- 10: end while
- 11: **end for**
- 12: Prune subtrees of V not involved above.
- 13: delete V.

14: return node (ex-neighbor of V) with highest degree increase.

Algorithm 2.3.3: DEGREEUP(V,I): Recursive Procedure to get a node of degree increase i + 1

**Theorem 2.3.** There exists a graph G such that for any locality aware algorithm on G there exists an adversary strategy that forces some node to increase it's degree by  $\log \log n$ , where n is the number of nodes in G.

*Proof.* It is sufficient to give example of a graph and an attack strategy such that any healing algorithm will have to increase a particular node's degree by  $\log \log n$ . Such a graph G is complete ternary tree with L levels where L is  $3.2^a$ , where  $a \ge 0$ .

The adversary strategies are described in Algorithms 2.3.2 and 2.3.4. The intuition behind the adversary strategy is that the strategy has to force any locality-aware

- 1: Init: Let G be a complete ternary tree of L levels, where L is  $3.2^a$ , where  $a \ge 0$ , and n is the total number of nodes. Let  $\delta(v)$  be the increase in degree experienced by node v. Let virgin subtrees be subtrees none of whose nodes have been involved in a deletion/self-healing process yet.
- 2:  $i \leftarrow 0$
- 3:  $V = Strategy-1 \ (Root \ of \ G)$
- 4: while  $\delta(V) < log_2 log_3 n$  do
- 5:  $V \leftarrow \text{DegreeUp}(V, \delta(V))$
- 6: end while

Algorithm 2.3.4: Increase degree of a node by log log n, for a  $3.2^a$ -level ternary tree, where  $a \ge 0$ 

self-healing strategy to have a degree increase. In particular, the adversary strategy wants to avoid the possibility of a node surrogating all the other neighbors of its deleted neighbor. Notice that if a node had four neighbors, three of which had a degree increase of 2, and the fourth has no degree increase, this fourth neighbor could simply connect to the three i.e. surrogate them and incur a degree increase of only 2. Moreover, the resulting geometry makes it difficult to construct a strategy. The way around this in Algorithm 2.3.4 is that for a node which is about to be deleted, have a parent with a degree increase higher or equal to that of it's three children. This forces some neighbor to register the required degree increase on self-healing. Algorithm 2.3.2 gives a method to get a degree increase of 2 for a node in a 3-level ternary tree. Algorithm 2.3.4 uses this as a recursive subroutine and the idea of a high-degree parent to obtain a certain node with degree increase of at least  $O(\log \log n)$ .

Consider the following cases for G:

1. L = 3

The adversary applies Algorithm 2.3.2.

#### 2. L > 3

The adversary applies Algorithm 2.3.4. To begin with, Algorithm 2.3.4 calls Algorithm 2.3.2 to obtain a top-level node x with degree increase of 2. To get a degree increase of 3, Algorithm 2.3.4 calls the algorithm DEGREEUP for each of its three children to get a child of degree increase 2 in each of these subtrees, using 3 more levels. Using the *graft* operation, these nodes are attached to x. The *prune* operation removes any other subtrees of x. Now x has exactly three neighbors of degree increase 2 each, and deletion of x leads to a node of degree increase 3. To get a degree increase of 4, the strategy uses the same strategy described above recursively for three *virgin* children of this node, using 6 more levels. This will give it three children with degree increase 3 and now we can obtain a node with degree increase 4. Notice, each subsequent degree increase involves exponentially larger number of levels in G.

Thus,

degree increase =  $O(\log_2(\text{number of levels in})G)$ =  $O(\log_2 \log_3 n)$ 

# 2.4 Experiments

We carried out a number of experiments to ascertain the performance of various healing algorithms. We used a number of attack strategies to measure how different healing strategies performed with regard to degree increase and stretch, where stretch is the maximum ratio of distance increase in the healed network compared to the original network, over all pairs of nodes. Our empirical results on stretch and a heuristic for maintaining low stretch are described in Section 2.4.7.

# 2.4.1 Methodology

Most of our experiments were conducted on random graphs. These graphs were generated by the *Preferential Attachment* model proposed by Barabasi [4, 5]. The experimental approach was the following:

- For each graph size, for a particular deletion and healing strategy, repeat for 30 random instances of the graph:
  - Repeat while there are nodes in the graph:
    - \* delete a single node according to the deletion strategy.
    - \* repair according to the self-healing strategy.
    - \* measure the statistics (e.g. maximum change of degree for any node) for the graph.
- average the statistics for each graph size.

# 2.4.2 Attack Strategies

The aim of the adversary is to collapse the network by trying to overload a node beyond it's maximum capacity. There are many possible attack strategies. One strategy is to delete the node with the maximum degree. We call this the *MaxNodestrategy*. It would seem that a strategy that leads to additional burden on an already high burden node would be a good strategy. For the adversary, one good adversarial strategy is to continuously attack/delete a randomly chosen neighbor of the highest degree node in the network. We call this the *Neighborof MaxStrategy(NMS)*. This would also seem plausible as in a real network or the kind of networks we are looking at, it would be reasonable that the hubs or the high degree nodes would be more well protected and resilient to attack while their less significant neighbors should be easy to take down.

# 2.4.3 Healing strategies

We attempted various locality-aware healing strategies, some of which are the following:

- *Graph heal*: On each deletion, we reconnect the neighbors of the deleted node in a binary tree regardless of whether we introduced any cycles in the graph formed by the new edges introduced for healing. This seems to be a naive algorithm since the nodes use more edges than what are required for maintaining connectivity.
- *Binary tree heal*: On each deletion, we reconnect the neighbors of the deleted node in a binary tree being careful not to introduce any cycles in the graph formed by the new edges introduced for healing. This is done using random IDs which can then be used to identify which tree a particular node belongs to. This is an improvement on the previous algorithm but still naive since it does not take into consideration the previous degree increase suffered by nodes during healing.
- DASH (*Degree Assisted binary tree heal*): DASH is smarter than the previous algorithms as borne out by the results of the experiments. The DASH algorithm has been earlier described in Section 2.2.1 and stated as Algorithm 2.2.1.
- SDASH (Surrogate Degree Assisted binary tree heal): (described in Section 2.4.7) A heuristic based on DASH that tries to both keep node degrees and path lengths small.

# 2.4.4 Connectivity

Figure 2.9 shows a series of snapshots from a simulation of DASH showing that the network stays connected, and no individual node seems to be getting a large number of healing edges during healing.

# 2.4.5 Degree increase

The Neighborof MaxStrategy consistently resulted in higher degree increase, hence, we report results for only this attack strategy. Our experimental results clearly show that DASH and SDASH are good healing strategies. It performed well against both adversary strategies. Figure 2.10 shows that DASH and SDASH have much lower degree increase than the other more naive strategies. Also, this degree increase was less than  $\log n$ , which is consistent with our theoretical results. SDASH has the additional nice property that it keeps path lengths small over multiple adversarial deletions.

## 2.4.6 Messages

Figure 2.11 shows that the number of time a nodes ID changes is less than  $\log n$ , as expected, for all healing strategies. Figure 2.12 shows the maximum number of messages a node sent out for the different strategies. Note that the number of messages a node sends out has to be less than or equal to the number of times a node changes ID times the degree of the node. Thus, algorithms with higher degree increase perform poorly.



Figure 2.9: A timeline of deletions and self healing in a network with 100 nodes. The gray edges are the original edges and the red edges are the new edges added by our self-healing algorithm.

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Figure 2.10: Maximum Degree increase: DASH vs other algorithms

## 2.4.7 Heuristics and experiments involving Stretch

Stretch is an important property we would also like our self-healing algorithms to minimize. The stretch for any two nodes is the ratio between their distance in the new healed network and their distance in the original network. Stretch for the network is the maximum stretch over all pairs of nodes. Stretch is also closely related to the diameter of the network. In some sense, maintaining low degree increase and low stretch are contradictory aims since a high-degree node will lead to shorter paths and possibly lower stretch in the network.

#### SDASH: a strategy with good empirical results

SDASH is an algorithm we have devised which empirically has both low degree increase and low stretch. During self-healing, we say a node *surrogates* if it replaces

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Figure 2.11: ID changes for nodes

its deleted neighbor in the network. i.e. it takes all the connections of the deleted neighbor to itself. Surrogation never increases stretch since the paths never increase in length. In certain situations, it turns out that surrogation can be done without degree increase. In such situations, SDASH does surrogation else it simply applies DASH. SDASH is described in Algorithm 2.4.1.

As can be seen in the figures that follow, SDASH seems to allow a degree increase up to  $O(\log n)$  and stretch up to  $O(\log n)$ . We are working on proving theoretical properties of this algorithm.

#### Stretch: empirical results

Figure 2.13 shows the performance of some of our algorithms for stretch. We determined that the MaxNodestrategy is most effective for the adversary when trying to

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Figure 2.12: Number of messages exchanged for Component(ID) information maintenance

maximize stretch and so our results in Figure 2.13 are against that adversarial strategy. The more naive degree-control healing strategies do a good job of minimizing stretch. However, it is important to keep in mind that these more naive algorithms increase the node degrees to a point where they are unlikely to be useful for many applications. In contrast, our experiments show that SDASH does a good job of minimizing both stretch and degree increase.

# 2.5 Conclusions and future work

In this chapter, we have studied the problem of self-healing in networks that are reconfigurable in the sense that new edges can be added to the network. We have described DASH, a simple, efficient and localized algorithm for self-healing, that 1: Init: for given network G(V, E), Initialize each vertex with a random number ID between [0,1] selected uniformly at random.

2: while true do

3: If a vertex v is deleted, do

- 4: Let  $m \in UN(v, G) \cup N(v, G_h)$  be the node with Maximum degree increase  $(\delta)$  of all nodes in  $UN(v, G) \cup N(v, G_h)$ .
- 5: if  $w \in UN(v,G) \cup N(v,G_h)$  and  $\delta(w) + |UN(v,G) \cup N(v,G_h)| 1 \le \delta(m)$ then

6: connect all nodes in  $UN(v, G) \cup N(v, G_h)$  to w.

- 7: else
- 8: Nodes in  $UN(v, G) \cup N(v, G_h)$  are reconnected into a *complete binary tree*. To connect the tree, go left to right, top down, mapping nodes to the *complete binary tree* in increasing order of  $\delta$  value.
- 9: end if
- 10: Let MINID be the minimum ID of any node in  $UN(v, G) \cup N(v, G_h)$ . Propagate MINID to all the nodes in the tree of  $UN(v, G) \cup N(v, G_h)$  in  $G_h$ . All these nodes now set their ID to MINID.
- 11: end while

Algorithm 2.4.1: SDASH: Surrogate Degree-Based Self-Healing

provably maintains network connectivity, even while increasing the degree of any node by no more than  $O(\log n)$ . We have shown that DASH is asymptotically optimal in terms of minimizing the degree increase of any node. Further, we have presented empirical results on power-law networks showing that DASH significantly outperforms the naive algorithms for this problem.

Several interesting problems remain open including the following: Can we not only maintain connectivity, but also provably ensure that lengths of shortest paths in the graph do not increase by too much? Can we remove the need for propagating
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Figure 2.13: Stretch for various algorithms

IDs in order to maintain connected component information, or is such information strictly necessary to keep the degree increase small? Can we use the self-healing idea to protect invariants for combinatorial objects besides graphs? For example, can we provide algorithms to rewire a circuit so that it maintains essential functionality even when multiple gates fail?

# Chapter 3

# Forgiving Tree

My roots are strong My branches free, But only because I'm a forgiving tree. *The Forgiving Tree* CHERYL MERRIWEATHER

In this chapter, we present the algorithm ForgivingTree which first appeared in *Principles of Distributed Computing 2008* [24]. We consider the problem of self-healing in peer-to-peer networks that are under repeated attack by an omniscient adversary. We assume that the following process continues for up to n rounds where n is the total number of nodes initially in the network: the adversary deletes an arbitrary node from the network, then the network responds by quickly adding a small number of new edges.

We present a distributed data structure that ensures two key properties. First, the diameter of the network is never more than  $O(\log \Delta)$  times its original diameter, where  $\Delta$  is the maximum degree of the network initially. We note that for many peer-to-peer systems,  $\Delta$  is polylogarithmic, so the diameter increase would be a

 $O(\log \log n)$  multiplicative factor. Second, the degree of any node never increases by more than 3 over its original degree. Our data structure is fully distributed, has O(1) latency per round and requires each node to send and receive O(1) messages per round. The data structure requires an initial setup phase that has latency equal to the diameter of the original network, and requires, with high probability, each node vto send  $O(\log n)$  messages along every edge incident to v. Our approach is orthogonal and complementary to traditional topology-based approaches to defending against attack.

# 3.1 Introduction

In Chapter 1, we have made a case highlighting the need of using *responsive* approaches for maintaining robustness and self-healing in networks.

In this chapter, we focus on a new, *responsive* approach for maintaining robust reconfigurable networks. Our approach is responsive in the sense that it responds to an attack (or component failure) by changing the topology of the network. Our approach works irrespective of the initial state of the network, and is thus orthogonal and complementary to traditional non-responsive techniques. There are many desirable invariants to maintain in the face of an attack. Here we focus only on the simplest and most fundamental invariants: ensuring the diameter of the network and the degrees of all nodes do not increase by much.

**Our Model:** We now describe our model of attack and network response. We assume that the network is initially a connected graph over n nodes. An adversary repeatedly attacks the network. This adversary knows the network topology and our algorithms, and it has the ability to delete arbitrary nodes from the network. However, we assume the adversary is constrained in that in any time step it can only

delete a single node from the network. We further assume that after the adversary deletes some node x from the network, that the neighbors of x become aware of this deletion and that the network has a small amount of time to react by adding and deleting some edges. This adversarial model captures what can happen when a worm or software error propagates through the population of nodes. Such an attack may occur too quickly for human intervention or for the network to recover via new nodes joining. Instead the nodes that remain in the network must somehow reconnect to ensure that the network remains functional.

We assume that the edges that are added can be added anywhere in the network. We assume that there is very limited time to react to deletion of x before the adversary deletes another node. Thus, the algorithm for deciding which edges to add between the neighbors of x must be fast. The detailed model used in ForgivingTree and its relation to the general model we described in Section 1.2 is given in Section 3.2.

Our Results: A naive approach to this problem is simply to 'surrogate' one neighbor of the deleted node to take on the role of the deleted node, reconnecting the other neighbors to this surrogate. However, an intelligent adversary can always cause this approach to increase the degree of some node by  $\theta(n)$ . On the other hand, we may try to keep the degree increase low by connecting neighbors of the deleted node as a straight line, or by connecting the neighbors of the deleted node in a binary tree. However, for both of these techniques the diameter can increase by  $\theta(n)$  over multiple deletions by an intelligent adversary [10, 53].

In this chapter, we describe a new, light-weight distributed data structure that ensures that: 1) the diameter of the network never increases by more than  $\log \Delta$ times its original diameter, where  $\Delta$  is the maximum degree of a node in the original network; and 2) the degree of any node never increases by more than 3 over over its original degree. Our algorithm is fully distributed, has O(1) latency per round

and requires each node to send and receive O(1) messages per round. The formal statement and proof of these results is in Section 4.7.1. Moreover, we show (in Section 4.7.2) that in a sense our algorithm is asymptotically optimal, since any algorithm that increases node degrees by no more than a constant must, in some cases, cause the diameter of a graph to increase by a log  $\Delta$  factor.

The algorithm requires a one-time setup phase to do the following two tasks. First, we must find a breadth first spanning tree of the original network rooted at an arbitrary node. In the synchronous communication model, this can be done with latency equal to the diameter of the original network, and, with high probability, each node v sending  $O(\log n)$  messages along every edge incident to v, as in the algorithm due to Cohen [11]. The second task required is to set up a simple data structure for each node that we refer to as a will. This will, which we will describe in detail in the Section 3.3, gives instructions for each node v on how the children of v should reestablish connectivity if v is deleted. Creating the will requires O(1)messages to be sent along the parent and children edges of the global breadth-first search tree created in the first task.

#### **Related Work:**

In this chapter, we build on earlier work in [10, 53].

There have been numerous papers on dealing with adversarial atttacks in networks. Kuhn et al [37, 38] describe efficient algorithms that provably ensure that node degree and network diameter stay small even in the case where an adversary can either add or delete up to a fixed number of nodes in any time step. They describe algorithms for the hypercube [38] and pancake topology [37] and suggest how their approach can apply to any recursively defined peer-to-peer topology. In contrast, our algorithm does not handle adversarial insertions, but it is immediately applicable to any arbitrary reconfigurable network, even those that are not recursively defined.

# 3.2 Delete and Repair Model

We now describe the details of our delete and repair model. Let  $G = G_0$  be an arbitrary graph on n nodes, which represent processors in a distributed network. One by one, the Adversary deletes nodes until none are left. After each deletion, the Player gets to add some new edges to the graph, as well as deleting old ones. The Player's goal is to maintain connectivity in the network, keeping the diameter of the graph small. At the same time, the Player wants to minimize the resources spent on this task, in the form of extra edges added to the graph, and also in terms of the number of connections maintained by each node at any one time (the degree increase). We seek an algorithm which gives performance guarantees under these metrics for each of the n! possible deletion orders.

Unfortunately, the above model still does not capture the behaviour we want, since it allows for a centralized Player who ignores the structure of the original graph, and simply installs and maintains a complete binary tree, using a leaf node to substitute for each deleted node.

To avoid this sort of solution, we require a distributed algorithm which can be run by a processor at each node. Initially, each processor only knows its neighbors in  $G_0$ , and is unaware of the structure of the rest of the  $G_0$ . After each deletion (forming  $H_t$ ), only the neighbors of the deleted vertex are informed that the deletion has occurred. After this, processors are allowed to communicate by sending a limited number of messages to their direct neighbors. We assume that these messages are always sent and received successfully. The processors may also request new edges be added to the graph to form  $G_t$ . The only synchronicity assumption we make is that the next vertex is not deleted until the end of this round of computation and communication has concluded. To make this assumption more reasonable, the pernode communication should be  $O(\log n)$  bits, and should moreover be parallelizable so that the entire protocol can be completed in O(1) time if we assume synchronous communication.

We also allow a certain amount of pre-processing to be done before the first deletion occurs. This may, for instance, be used by the processors to gather some topological information about  $G_0$ , or perhaps to coordinate a strategy. Another success metric is the amount of computation and communication needed during this preprocessing round. Our full model is described as Model 3.2.1.

This model can be seen as a special case of our general model (Section 1.2). We assume we begin with a connected graph of n vertices and do not explicitly discuss node insertions in ForgivingTree. Since only deletions happen, n can only decrease. For this reason, for our bounds, we need only compare our graph properties in the present graph at timestep t ( $G_t$ ), to the initial graph  $G_0$  which has n vertices.

# 3.3 The Forgiving Tree algorithm

At a high level, our algorithm works as follows. We begin with a rooted spanning tree T, which without loss of generality may as well be the entire network.

Each time a non-leaf node v is deleted, we think of it as being replaced by a balanced binary tree of "virtual nodes," with the leaves of the virtual tree taking v's place as the parents of v's children. Depending on certain conditions explained later, the root of this "virtual tree" or another virtual node (known as v's *heir*—this will be discussed later) takes v's place as the child of v's parent. This is illustrated in figure 4.5. Note that each of the virtual nodes which was added is of degree 3, except the heir, if present.

When a leaf node is deleted, we do not replace it. However, if the parent of the deleted leaf node was a virtual node, its degree has now reduced from 3 to 2, at

Each node of  $G_0$  is a processor.

Each processor starts with a list of its neighbors in  $G_0$ .

Pre-processing: Processors may send messages to and from their neighbors.

for t := 1 to n do

Adversary deletes a node  $v_t$  from  $G_{t-1}$ , forming  $H_t$ .

All neighbors of  $v_t$  are informed of the deletion.

#### Recovery phase:

Nodes of  $H_t$  may communicate (in parallel) with their immediate neighbors. These messages are never lost or corrupted, and may contain the names of other vertices.

During this phase, each node may insert edges joining it to any other nodes as desired. Nodes may also drop edges from previous rounds if no longer required.

At the end of this phase, we call the graph  $G_t$ .

end for

Success metrics: Minimize the following "complexity" measures:

- 1. Degree increase.  $\max_{t < n} \max_{v} \text{degree}(v, G_t) \text{degree}(v, G_0)$
- 2. Diameter stretch.  $\max_{t \leq n} \operatorname{diam}(G_t)/\operatorname{diam}(G_0)$
- 3. Communication per node. The maximum number of bits sent by a single node in a single recovery round.
- 4. **Recovery time.** The maximum total time for a recover round, assuming it takes 1 bit no more than 1 time unit to traverse any edge and unlimited local computational power at each node.

Model 3.2.1: The Delete and Repair Model – Distributed View.



Figure 3.1: Deleted node v replaced by its Reconstruction Tree. The nodes in the oval are helper nodes. Regular helper nodes are depicted by circles and the heir helper node by a rectangle.

which point we consider it redundant and "short-circuit" it, removing it from the graph, and connecting its surviving child directly to its parent. This helps to ensure that, except for heirs, every virtual node is of degree exactly 3.

After a long sequence of such deletions, we are left with a tree which is a patchwork mix of virtual nodes and original nodes. We note that the degrees of the original nodes never increase during the above procedure. Also, because the virtual trees are balanced binary trees, the deletion of a node v can, at worst, cause the distances between its neighbors to increase from 2 to  $2\lceil \log d \rceil$ , where d is the degree of v. This ensures that, even after an arbitrary sequence of deletions, the distance between any pair of surviving actual nodes has not increased by more than a  $\lceil \log \Delta \rceil$  factor, where  $\Delta$  is the maximum degree of the original tree.

Since our algorithm is only allowed to add edges and not nodes, we cannot really add these virtual nodes to the network. We get around this by assigning each virtual node to an actual node, and adding new edges between actual nodes in order to allow "simulation" of each virtual node. More precisely, our actual graph is the homomorphic image of the tree described above, under a graph homomorphism which fixes the actual nodes in the tree and maps each virtual node to a distinct actual node which is "simulating" it. The existence of such a mapping is a consequence of

the fact that all the virtual nodes have degree 3, except heirs, which have degree 2 (and there are not too many of these), and will be proved later. Note that, because each actual node ever simulates at most one virtual node at a time, and virtual nodes have degree at most 3, this ensures that the maximum degree increase of our algorithm is at most 3.

The heart of our algorithm is a very efficient distributed algorithm for keeping track of which actual node is assigned to simulate each virtual node, so that the replacement of each deleted node by its virtual tree can be done in O(1) time. We accomplish this using a system of "wills," in which each vertex v instructs each of its children (or their "heirs") in the event of v's deletion, how to simulate the virtual tree replacing v, and also the virtual node v was simulating (if any).

This will is prepared in advance, before v's deletion, and entrusted to v's children or their surviving heirs. An example of this is shown in figure 3.2. Certain events, such as the deletion of one of v's children, or a change in which virtual node v is simulating, may cause v to revise its will, informing the affected children or their surviving heirs. As shall be seen, the total number of messages and node IDs which must be sent is O(1) per deleted vertex; the number of bits sent is thus  $O(\log n)$ . In addition, there is a startup cost for communicating the initial wills: this is O(1)latency; and O(1) messages and  $O(\log n)$  bits per edge in the original network.

## 3.3.1 Distributed implementation

To begin with, in Table 4.1 we list the data kept by each real node v required for the ForgivingTree algorithm. We have four main classes of fields, according to the way they are used by the node. 'Current fields' give a node's present configuration and status in the tree. 'Reconstruction fields' hold the data needed for a node to reconstruct connections when one of its neighbors gets deleted. 'Helper fields' hold

information with regard to the helper node being simulated by this node. Each node also stores some special flags with regard to its helper or heir status. In the description that follows, we shall refer directly to these fields.

Current fields	Fields having information about a node's current neigh-
	bors.
parent(v)	Parent of $v$ .
children(v)	Children of $v$ .
SubRT(v)	Stores the Reconstruction Tree (RT) of $v$ minus a pos-
	sible helper node simulated by $heir(v)$ . This tree of
	helper and real nodes shall replace $v$ if $v$ is deleted.
heir(v)	The heir of $v$ .
Helper fields	Fields specifying a node's role as a helper node.
hparent(v)	Parent of the helper node $v$ may be simulating.
hchildren(v)	Children of the helper node $v$ may be simulating.
Reconstruction fields	Fields used by a node to reconstruct its connections
	when its neighbor is deleted.
nextparent(v)	The node which will be the next parent of $v$ .
nexthparent(v)	The node which will be the next hearent of $v$ .
nexthchildren(v)	The node(s) which will be the next hchildren of $v$ .
Flags	Specifying a node's helper or heir status.
ishelper(v)	(boolean field). True if $v$ is simulating a <i>helper</i> node,
	false otherwise.
<pre>isreadyheir(v)</pre>	(boolean field). True if $v$ is simulating an heir in ready
	state, false otherwise (wait or deployed state).

Table 3.1: The fields maintained by a node v

At the top level, our algorithm is specified as Algorithm 4.5.1 : FORGIVING TREE. Algorithm 4.5.1 uses Algorithms 2 to 9, which will be described at the appropriate places. As referred to earlier, FORGIVING TREE works on a tree which may be obtained from the original graph during a preprocessing phase. The next stage is an initialisation phase in which the appropriate data structures are setup. Once these are setup, the network is ready to face the adversarial attacks as and when they happen.





Figure 3.2: The leftmost column shows a small segment of the network. The RT(x) corresponding to this figure is shown. Every neighbor of node x stores the portion of RT(x) relevant to it. Each rectangular box is labelled with a neighbor and shows the portions and the value of the corresponding fields.

#### The Initialization phase

This phase is specified in Algorithm 4.5.2 : INIT(). We assume each node v has a unique identification number which we call ID(v). Every node in the tree initializes the fields we have listed in Table 4.1. In our descriptions if no data is available or appropriate for a field, we set it to *EMPTY*. Since no deletion has happened yet and there are no helper nodes in the system, the helper fields are set to *EMPTY*. The current fields parent(v) and children(v) are assigned pointers to the parent and children of v. Of course, if v is a leaf node children(v) is *EMPTY* and if v is the root of the tree parent(v) is *EMPTY*.

As stated earlier, the heart of our algorithm is the system of wills created by nodes and distributed among its neighbors. The will of a node, v, has two parts: firstly, a Reconstruction Tree (SubRT(v)), which will replace v when it is deleted by

Turn 1: Adversary deletes v. Vertices a through h take over helper nodes in RT(v).h is v's heir and connects to both p and q. Note that the real graph now contains a cycle, (b, c, d)



Turn 2: Adversary deletes p. Vertices h, i, j, and k take over helper nodes in RT(p). h takes over the helper role of v in RT(p). d attaches to i. k is p's heir and connects to both h and parent(p)



Turn 3: Adversary deletes d. The original helper node of c is made redundant by the deletion of d and so is bypassed. c takes over the helper nodes formerly held by d.



Turn 4: Adversary deletes h. Vertices m, n and o take over helper nodes of RT(h). o is heir of h and takes over h's and takes over h's helper role. Note that since the number of children of h was not a power of 2, not all the leaves of RT(h) are at the same depth.



Figure 3.3: An illustrative sequence of deletions and healings.

the Adversary, and secondly, the delegation of v's helper responsibilities (if any) to a child node, heir(v). For concreteness, we initially designate the child of v with the highest ID as heir(v). In the event that heir(v) is deleted, its role will be taken over by its heir, if any. If heir(v) is a leaf when it is deleted, then v will designate its new heir to be the surviving child whose helper node has just decreased in degree from 3 to 2.

Algorithm 3.3.5: GENERATESUBRT computes  $\operatorname{SubRT}(v)$ . If the node v has no helper responsibilities, as is during this phase,  $\operatorname{RT}(v)$  is simply  $\operatorname{SubRT}(v)$  with a helper node simulated by  $\operatorname{heir}(v)$  appended on as the parent of the root of  $\operatorname{SubRT}(v)$ . Figure 4.5 and Turn 1 in Fig 3.3 depict such Reconstruction Trees. If the node v has helper responsibilities  $\operatorname{RT}(v)$  is the same as  $\operatorname{SubRT}(v)$ . Node v uses Algorithm 3.3.5 to compute  $\operatorname{SubRT}(v)$  as follows: All the children of v are arranged as a single layer in sorted (say, ascending) order of their IDs. Then a set of helper nodes - one node for each of the children of v except the heir are arranged above this layer so as to construct a balanced binary search tree ordered on their IDs.

The last step of the initialization process is to finalize the will and transmit it to the children. Each child is given only the portion of the will relevant to it. Thus, only this portion needs to be updated whenever a will changes. The division of RT into these portions is shown in figure 3.2. There are fundamentally two different kinds of wills : one prepared by leaf nodes who have helper responsibilities and the other by non-leaf nodes. Obviously, during the initialization phase, only the second kind of will is needed. This is finalized and distributed as shown in Algorithm 3.3.6: MAKEWILL. The children of v initialize their reconstruction fields with the values from SubRT(v). If later v gets deleted these values will be copied to present and helper fields such that RT(v) is instantiated. Notice that the role the heir will assume is decided according to whether v is a helper node or not. Since v cannot be a helper node in this phase, the heir node simply sets its reconstruction fields so as

to be between the root of  $\operatorname{SubRT}(v)$  and  $\operatorname{parent}(v)$ . In this case when  $\operatorname{RT}(v)$  will be instantiated, the helper node simulated by  $\operatorname{heir}(v)$  shall have only one child: we will say that  $\operatorname{heir}(v)$  is in the ready phase (explained later) and set the flag isreadyheir(v) to true. In the initialization phase both the isreadyheir and ishelper flags will be set to false.

This completes the setup and initialization of the data structure. Now our network is ready to handle adversarial attacks. In the context of our algorithm, there are two main events that can happen repeatedly and need to be handled differently:

#### Deletion of an internal node

The healing that happens on deletion of a non-leaf node is specified in Algorithm 4.5.3: FIXNODEDELETION. In our model, we assume that the failure of a node is only detected by its neighbors in the tree, and it is these nodes which will carry out the healing process and update the changes wherever required. If the node v was deleted, the first step in the reconstruction process is to put RT into place according to Algorithm 4.5.8: MAKERT. Note that all children of v have lost their parent. Let us discuss the reconstruction performed by non-heir nodes first. They make an edge to their new parent (pointer to which was available as nextparent()) and set their current fields. Then they take the role of the helper nodes as specified in RT(v) and Algorithm 3.3.9: MAKEHELPER and make the required edges and field changes to instantiate RT(v).

To understand what the heir node does in this case, it will be useful here to have a small discussion on the states of a regular/heir node:

States of a heir/regular node: Consider a node v and its heir h. From the point of view of h, we can imagine h to be in one of three states which we call *wait*, *ready* 



Figure 3.4: The states of a node with respect to helper duties: Waiting, Ready and Deployed

and *deployed*. These states are illustrated in figure 3.4. For ease of discussion, let us call the helper node that a node is simulating helper(*node*). In brief, a node is considered to be in the wait state when it has no helper responsibilities, in the ready state when helper(*node*) with one child, and in the deployed state when helper(*node*) has two children (which is the maximum possible). Notice that the node can be in the wait state only when v has not been deleted and thus, h has assumed no helper responsibilities. It only has the will of v and is in limbo with regard to helper duties. Now consider the case when v gets deleted. Following are the possibilities:

node v had no helper responsibilities: This happens when v's original parent was not deleted. Thus, v could be a regular child or a heir in the wait state. On v's deletion h moves to the ready state and sets its flag isreadyheir to True. This is the state in which helper(h) has only one child i.e. the root of SubRT(v). This happens when h executes its portion of the will of v using Algorithm 4.5.8: MAKERT. Note that this may not be the final state for the helper node of h, and is thus called the ready state.

- node v had helper responsibilities: There are two further possibilities:
  - helper(v) had one child: This can only happen when v was a heir node in the ready state. Thus, v's flags ishelper and isreadyheir were both set to True. Node h will take over the helper responsibilities of v and thus, in turn, h will now have one child i.e. will be in the ready state and will set its flags ishelper and isreadyheir to True. Notice that if v was an heir, h will now also take over those responsibilities, and on future deletions of v's ancestors could move further up the tree either as an heir in ready state or in a deployed state become a full helper node.
  - helper(v) had two children: Node v could be a regular child or heir. h will fully take over the helper responsibilities of v, and thus helper(h) shall acquire two children and move on to the deployed state. Notice that previously h could have been in either wait or ready state. Since it is now not in the ready state, it will set its isreadyheir flag to False and ishelper flag to True.

It is easy to see that a regular i.e. non-heir node can be in either wait or deployed state.

Here we also define the following operation, which is used in Algorithms 3.3.4 and 4.5.8:

**bypass(x):** Precondition: |hchildren(x)| = 1 i.e the helper node has a single child. Operation: Delete helper(x) i.e. hparent(x) and hchildren(x) remove their edges with x and make a new edge between themselves. hparent(x)  $\leftarrow EMPTY$ ; hchildren(x)  $\leftarrow EMPTY$ .

We can now easily see how the heir of v, h takes part in the reconstruction according to Algorithm 4.5.8: MAKERT. Node h can be either in wait state or ready state. If it is in the wait state it simply takes its helper responsibilities according to Algorithm 3.3.9: MAKEHELPER, as in turn 1 of figure 3.3. Note that here hchecks if it has moved to the ready state and sets its isreadyheir flag accordingly. If h was already in ready state, it relinquishes its present helper role and moves on to the new helper role. To relinquish its present role, node h intimates hparent(h) and hchildren(h), and together they accomplish this as specified by the operation bypass(h). Turn 2 in Fig 3.3 illustrates this.

Once  $\operatorname{RT}(v)$  is in a place, there may be a need for the parent of v to recompute its will. This happens only when v did not already have a helper role or equivalently when heir(v) moves to a ready state. Lines 2 to 6 of Algorithm 4.5.3 deals with this situation. Node parent(v) simply replaces v by heir(v) in its will and retransmits it. At the end of this healing process, the children of the deleted nodes check if they need to leave the second kind of will, which we call a *LeafWill*. This will is required only for those nodes which are leaves in our tree and have virtual responsibilities. Since they have no children to take over their helper responsibilities they leave this responsibility to their parent. We will discuss this in greater detail in the next section.

#### Deletion of a leaf node

If the adversary removes a leaf node from the system, the healing is accomplished by its neighbors as specified in Algorithm 3.3.4: FIXLEAFDELETION. Let v be the deleted leaf node and p be its parent. Let us consider the simple case first. This is when the deleted node had no helper responsibility. This also implies its original parent did not suffer a deletion. Node p simply removes v from the list of its children and then recomputes and redistributes its will.





(d) z is an heir in Ready state.

Figure 3.5: Various cases of Leaf deletions

Now, consider the situation where the deleted node had helper responsibilities. In this case, the one node whose workload has been reduced by this deletion is p. Using Algorithm 3.3.7: MAKELEAFWILL v hands over the list of its helper responsibilities

to p. Here, a special case may arise when v is simulating a helper node which has v itself as one of its hchildren. Recall that parent(v) is v's ancestor closest to v in the tree. This implies that parent(v) = hparent(v) = p. The only thing that p needs to do if v is deleted is to remove v from its hchildren and add itself (for consistency). This is the will conveyed by v to p. When v is deleted, p simply updates its helper fields. For other cases, v simply sends its helper fields to p to be copied to p's helper reconstruction fields. In this situation, when v is actually deleted the following happens: the helper node that p is simulating is deleted and bypassed by the bypass operation defined earlier. Node p now simulates a new helper node that has the same helper responsibilities previously fulfilled by v. In case the deleted leaf node was itself an heir in ready state, p detects this and sets its flags accordingly. Again at the end of the reconstruction, the leaf nodes reconstruct their wills. An example of such a leaf deletion is the deletion of node d at Turn 3 as shown in figure 3.3.

**Important Note:** When implementing the pseudocode for Algorithm 3.3.6 (MAKEWILL), it is important to bear in mind that when RT(v) is being updated due to a node deletion, most of SubRT(v) will be unchanged. In fact, only O(1) nodes will need to have their fields updated. These can be found and updated more efficiently by a more detailed algorithm based on case analysis.

# 3.4 Results

## 3.4.1 Upper Bounds

Before considering the main theorem, we shall prove a couple of lemmas.

**Lemma 3.1.** In the Forgiving Tree, a real node can simulate at most one helper node at a time.

*Proof.* A node simulates a new helper node if and only if its parent is deleted (Section 3.3.1) or a sibling that is a leaf node in the Forgiving Tree is deleted (Section 3.3.1). We will show that whenever either of the above events happens and the node has to simulate a new helper node, it no longer needs to simulate the helper node it was simulating prior to these events occuring and thus it always simulates at most one helper node at a time. Let us consider the cases in more detail. Consider a node v and it's parent node p.

- *Parent node p is deleted:* There are three possibilities:
  - Node v is in Wait state (i.e. no previous helper role): Node v will now take over the role of exactly one helper node as specified for RT(p) (Figure 4.5).
  - Node v is in Ready heir: Node v will remove its previous helper node using operation bypass(v), and be redeployed in the Ready state or as a Deployed node (Figure 3.4). An example is node h at turn 2 in Figure 3.3.
  - Node v is in Deployed state: By construction and by definition of parent in the Forgiving Tree (Line 4, Algorithm 3.3.6:MAKEWILL), p is the parent of v through helper(p). This implies that v's parent in the Forgiving Tree is helper(p) (not p itself). Thus v does not feature in the will of p and will not simulate a new helper node on deletion of p.

• In the Forgiving Tree, a leaf node sibling of v is deleted: Refer to Figure 3.5, cases b,c and d, and node c in turn 3, Figure 3.3. On deletion of a leaf node, exactly one helper node becomes redundant, and this can be removed. If v takes on the role of a new helper node, its old helper node is removed using bypass(v).

Let  $FT_i$  be the Forgiving Tree which has undergone *i* rounds of deletions and healings. A time step is a single deletion followed by healing.

**Lemma 3.2.** If an original node x is an ancestor of another original node v in  $FT_i$  for some time step i, then node x must also have been an ancestor of node v in  $FT_0$ .

*Proof.* We will prove this by induction on time step i.

Base case: i = 0: This is trivially true.

Inductive step: Let  $v_x$  be the node deleted at time step i, and let v be an arbitrary node in FT<sub>i</sub>. By the inductive hypothesis, we need only show that the deletion of  $v_x$ will not violate the invariant. Note that if  $v_x$  has a helper node then when helper $(v_x)$ is deleted, no new original node become an ancestor of v in FT<sub>i</sub>, since either a new helper node takes the place of helper $(v_x)$  or helper $(v_x)$  is bypassed.

We also note that when  $v_x$  is deleted, no new original node can become the ancestor of v in FT<sub>i</sub>. To see this, note that when the deletion of  $v_x$  creates an RT no *original* node that was a child of  $v_x$  can becomes a new ancestor of v in FT<sub>i</sub>.

Let  $\Delta$  be its maximum degree of a node in FT<sub>0</sub>.

**Lemma 3.3.** Let  $\operatorname{danc}_i(v)$  be the number of ancestors of v in  $\operatorname{FT}_0$  that have been deleted by time step i.

For all nodes v,

 $\operatorname{depth}_{i}(v) \leq \operatorname{depth}_{0}(v) + \log \Delta \times \operatorname{danc}_{i}(v)$ 

*Proof.* We shall prove this by induction on time i.

Base case: i = 0: This is trivial since there have been no deletions so far.

Inductive step: Let  $v_i$  be the node deleted at the  $i^{th}$  deletion. Consider an arbitrary original node v in FT<sub>i</sub>. First, observe that the removal of helper $(v_i)$ , if it exists (helper $(v_i)$  will be removed on deletion of node  $v_i$ ), never increases the depth of any node. This is because the helper node is either replaced by another helper node or it is removed in the bypass operation, which will never increase the depth of any node. We now consider the deletion of the original node  $v_i$ . There are two cases for node v:

- Node v is not in the subtree rooted at v<sub>i</sub>: Here,
   depth<sub>i</sub>(v) ≤ depth<sub>i-1</sub>(v) and thus the induction holds.
- Node v is in the subtree rooted at  $v_i$ : By lemma 3.2, node  $v_i$  must have been an ancestor of v in FT<sub>0</sub>. Since Algorithm 4.5.3 replaces  $v_i$  with RT( $v_i$ ), which is a balanced binary tree, we know that,

 $\operatorname{depth}_{i}(v) \leq \operatorname{depth}_{i-1}(v) + \log \Delta$ 

Also, by the Inductive hypothesis,

 $\operatorname{depth}_{i-1}(v) \leq \operatorname{depth}_0(v) + \log \Delta \times \operatorname{danc}_{i-1}(v)$ 

These two equations imply that

$$\begin{aligned} \operatorname{depth}_{i}(v) &\leq \operatorname{depth}_{0}(v) + \log \Delta \times \operatorname{danc}_{i-1}(v) + \log \Delta \\ &\leq \operatorname{depth}_{0}(v) + \log \Delta \times \operatorname{danc}_{i}(v) \end{aligned}$$

Now, we prove our main theorem. Let  $FT_0$  be the original tree, and let D be its diameter.

**Theorem 3.1.** The Forgiving Tree has the following properties:

- 1. The Forgiving Tree increases the degree of any vertex by at most 3.
- 2. The Forgiving Tree always has diameter  $O(D \log \Delta)$ .
- The latency per deletion and number of messages sent per node per deletion is
   O(1); each message contains O(1) node IDs and thus O(log n) bits.

*Proof.* Parts 1 and 3 follow directly by construction of our algorithm. For part 1, we note that for a node v, any degree increase for v is imposed by its edges to hparent(v) and hchildren(v). By lemma 3.1, node v can play the role of at most one helper node at any time and the number of hchildren is never more than 2, because the reconstruction trees are binary trees. Thus the total degree increase is at most 3. Part 3 also follows directly by the construction of our algorithm, noting that, because the virtual nodes all have degree at most 3, healing one deletion results in at most O(1) changes to the edges in each affected reconstruction tree. In fact, the changes to RT(w) for an affected node w do not require new information, which allows these messages to be computed and distributed in parallel.

We next show Part 2, that the diameter of the Forgiving Tree is always  $O(D \log \Delta)$ . Consider the Forgiving Trees  $FT_0$  and  $FT_i$ . Let their respective heights be h and  $h_i$ . Consider a node x in  $FT_i$  which has the maximum depth, equal to  $h_i$ . By lemma 3.3,

$$h_i \leq \operatorname{depth}_0(x) + \log \Delta \times \operatorname{danc}_i(x)$$
$$\leq h + \log \Delta \times \operatorname{danc}_i(x)$$

Since, node x can have at most h ancestors,

$$\begin{aligned} \mathbf{h}_i &\leq \mathbf{h} + \log \Delta \times \mathbf{h} \\ &\leq \log \Delta \times (\mathbf{h} + 1) \end{aligned}$$

Since the diameter of a tree can at most be twice the height of the tree, the diameter of  $FT_i$  is at most  $2(h + 1) \log \Delta$ , or  $O(D \log \Delta)$ .

## 3.4.2 Lower Bounds

**Theorem 3.2.** Consider any self-healing algorithm that ensures that: 1) each node increases its degree by at most  $\alpha$ , for some  $\alpha \geq 3$ ; and 2) the diameter of the graph increases by a multiplicative factor of at most  $\beta$ . Then for any positive  $\Delta$ , for some initial graph with maximum degree  $\Delta$ , it must be the case that  $\beta \geq \frac{1}{2}[\log_{\alpha+1} \Delta - 1]$ .

*Proof.* Let G be a star on  $\Delta + 1$  vertices, where x is the root node, and x has  $\Delta$  edges with each of the other nodes in the graph. Let G' be the graph created after the adversary deletes the node x. Consider a breadth first search tree, T, rooted at some arbitrary node y in G'. We know that the self-healing algorithm can increase the degree of each node by at most  $\alpha$ , thus the root node in T can have at most  $\alpha + 1$ 



Figure 3.6: Deletion of the central node v of a star leads to an increase in the diameter. Here, the healing algorithm increases the degree of any node by at most  $\alpha$ .

children, and other nodes can have at most  $\alpha$  children. Let h be the height of T. Then we know that  $1 + (\alpha + 1) \sum_{i=0}^{h-1} \alpha^i \ge \Delta$ . This implies that  $(\alpha + 1)^{h+1} \ge \Delta$  for  $\alpha \ge 3$ , or  $h + 1 \ge \log_{\alpha+1} \Delta$ . Since the diameter of G is 2, we know that  $\beta \ge h/2$ , and thus  $2\beta + 1 \ge \log_{\alpha+1} \Delta$ . Rearranging, we get  $\beta \ge \frac{1}{2}[\log_{\alpha+1} \Delta - 1]$ . This is illustrated in figure 3.6.

We note that this lower-bound compares favorable with the general result achieved with our data structure. The Forgiving Tree can be modified so that it ensures that 1) the degree of any node increases by no more than  $\alpha$  for any  $\alpha \geq 3$ ; and that the diameter increases by no more than a multiplicative factor of  $\beta \leq 2 \log_{\alpha} \Delta + 2$ .

## 3.5 Conclusion

In this chapter, we have presented a distributed data structure that withstands repeated adversarial node deletions by adding a small number of new edges after each deletion. Our data structure ensures two key properties, even when up to all nodes in the network have been deleted. First, the diameter of the network never increases by more than  $O(\log \Delta)$  times its original diameter, where  $\Delta$  is the maximum original

degree of any node. For many peer-to-peer systems,  $\Delta$  is at most polylogarithmic, and so the diameter would increase by no more than a  $O(\log \log n)$  multiplicative factor. Second, no node ever increases its degree by more than 3 over its original degree.

Several open problems remain. For example, how do we extend our model and algorithm to handle insertions of nodes and multiple deletions? Can we protect other invariants? Can we extend our distributed data structure to ensure that the stretch between any pair of nodes increases by no more than a certain amount? Can we design our algorithms so they can work directly on graphs instead of spanning trees of those graphs? We have some preliminary positive results answering the above questions that build on this work. We can also consider extending self-healing beyond our present model. For example, Can we design algorithms for less flexible networks such as sensor networks? Can we extend the concept of self-healing to other objects besides graphs? For example, can we design algorithms to rewire a circuit so that it maintains its functionality even when multiple gates fail? Can our approach be used to better understand self-healing in biological systems such as the human brain?

```
1: Given a tree T(V, E)
2: INIT(T).
3: while true do
     if a vertex x is deleted then
4:
       if children(x) is EMPTY then
5:
          FIXLEAFDELETION(X)
6:
7:
       else
          FIXNODEDELETION(X)
8:
       end if
9:
     end if
10:
11: end while
```

Algorithm 3.3.1: FORGIVING TREE: The main function.

**Require:** each node of T has a unique ID

- 1: for each node  $v \in T$  do
- 2: children $(v) \leftarrow$  children of v.
- 3: parent $(v) \leftarrow \text{if } v \text{ is root of } T \text{ then } EMPTY \text{ else parent of } v.$
- 4: isreadyheir $(v) \leftarrow false$ .
- 5:  $ishelper(v) \leftarrow false.$
- 6: hparent $(v) \leftarrow EMPTY$ .
- 7: hchildren $(v) \leftarrow EMPTY$ .
- 8: heir $(v) \leftarrow$  if v is a leaf node then EMPTY else child of v with highest ID.
- 9:  $\operatorname{SubRT}(v) \leftarrow \operatorname{GENERATESUBRT}(v).$
- 10: MAKEWILL(v, SubRT(v)).

11: **end for** 

## Algorithm 3.3.2: INIT(T): initialization of the Tree T

- 1: MAKERT(children(v), parent(v)).
- 2: let h = heir(v).Let p = parent(v)
- 3: if is ready heir (h) = true then
- 4: hparent(h) replaces v by h in SubRT(hparent(h)).
- 5: MAKEWILL(hparent(h), SubRT(hparent(h))).
- 6: end if
- 7: for each node  $y \in \text{children}(v)$  do
- 8: **if** children(y) is *EMPTY* **then**
- 9: MAKELEAFWILL(y).
- 10: **end if**

11: **end for** 

**Algorithm 3.3.3:** FIXNODEDELETION(v): Self-healing on deletion of internal node

1: let p = parent(v)

- 2: if ishelper(p) = false then
- 3: p removes v from children(p)

```
4: SubRT(p) \leftarrow GENERATESUBRT(p)
```

```
5: MAKEWILL(p)
```

6: **else** 

```
7: Let z = \operatorname{parent}(v).
```

```
8: if z \neq \text{hparent}(v) then
```

```
9: bypass(z).
```

```
10: end if
```

11: z makes edges with nextparent(z), nextparent(z).

```
12: hparent(z) \leftarrow nexthparent(z).
```

```
13: hchildren(z) \leftarrow nexthchildren(z).
```

```
14: if |hchildren(z)|=1 then
```

```
15: isreadyheir(z) = true
```

```
16: end if
```

```
17: end if
```

```
18: for each node y \in \text{children}(v) do
```

```
19: if children(y) is EMPTY then
```

```
20: MAKELEAFWILL(y).
```

```
21: end if
```

```
22: end for
```

**Algorithm 3.3.4:** FIXLEAFDELETION(v): Self-healing on deletion of leaf node

- Let Lset be a set of vertices representing all members of children(v), and Iset be another set of vertices. representing all members of children(v) except the one with the highest ID.
- 2: Arrange *Lset* in ascending order of their *ID*s.
- 3: Using the arranged *Lset* as leaves and *Iset* as the internal nodes construct a Balanced Binary Search Tree SubRT ordered on the nodes *ID*.
- 4: return SubRT

**Algorithm 3.3.5:** GENERATESUBRT(v): Computes the Reconstruction Tree (RT) of v minus a possible helper node simulated by heir(v).

- 1: Let p = parent(v). Let rv be root of SubRT(v).
- 2: for each node  $y \in \text{children}(v)$  do
- 3: let ly be the leaf vertex representing y in SubRT(v). Let hy be the internal node in SubRT representing y.
- 4: If hy is ly's parent in SubRT(v) then nextparent $(y) \leftarrow$  parent of hy in SubRT else nextparent $(y) \leftarrow$  parent of ly in SubRT.

```
5: if y \neq heir(v) then
```

```
6: nexthchildren(y) \leftarrow children of hy in SubRT.
```

```
7: nexthparent(y) \leftarrow parent of hy in SubRT.
```

```
8: else
```

```
9: if ishelper(v) = true then
```

```
10: nexthchildren(y) \leftarrow hchildren(v).
```

```
11: \operatorname{nexthparent}(y) \leftarrow \operatorname{hparent}(v).
```

```
12: \operatorname{nexthparent}(rv) \leftarrow p.
```

```
13: else
```

```
14: nexthchildren(y) \leftarrow rv.
```

```
15: \operatorname{nexthparent}(y) \leftarrow p.
```

```
16: nexthparent(rv) \leftarrow y.
```

```
17: end if
```

```
18: end if
```

19: end for

**Algorithm 3.3.6:** MAKEWILL(v, SubRT(v)): Makes and distributes the will of v

```
1: let z = \operatorname{parent}(v).
```

```
2: if z = hparent(v) then
```

- 3: nexthparent(z)  $\leftarrow$  hparent(v).
- 4: nexthchildren $(z) \leftarrow$  hchildren $(z)/\{v\} \cup \{z\}$ . // z will take on itself as a child of its helper node.

5: else

- 6: nexthparent(z)  $\leftarrow$  hparent(v).
- 7: nexthchildren $(z) \leftarrow$  hchildren(v).

## 8: end if

Algorithm 3.3.7: MAKELEAFWILL(v): Leaf node leaves a will for its parent.

- 1: for each node  $x \in \text{children}(\mathbf{v})$  do
- 2: **if** is ready heir (x) = true **then**
- 3: bypass(x). // hparent(x) and hchildren(x) bypass x and connect themselves.
- 4: MAKEHELPER(x).
- 5: else
- 6: x makes edge between itself and nextparent(x).

```
7: parent(x) \leftarrow nextparent(x).
```

```
8: MAKEHELPER(x).
```

9: end if

10: end for

Algorithm 3.3.8: MAKERT(CHILDREN(V), PARENT(V)): Replace the deleted node by its RT

- 1: v makes edges between itself and nexthchildren(v), and nexthparent(v).
- 2:  $hparent(v) \leftarrow nexthparent(v)$ .
- 3: hchildren $(v) \leftarrow nexthchildren(v)$ .
- 4: ishelper(v) = true.
- 5: if |hchildren(v)| = 1 then
- 6: isreadyheir(v) = true. // Only an 'unemployed' heir has a single child.
- 7: end if

Algorithm 3.3.9: MAKEHELPER(v): v takes over helper node responsibilities

# Chapter 4

# Forgiving Graph

The weak can never forgive. Forgiveness is the attribute of the strong.

Mahatma Gandhi.

In this chapter, we present the final of our algorithms discussed in this Dissertation. To recap, we consider the problem of self-healing in peer-to-peer networks that are under repeated attack by an omniscient adversary. Here, we will assume that, over a sequence of rounds, an adversary either inserts a node with arbitrary connections or deletes an arbitrary node from the network. The network responds to each such change by quick "repairs," which consist of adding or deleting a small number of edges.

These repairs essentially preserve closeness of nodes after adversarial deletions, without increasing node degrees by too much, in the following sense. At any point in the algorithm, nodes v and w whose distance would have been  $\ell$  in the graph formed by considering only the adversarial insertions (not the adversarial deletions), will be at distance at most  $\ell \log n$  in the actual graph, where n is the total number of

#### Chapter 4. Forgiving Graph

vertices seen so far. Similarly, at any point, a node v whose degree would have been d in the graph with adversarial insertions only, will have degree at most 3d in the actual graph. Our distributed data structure, which we call the Forgiving Graph, has low latency and bandwidth requirements.

The Forgiving Graph improves on the Forgiving Tree distributed data structure from Chapter 3, [24], in the following ways: 1) it ensures low stretch over all pairs of nodes, while the Forgiving Tree only ensures low diameter increase; 2) it handles both node insertions and deletions, while the Forgiving Tree only handles deletions; 3) it does not require an initialization phase, while the Forgiving Tree initially requires construction of a spanning tree of the network.

# 4.1 Introduction

In Chapter 1, we have made case for the need of using *responsive* approaches in reconfigurable networks for maintaining robustness and self-healing in networks. In this chapter, we describe a distributed data structure for maintaining invariants in a reconfigurable network. We note that our approach is responsive in the sense that it responds to an attack by changing the network topology. Thus, it is orthogonal and complementary to traditional non-responsive techniques for ensuring network robustness.

This work builds significantly on results achieved in [24] (Presented in Chapter 3), which presented a responsive, distributed data structure called the *Forgiving Tree* for maintaining a reconfigurable network in the face of attack. Over a complete run of Forgiving Tree: 1) The diameter of the network can never exceed its original diameter by more than a multiplicative factor of  $O(\log \Delta)$  where  $\Delta$  is the maximum degree in the graph; and 2) the total increase in the degree of any node can never be more than 3. The Forgiving Tree ensured two invariants: 1) the diameter of the network never
increased by more than a multiplicative factor of  $O(\log \Delta)$  where  $\Delta$  is the maximum degree in the graph; and 2) the degree of a node never increased by more than an additive factor of 3.

In the following pages, we present a new, improved distributed data structure called the *Forgiving Graph*. The improvements of the Forgiving Graph over the Forgiving Tree are threefold. First, the Forgiving Graph maintains low stretch i.e. it ensures that the distance between any pair of nodes v and w is close to what their distance would be even if there were no node deletions. It ensures this property even while keeping the degree increase of all nodes no more than a multiplicative factor of 3. Moreover, we show that this tradeoff between stretch and degree increase is asymptotically optimal. Second, the Forgiving Graph handles both adversarial insertions and deletions, while the Forgiving Tree could only handle adversarial deletions (and no type of insertion). Finally, the Forgiving Graph does not require an initialization phase, while the Forgiving Tree required an initialization phase which involved sending  $O(n \log n)$  messages, where n was the number of nodes initially in the network, and had a latency equal to the initial diameter of the network. Additionally, the Forgiving Graph is divergent technically from the Forgiving Tree, it makes significant use of a novel distributed data structure that we call a Half-full Tree or "haft". hafts are discussed in Section 4.4. Our main algorithm is described in Section 4.3 and Section 4.5.

**Our Model:** We remind the reader about the model we have been using in this work. We assume that the network is initially a connected graph over n nodes. An adversary repeatedly attacks the network. This adversary knows the network topology and our algorithm, and it has the ability to delete arbitrary nodes from the network or insert a new node in the system which it can connect to any subset of the nodes currently in the system. However, we assume the adversary is constrained in

that in any time step it can only delete or insert a single node. The detailed model is described in Section 4.2.

Our Results: For a peer-to-peer network that has both insertions and deletions, let G' be the graph consisting of the original nodes and inserted nodes without any changes due to deletions. Let n be the number of nodes in G'. The Forgiving Graph ensures that: 1) the distance between any two nodes of the actual network never increases by more than  $\log n$  times their distance in G'; and 2) the degree of any node in the actual network never increases by more than 3 times its degree in G'. Our algorithm is completely distributed and resource efficient. Specifically, after deletion, repair takes  $O(\log d \log n)$  time and requires sending  $O(d \log n)$  messages, each of size  $O(\log n)$  where d is the degree of the node that was deleted. The formal statement and proof of these results is in Section 4.7.1.

**Related Work:** Our work significantly builds on work in [24] as described above. Our model of attack and repair builds on earlier work in [10, 53] (The later is presented in Chapter 2).

## 4.2 Node Insert, Delete and Network Repair Model

We now describe the details of our node insert, delete and network repair model. Let  $G = G_0$  be an arbitrary graph on n nodes, which represent processors in a distributed network. In each step, the adversary either deletes or adds a node. After each deletion, the algorithm gets to add some new edges to the graph, as well as deleting old ones. At each insertion, the processors follow a protocol to update their information. The algorithm's goal is to maintain connectivity in the network, keeping the distance between the nodes small. At the same time, the algorithm wants to minimize the resources spent on this task, especially keeping node degree small.

Initially, each processor only knows its neighbors in  $G_0$ , and is unaware of the structure of the rest of  $G_0$ . After each deletion or insertion, only the neighbors of the deleted or inserted vertex are informed that the deletion or insertion has occurred. After this, processors are allowed to communicate by sending a limited number of messages to their direct neighbors. We assume that these messages are always sent and received successfully. The processors may also request new edges be added to the graph. The only synchronicity assumption we make is that no other vertex is deleted or inserted until the end of this round of computation and communication has concluded. To make this assumption more reasonable, the per-node communication cost should be very small in n (e.g. at most logarithmic).

We also allow a certain amount of pre-processing to be done before the first attack occurs. This may, for instance, be used by the processors to gather some topological information about  $G_0$ , or perhaps to coordinate a strategy. Another success metric is the amount of computation and communication needed during this preprocessing round. Our full model is described in Figure 4.1.

For our success metrics, at any time T, we compare the actual graph  $G_T$  to the graph  $G'_T$  which is the graph with only the original nodes (those at  $G_0$ ) and insertions without regard to deletions and healing. This is the graph which would have been present if the adversary was not doing any deletions and (thus) no selfhealing algorithm was active. This is the natural graph for comparing results. Notice if there were no insertions happening in our model, we could have compared  $G_T$  to  $G_0$  but since insertions are happening,  $G_T$  may not even have the same nodes as  $G_0$  rendering a node-based comparison impossible. Figure 4.2 shows an example of  $G'_T$  and a corresponding  $G_T$ . The figure also shows, in  $G'_T$ , the nodes and edges inserted and deleted, and in  $G_T$ , the edges inserted by the healing algorithm, in

different colors, as the network evolved over time. Figure 4.3 shows how the two graphs compare with regards to degree of a particular node v, and figure 4.4 shows how the healing algorithm effects the distance between two nodes, u and v. Our algorithm gaurantees our invariants on the 'complexity' measures at every time step that the algorithms is in execution. Figure 4.1: The Node Insert, Delete and Network Repair Model – Distributed View.

Each node of  $G_0$  is a processor.

Each processor starts with a list of its neighbors in  $G_0$ .

Pre-processing: Processors may exchange messages with their neighbors.

for t := 1 to T do

Adversary deletes a node  $v_t$  from  $G_{t-1}$  or inserts a node  $v_t$  into  $G_{t-1}$ , forming  $H_t$ .

if node  $v_t$  is inserted then

 $\boldsymbol{v}_t$  and its new neighbors may update their information and exchange messages with their neighbors.

### end if

if node  $v_t$  is deleted then

All neighbors of  $v_t$  are informed of the deletion.

## Recovery phase:

Nodes of  $H_t$  may communicate (asynchronously, in parallel) with their immediate neighbors. These messages are never lost or corrupted, and may contain the names of other vertices.

During this phase, each node may add edges joining it to any other nodes as desired. Nodes may also drop edges from previous rounds if no longer required.

end if

At the end of this phase, we call the graph  $G_t$ .

### end for

Success metrics: Minimize the following "complexity" measures:

Consider the graph G' which is the graph consisting solely of the original nodes and insertions without regard to deletions and healings. Graph  $G'_t$  is G' at timestep t (i.e. after the  $t^{\text{th}}$  insertion or deletion).

1. Degree increase.

 $\max_{v \in G} \operatorname{degree}(v, G_T) / \operatorname{degree}(v, G'_T)$ 

- 2. Network stretch.  $\max_{x,y\in G_T} \frac{dist(x,y,G_T)}{dist(x,y,G'_T)}$ , where, for a graph G and nodes x and y in G, dist(x,y,G) is the length of the shortest path between x and y in G.
- 3. Communication per node. The maximum number of bits sent by a single node in a single recovery round.
- 4. **Recovery time.** The maximum total time for a recovery round, assuming it takes a message no more than 1 time unit to traverse any edge and we have unlimited local computational power at each node.





(a)  $G'_T$ : Nodes in red (dark gray in grayscale) deleted, and nodes in green (patterned) inserted, by the adversary.



(b)  $G_T$ : The actual graph. Edges added by the healing algorithm shown in gold (light shaded in grayscale) color.

Figure 4.2: Graphs at time T.  $G'_T$ : The graph of initial nodes and insertions over time,  $G_T$ : The actual healed graph.



Figure 4.3: Comparing degrees: In the figure the degree of node v in graph of only original and inserted nodes is 3, and in the actual healed network it is 5. The nodes in red (dark gray in grayscale) were deleted by the adversary and the golden (light shaded) edges were the ones added by the healing algorithm.





Figure 4.4: Comparing distances: In the figure nodes u and w have their distance increased to 5 in the actual healed network compared to their distance of 3 in the graph of only original and inserted nodes. The nodes in red (darker in grayscale) were deleted by the adversary and the golden edges (lighter shade) are the ones added by the healing algorithm



Figure 4.5: Deleted node v replaced by its Reconstruction Tree. The triangle shaped nodes are 'virtual' helper nodes simulated by the 'real' nodes which are in the leaf layer.

# 4.3 The Forgiving Graph algorithm

Here, we give a high level description of our algorithm. An adversary can effect the network in one of two ways: inserting a new node in the network or deleting an existing node from the network. Node insertion is straightforward and is dependent on the specific policies of the network. When an insertion happens, our incoming node and its neighbors update the data structures that are used by our algorithm. We

will also assume that nodes maintain some neighbor-of-neighbor information. There are many ways to maintain neighbor of neighbor information [43, 50]. Maintaining neighbor of neighbor information requires regular updates, and may be used for other purposes such as routing, thus, we do not explicitly include this maintenance cost in our analysis.

Each time a node v is deleted, we can think of it as being replaced by a Reconstruction Tree (RT(v), for short) which is a *haft* (defined in Section 4.4) having "virtual" nodes as internal nodes and neighbors of v (which we call real nodes) as the leaf nodes. Note that each virtual node has a degree of at most 3. A single real node itself is a trivial RT with one node. RT(v) is formed by merging all the neighboring RTs of v using the strip and merge operations from Section 4.4. Thus, following a deletion, we may have a graph with both real and virtual nodes. After a long sequence of such insertions and deletions, this graph is a patchwork mix of virtual nodes and real nodes. Let us call this graph FG (short for ForgivingGraph). As for the other graphs,  $FG_T$  is the graph FG at time T.

Also, because the virtual trees (hafts) are balanced binary trees, the deletion of a node v can, at worst, cause the distances between its neighbors to increase from 2 to  $2\lceil \log d \rceil$  by traveling through its RT, where d is the degree of v in G' (the graph consisting solely of the original nodes and insertions without regard to deletions and healings). However, since this deletion may cause many RTs to merge and the new RT formed may involve all the nodes in the graph, the distances between any pair of actual surviving nodes may increase by no more than a  $\lceil \log n \rceil$  factor.

Since our algorithm is only allowed to add edges and not nodes, we cannot really add these virtual nodes to the network. We get around this by assigning each virtual node to an actual node, and adding new edges between actual nodes in order to allow "simulation" of each virtual node. More precisely, our actual graph is the homomorphic image of the graph described above, under a graph homomorphism which fixes the actual nodes in the graph and maps each virtual node to a distinct actual node which is "simulating" it. Figure 4.15 shows this homomorphism where the graph FG is mapped to the graph G. We discuss this homomorphism and its relationship to our results in more detail in Section 4.7.

Note that, because each actual node simulates at most one virtual node for each of its deleted neighbors, and virtual nodes have degree at most 3, this ensures that the maximum degree increase of our algorithm is at most 3 times the node's degree in G'.

# 4.4 Half-full Trees ("HAFTS")

Is the glass half full, or half empty? It depends on whether you're pouring, or drinking. BILL COSBY

In this section, we define half-full trees (or hafts, for short), and describe their most important properties for our present application. This type of tree has been studied before, by Vaucher [59], who called them "staircase trees." However, our presentation will be self-contained.

Half-full tree: A half-full tree, or haft, is a rooted binary tree in which every nonleaf node v has the following properties:

- v has exactly two children.
- The left child of v is the root of a complete binary subtree that contains at least half of v's descendants.



(a) The first seven hafts. The nodes marked by a circle are the primary roots, and those in boxes are the spine nodes.



(b) Structure of a haft. Each  $T_i$  is a complete binary tree, with  $|T_1| > |T_2| > \cdots > |T_k|$ . The spine nodes are the nodes in red (darker in grayscale). The left child of each spine node, and the right child of the rightmost spine node are the primary roots, shown in green (lighter in grayscale).

Figure 4.6: haft (half-full tree)

**Primary root:** A *primary root* is a node in a haft such that:

- It is the root of a complete subtree.
- Its parent, if it has one, is not the root of a complete subtree.
- **Spine:** A *spine node* is the parent of a primary root. Equivalently, it is a node in a haft which is not the root of a complete subtree. The *spine* of a haft is the set of all spine nodes. We observe that, if non-empty, the spine consists of the vertices of a path, with the root of the haft as one endpoint.

Figure 4.6(a) shows several examples of hafts. We now give a simple structural lemma which completely characterizes any haft as a function of the number of its leaves. This will be useful later when we wish to perform merging operations on the hafts used by our algorithm.

**Lemma 4.1** (Binary representation of Hafts). Let  $\ell$  be a positive integer. Then there is a unique haft T having  $\ell$  leaves. Moreover, let h be the number of ones in the binary representation of  $\ell$ , and suppose  $x_1 > x_2 > \cdots > x_h$  are the indices of these ones, so that

$$\ell = \sum 2^{x_i}$$

Then either

- h = 1, and T is a complete tree of depth  $x_1$ , or
- h ≥ 2, and T consists of h − 1 spine nodes s<sub>1</sub>,...s<sub>h-1</sub>, together with h complete binary trees T<sub>1</sub>,...,T<sub>h</sub>, where
  - $-s_1$  is the root of T,
  - each  $T_i$  has depth  $x_i$ ,
  - each  $s_i$  has the root of  $T_i$  as its left child
  - for  $1 \leq i \leq h-2$ ,  $s_i$  has  $s_{i+1}$  as its right child
  - $s_{h-1}$  has the root of  $T_h$  as its right child

**Corollary 1.** Let T be a haft having  $\ell$  leaves. Then the depth of T equals  $\lceil \log \ell \rceil$ .

Proof of Lemma 4.1. We will prove the detailed structure of T, from which the uniqueness is apparent.

First, consider the case h = 1 (*i.e.*,  $\ell$  is a power of 2). If  $\ell = 1$ , there is nothing to prove. Assume  $\ell > 1$ . Now the left subtree of T is complete, and hence has number

of leaves equal to a power of two. Since at least half of the leaves are on the left subtree, this power of two is at least  $\ell/2$ . Since the root of T has two children, not all of the leaves are on the left subtree, and hence there are exactly  $\ell/2$  leaves on the left subtree, and thus also  $\ell/2$  leaves on the right subtree. Since it is immediate from the definition that any subtree of a haft is also a haft, it follows by induction on  $\ell$  (being a power of two) that the right subtree is also a complete subtree. Thus, T is complete.

Now, suppose  $h \ge 2$ . Let us denote the root of T by  $s_1$ . Because  $\ell$  is not a power of two,  $s_1$  must be a spine node. Since the left subtree,  $T_1$ , is complete and contains between  $\ell/2$  and  $\ell$  leaves, it must have depth  $x_1$ . Since the right subtree is a haft having number of leaves equal to

$$\ell - 2^{x_1} = \sum_{i=2}^h 2^{x_i}$$

it follows by induction on  $\ell$  (being any positive integer) that it has the claimed structure. Thus, T is also as claimed.

### 4.4.1 Operations on Hafts

We Define the following operations on hafts:

- 1. Strip: Suppose T is a haft with h ones in its binary representation. The Strip operation removes h 1 nodes from T returning a forest of h complete trees.
- 2. *Merge*: The Merge operation joins hafts together using additional isolated single nodes, to create a single new haft.

We now describe these operations in more detail:

#### Strip

By Lemma 4.1, if we remove the spine from a haft, T, we are left with a forest of h complete binary trees, where h is the number of ones in the binary representation of the number of leaves of T. The operation Strip(T) returns this forest.

The Strip operation works as follows: If T is a complete tree, then return T itself. Note that the root of the T is the only primary root in this case. If T is not a complete tree, then F is obtained as follows. Starting from the root of T, traverse the direct path towards the rightmost leaf of T. Remove a node if it is not a primary root. Stop when a primary root or a leaf node (which is a primary root too) is discovered. In figure 4.6(b) the Strip operation removes the nodes indicated by the square boxes.

We now give intuition as to why the Strip operation works.

**Lemma 4.2.** The Strip operation returns the subtrees rooted at all primary roots in the input haft.

*Proof.* By the definitions of haft and primary root, if a vertex is not the root of a complete subtree, its left child is guaranteed to be a primary root. Thus, either the root of the haft is a primary root or its left child is. If the left child is a primary root, there can be no other primary root in the left subtree, so we we return the tree rooted at that child. Recursively applying the same test to the right child, we get all the primary roots.



Figure 4.7: Deletion of a node and its helper nodes lead to breakup of RT into components. The Strip operation or a simple variant (for non-hafts) returns a set of complete trees, which can then be merged.

#### Merge

By Lemma 4.1, every haft is completely characterized by its number of leaves. Merging hafts is analogous to binary addition of these numbers. The new binary number obtained is the number of leaves in the haft produced by the Merge operation. This is illustrated in figure 4.8.

The first step of the Merge operation is to apply the Strip operation on the input trees. This gives a forest of complete trees. These complete trees can be recombined with the help of extra nodes to obtain a new haft. Let Size(X) be the number of nodes in a tree X. Consider two complete trees  $T_1$  and  $T_2$  (Size( $T_1$ ) > Size( $T_2$ )), with roots  $r_1$  and  $r_2$  respectively, and an extra node v. To merge these trees, make  $r_1$ the left child and  $r_2$  the right child of v by adding edges between them. The merged tree is always a haft. Thus, the merge operation Merge(haft\_1, haft\_2, ...) is as follows:

- 1. Apply Strip to all the hafts to get a forest of complete trees.
- 2. Let  $T_1, T_2, \ldots, T_k$  be the k complete trees sorted in ascending order of their size. Traverse the list from the left, let  $T_i$  and  $T_{i+1}$  be the first two adjacent trees of the same size and v be a single isolated vertex, join  $T_i$  and  $T_{i+1}$  by

making v the parent of the root of  $T_i$  and the root of  $T_{i+1}$ , to give a new tree. Reinsert this tree in the correct place in the sorted list. Continue traversal of the list from the position of the last merge, joining pairs of trees of equal sizes. At the end of this traversal, we are left with a sorted list of complete trees, all of different sizes.

3. Let  $T_1, T_2, \ldots, T_l$  be the sorted list of complete trees obtained after the previous step. Traverse the list from left to right, joining adjacent trees using single isolated vertices. Let w be a single isolated vertex. Join  $T_1$  and  $T_2$  by making the root of  $T_2$  the left child and the root of  $T_1$  the right child of w, respectively. This gives a new haft. Join this haft and  $T_3$  by using another available isolated vertex, making the larger tree  $(T_3)$  its left child. Continue this process till there is a single haft.



Figure 4.8: Merging three hafts. The vertices in the square boxes are the new isolated vertices used to join the complete The square shaped vertices are the isolated vertices used to join the complete trees. Merging is analogous to binary number addition, where the number of leaves are represented as binary numbers.

## 4.5 FG: Distributed implementation

As mentioned earlier, deletion of a node v leads to it being replaced by a Reconstruction Tree (RT(v), for short) in G (Refer to Table 4.1 for definitions). The RT is a haft (discussed in Section 4.4) having "virtual" nodes as internal nodes and real







(a) The original graph. Node v attacked. (b) Healed graph. The new nodes inside ellipse are helper nodes.





(d) Healed Graph. Notice two RTs with common leaf nodes.



(e) Node w attacked: notice w is a com- (f) Healed Graph. The RTs have merged. mon leaf of both RTs Some of the leaf nodes (x's, u's) are identical (so the picture no longer shows the RT resembling a haft. However, refer fig-

ure 4.10).

Figure 4.9: Effect of 3 deletions on a graph. The RT for each deleted node consists of the helper nodes, plus the neighbors of the deleted node which form the leaves of the tree. In this example, the deleted nodes form an independent set, so the structure of the RTs does not depend on the deletion order.



(a) From figure 4.9(f). Nodes x and u have two edges each going into the haft corresponding to two of their deleted neighbors.



(b) Nodes x and u repeated as leaf nodes of RTs with edges corresponding to their deleted neighbors. This shows the haft structure of the RT.

Figure 4.10: Equivalent Representations of a RT.

neighbors of v as the leaf nodes. The virtual nodes are called helper nodes. Recall that the graph G' is the graph consisting of solely the original nodes and insertions (Table 4.1).

Figure 4.9 shows a small series of deletions and repairs by the ForgivingGraph algorithm. Notice that after healing on the third deletion some nodes are occuring as leaf nodes multiple times (figure 4.9(f)). Here, edge information is useful for differentiating between these nodes. A node takes part in a RT only if one of its neighbors got deleted. It can only have two edges into a RT if two of its neighbors have already been deleted. Each edge from a real node into a RT corresponds to a deleted neighbor. We can imagine this edge never got deleted and just that its other endpoint got replaced by a helper node. Thus, if there was an edge between nodes xand y, and node y got deleted, we can keep this edge labelled as (x, y). Alternatively, the edge is labelled with it's name in G', which will always be (x, y) since G' has no deletions. For convenience, when a node occurs as a leaf node multiple times in a RT, we will often consider each occurance as a seperate node and depict it as such. Figure 4.10 shows this alternate representation. Notice that it is easy to see the haft structure in this representation and we stay in the realm of trees. Thus,

Processor v: $Edge(v,x)$	
Real node fields	
Endpoint	The node that represents the other end of the edge.
	For $edge(v,x)$ this will be node x if x is alive or
	RT parent if $x$ is not.
hashelper	(boolean field). True if there is a helper node simu-
	lated by $v$ corresponding to this edge.
RTparent	Parent of $v$ in RT. Non NULL only if $x$ has been
	deleted.
Representative	This is $v$ itself. Field used during merging of RTs.
Helper node fields	Fields for helper node corresponding to the
	edge. Non NULL only if the helper node ex-
	ists. Sometimes, we will refer to a helper field as
	edge.helper.field
hparent	Parent of helper node.
hrightchild	Right Child of helper node.
hleftchild	Left Child of helper node.
height	Height of the helper node.
descendantcount	The number of descendants of the helper node.
Representative	The unique leaf node of the subtree of $(v, x)$ .helper in
	(v, x).helper's RT that does not have a helper node
	in that subtree. This node is used during merging of
	RTs.

Table 4.1: The fields maintained by a processor v for edge(v, x), which is an edge in G', the graph of only original nodes and insertions. Here RT refers to the reconstruction tree of which v : edge(v, x) is a part.

when we refer to a leaf node of a RT, we will mean a real node augmented with the edge information. Thus, when we state that there is at most one helper node corresponding to a leaf node of a RT, this is equivalent to saying that there is at most one helper node in a RT corresponding to an edge in the graph G'.

The actual processor or entity in the network in which we are executing the algorithm is the one which has to keep track of its real nodes, edges and helper nodes. In Table 4.1, we list the information each processor v requires for each of

its edges in G' in order to execute the ForgivingGraph algorithm. For node v, the end point of the edge is stored in the field v.endpoint. For an edge (v, x), if x is a real node (i.e. not a helper node) then the field v.endpoint is simply the node x. When one of the nodes of the edge gets deleted, in FG, a helper node from the new RT may take place of the previous node. We will still refer to this edge as (v, x)i.e. by its name in G' but update the fields endpoint and RTparent. Moreover, the processor may now simulate a helper node corresponding to this edge. Since each edge is uniquely identified, the real nodes and helper nodes corresponding to that edge can also be uniquely identified. This identification is used by the processors to pass messages along the correct paths. The FORGIVING GRAPH algorithm is given in pseudocode form in Algorithm 4.5.1 along with the required subroutines.



Figure 4.11: On deletion of a node v, The RTfragments to be merged are connected by a binary tree  $BT_v$ . The leaf RTfragments merge with their parents till a single RT is left. The solid circles are the primary roots. The (red color) nodes in the square boxes are spine nodes removed at each step.

On deletion of a node, the repair proceeds in two phases. The first phase is a quick O(1) phase in which the neighbors of the deleted node connect themselves in the form of a binary tree (Algorithm 4.5.3, Figure 4.11). Consider the effect of the deletion of v on one of the RTs of which v is a leaf. Removal of this leaf and of the helper node corresponding to that leaf (if any) splits this RT into connected components. We select particular nodes which were neighbors of the deleted nodes from each of these components. Let *Nset* be the collection of all these nodes together



Figure 4.12: The underlined node d and corresponding helpers are deleted. This leads to the graph breaking into components which are then merged using  $BT_d$  (the binary tree of anchors) and the primary roots in the components. The dashed edges show the representative for that node.

with any undeleted neighbors of v in FG. We shall call a component taking part in the merge process (irrespective of whether it is a haft or not) as a *RTfragment*, to distinguish it from the final RT formed at the end of the merge process. In phase 2, the RTfragments are merged (Figure 4.11). Before we can reconnect these RTfragments into a single haft, we need to further break them up into hafts (we actually break them into complete trees) so that we can merge them. We now go into details of the communication protocol that achieves this merge. Let v be the processor deleted. Then, the nodes in *Nset* connect in the form of a binary tree we call  $BT_v$ . We call the nodes forming  $BT_v$  as *anchors*. Formally, we define an anchor as follows:

**Anchor** : An anchor is a designated node in a RT fragment that takes part in the binary tree  $BT_v$ .

The anchors send probe messages to discover the primary roots which head these complete trees (Algorithm 4). This is similar to the Strip operation described in Section 4.4.1. The nodes maintain information about their height and number of their children in their RT or RT fragment. Thus, they are able to identify themselves as primary roots. At the same time, the nodes outside the complete trees are identified and marked for removal. It is possible that a RT fragment may appear more than once in a  $BT_v$  through multiple nodes acting as anchors. However, we want one complete tree to take part only once in the merge. This is accomplished as follows: Every anchor sends probe messages to discover the primary roots in its RTfragment. Nodes further pass on these probes till they reach a primary node. However, if an anchor receives a probe message originating from another anchor, it will reject the message and return it to the sender, which will send it back towards the source anchor. This ensures that a primary root (thus, a complete tree) will be discovered by only one anchor. The complete trees are then merged pairwise in a bottomup fashion till only a single haft remains. This is illustrated in figure 4.11. At each round, every leaf RT in  $BT_v$  will merge with its parent RT. This can be done in parallel, so that the number of rounds of merges will be equivalent to the height of the tree. For two trees to merge, as shown in the Merge operation (Section 4.4.1), an additional node is needed that will become the parent of these two trees. This node must be simulated by a real node that is not already simulating a helper node in the trees. Since the number of internal nodes in a tree is one less than the leaf nodes, there is exactly one such leaf node for each tree. The roots of these two trees have the identity of this node for their tree. This node is called a *Representative* (of the root node). For merging, we use an algorithm that we call the *representative mechanism*. The formal definition of a representative and details of the representative mechanism are given in Section 4.5.1. Each node keeps the identity of its representative stored in the field *Representative* (Table 4.1).

Now, we briefly describe merging using representatives. When two trees (Note that a tree may even be a single node) are merged (Algorithm 4.5.8 and Algorithm 4.5.9), the representative of the root of the bigger tree (or of one of the trees, if they have the same size) instantiates a new helper node, and makes the two roots

its children. To make the new structure a haft, the root of the bigger tree shall become the left child of the new helper node. The new helper node will now inherit as its representative the representative of the root of its right subtree, since this is the node in the merged tree that does not have a helper node. An example of merging using this algorithm is shown in Figure 4.12.

At the end of each round, we have a new set of leaf RTs. Each new leaf is now a merged haft of the previous leaves and their parent. We need a new anchor for this haft. We can continue having the anchor of the parent RTfragment as the anchor. However, this node may be one of the extra nodes marked for removal. In this case, the anchor designates one of the nodes that was a primary root in its RTfragment as the new anchor, passes on its links and removes itself. The newly formed leaf hafts may have primary roots which are different from those of the previous ones. The new anchor will send probe messages and gather the relevant information and inform the new primary roots of their role. This process will continue till we are left with a single RT. This is shown in Figure 4.11.

### 4.5.1 Representative mechanism

In this section, we discuss representatives and their use in merging in more detail. Formally, we define a representative as follows:

**Representative:** In the Forgiving Graph FG, given a node y, the representative of y is a real node, decided as follows:

- If y is a real node, then y itself.
- If y is a helper node, then the unique leaf node that is a descendant of y and does not have a helper node in the subtree headed by y.

Recollect that one of our objectives is to maintain an invariant that a real node simulate at most one helper node. Moreover, this has to happen in the dynamic environment of nodes getting deleted, inserted, RTs breaking and merging. The representative mechanism allows us to do this in an efficient manner, as we shall show. Intuitively, a representative is a real node who we know is not simulating a helper node yet and so is available for providing a helper node. Each node in the Forgiving Graph FG has a representative. Formally, for a node y in FG, if y is a real node, y is its own representative. This makes sense since y is the root of a RT (a single node RT) and not simulating a real node. If node y is a helper node its representative is the unique leaf node that is y's descendant in y's subtree that is not simulating a helper node. Notice that there is exactly one such leaf node in any subtree since the number of internal nodes are one less than the number of the leaf nodes, and as a consequence of our invariant, all other leaf nodes are simulating exactly one helper node each in that subtree. Due to the way our merge operations operate, each helper node gets assigned a representative when the helper node is created and moreover it never changes its representative during its lifetime. This is a very useful property as we shall see later.



Figure 4.13: Merging with representatives: Two singleton hafts of real nodes a and b merge. Here a creates the parent helper node, and this helper node inherits the representative of its right child (b) as its representative. Notice b is the unique real node in a.helper's subtree that is not simulating a helper node. With regard to merging, the root nodes representatives are 'active' (shown in pink, dashed outline), while others are 'dormant' (shown in green, dotted outline).

First, let's see how representatives are used to merge hafts. The simplest example is shown in figure 4.13: two real nodes (a real node is a singleton haft) merge using their representatives. To recollect, when two hafts merge, a new helper node is needed to become the parent of both. We choose this node to be simulated by the representative of the root of the bigger haft. If the hafts are of the same size, either can be selected. The chosen representative is informed: it instantiates a new helper node and makes the two roots its children. To make the new structure a haft, the root of the bigger tree shall become the left child of this new helper node. The new helper node now needs a representative of its own. The obvious choice is the representative of its right child, since that leaf node still has not supplied a helper node. This is consistent with the definition of a representative (this can be verified for the small example of figure 4.13). This is the conceptual picture. In the distributed implementation, as described earlier, this communication takes place through the anchors which exchange information among the merging anchors. This information consists of the identity of the primary roots, their height and representative information. Each anchor is then able to run the merge algorithm in its memory, and it directly contacts the nodes with which it has to make edges. If this is a new node it is also provided with the identity of its representative.

What happens when a deletion happens and a RT splits into smaller complete trees? To merge back, we need to find the representatives of the roots of these trees. Should we traverse the subtree of these roots to find the representative? Obviously, this is expensive. Fortunately, the representative mechanism renders this unnecessary. To recall, merging happens using primary roots, which are the roots of complete trees. After a split, we are only left with complete trees. Obviously, complete trees have not had a deletion in their subtree, thus, none of the nodes in these trees need to change their representatives. Since only the nodes of the complete trees will be merging (via their roots) we need only worry about their representative information. This implies that no node need ever change its representative. This is



Figure 4.14: Reusing representative information: RTs split into complete trees on deletion of node a. A node always has a representative assigned to it at birth and it never changes its representative. In the figure, node c' has d as its representative:-'dormant' before the split (green, dotted outline), 'active' afterwards (pink, dashed outline).

shown in figure 4.14. As shown in the picture, we can imagine that the representatives of the primary roots are in an 'active' state i.e. they will be used for the upcoming merge, whereas representatives of all internal nodes are in a 'dormant' state meaning though they are not required at the present stage, they may be utilized in the future.

## 4.6 Real graph from the Forgiving Graph

It is easy to see that the Forgiving Graph FG maps to the real graph G in a straightforward way: map all the helper nodes to the real nodes simulating them. Figure 4.15 shows an example. More formally, G is a homomorphic image of FG. Consider two graphs  $G_1 = (V_1, E_1)$ , and  $G_2 = (V_2, E_2)$ . In this context, a homomorphism may be defined as follows: A homomorphism is a function  $f: V_1 \to V_2$  such that if undirected edge  $\{v, w\}$  is in  $E_1$  (the edge set of  $G_1$ ) this implies that the edge  $\{f(v), f(w)\}$  is in  $E_2$ . Moreover, we say that  $G_2$  is the homomorphic image of  $G_1$  under f if the edges of  $G_2$  are exactly the images of the edges of  $G_1$  under the homomorphism. We know that, in FG, there can be multiple real and helper nodes corresponding to



Figure 4.15: The actual graph G (on the right) is a homomorphic image of the Forgiving Graph FG (left) where the helper nodes are mapped to the nodes simulating them. Note both the node degrees and distances between nodes in the real graph cannot be more than those in the Forgiving Graph.

a processor in the network that performs all the functions required of those nodes. Each node is identified by its processor and some additional information. For node v in FG, let Processor(v) be the name of that processor. Also, in the graph G, there is only one node per processor and consider this node to be labelled with the name of that processor. Then, our homomorphism  $H: V(FG) \to V(G)$  is simply H(v) = Processor(v).

Let us make the following observations about homomorphisms which will be useful to us in proving our results (Section 4.7).

**Observation 4.1.** For any graph homomorphism  $F : G_1 \to G_2$ , for all nodes u, v in V,  $dist_{G_2}(F(u), F(v)) \leq dist_{G_1}(u, v)$  where  $dist_G(x, y)$  is the distance between two nodes x and y in a graph G.

**Observation 4.2.** If the graph  $G_2$  is the homomorphic image of graph  $G_1$  under a graph homomorphism  $F : G_1 \to G_2$ , then for all nodes v' in  $G_2$ ,  $deg_{G_2}(v') \leq \sum_{v \in F^{-1}(v')} deg_{G_1}(v)$ , where  $deg_G(x)$  is the degree of the node x in a graph G.

# 4.7 Results

## 4.7.1 Upper Bounds

As earlier, let G be the graph of the network, FG the Forgiving Graph, and G' the graph consisting solely of the original nodes and insertions without regard to deletions and healings. Let  $G_T$ , FG<sub>T</sub> and  $G'_T$  be these graphs at time T.

**Lemma 4.3.** Given the edge (v, x) in  $G'_T$ ,

- 1. There can be at most one helper node in  $FG_T$  corresponding to (v, x).
- 2. During the Repair phase, there can be at most two helper nodes corresponding to the edge (v, x). Moreover, one of these could also be an anchor in  $BT_v$ .

*Proof.* There is only one 'real' node in  $FG_T$  corresponding to an edge in  $G'_T$  (Figure 4.9). Let us refer to this node as simply v. Moreover, v can only be a leaf node of a RT, and a helper node can only be an internal node.

We prove part 1 by contradiction. Suppose there are two helper nodes in  $FG_T$  corresponding to the real node v. Let us call these nodes v' and v''. The following cases arise:

i. v' and v'' belong to different RTs:

This case is depicted in figure 4.16. We assume that both v' and v'' exist but that they are in different RTs. By the representative mechanism, a helper node is created only if the real node that simulates it is the representative of a node (e.g. in line 7 in Algorithm 4.5.9). By definition, the representative of a node is a unique leaf node in the subtree headed by that node in its RT. If both v'and v'' exist and belong to different RTs, this implies that node v exists as a leaf node in two different RTs. This is a contradiction.



Figure 4.16: Proof by contradiction: Case 1. Two helper nodes in different RTs.

ii. v' and v'' belong to the same RT:

Without loss of generality, assume that the v''. $height \ge v'$ .height. The following cases arise:

(a) v' is a node not in the subtree headed by v'':



Figure 4.17: Proof by contradiction: Case 2(a). Two helper nodes in same RT, but in different subtrees.

This case is shown in figure 4.17. We assume that both v and v'' exist, and that they are in the same RT but in different subtrees i.e. v'' is not an ancestor of v'. The proof is similar to that of case i. The representative mechanism and definition of a representative implies that node v was a representative in two non-intersecting subtrees in the same RT. This implies that node v occurs as a leaf twice in that RT. This is not possible.

(b) v' is a node in the subtree headed by v'':



Figure 4.18: Proof by contradiction: Case 2(b). Two helper nodes in the same subtree.

This case is shown in figure 4.18. We assume that both v and v'' exist, and that they are in the same RT and moreover v'' is not an ancestor of v'. Note that by the representative mechanism, when two nodes are to be joined, the representative of one of them provides the single node that will be their parent. This new node inherits the other (unused) representative as its representative. The tree gets built up bottom up with available representatives propagating upwards. Thus, node v' will be created before node v''. By definition of a representative, neither v' nor any of its ancestors can now have v as a representative since v is now already simulating a helper node. Thus, v'' was created without any of its children having v as a representative. However, this is not possible.

Now, we prove part 2. As stated earlier, at each stage of the merge procedure, RTfragments in  $BT_v$  will merge with their parent. Suppose that v' is a helper node simulated by real node v, and v' is not part of any complete subtree in such a RTfragment. This means that v' will be marked red and removed when this stage of merge is completed (Refer Figure 4.11). Let node y be the root of the complete subtree (i.e. a primary root in that RTfragment) that has v as a leaf node. Node v' is an ancestor of node y since v' cannot be y's descendant. By definition, y.Representative = v, since v will be the unique leaf node in y's subtree not simulating a helper node in that subtree. When the trees are being merged, v may be asked to create another helper node. Thus, v may have two helper nodes. Also, each RTfragment has exactly one anchor node. This anchor may be v' or another node. Thus, in the repair phase, a real node may simulate at most two helper nodes, and one of these helper nodes may be an anchor. However, node v' will be removed as soon as this stage is completed, and if v' was an anchor, a new anchor is chosen from the existing nodes. Since at the end of the merge,  $BT_v$  collapses to leave one RT, the extra helper nodes and the edges from the anchor nodes are not present in FG<sub>T</sub>, thus, not contradicting part 1.

**Lemma 4.4.** After each deletion, the repair phase requires the sending of at most  $O(d \log n)$  messages, each of length  $O(log^2n)$ . Moreover, this can be done in parallel by the neighbors of the deleted node, in time polylog(d, n).

*Proof.* There are mainly two types of messages exchanged by the algorithm. They are the probe messages sent by the FINDPRROOTS() (Algorithm 4.5.5) within a RT and the messages containing the information about the primary roots exchanged by the anchors in  $BT_v$  and among the primary roots themselves (Algorithm 4.5.7: COMPUTEHAFT()). Let  $size(BT_v)$  be the number of RTs of  $BT_v$ . Since a helper node can split a RT into maximum 3 parts, and there can be at most d helper nodes, where d is the degree of the deleted node v,  $size(BT_v) \leq 3d$ . Now, let us calculate the number of messages:

• Probe messages (Algorithm 4.5.5): A probe message is generated by an anchor of a RT. This is similar to the Strip operation (Section 4.4.1). The path that

the probe message follows is the direct path from the originating node to the rightmost node of the RT. At most 2 messages can be generated for every node on the way. Each node waits for a reply to its message. If it had a neighbor as a primary root, it will hear back from it with the root's identity. If it had an anchor as a neighbor, it will get an 'end of path' message. This node will then reply back to the message it had received from the its neighbor on the path from the requesting anchor. Thus, each message generated by the request from the anchor will get a reply back with identities of one or multiple primary roots or end of path messages. By the property of hafts, each node on this path will have a primary root as a neighbor, thus, the longest path a message can take is equal to the diameter of the tree, which is the longest path in the tree. Let *numnodes* be the number of nodes and *numprobes* be number of probe messages sent in a single RT. The length of the longest path is 2 log *numnodes*.

 $\begin{array}{rcl} numprobes & \leq & 2.2.2 \log numnodes \\ & \leq & 8 \log n \end{array}$ 

• Exchange of primary roots lists (Algorithm 4.5.7): At each step of Algorithm 4.5.4 (BOTTOMUPRTMERGE()), leaves in  $BT_v$  merge with their parents. Let rtlistmsgs be the number of messages exchanged for every such merge. The anchors of the leaves of  $BT_v$  send their primary roots lists to the parent, which in turn can send both it's list and the sibling's list to the child. Thus, rtlistmsgs = 4. In addition, every anchor will send this list to the primary roots in its RT, generating at most another log n messages (Let us call this AtoRmsgs).

As stated earlier, in the  $BT_v$ , leaves merge with their parents. The number of such merges before we are left with a single RT is  $\lceil \text{size}(BT_v)/2 - 1 \rceil$ . Also, at most 3

RTs are involved in each merge. Let *totmessages* be the total number of messages exchanged. Hence,

$$totmessages = \lceil \text{size}(BT_v)/2 - 1 \rceil$$

$$(3(numprobes + AtoRmsgs) + rtlistmsgs)$$

$$\leq \lceil 3d/2 - 1 \rceil (27 \log n + 4)$$

$$\in O(d \log n)$$

In  $BT_v$ , leaves and their parents merge. This can be done in parallel such that each time the level of  $BT_v$  reduces by one. Within each RT, the time taken for message passing is still bounded by  $O(\log n)$  assuming constant time to pass a message along an edge. Since there are at most  $\lceil logd \rceil$  levels, the time taken for passing the messages is  $O(\log d \log n)$  i.e polylog(d, n). The biggest message exchanged may have information about the primary roots of up to two RTs. This may be the message sent by a parent RT in  $BT_v$  to its children RT. Since there can be at most  $O(\log n)$ primary roots, the size of messages containing their ID is  $O(\log^2 n)$ .

We now state our main result. Recall that  $G_T$  is the graph produced after T steps of our algorithm, while  $G'_T$  is the graph resulting from the insertions only, with no deletions or repairs.

**Theorem 4.1.** The Algorithm ForgivingGraph has the following properties:

- 1. Degree increase: For any node v in  $V(G_T)$ , after any number of time steps, T, the degree of v in  $G_T$  is at most 3 times the degree of v in  $G'_T$ .
- 2. Stretch: For any nodes x, y in  $V(G_T)$ , after any number of time steps, T, the distance between x and y in  $G_T$  is at most  $\log(n)$  times the distance in  $G'_T$ .

3. Cost: After each deletion, the repair phase requires the sending of at most  $O(d \log n)$  messages, each of length  $O(log^2n)$ . Moreover, this can be done in parallel by the neighbors of the deleted node, in time polylog(d, n).

*Proof.* Part 1 follow directly by construction of our algorithm. Note that for a real node v in FG<sub>T</sub>, any degree increase for v is imposed by the edges of its helper node to hparent(v) and hchildren(v). From lemma 4.3 part 1, we know that, in FG<sub>T</sub>, node v can play the role of at most one helper node for any of its neighbors in G'<sub>T</sub> at any time (i.e. equal to the degree of v in G'<sub>T</sub>). The number of hchildren of a helper node are never more than 2, because the reconstruction trees are binary trees. Thus the total degree of v in FG<sub>T</sub> is at most 3 times its degree in G'<sub>T</sub>. From observation 4.1 and noting that G<sub>T</sub> is a homomorphic image of FG<sub>T</sub>, we can see that the degree of v in G<sub>T</sub> is at most 3 times its degree in G'<sub>T</sub>.

We next show Part 2. We show that the stretch of the Forgiving Graph  $FG_T$  is  $O(D \log n)$ , where n is the number of nodes in  $G_T$ . The distance between any two nodes x and y cannot increase by more than the factor of the longest path in the largest RT on the path between x and y. Since the number of nodes in  $FG_T$  is O(n), This factor is  $\log n$  at the maximum. Since there is a homomorphism from the graph  $FG_T$  to  $G_T$ , the result follows directly from observation 4.2.

The proof of Part 3 follows from Lemma 4.4. Note that besides the communication of the messages discussed, the other operations can be done in constant time in our algorithm.  $\Box$ 

### 4.7.2 Lower Bounds

**Theorem 4.2.** Let n be a positive integer,  $\alpha \geq 3$  and  $\beta = \frac{1}{2}(\log_{\alpha}(n-1)-1)$ . Then there exists a graph on n vertices and a vertex deletion such that any way of repairing this deletion under our model must either increase the degree of some node by more than a factor of  $\alpha$ , or it must increase the distance between some pair of nodes by at least a factor of  $\beta$ .



Figure 4.19: Deletion of the central node v of a star leads to an increase in the stretch. Here, the healing algorithm can increase the degree of any node by at most a factor of  $\alpha$ .

Proof. Let G be a star on n vertices, where x is the root node, and x has an edge with each of the other nodes in the graph. The other nodes (besides x) have a degree of only 1. Let G' be the graph created after the adversary deletes the node x. Consider a breadth first search tree, T, rooted at some arbitrary node y in G'. We know that the self-healing algorithm can increase the degree of each node by at most a factor of  $\alpha$ , thus every node in T besides y can have at most  $\alpha - 1$  children. Let h be the height of T. Then we know that  $1 + \alpha \sum_{i=0}^{h-1} (\alpha - 1)^i \ge n - 1$ . This implies that  $(\alpha)^{h+1} \ge n-1$  for  $\alpha \ge 3$ , or  $h+1 \ge \log_{\alpha}(n-1)$ . Let z be a leaf node in T of largest depth. Then, the distance between y and z in G' is h and the distance between y and z in G is 2. Thus,  $\beta \ge h/2$ , and  $2\beta \ge \log_{\alpha}(n-1) - 1$ , or  $\beta \ge \frac{1}{2}(\log_{\alpha}(n-1) - 1)$ . This is illustrated in figure 4.19. Note that the upper bound on the degree increase and stretch of our algorithm is within a constant factor of matching this lower bound.

# 4.8 Conclusion

In this chapter, we have presented a distributed data structure that withstands repeated adversarial node deletions by adding a small number of new edges after each deletion. Our data structure is efficient and ensures two key properties, even in the face of both adversarial deletions and adversarial insertions. First, the distance between any pair of nodes never increases by more than a  $\log n$  multiplicative factor than what the distance would be without the adversarial deletions. Second, the degree of any node never increases by more than a 3 multiplicative factor.

Several open problems remain including the following. Can we design algorithms for less flexible networks such as sensor networks? For example, what if the only edges we can add are those that span a small distance in the original network? Can we extend the concept of self-healing to other objects besides graphs? For example, can we design algorithms to rewire a circuit so that it maintains its functionality even when multiple gates fail?

1: given a Graph G(V, E)**Require:** each node of G has a unique ID 2: for each node  $v \in G$  do INIT(v)3: 4: end for 5: while true do if a vertex v is inserted then 6: vertex v and new neighbors add appropriate edges 7: INIT(v)else if a vertex v is deleted then DeleteFix(v)end if

```
8:
```

9:

```
10:
```

- 11:
- 12: end while



- 1: for each edge(v, x) do
- 2: (v, x). Representative = v
- 3: set other fields to NULL
- 4: end for
### Chapter 4. Forgiving Graph

- 1: Nset =  $\{\}$
- 2: for each edge(v, x) do
- 3: **if** (v, x).hashelper = TRUE **then**
- 4: Nset = Nset  $\cup$  (v, x).hparent  $\cup$  (v, x).hrightchild
- 5: **end if**
- 6: Nset = Nset  $\cup$  (v, x).endpoint
- 7: end for
- 8: Nodes in Nset make new edges to make a balanced binary tree  $BT_v(Nset, E_v)$
- 9: BOTTOMUPRTMERGE $(BT_v, v)$
- 10: delete the edges  $E_v$

Algorithm 4.5.3: DELETEFIX(v): Self-healing on deletion of a node

```
1: if BT_v has only one node then
2:
      return
 3: end if
4: for y \in BT_v do
      if y is a real node then
5:
        let y.PrRoots \leftarrow y
6:
      else if y = (v, x).endpoint then
7:
        y.PrRoots \leftarrow FINDPRROOTS(y, 1, (v, x), TRUE, y)
8:
      else if y.helper.hparent
                                    = v \text{ OR } y.\text{helper.}hleftchild
9:
                                                                                 v OR
                                                                            =
      y.helper.hrightchild = v then
        let y.PrRoots \leftarrow FINDPRROOTS(y, v.desccount, v.helper, TRUE, y)
10:
      else
11:
        let y.PrRoots \leftarrow FINDPRROOTS(y, v.desccount, v.helper, FALSE, y)
12:
      end if
13:
14: end for
15: for all nodes y s.t. node y is a parent of a leaf in BT_v do
      if y has two children in BT_v then
16:
        HAFT_MERGE(y, y \text{ 's left child in } BT_v, y \text{ 's right child in } BT_v)
17:
      else
18:
        HAFT_MERGE(y, y)'s left child, NULL)
19:
20:
      end if
21: end for
22: BOTTOMUPRTMERGE(BT<sub>v</sub>) // New leaf nodes merge again till only one is left.
Algorithm 4.5.4: BOTTOMUPRTMERGE(BT_v, v): The nodes of BT_v merge their
```

RTs starting from the leaves going up forming a new  $BT_v$ .

```
1: if y is an Anchor node AND y \neq origin then
     return NULL // Anchors reject probe messages from other anchors.
 2:
 3: end if
4: if Breakflag = TRUE AND (sender = y.hrightchild OR sender = y.hleftchild )
   then
      y.desccount = y.desccount - numchild
 5:
 6: end if
7: if y.desccount = 2^{y.height then
8:
     if TESTPRIMARYROOT(y) = TRUE then
        return {y,FINDPRROOTS(y.hparent, 0, y, Breakflag, origin) }
9:
10:
     else
        return {FINDPRROOTS(y,hparent, 0, y, Breakflag, origin) } // Node itself
11:
        not a primary root but parent maybe.
12:
      end if
13: else
     mark node red
14:
15:
     if exists(y.hleftchild) AND sender \neq y.hleftchild then
        FINDPRROOTS(y.hleftchild, y.desccount, y, Breakflag, origin)
16:
17:
      else if exists(y.hrightchild) AND sender \neq y.hrightchild then
18:
        FINDPRROOTS(y.hrightchild, y.desccount, y, Breakflag, origin)
19:
      else if exists(y.hparent) AND sender \neq y.hparent then
20:
        FINDPRROOTS(y.hparent, y.desccount, y, Breakflag, origin)
     end if
21:
22: end if
```

Algorithm 4.5.5: FINDPRROOTS(y), numchild, sender, Breakflag, origin): Find primary roots in the RTfragment (Section 4.5 of main text) containing node y. If Breakflag is set, the tree is a RTfragment formed due to the deletion of the node prior to any merges and the nodes need to adjust their descendant count.

```
1: if y.desccount = 2^{y.height then
```

2: **if** y.hparent = NULL **then** 

```
3: return TRUE
```

4: else if y.hparent.desccount  $\neq 2^{y.hparent.height}$  then

```
5: return TRUE
```

```
6: end if
```

7: end if

```
8: return FALSE
```

**Algorithm 4.5.6:** TESTPRIMARYROOT(y): Tell if helper node y is a primary root in RT

- 1: Nodes  $p, \ell$  and r exchange  $p.PrRoots, \ell.PrRoots(l), PrRoots(r)$
- 2: let  $RT \leftarrow MAKERT(PrRoots(p), \ell.PrRoots, r.PrRoots)$
- 3: if p is marked red then
- 4: p transfers its edges in  $BT_v$  to one of p.PrRoots // p needs to be removed,  $BT_v$  needs to be maintained
- 5: end if
- 6: remove all helper nodes marked red // Some helper nodes marked red may have been reused and unmarked by MAKERT

**Algorithm 4.5.7:** HAFT\_MERGE $(p, \ell, r)$ : Merge the hafts mediated by anchors  $p, \ell$  and r

- 1: for all  $y \in (PRoots1 \cup PRoots2 \cup PRoots3)$  do
- 2: let  $T \leftarrow \text{COMPUTEHAFT}(\text{PRoots1}, \text{PRoots2}, \text{PRoots3})$
- 3: make helper nodes and set fields and make edges according to T
- 4: end for

Algorithm 4.5.8: MAKERT(PRoots1, PRoots2, PRoots3): The sets of Primary roots make a new RT

1: let  $R = PRoots1 \cup PRoots2 \cup PRoots3$ 2: let L = R sorted in ascending order of number of children, NodeID 3: suppose L is  $(r_1, r_2, \ldots, r_k)$  where the  $r_i$  are the k ordered primary roots. 4: set ctr = 1, count = k5: while ctr < count do if  $r_{ctr}$ .numchildren =  $r_{ctr+1}$ .numchildren then 6: 7: Make helper node helper( $r_{ctr}$ . Representative). Initialize fields to NULL. 8: make helper( $r_{ctr}$ . Representative) the parent of  $r_{ctr}$  and  $r_{ctr+1}$ 9: if  $r_{ctr}$  is a real node then 10: set helper( $r_{ctr}$ .Representative).height = 1 else 11: 12:set helper( $r_{ctr}$ .Representative).height =  $2r_{ctr}$ .height end if 13:14: set helper( $r_{ctr}$ .Representative).Representative =  $r_{ctr+1}$ .Representative remove  $r_{ctr}, r_{ctr+1}$ , insert helper $(r_{ctr}$ . Representative) in correct place in L. 15:16:set  $ctr \leftarrow ctr - 1$ ,  $count \leftarrow count - 1$ end if 17:set  $ctr \leftarrow ctr + 1$ . 18:19: end while 20: set ctr = 121: while ctr < count do 22:make helper node helper( $r_{ctr+1}$ .Representative). Initialise its fields to NULL 23: set helper( $r_{ctr+1}$ .Representative).hleftchild =  $r_{ctr+1}$ 24:set helper( $r_{ctr+1}$ .Representative).hrightchild =  $r_{ctr}$ 25:set helper $(r_{ctr+1}$ .Representative).height =  $r_{ctr+1}$ .height + 1 26:set helper( $r_{ctr+1}$ .Representative).Representative =  $r_{ctr}$ .Representative 27:In L, replace  $r_{ctr+1}$  by helper $(r_{ctr+1}$ .Representative) 28: end while

**Algorithm 4.5.9:** COMPUTEHAFT(PRoots1, PRoots2, PRoots3): (Implementation of Haft Merge) The primary roots compute the new haft

## Chapter 5

## **Future Directions**

There is no such thing as a failed experiment, only experiments with unexpected outcomes RICHARD BUCKMINSTER FULLER

In this chapter, we point out some related open problems and discuss the future directions in which this research can be extended.

## 5.1 Empirical study of self-healing algorithms beyond assumptions

How would our algorithms perform beyond the assumptions of the model we have used? There are certain assumptions our algorithms make and we would like to know how well our algorithms perform even when those assumptions don't hold e.g. our model assumes single failure before each recovery. How would our algorithms perform if there are multiple failures in close physical or temporal proximity? Akin to an ecological disaster, we would see how the algorithms perform if a set of nodes

(a clump of species) are simultaneously deleted or there are cascading failures. We will also place restrictions on the topology of the network and add additional rules to the algorithm to simulate different networks found in nature. In particular, we have already begun work on simulating ForgivingGraph for these purposes.

### 5.2 Routing in Self-healing structures

Can we implement efficient updates to routing tables? Small changes to the network, e.g., deletion of an edge or a node can lead to major changes in the tables. Can our algorithms keep track of these? Self-healing routing is an important research question especially given the dynamic nature of modern networks [30, 21, 45]. We will like to propose solutions in our framework which incorporate routing in addition to the invariants we already maintain. This could involve proposing efficient routing schemes to go with our self-healing structures or developing new structures that help routing.

### 5.3 Load balanced Self-healing

Trees are not the best structure for effective load balancing e.g. in a balanced tree, half of the paths will go through the root. Can we improve the load balancing using a different self-healing data structure? Good load balancing would be ensured if upon healing there are not likely to be bottlenecks for communication traffic. There has been some previous work on load balancing in structured P2P systems [32]. This may also be related to the earlier question (Section 5.2) on self-healing Routing. There are many interesting ideas we are looking at out there which may potentially contribute to a solution that we are looking at e.g. The Chord P2P structure [54], Skip graphs [54], and Small-world network models [36].

### 5.4 Self-healing in Sensor Networks

Directional antennas are increasingly becoming important in sensor networks e.g. [26]. They also allow us to use our concept of self-healing where we have an edge in the underlying graph for two nodes in communication with each other. In a wireless ad-hoc network multi-hop connectivity can be easily lost when a transceiver goes silent and does not relay messages any longer. Successful pairwise communication occurs in a wireless network only in the absence of interference which is usually achieved by frequency or time or code division multiplexing, i.e., by assigning non-interfering channels (colors) to the pairwise links (edges) that are necessary for global connectivity. Therefore, to restore connectivity after a node failure, it is important to also restore an interference-free channel assignment for the pairwise links in the repaired network.

In the disk graph model of a wireless ad-hoc network, there are *n* transceivers and the transmission and reception range of a transceiver *u* is a disk D(u) centered at *u* with radius r(u). The transceivers are vertices of a directed graph G = (V, E). The directed edge  $u \to v$  belongs to *E* if and only if *v* is in D(u). Two transceivers *u* and *v* can communicate directly (without intermediate hops) if and only if both directed edges  $u \to v$  and  $v \to u$  are present. We say that a pair of transceivers (u, v) are connected if there exists a path between *u* and *v* consisting of bidirectional edges. Two edges (u, v) and (p, q) may exhibit *primary interference* if either  $u \in \{p, q\}$ or  $v \in \{p, q\}$ , i.e., if they have a common vertex. They may exhibit *secondary interference* if they share a common edge i.e. there is an edge whose one end-point is either *u* or *v* and the other is either *p* or *q*.

The question of maintaining this interference-free communication graph can then be reduced to maintenance of strong edge coloring where each edge is assigned a color such that no interfering edge shares a color, in the presence of an adversary. We can again assume that the adversary removes one node at a time and the neighbors are alerted of this. One possible approach is to use the self-healing idea such as the notion of "wills" (as in Forgiving Tree) to compute an efficient, local way to repair the network by re-connecting (a subset of) the nodes in the neighborhood of the deleted vertex. We can then use a distributed, randomized algorithm (i.e., a protocol), a la Luby [41], to implement the repair. In [6] Barett at al adapted Luby's algorithm to the case of distance-2 coloring and showed that it was sufficient for each node to know the so-called "active degree" to determine its wake-up probability. Much of the ideas in this section were from discussion with Shripad Thite (Google).

# 5.5 Self-healing/ Behavioral robustness in Social Networks

There are some interesting avenues to explore in the context of robustness in social networks. Some of the questions in this context may involve achieving behavioral robustness as opposed to topological invariance like we have used so far in our self-healing work. One of the question we want to explore is the following: Does a phenomena like the minority game which normally achieves equilibrium achieves homeostasis even in the presence of an adversary. This has the flavor of behavioral invariance. In [33], Willemien et al show that a learning process in which players best-reply to a history of limited length and in which they have a preference for more recent best replies ("recency bias") eventually settles down in one of the pure Nash equilibria (optimal anti-coordination) if the memory length of players is at least 2. The proof uses the fact that you can construct a path from any initial history to a state where players play according to a pure Nash equilibrium in each following time period, and that such a path will occur with probability 1 in the long run. This gives

an algorithm for reaching an anti-coordination equilibrium if players best-reply to beliefs based on a limited history of play and they have a recency bias.

Our idea is to study what will happen to the equilibrium if an adversary (in the sense of external perturbations) is introduced into the mix. Will we still achieve the anti-coordination equilibrium?, and what are the implications?

### 5.6 Self-\* problems

Can we go beyond Self-healing (demand even stronger guarantees)? There is strong interest in the so-called self-\* algorithms. We have earlier discussed these properties in Section 1.5.1. One such objective is self-stabilization. A distributed system that is self-stabilizing will end up in a correct state no matter what state it is initialized with. This is a highly desirable property for distributed systems, and worth investigating. Another direction would be too look at the network layers themselves. Our work is based on overlay networks. However, it may be beneficial to consider what happens below that layer, at the physical layer itself, to come up with practical, efficient and robust network designs.

## 5.7 Evolution of social and computer networks and study of group formation

It is important to study the mechanisms behind the formation and evolution of networks, particularly, networks like the Internet, and social networks, in particular with regards to their stability and self-\* properties. Techniques from various areas like game theory can often be profitably applied here. There are many models seeking to explain network formation e.g. [40]; Some models seek to explain the formation of

networks in a game theoretic manner by having nodes as players making connections (edges) with other players to maximize their utility function [16].

There is interest in discovering mechanisms for formation of groups. Our attempts at simple toy models suggest this is a difficult problem. However, there has been interesting research in this area incorporating both theoretical and experimental (including field observations) work. Dan Rubenstein, an ecologist from Princeton, collected data on the social structure graphs of the thriving plains zebra and the endangered Grevy's zebras, from the plains of Africa. He and Tanya Berger-Wolff, from University of Illinois Chicago, then modeled the Zebra's group behavior by looking at the network of their social behavior to find interesting patterns [52, 56]. Jared Saia and Tanya Berger-Wolff have also proposed mathematical and computational framework that enables analysis of dynamic social networks and that explicitly makes use of information about when social interactions occur [7]. There are also many interesting data sets e.g. on mobile phone usage patterns [39], which can help investigate such questions as routing of messages, group formation and social motivation.

There are many interesting questions: How do groups self-heal i.e are groups sensitive to perturbation, leaving and joinings of agents? What are the mechanisms that explain formation and dissolution of groups in real networks? Can we propose such game theoretic cost functions? When agents cooperate to form a group, how does that influence formation of other groups?

# 5.8 Byzantine agreement: Distributed computing in presence of byzantine faults

This section owes itself to discussions with Professor Valerie King. The failure models we have considered so far ignore byzantine faults (e.g. by adversarial code corrup-

tion), but it is important for the network to be able to function/self-heal in presence of these faults. A fundamental problem in distributed computing is that of coordinating behavior by processors in the presence of an adversary who controls a constant fraction of processors. At its most basic, it is formulated as the Byzantine Agreement Problem. Each of n processors are given an input bit; they execute a protocol, at the end of which all output the same bit equal to one of their input bits.

This problem, in the asynchronous model (an adversary controls the order in which messages are delivered), is known to be impossible to solve deterministically in the full information model, i.e., if the adversary has access to all messages sent and there are no cryptographic assumptions made. A randomized protocol exists in which each processor has private random bits but it requires an exponential number of messages. Both of these results were shown in the 1980's. Last year, Kapron, Kempe, King, Saia and Sanwalani [31] showed a polylogarithmic time protocol which succeeds with high probability for this problem if the choice of corrupt processors is made independently of the random bits, and the adversary is "non-adaptive". In addition, King and Saia showed that  $\tilde{O}(n^{3/2})$  total bits of communication suffice [34]. Without the assumption, all known Byzantine Agreement protocols in the synchronous model (where messages are delivered in rounds) and the asynchronous model use  $\Omega(n^2)$ messages, even with private channels and cryptographic assumptions.

Several intriguing problems remain open, in decreasing order of difficulty:

- 1. Can we close the gap between the lower bound of  $n^2$  and the upper bound of exponential time for asynchronous Byzantine agreement (with an adaptive adversary) in the full information model?
- 2. Can we do Byzantine agreement with cryptography or private channels with an adaptive adversary in  $o(n^2)$  bits per processor? Is it possible to prove a nontrivial lower bound here? Is there a practical protocol for this? (Recently,

King and Saia have published an algorithm which solves this problem in the synchronous model [35]. Their algorithm assumes private channels and takes only  $\tilde{O}(\sqrt{n})$  bits per processor and has polylog latency).

- 3. Can we load balance the Byzantine agreement problem so that no processor uses more than o(n) bits with the assumption, for the synchronous model? For the asynchronous model?
- 4. Can we enhance the protocols designed by King and Saia, so that they are robust to an adversary who can also remove and insert new nodes, some of which are corrupt, still in the full information model?

Techniques for proving lower bounds for randomized distributed problems like this are scarce and may involve techniques from communication complexity. There is a well known method for deterministic lower bounds in distributed computing using algebraic topology, but there is no known extension to randomized algorithms. This would be interesting to explore. Any answer to the first question will be a major breakthrough in a widely studied problem area that has been open for over 25 years.

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