Towards a Framework for DHT Distributed Computing

by

Andrew Benjamin Rosen

Under the Direction of Anu G. Bourgeois, PhD

Abstract

Distributed Hash Tables (DHTs) are protocols and frameworks used by peer-to-peer (P2P) systems. They are used as the organizational backbone for many P2P file-sharing systems due to their scalability, fault-tolerance, and load-balancing properties. These same properties are highly desirable in a distributed computing environment, especially one that wants to use heterogeneous components.

We show that DHTs can be used not only as the framework to build a P2P file-sharing service, but as a P2P distributed computing platform. We propose creating a P2P distributed computing framework using distributed hash tables, based on our prototype system ChordReduce. This framework would make it simple and efficient for developers to create their own distributed computing applications. Unlike Hadoop and similar MapReduce frameworks, our framework can be used both in both the context of a datacenter or as part of a P2P computing platform. This opens up new possibilities for building platforms to distributed computing problems.

One advantage our system will have is an autonomous load-balancing mechanism. Nodes will be able to independently acquire work from other nodes in the network, rather than sitting idle. More powerful nodes in the network will be able use the mechanism to acquire more work, exploiting the heterogeneity of the network.

By utilizing the load-balancing algorithm, a datacenter could easily leverage additional P2P resources at runtime on an as needed basis. Our framework will allow MapReduce-like or distributed machine learning platforms to be easily deployed in a greater variety of contexts.

Index Words: Distributed Hash Tables, P2P, Voronoi, Delaunay, Networking

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Andrew Benjamin Rosen

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by

Andrew Benjamin Rosen

Committee Chair Anu G. Bourgeois

Committee Robert Harrison

Zhipeng Cai

Michael Stewart

Electronic Version Approved:

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College of Arts and Sciences

Georgia State University

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Dedication

To Annie-Rae Rosen, without whom, I would not be who I am today.

To my mother, who understands the power of names. Whenever I doubted myself, I only had to remember my name and what it meant.

Acknowledgments

I would like to take the chance to thank the following people who helped me in my work.

- Dr. Anu Bourgeois, my advisor, for guiding me through the PhD study and directing me, while simultaneously giving me enough room to let me research independently.
- Dr. Robert Harrison, for acting as a mentor.
- Dr. Brendan Benshoof, code monkey and captain of Team Chaos.

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Chapter 1

Introduction

Distributed Hash Tables (DHTs) are protocols and frameworks used by peer-to-peer (P2P) systems. They are used as the organizational backbone for many P2P file-sharing systems due to their scalability, fault-tolerance, and load-balancing properties. These same properties are highly desirable in a distributed computing environment, especially one that wants to use heterogeneous components. We will show that DHTs can be used not only as the framework to build a P2P file-sharing service, but a more generic distributed computing platform.

1.1 Objective

Our goal is to create a framework to further generalize Distributed Hash Tables (DHTs) to be used for distributed computing. Distributed computing platforms need to be scalable, fault-tolerant, and load-balancing. We will discuss what each of these mean and why they are important in section **??**, but briefly:

- The system should be able to work effectively no matter how large it gets. As the system grows in size, we can expect the overhead to grow in size as well, but at an extremely slower rate.
- The more machines integrated into the system, the more we can expect to see hardware failures. The system needs to be able to automatically handle these hardware failures.
- Having a large number of machines to use is worthless if the amount of work is divided

unevenly among the system. The same is true if the system hands out larger jobs to less powerful machines or smaller jobs to the more powerful machines.

These are many of the same challenges that Peer-to-peer (P2P) file sharing applications have. Many P2P applications use DHTs to address these challenges, since DHTs are designed with these problems in mind. We propose that DHTs can be used to create P2P distributed computing platforms that are completely decentralized. There would be no need for some central organizer or scheduler to coordinate the nodes in the network. Our framework would not be limited to only a P2P context, but could be applied in data centers, a normally centrally organized context.

A successful DHT-based computing platform would need to address the problem of dynamic load-balancing. This is currently an unsolved[1] problem. If an application can dynamically reassign work to nodes added at runtime, this opens up new options for resource management. Similarly. if a distributed computation is running too slow, new nodes can be added to the network during runtime or idle nodes can boot up more virtual nodes.

Chapter **??** will delve into how DHTs work and examine specific DHTs. The remainder of the dissertation will then discuss the work we have completed and plan on doing to demonstrate the viability of using DHTs for distributed computing and other non-traditional tasks.

1.2 Applications of Distributed Hash Tables

Distributed Hash Tables have been used in numerous applications:

- *P2P file sharing* is by far the most prominent use of DHTs. The most well-known application is BitTorrent [**?**], which is built on Mainline DHT [**?**].
- DHTs have been used for *distributed storage* systems [**?**].
- *Distributed Domain Name Systems* (DNS) have been built upon DHTs [**?**] [**?**]. Distributed DNSs are much more robust that DNS to orchestrated attacks, but otherwise require more overhead.
- DHT was used as the name resolution layer of a large *distributed database* [**?**].

[1] As far as we know.

- Distributed *machine learning* [**?**].
- Many *botnets* are now P2P based and built using well established DHTs [**?**]. This is because the decentralized nature of P2P systems means there is no single vulnerable location in the botnet.
- *Live video streaming* (BitTorrent Live) [**?**].

We can see from this list that DHTs are primarily used in P2P applications, but other applications, such as botnets, use DHTs for their decentralization. We want to use DHTs primarily for their intuitive way of organizing a distributed system.

Our goal was to further extend the use of DHTs. In previous work [**?**], we showed that a DHT can be to create a distributed computing framework. We used the same mechanism used in P2P applications that assigns nodes their location in the network to evenly distribute work among members of a DHT. The most direct application of a DHT distributed computing framework is a quick and intuitive way to solve embarrassingly parallel problems, such as:

- Brute force cryptography.
- Genetic algorithms.
- Markov chain Monte Carlo methods.
- Random forests.
- Any problem that could be phrased as a MapReduce problem.

Unlike the current distributed applications that utilize DHTs, we want to create a complete framework that can be used to build decentralized applications. We have found no existing projects that provide a means of building your own DHT or DHT based applications.

1.3 Why Use Distributed Hash Tables in Distributed Computing

Using Distributed Hash Tables for distributed computing is not necessarily the most intuitive step. To understand why we want to use DHTs for distributed computing, we will first examine some of the more prominent challenges in distributed computing.

1.3.1 General Challenges of Distributed Computing

As we mentioned earlier, distributed computing platforms need to be scalable, fault-tolerant, and load-balancing. We will look at these individually:

Scalability - Distributed computing platforms should not be completely static and should grow to accommodate new needs. However, as systems grow in size, the cost of keeping that system organized grows too. The challenge of scalability is designing a protocol that grows this organizational cost at an extremely slow rate. For example, a single node keeping track of all members of the system might be a tenable situation up to a certain point, but eventually, the cost becomes too high for a single node. We want this organizational cost spread among many nodes to the point where this cost is insignificant.

Fault Tolerance The quality of fault-tolerance or *robustness* means that the system still works even after a component breaks (or many components break). We want our platform to gracefully handle failures during runtime and be able to quickly reassign work to other workers. In addition, the network should be equally graceful in handling the introduction of new nodes during runtime.

Load-Balancing The challenge of load balancing is to evenly distribute the work among nodes in the network. This is always an approximation; rarely are there exactly enough pieces for every node to get the same amount of work. The system needs an efficient set of rules for dividing arbitrary jobs into small pieces and sending those pieces to the nodes, without incurring a large overhead.

A subproblem here is handling *heterogeneity*,[2] or how should the system should handle different pieces of hardware with different amounts of computational power.

Note that there is some crossover between these categories. For example, adding new nodes to the system needs to have a low organizational overhead (scalability) and will change the network configuration, which will need to be updated (fault-tolerance).

[2]It could even be considered a problem in its own right.

1.3.2 How DHTs Address these Challenges

Distributed Hash Tables are essentially distributed lookup tables. DHTs use a consistent hashing algorithm, such as SHA-1 [**?**], to associate nodes and file identifiers with keys. These keys dictate where the nodes and files will be located on the network. The connections between nodes are organized such that any node can efficiently lookup the value associated with any given key, even though the node only knows a small portion of the network. We discuss the specifics of this in Chapter **??**.

Nearly every DHT was designed with large P2P applications in mind, with millions of nodes in the network and new nodes entering and leaving continuously.

Scalability The organizational responsibility in DHTs is spread among all members of the network. Each node only knows a small subset of the network,[3] but can use the nodes it knows to efficiently find any other node in the network. Because each individual node only knows a small part of the network, the maintenance costs associated with organization are correspondingly small.

Using consistent hashing allows the network to scale up incrementally, adding one node at a time [**?**]. In addition, each join operation has minimal impact on the network, since a node affects only its immediate neighbors on a join operation. Similarly, the only nodes that need to react to a node leaving are its neighbors. Other nodes can be notified of the missing node passively through maintenance or in response to a lookup.

There have been multiple proposed strategies for tackling scalability, and it is these strategies that play the greatest role in driving the variety of DHT architectures. Each DHT must strike a balance between the size of the lookup table and lookup time. The vast majority of DHTs choose to use $\lg(n)$ sized tables and $\lg(n)$ hops, where n is the number of nodes in the network. Chapter **??** discusses these tradeoffs in greater detail and how they affect the each DHT.

Fault-Tolerance One of the most important assumptions of DHTs is that they are deployed on a constantly changing network. DHTs are built to account for a high level of *churn*.[4] *Churn* is the disruption of routing caused by the constant joining and leaving of nodes. In other words, the network topology is assumed to always be in flux. This is mitigated by a few factors.

[3] Except for ZHT [**?**], which breaks this rule deliberately by giving each node a full copy of the routing table.
[4] Again, except for ZHT.

First, the network is decentralized, with no single node acting as a single point of failure. This is accomplished by each node in the routing table having a small portion of the both the routing table and the data stored on the DHT.

Second is that each DHT has an inexpensive maintenance processes that mitigates the damage caused by churn. DHTs often integrate a backup process into their protocols so that when a node goes down, one of the neighboring nodes can immediately assume responsibility. The join process also slightly disrupts the topology, as affected nodes must adjust their the list of peers they know to accommodate the joiner.

The last property is that the hashing algorithm used to distribute content evenly across the DHT also distributes nodes evenly across the DHT. This means that nodes in the same geographic region occupy vastly different locations in the network. If an entire geographic region is affected by a network outage, this damage is spread evenly across the DHT, and can be handled, rather than if a contiguous portion were lost.

The fault tolerance mechanisms in DHTs also provide near constant availability for P2P applications. The node that is responsible for a particular key can always be found, even when numerous failures or joins occur [**?**].

Load-Balancing Consistent hashing is also used to ensure load-balancing in DHTs. Consistent hashing algorithms associate nodes and file identifiers with keys. These keys are generated by passing the identifiers into a hash function, typically SHA-160. The chosen hash function is typically large enough to avoid hash collisions[5] and generates keys in a uniform manner.

Essentially, both nodes and data are spread about the network uniformly at random. Nodes are responsible for the files with keys "close" to their own. What "close" means depends on the specific implementation. For example, "close" might mean "closest without going over" or "shortest distance."

We found defining the meaning of "close" equivalent choosing a metric for Voronoi tessellation [**?**]. However, because this is a random process, not all values are evenly distributed, but enough hash keys yield a close enough approximation.

Heterogenity presents a challenge for load-balancing DHTs due to conflicting assumptions and

[5]A hash collision occurs when the hashing algorithm outputs the same key for two different inputs. This is so exceedingly rare, that most authors working on DHTs do not even account for this possibility.

goals. DHTs assume that members are usually going to be varied in hardware, but the load-balancing process defined in DHTs treats each node equally. In other words, DHTs support heterogeneity, but do not attempt to exploit it.

This does not mean that heterogeneity cannot be exploited. Nodes can be given addition responsibilities manually, by running multiple instances of the P2P application on the same machine or creating more virtual nodes. We will take advantage of this for distributing the workload automatically.

1.4 Outline

In this section, we give a brief overall summary overview of our work, followed by a summary of each individual chapter in the dissertation. We also provide a list of publications for this work.

1.4.1 Summary of Dissertation

One of our first projects was to create a distributed computing platform using the Chord DHT [**?**]. Our goal here was to create a completely decentralized distributed computing framework that was fault-tolerant during job execution. We did this by implementing MapReduce over Chord. We then tested our prototype's fault-tolerance by executing MapReduce jobs under churn.

Our experiments with excessively high levels of churn created an anomaly in the runtime of our computations. Under beyond practical levels of experimental churn, we found that our computation was quicker than our experiments without churn. We hypothesized that this is because the random churn is acting as a (inefficient) process for autonomous load-balancing. This phenomena is described in detail in Chapter **??**, but suggested to us that there was a way to dynamically load-balance during execution.

Our second project was to develop VHash [**?**] [**?**], a distributed hash table based on Delaunay Triangulation. VHash is unique due to the way it could work in multidimensional spaces. Other DHTs typically use a space with a single dimension and optimize for the number of hops. VHash can optimize for whatever attributes are used to define the space. Our experiments showed that VHash outperforms Chord in terms of routing latency. VHash eventually morphed into a more generic DHT, UrDHT [**?**], which is the subject of Chapter **??**.

Our third project which analyzed the amount of effort that would be required to attack a DHT using a method known as the Sybil attack [**?**]. The Sybil attack [**?**] is a well known attack against distributed systems, but it had not been fully analyzed from the perspective of an attacker. Our results showed that attackers required relatively few resources to compromise a much larger network. We believe that some of the components that are used to perform a Sybil attack can be used for autonomous load balancing.

Finally, we studied how we could use churn and intentional injection of benign Sybil nodes into the network to speed up execution of a distributed process or dynamically load-balance a network during runtime. This process could be done completely autonomously by each node without any control from a centralized source. In other words, we have developed completely decentralized strategies that a DHT can use to load-balance the network.

1.4.2 Chapter Summaries

The dissertation is divided into distinct, but mutually dependent parts. Chapter **??** covers the requisite background material. It is also suitable as a primer on Distributed Hash Tables.

Each subsequent chapter, summarized below, covers a specific publication. Chapter **??**, closes with remarks on our work.

ChordReduce - DHT Distributed Computing

We present our first project, ChordReduce [**?**], in Chapter **??**. ChordReduce utilized Chord [**?**] to create a distributed computing platform using the MapReduce [**?**] platform. The novel contribution of ChordReduce was it's ability to perform completely decentralized MapReduce operations in either a P2P environment or a datacenter.

Using our created framework, we will create implement and test distributed computing problems on different DHT implementations, such as Chord [**?**] and Kademlia [**?**].

DGVH

Chapter **??** covers the origin of our Distributed Greedy Voronoi Heuristic (DGVH). This provides an efficient way to create (with some error) Voronoi Tessellations and the corresponding Delaunay Triangulation. While DGVH produces only approximates the solution for Voronoi Tessellations, it

can do so in any geometric space with distance function in any number of dimensions. In addition, the computational complexity is independent of the number of dimensions and can be performed locally at each node, rather than requiring global knowledge of the network's state.

This directly leads into Chapter **??**, which using DGVH to abstract DHTs.

UrDHT – an Abstract DHT Framework

In Chapter **??**, we found that DHTs can be mapped to the constructs of Delaunay Triangulation and Voronoi Tessellation. Thus, creating the topology of a DHT can be done by solving for the appropriate Delaunay Triangulation. UrDHT is an open source project for creating DHTs using this principle.

Distributed Decentralized Domain Name Service

D^3NS (Chapter **??**) is a system to replace the current top level DNS system and certificate authorities, offering increased scalability, security and robustness. D^3NS is based on a distributed hash table and utilizes a domain name ownership system based on the Bitcoin blockchain [**?**] and addresses previous criticism that a DHT would not suffice as a DNS replacement.

Our system provides solutions to current DNS vulnerabilities such as DDOS attacks, DNS spoofing and censorship by local governments. It eliminates the need for certificate authorities by providing a decentralized authenticated record of domain name ownership. Unlike many other DNS replacement proposals, D^3NS is reverse compatible with DNS and allows for incremental implementation within the current system.

Sybil Analysis

Chapter **??** analyses the cost of performing a Sybil attack from the perspective of an adversary. Previous analyses have all focused on defending from the aforementioned adversary, but little to no work has been performed quantifying the attacker's capabilities. Our analysis places reasonable constraints on the attacker and evaluates the resources the attacker needs to effectively own a target network.

Autonomous Load-Balancing

Chapter **??** presents strategies for nodes to balance the workload among members of the DHT. Load balancing schemes do exist for file storage, but none exist for computation. What makes our strategies completely different is that they can be executed at runtime.

Furthermore, we wanted to develop a system that takes into account the heterogeneity of a given system, allowing more powerful nodes to take on more responsibility.

Our strategies use churn and a benign variation of the Sybil attack to perform a decentralized redistribution of work.

1.4.3 Publications

- Andrew Rosen, Brendan Benshoof, Robert W. Harrison, Anu G. Bourgeois "MapReduce on a Chord Distributed Hash Table" Poster at IPDPS 2014 PhD Forum [**?**]
- Andrew Rosen, Brendan Benshoof, Robert W. Harrison, Anu G. Bourgeois "MapReduce on a Chord Distributed Hash Table" Presentation ICA CON 2014
- Brendan Benshoof, Andrew Rosen, Anu G. Bourgeois, Robert W. Harrison "VHASH: Spatial DHT based on Voronoi Tessellation" Short Paper ICA CON 2014 [**?**]
- Brendan Benshoof, Andrew Rosen, Anu G. Bourgeois, Robert W. Harrison "VHASH: Spatial DHT based on Voronoi Tessellation" Poster ICA CON 2014
- Brendan Benshoof, Andrew Rosen, Anu G. Bourgeois, Robert W. Harrison "A Distributed Greedy Heuristic for Computing Voronoi Tessellations With Applications Towards Peer-to-Peer Networks" IEEE IPDPS 2015 - Workshop on Dependable Parallel, Distributed and Network-Centric Systems [**?**]
- Brendan Benshoof, Andrew Rosen, Anu G. Bourgeois, Robert W. Harrison "Distributed Decentralized Domain Name Service" IEEE IPDPS 2016 - Workshop on Dependable Parallel, Distributed and Network-Centric Systems

The following papers are in progress:

- Brendan Benshoof, Andrew Rosen, Anu G. Bourgeois, Robert W. Harrison "UrDHT: A Generalized DHT"

- Andrew Rosen, Brendan Benshoof, Robert W. Harrison, Anu G. Bourgeois "The Sybil Attack on Peer-to-Peer Networks From the Attacker's Perspective"

- Andrew Rosen, Brendan Benshoof, Robert W. Harrison, Anu G. Bourgeois "Autonomous Load Balancing in Distributed Hash Tables Using Churn and The Sybil Attack"

- Chaoyang Li, Andrew Rosen, Anu G. Bourgeois "On Minimum Camera Set Problem in Camera Sensor Networks"

Below are publications with other authors not relevant to the work discussed in this dissertation.

- Erin-Elizabeth A. Durham, Andrew Rosen, Robert W. Harrison "A Model Architecture for Big Data applications using Relational Databases" 2014 IEEE BigData - C4BD2014 - Workshop on Complexity for Big Data [**?**]

- Chinua Umoja, J.T. Torrance, Erin-Elizabeth A. Durham, Andrew Rosen, Dr. Robert Harrison "A Novel Approach to Determine Docking Locations Using Fuzzy Logic and Shape Determination" 2014 IEEE BigData - Poster and Short Paper [**?**]

- Erin-Elizabeth A. Durham, Andrew Rosen, Robert W. Harrison "Optimization of Relational Database Usage Involving Big Data" IEEE SSCI 2014 - CIDM 2014 - The IEEE Symposium Series on Computational Intelligence and Data Mining [**?**]

Chapter 2

Background

This chapter gives a broad overview of the concepts and implementations of Distributed Hash Tables (DHTs). This will provide context for our completed and future work.

DHTs have been a vibrant area of research for the past decade, with several of the concepts dating further back [**?**] [**?**] [**?**] [**?**] [**?**] [**?**] [**?**]. Numerous DHTs have been developed over the years and each of the major topologies have had multiple implementation and derivatives. This is partly because the process of designing DHTs involves making trade-offs in maintenance schemes, topology, and memory, with no choice being strictly better than any other.

In practice, only two DHTs see heavy use. Chord [**?**] is heavily favored in academia, due to it's simplicity and being once of the earlier DHTs implemented.[1] Kademlia [**?**] is used for most real-world applications, most significantly BitTorrent [**?**].

2.1 What is Needed to Define a DHT

There are a couple of ways to define what a DHT is. A distributed hash table assigns each node and data object in the network a unique key. The key corresponds to the identifier for the node or the data in question, typically IP/port combination or filename. This mapping is consistent, so that even though the keys are distributed uniformly at random, the key is always the same for the same input.

DHTs are traditionally used to form a peer-to-peer overlay network, in which the DHT defines

[1] We personally believe the ability to easily draw or visualize Chord ring is a significant factor in its popularity, but we have no means of testing this easily.

the network topology. Any member of the network can efficiently find the node that corresponds to a particular key. Data can be stored in the network and can be retrieved by finding the node that is responsible for that key.

A distributed hash table can also be thought of as a space with points (data) and Voronoi generators (nodes). A node is responsible for data that falls within its Voronoi region, which is defined by the peers closest to it. The peers that share a border for a Voronoi region are members of the node's Delaunay triangulation. Starting from any node in the network, we can find any particular node or the node responsible for a particular point in sublinear time. Regardless of the definitions, each DHT protocol needs to specify specific qualities:

Distance Metric There needs to be a way to establish how far things are from one another. Once we have a distance metric, we define what we mean when we say a node is responsible for all data *close* to it.

Closeness Definition This definition of *closeness* is essential, since it defines what a node is responsible for and who its short hops are. The definition of closeness and distance are related but different.

We shall use Chord [**?**] as an example. The distance from a to b is defined as the shortest distance around the circle in either direction. However, a node is responsible for the points between its predecessor and it. The corresponding Voronoi diagram is showing in Figure **??**.

However, say we were to use a more intuitive definition for closeness, where a node is responsible for the keys that were closer to it than any other node. In this case, we end up with the diagram in Figure **??**.

A Midpoint Definition This defines the point which is the *minimal* equidistant point between two given points.

Peer Management Strategy This is the meat of the definition of a Distributed Hash Table. The peer management strategy includes how big peerlists are, what goes in it, and how often peers are checked to see if they are still alive. This is where almost all trade-offs are made.

Surprisingly, there is no need to define a routing strategy for individual DHTs. This is because all DHTs use the same overall routing strategy: forward the message to the known node closest to

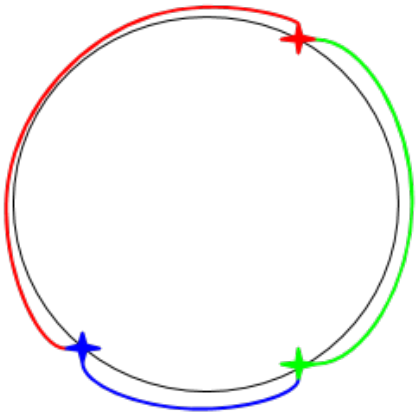


Figure 2.1: A Voronoi diagram for a Chord network, using Chord's definition of closest.

the destination. *How* routing is implemented depends on the protocol in question. Chord's routing can be implemented recursively or iteratively, while Kademlia's uses parallel iterative queries.

2.1.1 Terminology

The large number of DHTs have lead many papers to use different terms to describe congruent elements of DHTs, as some terms may make sense only in one context. Since this paper will cover multiple DHTs that use different terms, we have created a unified terminology:

key - The identifier generated by a hash function corresponding to a unique[2] node or file. SHA-1, which generates 160-bit hashes, is typically used as a hashing algorithm.[3]

ID - The ID is a key that corresponds to a particular node. The ID of a node and the node itself are referred to interchangeably. In this dissertation, we refer to nodes by their ID and files by their keys.

[2]Unique with extremely high probability. The probability of a hash collision is extremely low and are ignored in most formal specifications for DHTs. This could be resolved for any file by using any number of the collision resolution strategies, such as chaining or linear probing. However, resolving a collision of two nodes is much more problematic with no canonical solution other than praying it won't happen.

[3]Due to the research into hash collisions [**?**], and the glut of hardware that currently exists to perform SHA hash collisions, SHA1 is being depreciated by many companies in 2017. This will undoubtedly lead to some kind of security flaw in a decade or so, when some entrepreneuring hacker figures out a way to force websites to accept a forged SHA1 key.

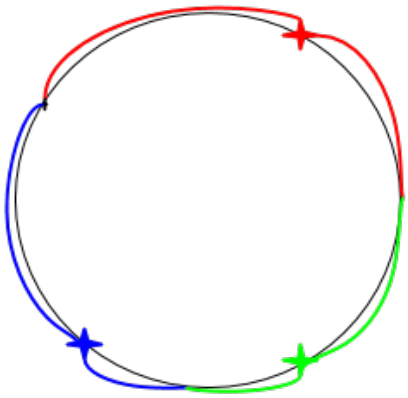


Figure 2.2: A Voronoi diagram for a Chord network, where closest is defined by the node being the closest in either direction.

Peer - Another active member on the network. For this section, we assume that all peers are different pieces of hardware.

Peerlist - The set of all peers that a node knows about. This is sometimes referred to as the *routing table*, but certain DHTs [**?**] [**?**] overload the terminology. Any table or list of peers is a subset of the entire peerlist.

Short-hops - The subset of peers that are "closest/adjacent" to the node in the keyspace, according to the DHT's metric. In a 1-dimensional ring, such a Chord [**?**], this is the node's *predecessor(s)* and *successor(s)*. They may also be called *neighbors*.

Long-hops - The subset of the peerlist that the node is not adjacent to. These are sometimes referred to as fingers, long links, or shortcuts.

Root Node - The node responsible for a particular key.

Successor - Alternate name for the root node. The successor of a node is the neighbor that will assume a nodes responsibilities if that node leaves.

n **nodes** - The number of nodes in the network.

Similarly, All DHTs perform the same operations with minor variation.

`lookup(key)` - This operation finds the root node of `key`. Almost every operation on a DHT needs to leverage the `lookup` operation in some way.

`put(key,value)` - Stores `value` at the root node of `key`. Unless otherwise specified, `key` is assumed be the hashkey of `value`. This assumption is broken in Tapestry.

`get(key)` - This operates like lookup, except the context is to return the value stored by a `put`. This is a subtle difference, since one could `lookup(key)` and ask the corresponding node directly. However, many implementations use backup operations and caching, which will store multiple copies of the value along the network. If we do not care which node returns the value mapped with `key`, or if it is a backup, we can express it with `get`.

`delete(key, value)` - This is self-explanatory. Typically, DHTs do not worry about key deletion and leave that option to the specific application. When DHTs do address the issue, they often assume that stored key-value pairs have a specified time-to-live, after which they are automatically removed.

On the local level, each node has to be able to *join* and perform maintenance on itself.

`join()` The join process encompasses two steps. First, the joining node needs to initialize its peerlist. It does not necessarily need a complete peerlist the moment it joins, but it must initialize one. Second, the joining node needs to inform other nodes of its existence.

Maintenance Maintenance procedures generally are either *active* or *lazy*. In active maintenance, peers are periodically pinged and are replaced when they are no longer detected. Lazy maintenance assumes that peers in the peerlist are healthy until they prove otherwise, in which case they are either replaced immediately. In general, lazy maintenance is used on everything, while active maintenance is only used on neighbors[4].

When analyzing the DHTs in this chapter, we look at the overlay's geometry, the peerlist, the `lookup` function, and how fault-tolerance is performed in the DHTs. We assume that nodes never politely leave the network but always abruptly fail, since a `leave()` operation is fairly trivial and has minimal impact.

[4]check this statement for consistency

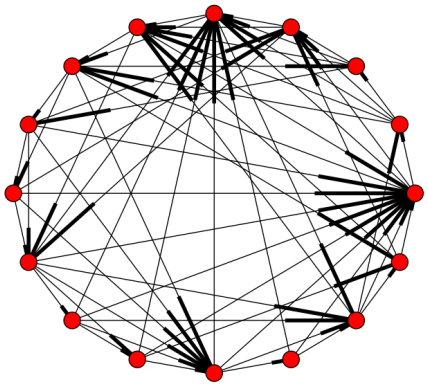


Figure 2.3: A Chord ring with 16 nodes. The fingers (long hop connections) are shown cutting across the ring.

2.2 Chord

Chord [**?**] is the archetypal ring-based DHT and it is impossible to create a new ring-based DHT without making some comparison to Chord. It is notable due its straightforward routing, its rules which make ownership of keys very easy to sort out, and the large number of derivatives.

Chord is extremely well known in Computer Science, and was awarded the prestigious 2011 SIGCOMM Test of Time Award. However, recent research has demonstrated that there have been no correct implementations of Chord in over a decade, and many of the properties Chord claimed to be invariants could break under certain trivial conditions [**?**].

Peerlist and Geometry

Chord is a 1-dimensional modular ring in which all messages travel in one direction - upstream, hopping from one node to another node with a greater ID until it wraps around. Each member of the network and the data stored within it is hashed to a unique m-bit key or ID, corresponding to one of the 2^m locations on a ring. An example Chord network is shown in Figure **??**.

A node in the network is responsible for all the data with keys upstream from its predecessor's ID, up through and including its own ID. If a node is responsible for some key, it is referred to being the root or successor of that key.

Lookup and routing is performed by recursively querying nodes upstream. Querying only neigh-

bors in this manner would take $O(n)$ time to lookup a key.

To speedup lookups, each node maintains a table of m shortcuts to other peers, called the *finger table*. The ith entry of a node n's finger table corresponds to the node that is the successor of the key $n + 2^{i-1} \mod 2^m$. During a lookup, nodes query the finger that is closest to the sought key without going past it, until it is received by the root node. Each hop essentially cuts the search space for a key in half. This provides Chord with a highly scalable $\log_2(n)$ lookup time for any key [**?**], with an average $\frac{1}{2}O(\log_2(n))$ number of hops.

Besides the finger tables, the peerlist includes a list of s neighbors in each direction for fault tolerance. This brings the total size of the peerlist to $log_2(2^m) + 2 \cdot s = m + 2 \cdot s$, assuming the entries are distinct.

Joining

To join the network, node n first asks n' to find `successor(`n`)`. Node n uses the information to set his successor, and maintenance will inform the other nodes of n's existence. Meanwhile, n will takeover some of the keys that his successor was responsible for.

Fault Tolerance

Robustness in the network is accomplished by having nodes backup their contents to their s immediate successors, the closest nodes upstream. This is done because when a node leaves the or fail, the most immediate successor would be responsible for the keys. In the case of multiple nodes failing all at once, having a successor list makes it extremely unlikely that any given stored value will be lost.

As nodes enter and leave the ring, the nodes use their maintenance procedures to guide them into the right place and repair any links with failed nodes. The process takes $O(\lg^2(n))$ messages. Full details on Chord's maintenance cycle can be found here [**?**].

2.3 Kademlia

Kademlia [**?**] is perhaps the most well known and most widely used DHT, as a modified version of Kademlia (Mainline DHT) is forms backbone of the BitTorrent protocol. The motivation of

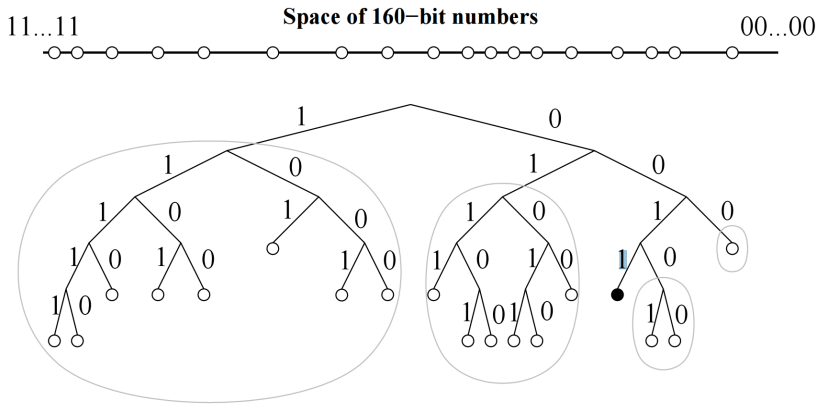


Figure 2.4: An example Kademlia network from the original paper [**?**]. The ovals are the node's k-buckets.

Kademlia was to create a way for nodes to incorporate peerlist updates with each query made.

Peerlist and Geometry

Like Chord, Kademlia uses m-bit keys for nodes and files. However, Kademlia utilizes a binary tree-based structure, with the nodes acting as the leaves of the tree. Distance between any two nodes in the tree is calculated by XORing their IDs. The XOR distance metric means that distances are symmetric, which is not the case in Chord.

Nodes in Kademlia maintain information about the network using a routing table that contains m lists, called k-buckets. For each k-bucket contains up to k nodes that are distance 2^i to 2^{i+1}, where $0 \leq i < m$. In other words, each k-bucket corresponds to a subtree of the network not containing the node. An example network is shown in Figure **??**.

Each k-bucket is maintained by a least recently seen eviction algorithm that skips live nodes. Whenever the node receives a message, it adds the sender's info to the tail of the corresponding k-bucket. If that info already exists, the info is moved to the tail.

If the k-bucket is full, the node starts pinging nodes in the list, starting at the head. As soon as a node fails to respond, that node is evicted from the list to make way for the new node at the tail.

If there are no modifications to a particular k-bucket after a long period of time, the node does a `refresh` on the k-bucket. A refresh is a `lookup` of a random key in that k-bucket.

Lookup

In most DHTs, `lookup(key)` sends a single message and returns the information of a single node. The `lookup` operation in Kademlia differs in both respects: `lookup` is done in parallel and each node receiving a `lookup(key)` returns the k closest nodes to `key` it knows about.

A `lookup(key)` operation begins with the seeking node sending lookups in parallel to the α nodes from the appropriate k-bucket. Each of theses α nodes will asynchronously return the k closest nodes it knows closest to `key`. As lookups return their results, the node continue to send lookups until no new nodes[5] are found.

Joining

A joining node starts with a single contact and then performs a *lookup* operation on its own ID. Each step of the *lookup* operation yields new nodes for the joining node's peerlist and informs other nodes of its existence. Finally, the joining node performs a `refresh` on each k-bucket farther away than the closest node it knows of.

Fault-Tolerance

Nodes actively republish each file stored on the network each hour by rerunning the `store` command. To avoid flooding the network, two optimizations are used.

First if a node receives a `store` on a file it is holding, it assumes $k - 1$ other nodes got that same command and resets the timer for that file. This means only one node republishes a file each hour. Secondly, `lookup` is not performed during a republish.

Additional fault tolerance is provided by the nature of the `store(data)` operation, which `puts` the file in the k closest nodes to the key. However, there is very little in the way of frequent and active maintenance other than what occurs during `lookup` and the other operations.

[5] If a file being stored on the network is the objective, the `lookup` will also terminate if a node reports having that file.

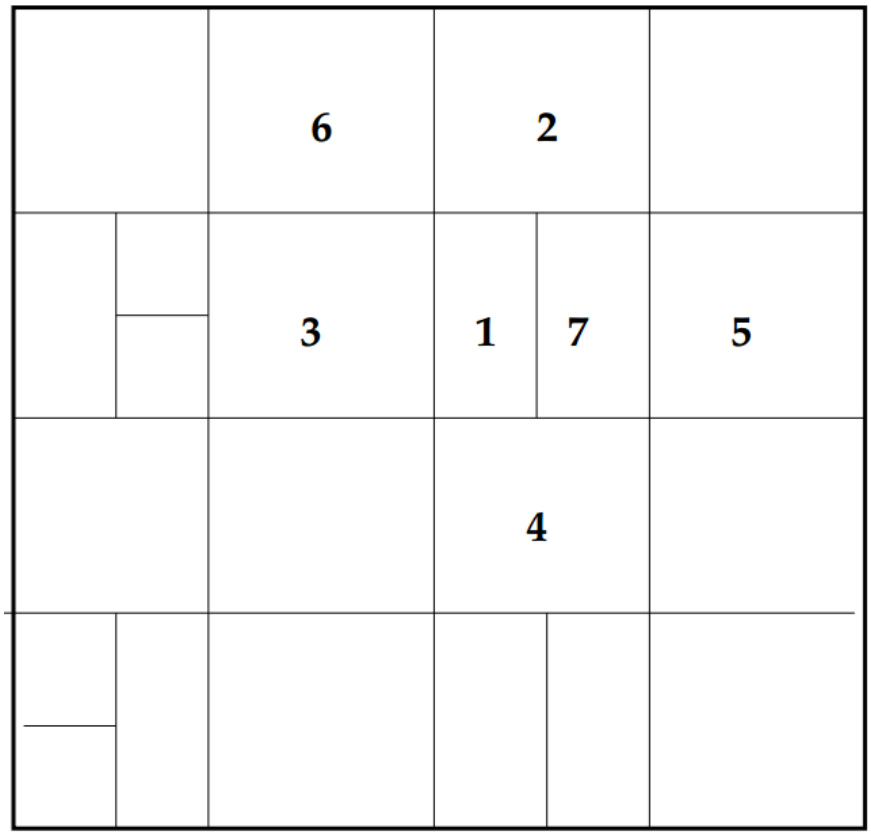


Figure 2.5: An example CAN network from [**?**].

2.4 CAN

Unlike the previous DHTs presented in this chapter, the Content Addressable Network (CAN) [**?**] works in a d-dimensional torus, with the entire coordinate space divided among members. A node is responsible for the keys that fall within the "zone" that it owns. Each key is hashed into some point within the geometric space.

Peerlist and Geometry

CAN uses an exceptionally simple peerlist consisting only of neighbors. Every node in the CAN network is assigned a geometric region in the coordinate space and each node maintains a routing table consisting each node that borders the node's region. An example CAN network is shown in Figure **??**

The size of the routing table is a function of the number of dimensions, $O(d)$. The lower bound on the routing tables size in a populated network (eg, a network with at least $2d$ nodes) is $\Omega(2d)$.

This is obtained by looking at each axis, where there is at least one node bordering each end of the axis. The size of the routing table can grow as more nodes join and the space gets further divided; however, maintenance algorithms prevent the regions from becoming too fragmented.

Lookup

As previously mentioned, each node maintains a routing table corresponding to their neighbors, those nodes it shares a face with. Each hop forwards the lookup to the neighbor closest to the destination, until it comes to the responsible node. In a space that is evenly divided among n nodes, this simple routing scheme uses only $2 \cdot d$ space while giving average path length of $\frac{d}{4} \cdot n^{\frac{1}{d}}$. The overall lookup time of in CAN is bounded by $O(n^{\frac{1}{d}})$ hops[6].

If a node encounters a failure during lookup, the node simply chooses the next best path. However, if lookups occur before a node can recover from damage inflicted by churn, it is possible for the greedy lookup to fail. The fallback method is to use an expanding ring search until a candidate is found, which recommences greedy forwarding.

Joining

Joining works by splitting the geometric space between nodes. If node n with location P wishes to join the network, it contacts a member of the node to find the node m currently responsible for location P. Node n informs m that it is joining and they divide m's region such that each becomes responsible for half.

Once the new zones have been defined, n and m create its routing table from m and its former neighbors. These nodes are then informed of the changes that just occurred and update their tables. As a result, the join operation affects only $O(d)$ nodes. More details on this splitting process can be found in CAN's original paper [**?**].

Repairing

A node in a DHT that notifies its neighbors that its leaves usually has minimal impact to the network and in this is true for most cases in CAN. A leaving node, f, simply hands over its zone

[6] Around the same time CAN was being developed, Kleinberg was doing research into small world networks [**?**]. He proved similar properties for lattice networks with a single shortcut. What makes this network remarkable is lack of shortcuts.

to one of its neighbors of the same size, which merges the two zones together. Minor complications occur if this is not possible, when there is no equally-sized neighbor. In this case, f hands its zone to its smallest neighbor, who must wait for this fragmentation to be fixed.

Unplanned failures are also relatively simple to deal with. Each node broadcasts a heartbeat to its neighbors, containing its and its neighbors' coordinates. If a node fails to hear a heartbeat from f after a number of cycles, it assumes f must have failed and begins a `takeover` countdown. When this countdown ends, the node broadcasts[7] a `takeover` message in an attempt to claim f's space. This message contains the node's volume. When a node receives a `takeover` message, it either cancels the countdown or, if the node's zone is smaller than the broadcaster's, responds with its own `takeover`.

The general rule of thumb for node failures in CAN is that the neighbor with the smallest zone takes over the zone of the failed node. This rule leads to quick recoveries that affect only $O(d)$ nodes, but requires a zone reassignment algorithm to remove the fragmentation that occurs from `takeovers`.

To summarize, a failed node is detected almost immediately, and recovery occurs extremely quickly, but fragmentation must be fixed by a maintenance algorithm.

2.5 Pastry

Pastry [**?**] and Tapestry [**?**] are extremely similar use a prefix-based routing mechnism introduced by Plaxton et al. [**?**]. In Pastry and Tapestry, each key is encoded as a base 2^b number (typically $b = 4$ in Pastry, which yields easily readable hexadecimal). The resulting peerlist best resembles a hypercube topology [**?**], with each node being a vertice of the hypercube.

One notable feature of Pastry is the incorperation of a proximity metric. The peerlist uses IDs that are close to the node according to this metric.

Peerlist

Pastry's peerlist consists of three components: the routing table, a leaf set, and a neighborhood set. The routing table consists of $\log_{2^b}(n)$ rows with $2^b - 1$ entries per row. The ith level of the

[7] This message is sent to all of f's neighbors.

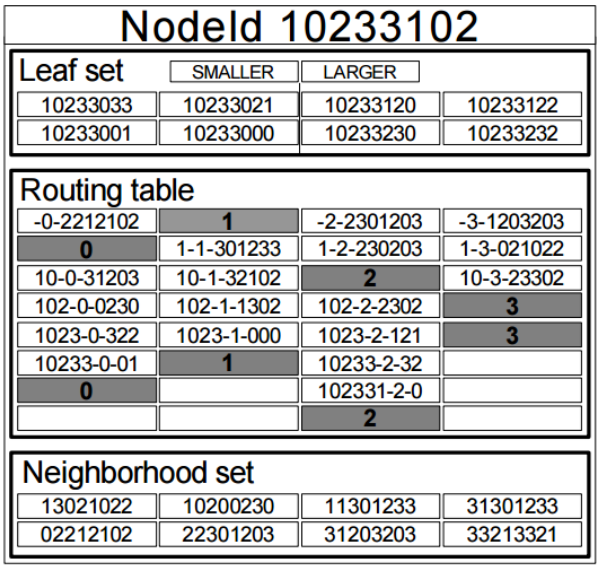


Figure 2.6: An example peerlist for a node in Pastry [**?**].

routing table correspond to the peers with that match first i digits of the example nodes ID.

Thus, the 0th row contains peers which don't share a common prefix with the node, the 1st row contains those that share a length 1 common prefix, the 2nd a length 2 common prefix, etc. Since each ID is a base 2^b number, there is one entry for each of the $2^b - 1$ possible differences.

For example, let is consider a node 05AF in system where $b = 4$ and the hexadecimal keyspace ranges from 0000 to FFFF.

- 1322 would be an appropriate peer for the 1st entry of level 0.
- 0AF2 would be an appropriate peer for the 10th[8] entry of level 1.
- 09AA would be an appropriate peer for the 9th entry of level 1.
- 05F2 would be an appropriate peer for the 2nd entry of level 3.

The leaf set is used to hold the L nodes with the numerically closest IDs; half of it for smaller IDs and half for the larger. A typical value for L is 2^b or 2^{b+1}. The leaf set is used for routing when the destination key is close to the current node's ID. The neighborhood set contains the L closest nodes, as defined by some proximity metric. It, however, is generally not used for routing. Figure **??** shows an example peerlist of a node in PAST.

[8] 0 is the 0th level.

Lookup

The `lookup` operation is a fairly straightforward recursive operation. The `lookup(key)` terminates when the `key` is falls within the range of the leaf set, which are the nodes *numerically* closest to the current node. In this case, the destination will be one of the leaf set, or the current node.

If the destination node is not immediately apparent, the node uses its routing table to select the next node. The node looks at the length l shared prefix, at examines the lth row of its routing table. From this row, the `lookup` continues with the entry that matches at least another digit of the prefix. In the case that this entry does not exist or has failed, the `lookup` continues from the closest ID chosen from the entire peerlist. This process is described by Algorithm **??**. Lookup is expected to take $\lceil \log_{2^b} \rceil$, as each hop along the routing table reduces the search space by $\frac{1}{2^b}$.

Algorithm 1 Pastry lookup algorithm

```
Let L be the routing
function LOOKUP(key)
    if key is in the range of the leaf set  then
        destination is closest ID in the leaf set or self
    else
        next ← entry from routing table that matches ≥ 1 more digit
        if next ≠ null then
            forward to next
        else
            forward to the closest ID from the entire peerlist
        end if
    end if
end function
```

Joining

To join the network, node J sends a `join` message to A, some node that is close according to the proximity metric. The `join` message is forwarded along like a `lookup` to the root of X, which we'll call *root*. Each node that received the `join` sends a copy of the their peerlist to J.

The leaf set is constructed from copying *root*'s leaf set, while ith row in the routing table routing table is copied from the ith node contacted along the `join`. The neighborhood set is copied from A's neighborhood set, as `join` predicates that A be close to J. This means A's neighborhood set would be close to A.

After the joining node creates its peerlist, it sends a copy to each node in the table, who then can update their routing tables. The cost of a `join` is $O(log_2^b n)$ messages, with a constant coefficient of $3 * 2^b$

Fault Tolerance

Pastry lazily repairs its leaf set and routing table. When node from the leaf set fails, the node contacts the node with largest or smallest ID (depending if the failed node ID was smaller or larger respectively) in the leaf set. That node returns a copy of its leaf set, and the node replaces the failed entry. If the failed node is in the routing table, the node contacts a node with an entry in the same row as the failed node for a replacement.

Members of the neighborhood set are actively checked. If a member of the neighborhood set is unresponsive, the node obtains a copy of another entry's neighborhood set and repairs from a selection.

2.6 Symphony and Small World Routing

Symphony [**?**] is a $1d$ ring-based DHT similar to Chord [**?**], but is constructed using the properties of small world networks [**?**]. Small world networks owe their name to a phenomena observed by psychologists in the late 1960's.

Subjects in experiments were to route a postal message to a target person; for example the wife of a Cambridge divinity student in one experiment and a Boston stockbroker in another [**?**]. The messages were only to be routed by forwarding them to a friend they thought most likely to know the target. Of the messages that successfully made their way to the destination, the average path length from a subject to a participant was only 5 hops.

This lead to research investigating creating a network with randomly distributed links, but with a efficient lookup time. Kleinberg [**?**] showed that in a 2-dimensional lattice network, nodes could route messages in $O(\log^2 n)$ hops using only their neighbors and a single randomly chosen[9] finger. In other words, $O(\log^2 n)$ lookup is achievable with a $O(1)$ sized routing table.

[9]Randomly chosen from a specified distribution.

Peerlist

Rather than the 2-dimensional lattice used by Kleinberg, Symphony uses a 1-dimensional ring[10] like Chord. Symphony assigns m-bit keys to the modular unit interval $[0, 1)$, instead of using a keyspace ranging from 0 to $2^n - 1$. This location is found with $\frac{hashkey}{2^m}$. This is arbitrary from a design standpoint, but makes choosing from a random distribution simpler.

Nodes know both their immediate predecessor and successor, much like in Chord. Nodes also keep track of some $k \geq 1$ fingers, but, unlike in Chord, these fingers are chosen at random. These fingers are chosen from a probability distribution corresponding to the expression $e^{ln(n)+(rand48()-1.0)}$, where n is the number of nodes in the network and `rand48()` is a C function that generates a random float?double between 0.0 and 1.0. Because n os difficult to compute due to the changing nature of P2P networks, each node uses an approximation is used based on the distance between themselves and their neighbors.

A final feature of note is that links in Symphony are bidirectional. Thus, if a node creates a finger to a peer, that peer creates a, so nodes in Symphony have a grand total of $2k$ fingers.

Joining and Fault Tolerance

The joining and fault tolerance processes in Symphony are extremely straightforward. After determining its ID, a joining node asks a member to find the root node for its ID. The joining node integrates itself in between its predecessor and successor and then randomly generates its fingers.

Failures of immediate neighbors are handled by use of successor and predecessor lists Failures for fingers are handled lazily and are replaced by another randomly generated link when a failure is detected.

2.7 ZHT

One of the major assumptions of DHT design is that churn is a significant factor, which requires constant maintenance to handle. A consequence of this assumption is that nodes only store a small subset of the entire network to route to. Storing the entire network is not scalable for the

[10]This is technically a 1-dimensional lattice.

vast majority of distributed systems due to bandwidth constraints and communication overhead incurred by the constant joining and leaving of nodes.

In a system that does not expect churn, the memory and bandwidth costs for each node to keep a full copy of the routing table are minimal. An example of this would be a data center or a cluster built for higher-performance computing, where churn would overwhelmingly be the result of hardware failure, rather than users quitting.

ZHT [**?**] is an example of such a system, as is Amazon's Dynamo [**?**]. ZHT is a "zero-hop hash table," which takes advantage of the fact that nodes in High-End Computing environments have a predictable lifetime. Nodes are created when a job begins and are removed when a job ends. This property allows ZHT to `lookup` in $O(1)$ time.

Peerlist

ZHT operates in a 64-bit ring, for a total of $N = 2^{64}$ addresses. ZHT places a hard limit of n on the maximum number of physical nodes in the network, which means the network has n partitions of $\frac{N}{n} = \frac{2^{64}}{n}$ keys. The partitions are evenly divided along the network.

The network consists of k physical nodes which each are running at least one instance (virtual nodes) of ZHT, with a combined total of i . Each instance is responsible for some span of partitions in the ring.

Each node maintains a complete list of all nodes in the network, which do not have to be updated very often due to the lack of or very low levels of churn. The memory cost is extremely low. Each instance has a 10MB footprint, and each entry for the membership table takes only 32 bytes per node. This means routing takes anywhere between 0 to 2 hops (explained below).

Joining

ZHT operates under a static or dynamic membership. In a static membership, no nodes will be joining the network once the network has been bootstrapped. Nodes can join at any time when ZHT is using dynamic membership.

To join, the joiner asks a random member for a copy of the peerlist The joiner can then determine which node is the most heavily overloaded. The joiner chooses an address in the network to take over partitions from that node.

Fault Tolerance

Fault tolerance exists to handle only hardware failure or planned departures from the network. Nodes backup their data to their neighbors.

2.8 Summary

We have seen that there are a wide variety of distributed hash tables, but they have some clearly defined characteristics that bind them all together. Table **??** summarizes the information presented in this chapter.

DHT	Routing Table Size	Lookup Time	Join/Leave	Comments
Chord [**?**]	$O(\log n)$, maximum $m + 2s$	$O(\log n)$, avg $(\frac{1}{2}\log n)$	$< O(\log n^2)$ total messages	m = keysize in bits, s is neighbors in 1 direction
Kademlia [**?**]	$O(\log n)$, maximum $m \cdot k$	$(\lceil \log n \rceil) + c$	$O(\log(n))$	This is without considering optimization
CAN [**?**]	$\Omega(2d)$	$O(n^{\frac{1}{d}})$, average $\frac{d}{4} \cdot n^{\frac{1}{d}}$	Affects $O(d)$ nodes	d is the number of dimensions
Plaxton-based DHTs, Pastry [**?**], Tapestry [**?**]	$O(\log_\beta n)$	$O(\lceil \log_{2^\beta} \rceil)$	$O(\log_\beta n)$	NodeIDs are base β numbers
Symphony [**?**]	$2k + 2$	average $O(\frac{1}{k}\log^2 n)$	$O(\log^2 n)$ messages, constant < 1	$k \geq 1$, fingers are chosen at random
ZHT [**?**]	$O(n)$	$O(1)$	$O(n)$	Assumes an extremely low churn
VHash	$\Omega(3d+1) + O((3d+1)^2)$	$O(\sqrt[d]{n})$ hops	$3d + 1$	approximates regions, hops are based least latency

Table 2.1: A comparison of and summary of the various DHTs.

Chapter 3

ChordReduce

Distributed computing is a current trend and will continue to be the approach for intensive applications. We see this in the development of cloud computing [**?**], volunteer computing frameworks like BOINC [**?**] and Folding@Home [**?**], and MapReduce [**?**]. Google's MapReduce in particular has rapidly become an integral part in the world of data processing. A user can use MapReduce to take a large problem, split it into small, equivalent tasks and send those tasks to other processors for computation. The results are sent back to the user and combined into one answer.

Popular platforms for MapReduce, such as Hadoop [**?**] [**?**], are explicitly designed to be used in large datacenters [**?**] and the majority of research has been focused there. However, as we have previously mentioned, there are notable issues with a centralized design.

First and foremost is the issue of fault-tolerance. Centralized designs have a single point of failure [**?**]. So long as all computing resources are located in one geographical area or rely on a particular node, a power outage or catastrophic event could interrupt computations or otherwise disrupt the platform [**?**].

A centralized design assumes that the network is relatively unchanging and may not have mechanisms to handle node failure during execution or, conversely, cannot speed up the execution of a job by adding additional workers on the fly. Many environments also anticipate a certain degree in homogeneity in the system. Finally deploying these systems and developing programs for them has an extremely steep learning curve.

There is no reason that these assumptions need to be the case for MapReduce, or for many distributed computing frameworks in general. Moving away from the data center context opens up

more possibilities for distributed computing, such as P2P clouds [**?**]. However, without a centralized framework, the network needs some kind of protocol to organize the various components in the network. As part of our research, we developed a highly robust and distributed MapReduce framework based on Chord, called ChordReduce [**?**].

It is a system that can scale, is fault tolerant, has a minimal amount of latency, and distributes tasks evenly. ChordReduce leverages the underlying protocol from Chord [**?**] to distribute Map and Reduce tasks to nodes evenly, provide greater data redundancy, and guarantee a greater amount of fault tolerance. Rather than viewing Chord solely as a means for sharing files, we see it as a means for distributing work. We established the effectiveness of using Chord as a framework for distributed programming. At the same time we avoid the architectural and file system constraints of systems like Hadoop.

3.1 Background

ChordReduce takes its name from the two components it is built upon. Chord [**?**] provides the backbone for the network and the file system, providing scalable routing, distributed storage, and fault-tolerance. MapReduce runs on top of the Chord network and utilizes the underlying features of the distributed hash table. This section provides an extensive and expanded background on Chord and MapReduce.

3.1.1 Chord

We introduced Chord in Chapter **??**, but we present it here again in greater depth. Chord [**?**] is a P2P protocol for file sharing that uses a hash function to assign addresses to nodes and files for a ring overlay. The Chord protocol takes in some key and returns the identity (ID) of the node responsible for that key.

As we have mentioned discussed in Chapter **??**, these keys can be generated by hashing a value of the node, such as the IP address and port, or by hashing the filename of a file. The hashing process creates a m-bit hash identifier.

The nodes are then arranged in a ring from the lowest hash-value to highest. Chord takes the files and places each in the node that has the same hashed identifier as it. If no such node exists,

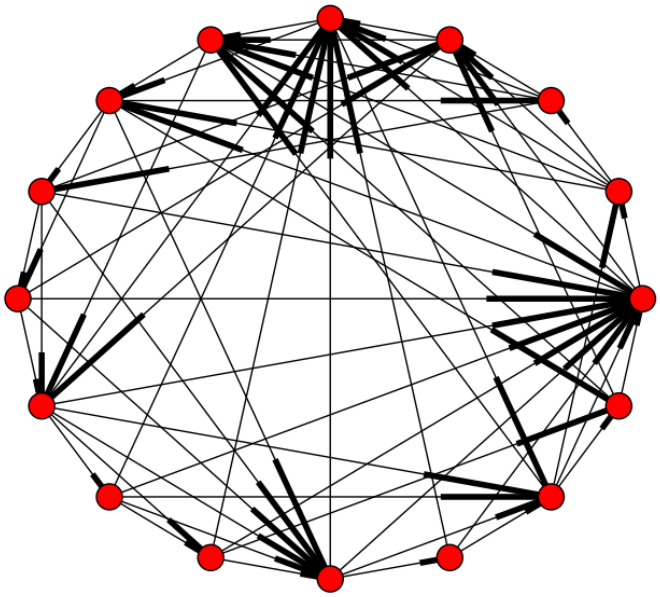


Figure 3.1: A Chord ring with 16 nodes. The bold lines are incoming edges. Each node has a connection to its successor, as well as 4 fingers, some of which are duplicates.

the node with the first identifier that follows this value is selected. Since the overlay is a circle, this assignment is computed in modulo 2^m space.

The node responsible for the key κ is called the *successor* of κ, or $successor(\kappa)$. For example, if there were some portion of the network with nodes 20, 25, and 27, node 25 would be responsible for the files with the keys (21,22,23,24,25). If node 25 were to decide to leave the network, its absence would be detected by node 27, who would then be responsible for all the keys node 25 was covering, in addition to its own keys.

With this scheme, we can reliably find the node responsible for some key by asking the next node in the circle for the information, who would then pass the request through the circle until the successor was found. We can then proceed to directly connect with the successor to retrieve the file. This naive approach is largely inefficient, and is a simplification of the lookup process, but it is the basis of how Chord theoretically works.

To speed up the lookup time, each node builds and maintains a *finger table*. The *finger table* contains the locations of up to m other nodes in the ring. The ith entry of node n's *finger table*

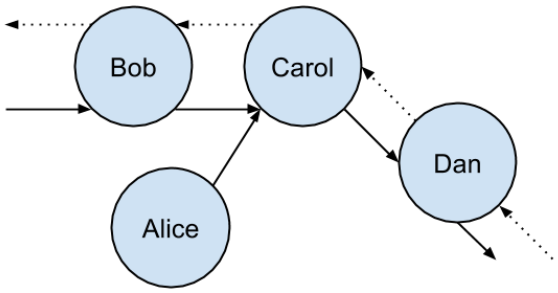


Figure 3.2: Alice has incorrectly determined that Carol is her appropriate successor. When Alice stabilizes, Carol will let her know about Bob.

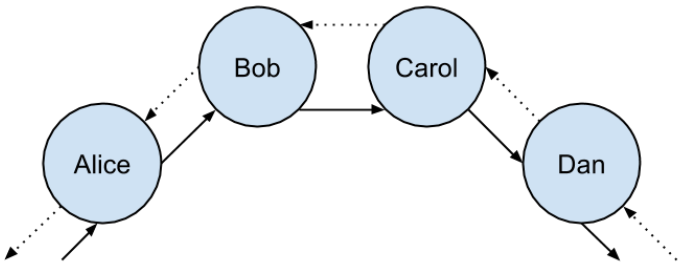


Figure 3.3: After completing stabilize, Alice makes Bob her successor and notifies him. Bob then made Alice as his predecessor.

corresponds to the node that is the $successor(n + 2^{i-1})$ mod 2^m. Hash values are not perfectly distributed, it is possible to have duplicate entries in the *finger table*. An example Chord network with fingers is shown in in Fig. **??**.

When a node n is told to find some key, n looks to see if the key is between n and $successor(n)$ and return $successor(n)$'s information to the requester. If not, it looks for the entry in the finger table for the closest preceding node n' it knows and asks n' to find the successor. This allows each step to skip up to half the nodes in the network, giving a $\log_2(n)$ lookup time. Because nodes can constantly join and leave the network, each entry in the table is periodically checked and updated during a finger maintenance period.

To join the network, node n first asks n' to find $successor(n)$ for it. Node n uses the information to set his successor, but the other nodes in the ring will not acknowledge n's presence yet. Node n relies on the stabilize routine to fully integrate into the ring.

The stabilize routine helps the network integrate new nodes and route around nodes who have left the network. Each node periodically checks to see who their successor's predecessor is. In the

case of a static network, this would be the checking node. However, if the checking node gets back a different node, it looks at that returned node's ID and changes its own successor if needed.

Regardless of whether the checking node changes its successor, that node then notifies the (possibly) new successor, who then checks if he needs to change his predecessor based on this new information. While complex, the stabilization process is no more expensive than a heartbeat function. A more concrete example:

Suppose Alice, Bob, Carol, and Dan are members of the ring and everyone is ordered alphabetically (Fig. **??**). Alice is quite sure that Carol is her successor. Alice asks Carol who her predecessor is and Carol says Bob is. Since Bob is closer to Alice than Carol, Alice changes her successor to Bob and notifies him.

When Bob sees that notification, he can see Alice is closer than whoever his previous predecessor is and sets Alice to be his predecessor. During the next stabilization cycle, Alice will see that she is still Bob's predecessor and notify him that she's still there (Fig. **??**).

To prevent loss of data due to churn, each node sends a backup of their data to their successor, or multiple successors upstream. Section **??** discusses the implementation of the backup process in ChordReduce and expands upon it for backing up Map and Reduce tasks.

3.1.2 Extensions of Chord

The Cooperative File System (CFS) is an anonymous, distributed file sharing system built on top of Chord [**?**]. In CFS, rather than storing an entire file at a single node, the file is split up into multiple chunks around 10 kilobytes in size. These chunks are each assigned a hash and stored in nodes corresponding to their hash in the same way that whole files are. The node that would normally store the whole file instead stores a *key block*, which holds the hash address of the chunks of the file.

The chunking allows for numerous advantages. First, it promotes load balancing. Each piece of the overall file would (ideally) be stored in a different node, each with a different backup or backups. This would prevent any single node from becoming overwhelmed from fulfilling multiple requests for a large file. It would also prevent retrieval from being bottlenecked by a node with a relatively low bandwidth. Finally, when Chord uses some sort of caching scheme like that described in CFS [**?**], caching chunks as opposed to the entire file resulted in about 1000 times less storage

overhead.

Mutable files and IRM, which is short for Integrated File Replication and Consistency Maintenance [**?**], has nodes keep track of file requests they initiate or forward. If nodes find they are frequently forwarding a request for a particular file, they store that file locally until it is no longer requested frequently.

Chunking also opens up the options for implementing additional redundancy such as erasure codes [**?**]. With erasure codes, redundant chunks are created but any combination of a particular number of chunks is sufficient to recreate the file. For example, a file that would normally be split into 10 chunks might be split into 15 encoded chunks. The retrieval of any 10 of those 15 chunks is enough to recreate the file. Implementing erasure codes would presumably make a DHT more fault tolerant, but that is an exercise left for future work.

Generally, related files should be kept together for quick retrieval; Chord, however, just hashes the filename to find the responsible node and sends it to that location without any thought to organization. One solution to this is to use allow the file owner to select the first β bits of a file's hash, then generating the remaining least significant bits by hashing the filename. It does not matter if a file owner, in some infinitesimally small coincidence, chooses the same β bit prefix as another file owner, as the purpose is to keep related files together.

3.1.3 MapReduce

At its core, MapReduce [**?**] is a system for division of labor, providing a layer of separation between the programmer and the more complicated parts of concurrent processing. The programmer sends a large task to a master node, who then divides that task among slave nodes (which may further divide the task). This task has two distinct parts: Map and Reduce. Map performs some operation on a set of data and then produces a result for each Map operation. The resulting data can then be reduced, combining these sets of results into a single set, which is further combined with other sets. This process continues until one set of data remains. A core concept here is the tasks are distributed to the nodes that already contain the relevant data, rather than the data and task being distributed together among arbitrary nodes.

The archetypal example of using MapReduce is WordCount – the task of counting the occurrence of each word in a collection of documents. These documents have been split up into blocks and

stored on the network over the distributed file system. The master node locates the worker nodes with blocks and sends the Map and Reduce tasks associated with WordCount. Each worker then goes through their blocks and creates a small word frequency list. These lists are then used by other workers, who combine them into larger and larger lists, until the master node is left with a word frequency list of all the words in the documents.

The most popular platform for MapReduce is Hadoop [**?**]. Hadoop is an open-source Java implementation developed by Apache and Yahoo! [**?**]. Hadoop has two components, the Hadoop Distributed File System (HDFS) [**?**] and the Hadoop MapReduce Framework [**?**]. Under HDFS, nodes are arranged in a hierarchical tree, with a master node, called the NameNode, at the top. The NameNode's job is to organize and distribute information to the slave nodes, called DataNodes. This makes the NameNode a single point of failure [**?**] in the network, as well as a potential bottleneck for the system [**?**].

To do work on Hadoop, the user stores their data on the network. This is handled by the NameNode, which equally apportions the data among the DataNodes. When a user wants to run some analysis on the data or some subset the data, then that function is sent by the NameNode to each of the DataNodes that is responsible for the indicated data. After the DataNode finishes processing, the result is handled by other nodes called Reducers which collect and reduce the results of multiple DataNodes.

3.2 Related Work

We have identified two papers that focus on combining P2P concepts with MapReduce. Both papers are similar to our research, but differ in crucial ways, as described below.

3.2.1 P2P-MapReduce

Marozzo et al. [**?**] investigated the issue of fault tolerance in centralized MapReduce architectures such as Hadoop. They focused on creating a new P2P based MapReduce architecture built on JXTA [**?**] called P2P-MapReduce. P2P-MapReduce is designed to be more robust at handling node and job failures during execution.

Rather than use a single master node, P2P-MapReduce employs multiple master nodes, each

responsible for some job. If one of those master nodes fails, another will be ready as a backup to take its place and manage the slave nodes assigned to that job. This avoids the single point of failure that Hadoop is vulnerable to. Failures of the slave nodes are handled by the master node responsible for it.

Experimental results were gathered via simulation and compared P2P-MapReduce to a centralized framework. Their results showed that while P2P-MapReduce generated an order of magnitude more messages than a centralized approach, the difference rapidly began to shrink at higher rates of churn. When looking at actual amounts of data being passed around the network, the bandwidth required by the centralized approach greatly increased as a function of churn, while the distributed approach again remained relatively static in terms of increased bandwidth usage.

They concluded that P2P-MapReduce would, in general, use more network resources than a centralized approach. However, this was an acceptable cost as the P2P-MapReduce would lose less time from node and job failures [**?**].

While P2P-MapReduce is decentralized, it still relies on a very definite master/slave hierarchy for organization, computations, and scaling. During simulation, 1% of the entire network was assigned as master nodes. This means for a simulation of 40000 nodes, 400 were required to organize and coordinate jobs, rendering them unable to do any processing. In addition, a loosely-consistent Distributed Hash Table (DHT) such as JXTA can be much slower and fails to maintain the same level of guarantees as an actual DHT, such as Chord [**?**].

3.2.2 MapReduce using Symphony

Lee et al.'s work [**?**] draws attention to the fact that a P2P network can be much more than a way to distribute files and demonstrates how to accomplish different tasks using Map and Reduce functions over a P2P network. Rather than using Chord, Lee et al. used Symphony [**?**], another DHT protocol with a ring topology. To run a MapReduce job over the Symphony ring, a node is selected by the user to effectively act as the master. This ad-hoc master then performs a bounded broadcast over a subsection the ring. Each node repeats this broadcast over a subsection of that subsection, resulting in a tree with the first node at the top. Map tasks are disseminated evenly throughout the tree and their results are reduced on the way back up to the ad-hoc master node. This allows the ring to disseminate Map and Reduce tasks without the need for a coordinator

responsible for distributing these tasks and keeping track of them, unlike Hadoop.

Their experimental results showed that the latency experienced by a centralized configuration is similar to the latency experienced in a completely distributed framework. However, there are no mechanisms in place to handle churn in the network. If a node joins during a MapReduce job, it will be unable to contribute any of its resources to the problem. If a node in the bounded broadcast tree fails, or worse the ad-hoc master node fails, the data that node is responsible for is lost.

3.3 ChordReduce

Marozzo et al. [**?**] shows that adding additional fault-tolerance features to a MapReduce architecture is worth the added cost of maintenance, as the time lost due to node failures is greatly reduced. However, Marozzo et al. do not explore the benefits of leveraging the properties of a P2P protocol to reduce the complexity of the architecture and completely distribute the responsibility of the task across the network. As a result, P2P-MapReduce still relies on a ratio of masters to slaves to coordinate and organize the network, meaning a percentage of the network is unable to contribute processing power to the actual solving of a problem.

Lee et al. [**?**] explores the benefits of building a MapReduce module to run on top of Symphony [**?**], a P2P protocol. Unlike Hadoop, this allows the MapReduce tasks to be executed without the need of a central source of coordination by distributing tasks over a bounded broadcast tree created at runtime. The Symphony based MapReduce architecture would be greatly improved by the addition of components to handle the failure of nodes during execution. As it stands now, if a node crashes the job will fail due to the loss of data.

While both of these papers have promising results and confirm the capability of our own framework, both solely look at P2P networks for the purpose of routing data and organizing the network. Neither examines using a P2P network as a means of efficiently distributing responsibility throughout the network and using existing features to add robustness to nodes working on Map and Reduce tasks.

ChordReduce uses Chord to act as a completely distributed topology for MapReduce, negating the need to assign any explicit roles to nodes or have a scheduler or coordinator. ChordReduce does not need to assign specific nodes the task of backing up work; nodes backup their tasks using

the same process that would be used for any other data being sent around the ring. Finally, results work their way back to a specified hash address, rather than a specific hash node, eliminating any single point of failure in the network. These features help prevent a bottleneck from occurring. The result is a simple, distributed, and highly robust architecture for MapReduce.

3.3.1 Handling Node Failures in Chord

Due to the potentially volatile nature of a peer-to-peer network, Chord has to be able to handle (or at the very least, tolerate) an arbitrary amount of churn. Section **??** described how Chord gradually guides nodes into their correct locations after they join the network. The same is true for when a node leaves the network; the stabilize procedure will guide nodes to their correct successors and predecessors. However, we can exert more control over how to handle nodes leaving the network.

When a node n changes his successor, n asks if the successor is holding any data n should be responsible for. The successor looks at all the data n is responsible for and sends it to n. The successor does not have to delete this data. In fact, keeping this data as a backup is beneficial to the network as a whole, as n could decide to leave the network at any point.

Chord specifies two ways a node can leave the ring. A node can either suddenly drop out of existence, or a node can tell the network he is about to leave, letting his successor and predecessor immediately perform the needed changes.

When a node politely quits, he informs both his successor and predecessor and gives them all the information they need to fill the resulting gap. He also sends all of the data he is responsible for to his successor, who becomes responsible for that data when the node leaves. Fingers that pointed to that node would be corrected during the finger maintenance period. This allows for the network to adjust to churn with a minimum of overhead.

It is unlikely that every time a node leaves the network, it will do so politely. If a node suddenly quits, the data it had stored is lost. To prevent data from becoming irretrievable, a node periodically sends backups to its successor. In order to prevent a cascade of backups of backups, the node only passes along what it considers itself responsible for. What a node is responsible for changes as nodes enter and leave the network. If a node's successor leaves, the node sends a backup to his new successor.

Our prototype framework does not implement a polite disconnect; when a node quits, it does

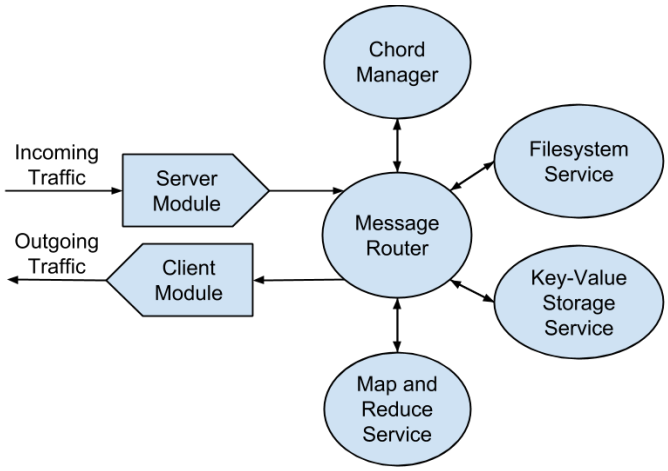


Figure 3.4: The basic architecture of a node in ChordReduce. MapReduce runs as a service on top of each node.

so quickly and abruptly. This design ensures that the system would be able to handle churn under the worst of cases. Polite quit could be implemented quite easily.

3.3.2 Implementation

ChordReduce is a fully functional Chord implementation in Python. Our installation was designed to be as simple as possible. It consists of downloading our code [**?**] and running `chord.py`. A user can specify a port and IP of a node in the ring they wish to join. The node will automatically integrate into the ring with this minimal information. The ring as implemented is stable and well organized. We created various services to run on top the network, such as a file system and distributed web server. Our file system is capable of storing whole files or splitting the file up among multiple nodes the ring. Our MapReduce module is a service that runs on top of our Chord implementation, similar to the file system (Fig. **??**). We avoided any complicated additions to the Chord architecture; instead we used the protocol's properties to create the features we desired in our MapReduce framework.

In our implementation of MapReduce, each node takes on responsibilities of both a worker and master, much in the same way that a node in a P2P file-sharing service will act as both a client and a server. Jobs still must start from a single location. To start a job, the user contacts a node at a specified hash address and provides it with the tasks and data. This address can be chosen arbitrarily or be a known node in the ring. The node at this hash address is designated as the

stager.

The job of this stager is to take the work and divide it into *data atoms*, which are the smallest individual units that work can be done on. This might be a line of text in a document, the result of a summation for a particular intermediate value, or a subset of items to be sorted. The specifics of how to divide the work are defined by the user in a *stage* function. The data atoms are then each given a random hash and sent to the node responsible for that hash address, guaranteeing they are evenly distributed throughout the network. The data atoms also contain the Map function and Reduce function as defined by the user. A job ID is also included, so that data atoms from different jobs can be differentiated. Once the data atoms are sent out, the stager's job is done and it behaves like any other node in the network. The staging period is the only time ChordReduce is vulnerable to churn, and only if the stager leaves the ring in the middle of sending out data atoms. The user would get some results back, but only for the data the stager managed to send out.

Nodes that receive data atoms apply the Map function to the data to create result data atoms, which are then sent back to the stager's hash address (or some other user defined address). This will take $\log_2 n$ hops traveling over Chord's fingers. At each hop, the node waits a predetermined minimal amount of time to accumulate additional results (In our experiments, this was 100 milliseconds).

Nodes that receive at least two results merge them using the Reduce function. The results are continually merged until only one remains at the hash address of the stager.

Once the reductions are finished, the user retrieves his results from the node at the stager's address. This may not be the stager himself, as the stager may no longer be in the network. The stager does not need to collect the results himself, since the work is sent to the stager's hash address, rather than the stager itself. Thus, the stager could quit the network after staging, and both the user and the network would be unaffected by the change.

Similar precautions are taken for nodes working on Map and Reduce tasks. Those tasks are backed up by a node's successor, who will run the task if the node leaves before finishing its work (e.g. the successor loses his predecessor). The task is given a timeout by the node. If the backup node detects that the responsible node has failed, he starts the work and backs up again to *his* successor. Otherwise, the data is tossed away once the timeout expires. This is done to prevent a job being submitted twice.

An advantage of our system is the ease of development and deployment. The developer does not need to worry about distributing work evenly, nor does he have to worry about any node in the network going down. The stager does not need to keep track of the status of the network. The underlying Chord ring handles that automatically. If the user finds they need additional processing power during runtime, they can boot up additional nodes, which would automatically be assigned work based on their hash value. If a node goes down while performing an operation, his successor takes over for him. This makes the system extremely robust during runtime.

All a developer needs to do is write three functions: the staging function, Map, and Reduce. These define how to split up the work into manageable portions, the work to be performed on each portion to obtain results, and how to combine these results into a single result, respectively.

3.4 Experiments

In order for ChordReduce to be a viable framework, we had to show these three properties:

1. ChordReduce provides significant speedup during a distributed job.
2. ChordReduce scales.
3. ChordReduce handles churn during execution.

Speedup can be demonstrated by showing that a distributed job is generally performed more quickly than the same job handled by a single worker. More formally we need to establish that $\exists n$ such that $T_n < T_1$, where T_n is the amount of time it takes for n nodes to finish the job.

To establish scalability, we need to show that the cost of distributing the work grows logarithmically with the number of workers. In addition, we need to demonstrate that the larger the job is, the number of nodes we can have working on the problem without the overhead incurring diminishing returns increases. This can be stated as

$$T_n = \frac{T_1}{n} + k \cdot \log_2(n)$$

where $\frac{T_1}{n}$ is the amount of time the job would take when distributed in an ideal universe and $k \cdot \log_2(n)$ is network induced overhead, k being an unknown constant dependent on network

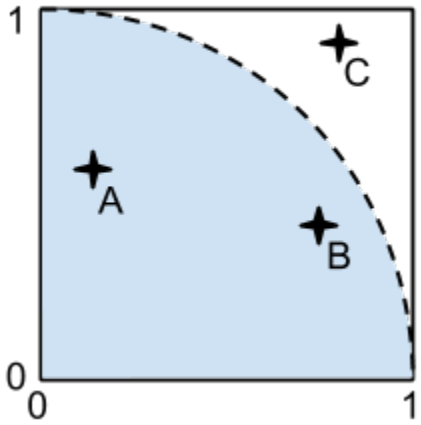


Figure 3.5: The "dartboard." The computer throws a dart by choosing a random x and y between 0 and 1. If $x^2 + y^2 < 1^2$, the dart landed inside the circle. A and B are darts that landed inside the circle, while C did not.

latency and available processing power.

Finally, to demonstrate robustness, we need to show that ChordReduce can handle arbitrary node failure in the ring and that such failures minimally impair the overall speed of the network.

3.4.1 Setup

To stress test our framework, we ran a Monte-Carlo approximation of π. This process is largely analogous to having a square with the top-right quarter of a circle going through it (Fig. **??**), and then throwing darts at random locations. Counting the ratio of darts that land inside the circle to the total number of throws gives us an approximation of $\frac{\pi}{4}$. The more darts thrown, i.e. the more samples that are taken, the more accurate the approximation[1].

We chose this experiment for a number of reasons. The job is extremely easy to distribute. This also made it very easy to test scalability. By doubling the amount of samples, we can double the amount of work each node gets. We could also test the effectiveness of distributing the job among different numbers of workers.

Each Map job is defined by the number of throws the node must make and yields a result containing the total number of throws and the number of throws that landed inside the circular section. Reducing these results is then a matter of adding the respective fields together.

[1]This is not intended to be a particularly good approximation of π. Each additional digit of accuracy requires increasing the number of samples taken by an order of magnitude.

We ran our experiments using Amazons's Elastic Compute Cloud (EC2) service. Amazon EC2 allows users to purchase an arbitrary amount of virtual machines by the hour. Each node was an individual EC2 small instance [**?**] with a preconfigured Ubuntu 12.04 image. These instances were capable enough to provide constant computation, but still weak enough that they would be overwhelmed by traffic on occasions, creating a constant churn effect in the ring.

Once started, nodes retrieve the latest version of the code and run it as a service, automatically joining the network. We can choose any arbitrary node as the stager and tell it to run the MapReduce process. We found that the network was robust enough that we could take a node we wanted to be the stager out of the network, modify its MapReduce test code, have it rejoin the network, and then run the new code without any problems. Since only the stager has to know how to create the Map tasks, the other nodes do not have to be updated and execute the new tasks they are given.

We ran our experiments on groups of 1, 10, 20, 30, and 40 workers, which generated a 10^8 sample set and a 10^9 sample set. Additionally, we gathered data on a 10^7 sample set using 1, 5, 10, 20, 30 workers. To test churn, we ran an experiment where each node had an equal chance of leaving and joining the network and varied the level of churn over multiple runs.

We also utilized a subroutine we wrote called *plot*, which sends a message sequentially around the ring to establish how many members there are. If *plot* failed to return in under a second, the ring was experiencing structural instability.

3.4.2 Results

Fig. **??** and Fig. **??** summarize the experimental results of job duration and speedup. Our default series was the 10^8 samples series. On average, it took a single node 431 seconds, or approximately 7 minutes, to generate 10^8 samples. Generating the same number of samples using ChordReduce over 10, 20, 30, or 40 nodes was always quicker. The samples were generated fastest when there were 20 workers, with a speedup factor of 4.96, while increasing the number of workers to 30 yielded a speedup of only 4.03. At 30 nodes, the gains of distributing the work were present, but the cost of overhead ($k \cdot \log_2(n)$) had more of an impact. This effect is more pronounced at 40 workers, with a speedup of 2.25.

Since our data showed that approximating π on one node with 10^8 samples took approximately

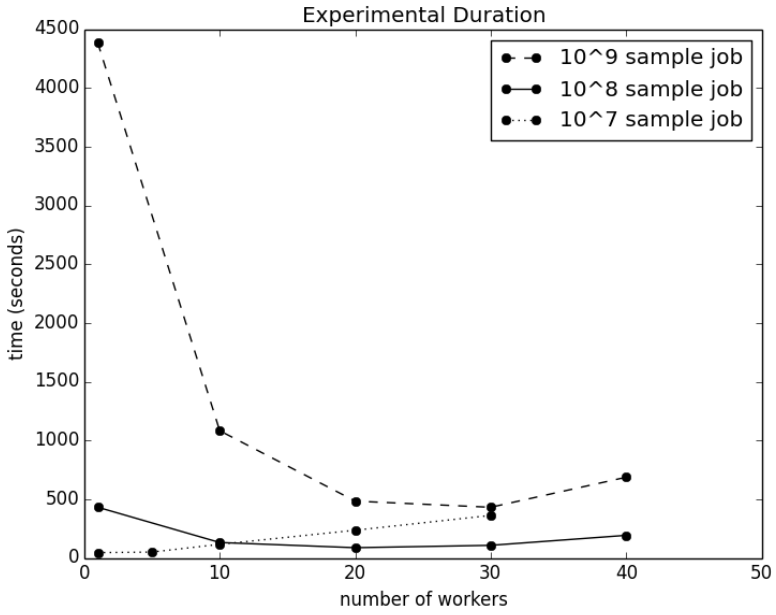


Figure 3.6: For a sufficiently large job, it was almost always preferable to distribute it. When the job is too small, such as with the 10^7 data set, our runtime is dominated by the overhead. Our results are what we would expect when overhead grows logarithmically to the number of workers.

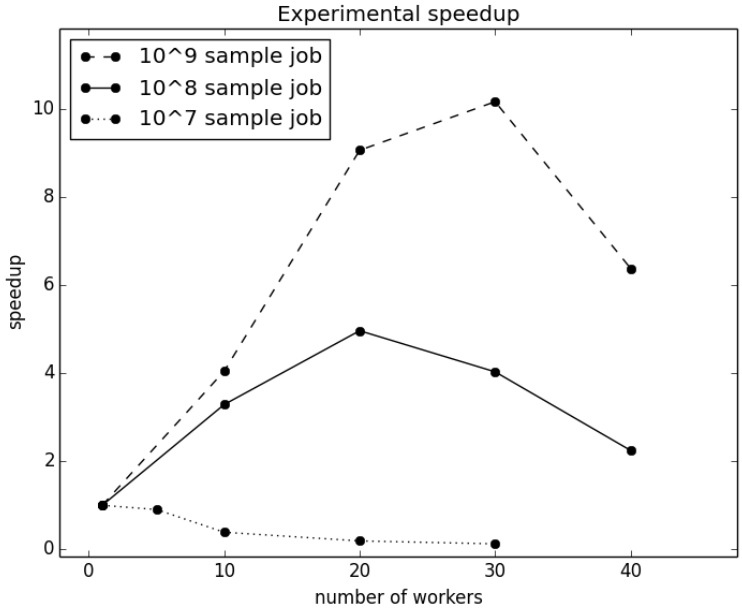


Figure 3.7: The larger the size of the job, the greater the gains of distributing with ChordReduce. In addition, the larger the job, the more workers can be added before we start seeing diminishing returns. This demonstrates that ChordReduce is scalable.

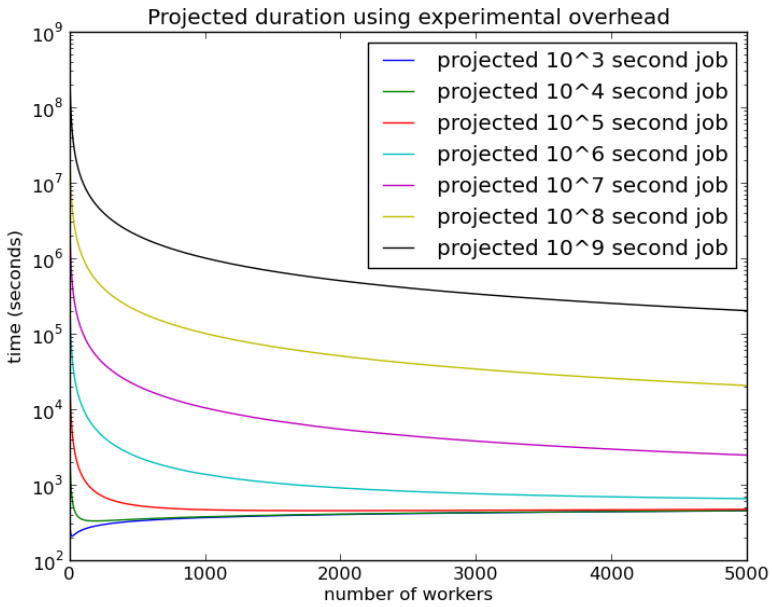


Figure 3.8: The projected runtime using ChordReduce for differently sized jobs. Each curve projects the expected behavior for job that takes a single worker the specified amount of time.

7 minutes, collecting 10^9 samples on a single node would take 70 minutes at minimum. Fig. **??** shows that the 10^9 set gained greater benefit from being distributed than the 10^8 set, with the speedup factor at 20 workers being 9.07 compared to 4.03. In addition, the gains of distributing work further increased at 30 workers and only began to decay at 40 workers, compared with the 10^8 data set, which began its drop off at 30 workers. This behavior demonstrates that the larger the job being distributed, the greater the gains of distributing the work using ChordReduce.

The 10^7 sample set confirms that the network overhead is logarithmic. At that size, it is not effective to run the job concurrently and we start seeing overheard acting as the dominant factor in runtime. This matches the behavior predicted by our equation, $T_n = \frac{T_1}{n} + k \cdot \log_2(n)$. For a small T_1, $\frac{T_1}{n}$ approaches 0 as n gets larger, while $k \cdot \log_2(n)$, our overhead, dominates the sample. The samples from our data set fit this behavior, establishing that our overhead increases logarithmically with the number of workers.

Since we have now established that $T_n = \frac{T_1}{n} + k \cdot \log_2(n)$, we can estimate how long a job that takes an arbitrary amount of time to run on a single node would take using ChordReduce. Our data points indicated that the mean value of k for this problem was 36.5. Fig. **??** shows that for jobs that would take more than 10^4 seconds for single worker to complete, we can expect there

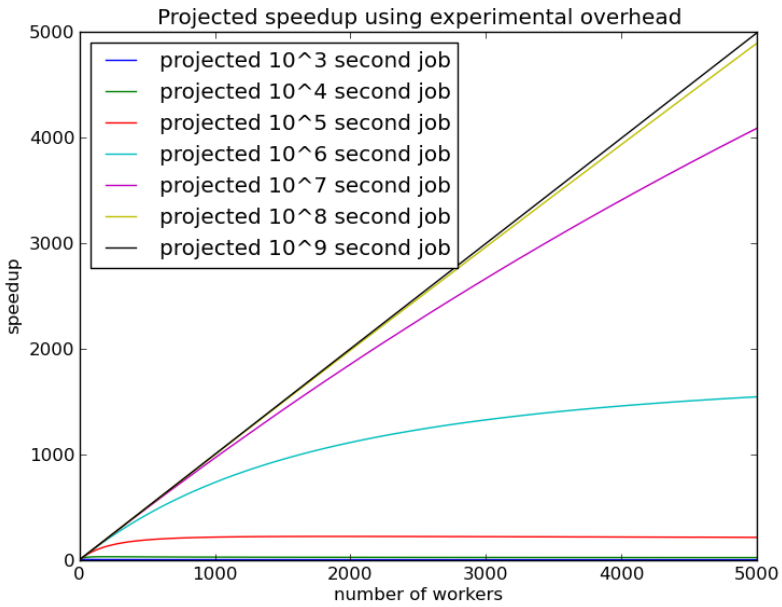


Figure 3.9: The projected speedup for different sized jobs.

Churn rate per second	Average runtime (s)	Speedup vs 0% churn
0.8%	191.25	2.15
0.4%	329.20	1.25
0.025%	431.86	0.95
0.00775%	445.47	0.92
0.00250%	331.80	1.24
0%	441.57	1.00

Table 3.1: Experimental results of different rates of Churn

would still be benefit to adding an additional worker, even when there are already 5000 workers already in the ring. Fig. **??** further emphasizes this. Note that as the jobs become larger, the expected speedup from ChordReduce approaches linear behavior.

Table **??** shows the experimental results for different rates of churn. These results show the system is relatively insensitive to churn. We started with 40 nodes in the ring and generated 10^8 samples while experiencing different rates of churn, as specified in Table **??**. At the 0.8% rate of churn, there is a 0.8% chance each second that any given node will leave the network followed by another node joining the network at a different location. The joining rate and leaving rate being identical is not an unusual assumption to make [**?**] [**?**].

Our testing rates for churn are an order of magnitude higher than the rates used in the P2P-

MapReduce simulation [**?**]. In their paper, the highest rate of churn was only 0.4% per minute. Because we were dealing with fewer nodes, we chose larger rates to demonstrate that ChordReduce could effectively handle a high level of churn.

Our experiments show that for a given problem, ChordReduce can effectively distribute the problem, yielding a substantial speedup. Furthermore, our results showed that the larger the problem is, the more workers could be added before diminishing returns were incurred. During runtime, we experienced multiple instances where *plot* would fail to run and the stager would report socket errors, indicating that it had lost connection with a node in the ring. Despite this turbulence, every node managed to reestablish connection with each other and report back all the data. This further demonstrated that we were able to handle the churn in the network.

3.5 Remarks

During our experiments testing the capabilities of ChordReduce, we experienced a significant and completely unexpected anomaly while testing churn. One of the things previous research [**?**] [**?**] in the same area we felt we needed to explore better was how a completely decentralized computation could handle churn. Now, despite our initial prototype having numerous bugs and only able to handle small networks, we were fairly certain of it's ability to handle churn.

Marozzo et al. [**?**] tested their network using churn rates of 0.025%, 0.05%, 0.1%, 0.2%, and 0.4% per minute. The churn rate of $cr << 1$ per minute means that each minute on average, $cr \cdot n$ nodes leave the network and $cr \cdot n$ new nodes join the network.[2] This could effectively be thought of as each node flipping a weighted coin every minute. When the coin lands on tails, the node leaves. A similar process happens for nodes wanting to join the network.

We wanted the robustness of our system to be beyond reproach, so we tested at rates from 0.0025% to 0.8% ***per second***, 120 times the fastest rate used to test P2P-MapReduce. This is an absurdly fast and unrealistic speed, the only purpose of which was to cement the fault tolerance of the system. Since we were testing ChordReduce on Amazon's EC2 and paying per instance per hour, we limited the number of nodes. Rather than having a pool of nodes waiting to join the network, we conserved our funds by having leaving nodes immediately rejoin the network under a

[2]It is standard practice to assume the joining rate and leaving rate are equal.

new IP/port combo. The meant our churn operation was essentially a simultaneous leave and join.

What we found was that jobs on ChordReduce finished twice as fast under the unrealistic levels churn (0.8% per second) than no churn (Table **??**). This completely mystified us. Churn is a disruptive force; how can it be aiding the network?

Hypothesis

We hypothesize this was due to the number of data pieces (larger) vs the number of workers (smaller). There were more workers than there were pieces of data, so some workers ended up with more data than others in the initial distribution. This means that there was some imbalance in the way data was distributed among nodes. This was *further* exacerbated by small number of workers distributed over a large hash space, leading some nodes to have larger swaths of responsibility than others.

Given this setup, without any churn, the operation would be: Workers get triggered, they start working, and the ones with little work finish their work quickly, and the network waits for the node with higher loads of work.

Its important to note here that the work in ChordReduce was performed atomically, a piece at a time. When a node was working on a piece, it informed it's successor, then informed them when it finished. These pieces of work were also small, possibly too small.

As mentioned previously, under our induced experimental churn, we had the nodes randomly fail and immediately join under a new IP/port combination, which yields a new hash. The failure rates were orders of magnitude higher than what would be expected in a "real" (nonexperimental) environment. The following possibilities could occur:

- A node without any active jobs leaves. It dies and and comes back with a new port chosen. This new ID has a higher chance of landing in a larger region of responsibility (since new joining nodes have a greater chance of hashing to a larger region than a smaller). In other words, it has a (relatively) higher chance of moving into an space where it becomes acquires responsibility for enqueued jobs. The outcomes of this are:
  - The node rejoins in a region and does not acquire any new jobs. This has no impact on the network (Case I).

  - The node rejoins in a region that has jobs waiting to be done. It acquires some of these jobs. This speeds up performance (Case II).

- A node with active jobs dies. It rejoins in a new space. The jobs were small, so not too much time is lost on the active job, and the enqueued jobs are backed up and the successor knows to complete them. However, the node can rejoin in a more job-heavy region and acquire new jobs. The outcomes of this are:

  - A minor negative impact on runtime and load balancing (since the successor has more jobs to handle) (Case III).
  - A possible counterbalance in load balancing by acquiring new jobs off a busy node (Case IV).

The longer the nodes work on the jobs, the more nodes finish and have no jobs. This means as time increases, so do the occurrences of Case I and II.

This leads us to two hypotheses:

- Deleting nodes motivates other nodes to work harder to avoid deletion (a "beatings will continue until morale improves" situation).

- Our high rate of churn was dynamically load-balancing the network. It appears even the smallest effort of trying to dynamically load balance, such as rebooting random nodes to new locations, has benefits for runtime. Our method is a poor approximation of dynamic load-balancing, and it still shows improvement.

The first hypothesis is mentally pleasing to anyone who has tried to create a distributed system, but lacks rigor. Verification, analysis, and exploitation of this phenomena is the subject of (Chapter **??**).

Once we have established that it does exist, we need a better load-balancing strategy than randomly inducing. We want nodes to have a precomputed list of locations in which they can insert nodes to perform load-balancing on an ad-hoc basis during runtime. This precomputed list ties directly into the security research on DHTs we have done [**?**] and is the subject of Chapter **??**.

Chapter 4

VHash And DGVH

DHTs all seek to minimize lookup time for their respective topologies. This is done by minimizing the number of overlay hops needed for a lookup operation. This is a good approximation for minimizing the latency of lookups, but does not actually do so, as each hop has a different amount of latency. Furthermore, a network might need to minimize some arbitrary metric, such as energy consumption.

VHash is a multi-dimensional DHT that minimizes routing over some given metric. It uses a fast approximation of a Delaunay Triangulation to compute the Voronoi tessellation of a multi-dimensional space.

Arguably all Distributed Hash Tables (DHTs) are built on the concept of Voronoi tessellations. In all DHTs, a node is responsible for all points in the overlay to which it is the "closest" node. Nodes are assigned a key as their location in some keyspace, based on the hash of certain attributes. Normally, this is just the hash of the IP address (and possibly the port) of the node [**?**] [**?**] [**?**] [**?**], but other metrics such as geographic location can be used as well [**?**].

These DHTs have carefully chosen metric spaces such that these regions are very simple to calculate. For example, Chord [**?**] and similar ring-based DHTs [**?**] utilize a unidirectional, one-dimensional ring as their metric space, such that the region for which a node is responsible is the region between itself and its predecessor.

Using a Voronoi tessellation in a DHT generalizes this design. Nodes are Voronoi generators at a position based on their hashed keys. These nodes are then responsible for any key that falls within its generated Voronoi region.

Messages get routed along links to neighboring nodes. This would take $O(n)$ hops in one dimension. In multiple dimensions, our routing algorithm (Algorithm **??**) is extremely similar to the one used in Ratnasamy et al.'s Content Addressable Network (CAN) [**?**], which would be $O(n^{\frac{1}{d}})$ hops.

Algorithm 2 The DHT Greedy Routing Algorithm, presented in the terms used in this paper.

```
1: Given node n
2: Given m is a message addressed for loc
3: potential_dests ← n ∪ n.short_peers ∪ n.long_peers
4: c ← node in potential_dests with shortest distance to loc
5: if c == n then
6:     return n
7: else
8:     return c.lookup(loc)
9: end if
```

Efficient solutions, such as Fortune's sweepline algorithm [**?**], are not usable in spaces with 2 more dimensions. As far as we can tell, there is no way efficient to generate higher dimension Voronoi tessellations, especially in the distributed Churn-heavy context of a DHT. Our solution is the Distributed Greedy Voronoi Heuristic.

VHash served as the kernel from which we built UrDHT [**?**] and necessitated the creation of our Distributed Greedy Voronoi Heuristic [**?**]. UrDHT and VHash differ in that UrDHT seeks to completely abstract any DHT topology in terms of Voronoi Tessellation and Delaunay Triangulation. VHash is a DHT in its own right and does not aim to implement other DHT topologies. UrDHT has not so succeeded VHash as that UrDHT was built around the concept VHash, which still exists a default setting of sorts for UrDHT.

4.1 Distributed Greedy Voronoi Heuristic

A Voronoi tessellation is the partition of a space into cells or regions along a set of objects O, such that all the points in a particular region are closer to one object than any other object. We refer to the region owned by an object as that object's Voronoi region. Objects which are used to create the regions are called Voronoi generators. In network applications that use Voronoi tessellations, nodes in the network act as the Voronoi generators.

The Voronoi tessellation and Delaunay triangulation are dual problems, as an edge between

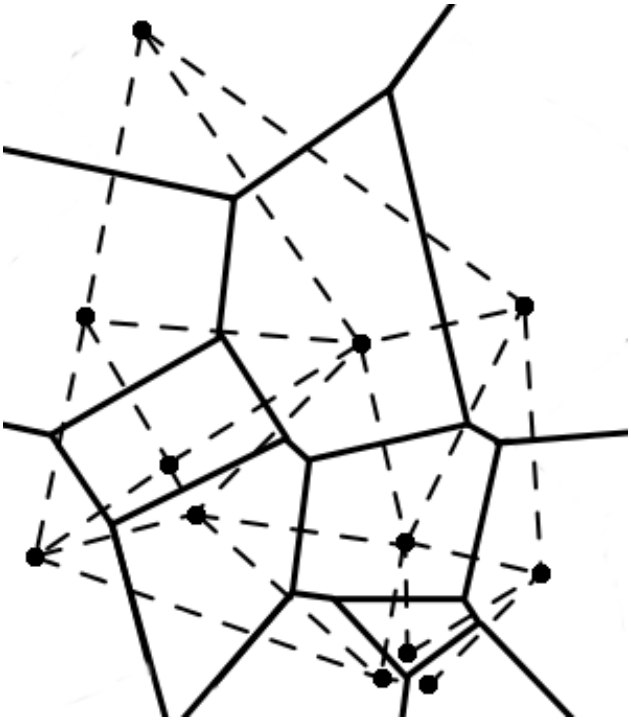


Figure 4.1: An example Voronoi diagram for objects on a 2-dimensional space. The black lines correspond to the borders of the Voronoi region, while the dashed lines correspond to the edges of the Delaunay Triangulation.

two objects in a Delaunay triangulation exists if and only if those object's Voronoi regions border each other. This means that solving either problem will yield the solution to both. An example Voronoi diagram is shown in Figure **??**. For additional information, Aurenhammer [**?**] provides a formal and extremely thorough description of Voronoi tessellations, as well as their applications.

The Distributed Greedy Voronoi Heuristic (DGVH) is a fast method for nodes to define their individual Voronoi region (Algorithm **??**). This is done by selecting the nearby nodes that would correspond to the points connected to it by a Delaunay triangulation. The rationale for this heuristic is that, in the majority of cases, the midpoint between two nodes falls on the common boundary of their Voronoi regions.

During each cycle, nodes exchange their peer lists with a current neighbor and then recalculate their neighbors. A node combines their neighbor's peer list with its own to create a list of candidate neighbors. This combined list is sorted from closest to furthest. A new peer list is then created starting with the closest candidate. The node then examines each of the remaining candidates in the sorted list and calculates the midpoint between the node and the candidate. If any of the

Algorithm 3 Distributed Greedy Voronoi Heuristic

```
1: Given node n and its list of candidates.
2: Given the minimum table_size
3: short_peers ← empty set that will contain n's one-hop peers
4: long_peers ← empty set that will contain n's two-hop peers
5: Sort candidates in ascending order by each node's distance to n
6: Remove the first member of candidates and add it to short_peers
7: for all c in candidates do
8:     if Any node in short_peers is closer to c than n then
9:         Reject c as a peer
10:    else
11:        Remove c from candidates
12:        Add c to short_peers
13:    end if
14: end for
15: while |short_peers| < table_size and |candidates| > 0 do
16:    Remove the first entry c from candidates
17:    Add c to short_peers
18: end while
19: Add candidates to the set of long_peers
20: if |long_peers| > table_size^2 then
21:    long_peers ← random subset of long_peers of size table_size^2
22: end if
```

nodes in the new peer list are closer to the midpoint than the candidate, the candidate is set aside. Otherwise the candidate is added to the new peer list.

DGVH never actually solves for the actual polytopes that describe a node's Voronoi region. This is unnecessary and prohibitively expensive [**?**]. Rather, once the heuristic has been run, nodes can determine whether a given point would fall in its region.

Nodes do this by calculating the distance of the given point to itself and other nodes it knows about. The point falls into a particular node's Voronoi region if it is the node to which it has the shortest distance. This process continues recursively until a node determines that itself to be the closest node to the point. Thus, a node defines its Voronoi region by keeping a list of the peers that bound it.

4.1.1 Algorithm Analysis

DVGH is very efficient in terms of both space and time. Suppose a node n is creating its short peer list from k candidates in an overlay network of N nodes. The candidates must be sorted, which

takes $O(k \cdot \lg(k))$ operations. Node n must then compute the midpoint between itself and each of the k candidates. Node n then compares distances to the midpoints between itself and all the candidates. This results in a cost of

$$k \cdot \lg(k) + k^2 \text{ distances}$$

Since k is bounded by $\Theta(\frac{\log N}{\log \log N})$ [**?**] (the expected maximum degree of a node), we can translate the above to

$$O(\frac{\log^2 N}{\log^2 \log N})$$

In the vast majority of cases, the number of peers is equal to the minimum size of *Short Peers*. This yields $k = (3d + 1)^2 + 3d + 1$ in the expected case, where the lower bound and expected complexities are $\Omega(1)$.

4.2 Experimental Results

We evaluated the effectiveness of VHash and DGVH in creating a set of experiments.[1] The first experiment showed how VHash could use DGVH to create a routing mesh. Our second showed how optimizing for latency yielded better results than optimizing for least hops.

4.2.1 Convergence

Our first experiment examined how DGVH could be used to create a routing overlay and how well it performed in this task. The simulation demonstrated how DGVH formed a stable overlay from a chaotic starting topology after a number of cycles. We compared our results to those in RayNet [**?**]. The authors of Raynet proposed a random k-connected graph would be a challenging initial configuration for showing a DHT relying on a gossip mechanism could converge to a stable topology.

In the initial two cycles of the simulation, each node bootstrapped its short peer list by appending 10 nodes, selected uniformly at random from the entire network. In each cycle, the nodes

[1] Our results are pulled directly from [**?**] and [**?**].

gossiped , swapping peer list information. They then ran DGVH using the new information. We calculated the hit rate of successful lookups by simulating 2000 lookups from random nodes to random locations, as described in Algorithm **??**. A lookup was considered successful if the network was able to determine which Voronoi region contained a randomly selected point.

Our experimental variables for this simulation were the number of nodes in the DGVH generated overlay and the number of dimensions. We tested network sizes of 500, 1000, 2000, 5000, and 10000 nodes each in 2, 3, 4, and 5 dimensions. The hit rate at each cycle is $\frac{hits}{2000}$, where *hits* are the number of successful lookups.

Algorithm 4 Routing Simulation Sample

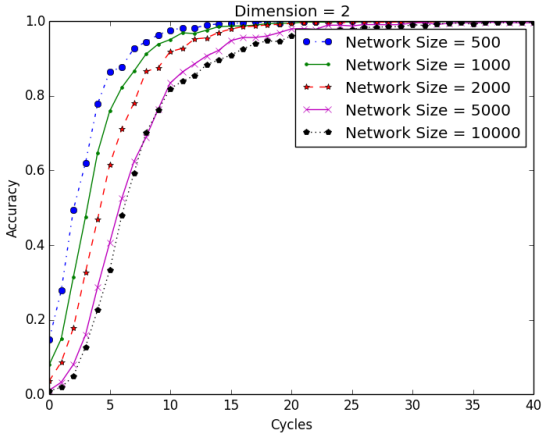
```
1: start ← random node
2: dest ← random set of coordinates
3: ans ← node closest to dest
4: if ans == start.lookup(dest) then
5:     increment hits
6: end if
```

The results of our simulation are shown in Figure **??**. Our graphs show that a correct overlay was quickly constructed from a random configuration and that our hit rate reached 90% by cycle 20, regardless of the number of dimensions. Lookups consistently approached a hit rate of 100% by cycle 30. In comparison, RayNet's routing converged to a perfect hit rate at around cycle 30 to 35 [**?**]. As the network size and number of dimensions each increase, convergence slows, but not to a significant degree.

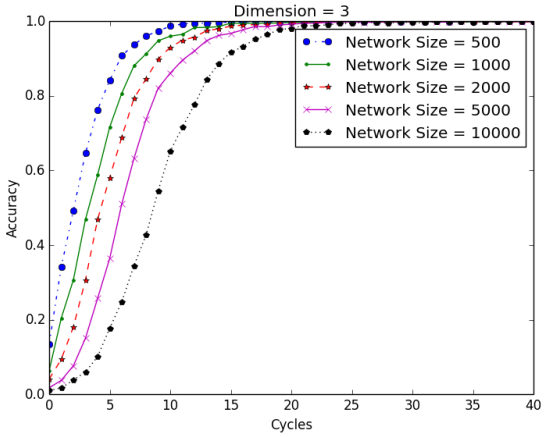
4.2.2 Latency Distribution Test

The goal of our second set of experiments was to demonstrate VHash's ability to optimize a selected network metric: latency in this case. In our simulation, we used the number of hops on the underlying network as an approximation of latency. We compared VHash's performance to Chord [**?**]. As we discussed in Chapter **??** Chord is a well established DHT with an $O(\log(n))$ sized routing table and $O(\log(n))$ lookup time measured in overlay hops.

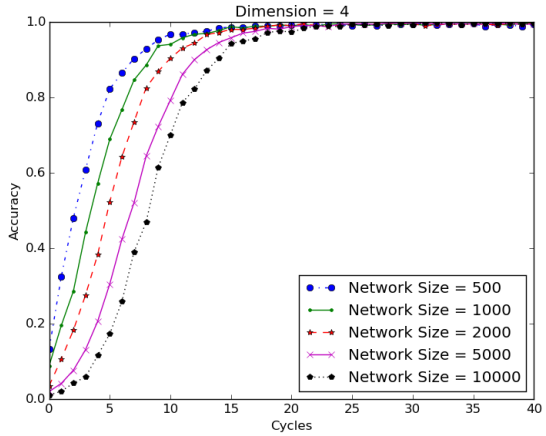
Instead of using the number of hops on the overlay network as our metric, we are concerned with the actual latency lookups experience traveling through the *underlay* network, the network upon which the overlay is built. Overlay hops are used in most DHT evaluations as the primary



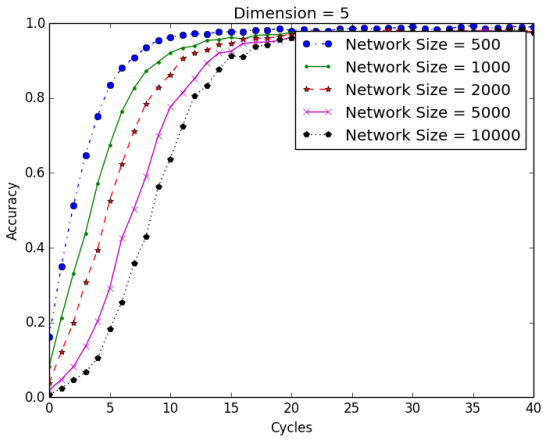
(a) This plot shows the accuracy rate of lookups on a 2-dimensional network as it self-organizes.



(b) This plot shows the accuracy rate of lookups on a 3-dimensional network as it self-organizes.



(c) This plot shows the accuracy rate of lookups on a 4-dimensional network as it self-organizes.



(d) This plot shows the accuracy rate of lookups on a 5-dimensional network as it self-organizes.

Figure 4.2: These figures show that, starting from a randomized network, DGVH forms a stable and consistent network topology. The Y axis shows the success rate of lookups and the X axis show the number of gossips that have occurred. Each point shows the fraction of 2000 lookups that successfully found the correct destination.

measure of latency. It is the best approach available when there are no means of evaluating the characteristics of the underlying network. VHash is designed with a capability to exploit the characteristics of the underlying network. With most realistic network sizes and structures, there is substantial room for latency reduction in DHTs.

For this experiment, we constructed a scale free network with 10000 nodes placed at random (which has an approximate diameter of 3 hops) as an underlay network [**?**] [**?**] [**?**]. We chose to use a scale-free network as the underlay, since scale free networks model the Internet's topology [**?**] [**?**]. We then chose a random subset of nodes to be members of the overlay network. Our next step was to measure the distance in underlay hops between 10000 random source-destination pairs in the overlay. VHash generated an embedding of the latency graph utilizing a distributed force directed model, with the latency function defined as the number of underlay hops between it and its peers.

Our simulation created 100, 500, and 1000 node overlays for both VHash and Chord. We used 4 dimensions in VHash and a standard 160 bit identifier for Chord.

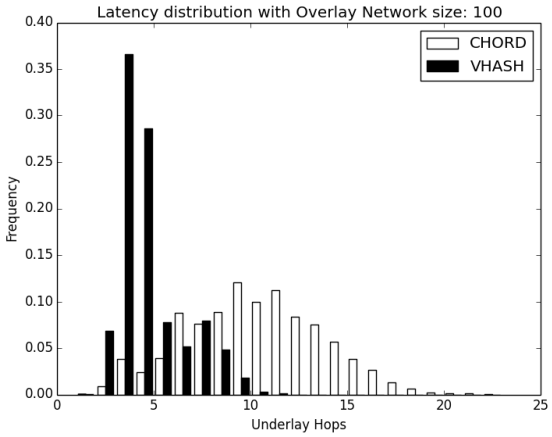
Figure **??** shows the distribution of path lengths measured in underlay hops in both Chord and VHash. VHash significantly outperformed Chord and considerably reduced the underlay path lengths in three network sizes.

We also sampled the lookup length measured in overlay hops for a 1000 sized Chord and VHash network. As seen in Figure **??**, the paths measured in overlay for VHash were significantly shorter than those in Chord. In comparing the overlay and underlay hops, we find that for each overlay hop in Chord, the lookup must travel 2.719 underlay hops on average; in VHash, lookups must travel 2.291 underlay hops on average for every overlay hop traversed.

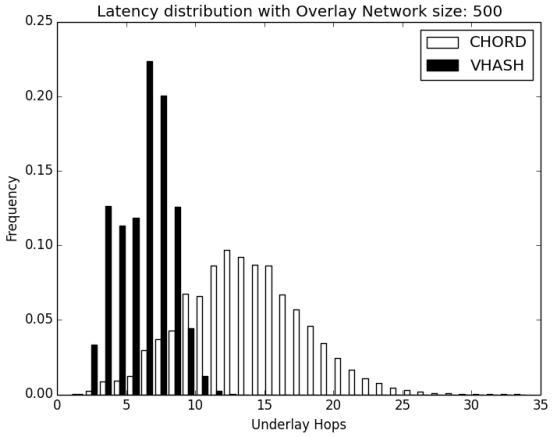
Recall that this work is based on scale free networks, where latency improvements are difficult. An improvement of 0.4 hops over a diameter of 3 hops is significant. VHash has on average less overlay hops per lookup than Chord, and for each of these overlay hops we consistently traverse more efficiently across the underlay network.

4.3 Remarks

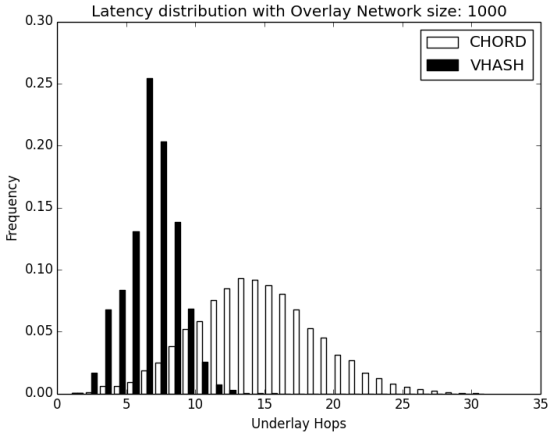
Voronoi tessellations have a wide potential for applications in ad-hoc networks, massively multi-player games, P2P, and distributed networks. However, centralized algorithms for Voronoi tessel-



(a) Frequency of path lengths on Chord and VHash in a 100 node overlay.



(b) Frequency of path lengths on Chord and VHash in a 500 node overlay.



(c) Frequency of path lengths on Chord and VHash in a 1000 node overlay.

Figure 4.3: Figures **??**, **??**, and **??** show the difference in the performance of Chord and VHash for 10,000 routing samples on a 10,000 node underlay network for differently sized overlays. The Y axis shows the observed frequencies and the X axis shows the number of hops traversed on the underlay network. VHash consistently requires fewer hops for routing than Chord.

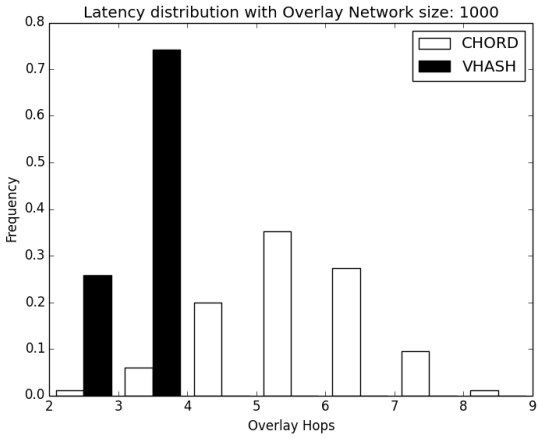


Figure 4.4: Comparison of Chord and VHash in terms of overlay hops. Each overlay has 1000 nodes. The Y axis denotes the observed frequencies of overlay hops and the X axis corresponds to the path lengths in overlay hops.

lation and Delaunay triangulation are not applicable to decentralized systems. In addition, solving Voronoi tessellations in more than 2 dimensions is computationally expensive.

We created a distributed heuristic for Voronoi tessellations in an arbitrary number of dimensions. Our heuristic is fast and scalable, with a expected memory cost of $(3d+1)^2+3d+1$ and expected maximum runtime of $O(\frac{\log^2 N}{\log^2 \log N})$.

We ran two sets of experiments to demonstrate VHash's effectiveness. Our first set of experiments demonstrated that our heuristic is reasonably accurate and our second set demonstrates that reasonably accurate is sufficient to build a P2P network which can route accurately. Our second experiment showed that VHash could significantly reduced the latency in Distributed Hash Tables. These results eventually led us to try and completely map DHTs to Voronoi Tessellation and Delaunay Triangulation in UrDHT, the subject of Chapter **??**.

Chapter 5

UrDHT

As we have previously discussed, Distributed Hash Tables (DHTs) have an inherent set of qualities, such as greedy routing, maintaining lists of peers which define the topology, and forming an overlay network. All DHTs use functionally similar protocols to perform lookup, storage, and retrieval operations. Despite this, no one has created a cohesive formal DHT specification.

Our primary motivation for this project was to create an abstracted model for Distributed Hash Tables based on observations we made during previous research [**?**]. We found that all DHTs can cleanly be mapped to the primal-dual problems of Voronoi Tessellation and Delaunay Triangulation. Rather than having a developer be concerned with the details of a given DHT, we have constructed a new framework, UrDHT, that generalizes the functionality and implementation of various DHTs.

UrDHT is an abstract model of a Distributed Hash Table that implements a self-organizing web of computational units. It maps the topologies of DHTs to the primal-dual problem of Voronoi Tessellation and Delaunay Triangulation. By completing a few simple functions, a developer can implement the topology of any DHT in any arbitrary space using UrDHT. For example, we implemented a DHT operating in a hyperbolic geometry, a previously unexplored nontrivial metric space with potential applications, such as latency embedding.

5.1 What Defines a DHT

A distributed hash table is usually defined by its protocol; in other words, what it can do. Nodes and data in a DHT are assigned unique[1] keys via a consistent hashing algorithm. To make it easier to intuitively understand the context, we will call the key associated with a node its ID and refer to nodes and their IDs interchangeably.

A DHT can perform the `lookup(key)`, `get(key)`, and `store(key, value)` operations.[2] The `lookup` operation returns the node responsible for a queried key. The `store` function stores that key/value pair in the DHT, while `get` returns the value associated with that key.

However, these operations define the functionality of a DHT, but do not define the requirements for implementation. We define the necessary components that comprise DHTs. We show that these components are essentially Voronoi Tessellation and Delaunay Triangulation.

5.1.1 DHTs, Delaunay Triangulation, and Voronoi Tessellation

Nodes in different DHTs have, what appears at the first glance, wildly disparate ways of keeping track of peers - the other nodes in the network. However, peers can be split into two groups.

The first group is the *short peers*. These are the closest peers to the node and define the range of keys the node is responsible for. A node is responsible for a key if and only if its ID is closest to the given key in the geometry of the DHT. Short peers define the DHTs topology and guarantee that the greedy routing algorithm shared by all DHTs works.

Long peers are the nodes that allow a DHT to achieve faster routing speeds than the topology would allow using only short peers. This is typically $O(\log(n))$ hops, although polylogarithmic time is acceptable [**?**]. A DHT can still function without long peers.

Interestingly, despite the diversity of DHT topologies and how each DHT organizes short and long peers, all DHTs use functionally identical greedy routing algorithms (Algorithm **??**):

The algorithm is as follows: If I, the node, am responsible for the key, I return myself. Otherwise, if I know who is responsible for this key, I return that node. Finally, if that is not the case, I forward this query to the node I know with shortest distance from the node to the desired key.[3]

[1] Unique with astronomically high probability, given a large enough consistent hashing algorithm.
[2] There is typically a *delete(key)* operation too, but it is not strictly necessary.
[3] This order matters, as some DHTs such as Chord are unidirectional.

Algorithm 5 The DHT Generic Routing algorithm

```
1: function n.LOOKUP((key))
2:     if key ∈ n's range of responsibility then
3:         return n
4:     end if
5:     if One of n's short peers is responsible for key then
6:         return the responsible node
7:     end if
8:     candidates = short_peers + long_peers
9:     next ← min(n.distance(candidates, key))
10:    return next.lookup(key)
11: end function
```

Depending of the specific DHT, this algorithm might be implemented either recursively or iteratively. It will certainly have differences in how a node handles errors, such as how to handle connecting to a node that no longer exists. This algorithm may possibly be run in parallel, such as in Kademlia [**?**]. The base greedy algorithm is always the same regardless of the implementation.

With the components of a DHT defined above, we can now show the relationship between DHTs and the primal-dual problems of Delaunay Triangulation and Voronoi Tessellation. An example Delaunay Triangulation and Voronoi Tessellation is show in Figure **??**.

We can map a given node's ID to a point in a space and the set of short peers to the Delaunay Triangulation. This would make the range of keys a node is responsible correspond to the node's Voronoi region. Long peers serve as shortcuts across the mesh formed by Delaunay Triangulation.

Thus, if we can calculate the Delaunay Triangulation between nodes in a DHT, we have a generalized means of creating the overlay network. This can be done with any algorithm that calculates the Delaunay Triangulation.

Computing the Delaunay Triangulation and/or the Voronoi Tessellation of a set of points is a well analyzed problem. Many algorithms exist which efficiently compute a Voronoi Tessellation for a given set of points on a plane, such as Fortune's sweep line algorithm [**?**].

However, DHTs are completed decentralized, with no single node having global knowledge of the topology. Many of the algorithms to compute Delaunay Triangulation and/or Voronoi Tessellation are unsuited to a distributed environment. In addition, the computational cost increases when we move into spaces with greater than two dimensions. In general, finding the Delaunay Triangulation of n points in a space with d dimensions takes $O(n^{\frac{2d-1}{d}})$ time [**?**].

Is there an algorithm we can use to efficiently calculate Delaunay Triangulation for a distributed

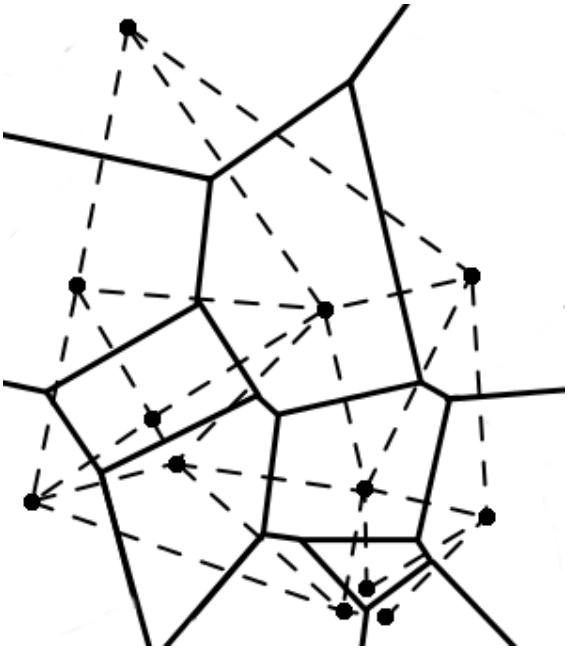


Figure 5.1: An example Voronoi diagram for objects on a 2-dimensional space. The black lines correspond to the borders of the Voronoi region, while the dashed lines correspond to the edges of the Delaunay Triangulation.

system in an arbitrary space? We created an algorithm called the Distributed Greedy Voronoi Heuristic (DGVH), explained below [**?**].

5.1.2 Distributed Greedy Voronoi Heuristic

The Distributed Greedy Voronoi Heuristic (DGVH) is an efficient method for nodes to approximate their individual Voronoi region (Algorithm **??**). DGVH selects nearby nodes that would correspond to points connected to it within a Delaunay Triangulation. Our previous implementation relied on a midpoint function [**?**]. We have refined our heuristic to render a midpoint function unnecessary.

The heuristic is described in Algorithm **??** in Chapter **??**. Every maintenance cycle, nodes exchange their peer lists with their short peers. A node creates a list of candidates by combining their peer lists with their neighbor's peer lists.[4] Sort the list of peers from closest to furthest distance. The node then initializes a new peer list, initially containing the closest candidate. For each of the remaining candidates, the node compares the distance between the current short peers and the candidate. If the new peer list does not contain any short peers closer to the candidate

[4]In our previous paper, nodes exchange short peer lists with a single peer. Calls to DGVH in this paper use both short and long peer information from all of their short peers.

than the node, the candidate is added to the new peer list. Otherwise, the candidate is set aside.

The resulting short peers are a subset of the node's actual Delaunay neighbors. A crucial feature is that this subset guarantees that DGVH will form a routable mesh.

Candidates are gathered via a gossip protocol as well as notifications from other peers. How long peers are handled depends on the particular DHT implementation. This process is described more in Section **??**.

The expected maximum size of *candidates* corresponds to the expected maximum degree of a vertex in a Delaunay Triangulation. This is $\Theta(\frac{\log n}{\log \log n})$, regardless of the number of the dimensions [**?**]. We can therefore expect *short peers* to be bounded by $\Theta(\frac{\log n}{\log \log n})$.

The expected worst case cost of DGVH is $O(\frac{\log^3 n}{\log^3 \log n})$ [**?**], regardless of the dimension [**?**].[5] In most cases, this cost is much lower. Additional details can be found in our previous work [**?**].

We have tested DGVH on Chord (a ring-based topology), Kademlia (an XOR-based tree topology), general Euclidean spaces, and even in a hyperbolic geometry. This is interesting because not only can we implement the contrived topologies of existing DHTs, but more generalizable topologies like Euclidean or hyperbolic geometries. We show in Section **??** that DGVH works in all of these spaces. DGVH only needs the distance function to be defined in order for nodes to perform lookup operations and determine responsibility. We will now show how we used this information and heuristic to create UrDHT, our abstract model for distributed hash tables.

5.2 UrDHT

The name UrDHT comes from the German prefix *ur*, which means "original." The name is inspired by UrDHT's ability to reproduce the topology of other distributed hash tables.

UrDHT is divided into 3 broad components: Storage, Networking, and Logic. Storage handles file storage and Networking dictates the protocol for how nodes communicate. These components oversee the lower level mechanics of how files are stored on the network and how bits are transmitted through the network. The specifics are outside the scope of the paper, but can be found on the UrDHT Project site [**?**].

[5] As mentioned in the previous footnote, if we are exchanging only short peers with a single neighbor rather than all our neighbors, the cost lowers to $O(\frac{\log^2 n}{\log^2 \log n})$.

Most of our discussion will focus on the Logic component. The Logic component is what dictates the behavior of nodes within the DHT and the construction of the overlay network. It is composed of two parts: the DHT Protocol and the Space Math.

The DHT Protocol contains the canonical operations that a DHT performs, while the Space Math is what effectively distinguishes one DHT from another. A developer only needs to change the details of the `space math` package in UrDHT to create a new type of DHT. We discuss each in further detail below.

5.2.1 The DHT Protocol

The DHT Protocol (`LogicClass.py`) [**?**] is the shared functionality between every single DHT. It consists of the node's information, the short peer list that defines the minimal overlay, the long peers that make efficient routing possible, and all the functions that use them. There is no need for a developer to change anything in the DHT Protocol, but it can be modified if so desired. The DHT Protocol depends on functions from Space Math in order to perform operations within the specified space.

Many of the function calls should be familiar to anyone who has study DHTs. We will discuss a few new functions we added and the ones that contribute to node maintenance.

The first thing we note is the absence of `lookup`. In our efforts to further abstract DHTs, we have replaced `lookup` using the function `seek`. The `seek` function acts a single step of `lookup`. It returns the closest node to *key* that the node knows about.

Nodes can perform `lookup` by iteratively calling `seek` until it receives the same answer twice. We do this because we make no assumptions as to how a client using a DHT would want to perform lookups and handle errors that can occur. It also means that a single client implementing `lookup` using iterative `seek` operations could traverse any DHT topology implemented with UrDHT.

Maintenance is done via gossip. Each maintenance cycle, the node recalculates its Delaunay (short) peers using its neighbors' peer lists and any nodes that have notified it since the last maintenance cycle. Short peer selection are done using DGVH by default. While DGVH has worked in every single space we have tested, this is not proof it will work in every single case. It is reasonable and expected that some spaces may require a different Delaunay Triangulation calculation or approximation method.

Once the short peers are calculated, the node handles modifying its long peers. This is done using the `handleLongPeers` function described in Section **??**.

5.2.2 The Space Math

The Space Math consists of the functions that define the DHT's topology. It requires a way to generate short peers to form a routable overlay and a way to choose long peers. Space Math requires the following functions when using DGVH:

- The `idToPoint` function takes in a node's ID and any other attributes needed to map an ID onto a point in the space. The ID is generally a large integer generated by a cryptographic hash function.

- The `distance` function takes in two points, a and b, and outputs the shortest distance from a to b. This distinction matters, since distance is not symmetric in every space. The prime example of this is Chord, which operates in a unidirectional toroidal ring.

- We use the above functions to implement `getDelaunayPeers`. Given a set of points, the *candidates*, and a center point *centers*, `getDelaunayPeers` calculates a mesh that approximates the Delaunay peers of *center*. We assume that this is done using DGVH (Algorithm **??**).

- The function `getClosest` returns the point closest to *center* from a list of *candidates*, measured by the distance function. The `seek` operation depends on the `getClosest` function.

- The final function is `handleLongPeers`. `handleLongPeers` takes in a list of *candidates* and a *center*, much like `getDelaunayPeers`, and returns a set of peers to act as the routing shortcuts.

  The implementation of this function should vary greatly from one DHT to another. For example, Symphony [**?**] and other small-world networks [**?**] choose long peers using a probability distribution. Chord has a much more structured distribution, with each long peer being increasing powers of 2 distance away from the node [**?**]. The default behavior is to use all candidates not chosen as short peers as long peers, up to a set maximum. If the size of

long peers would exceed this maximum, we instead choose a random subset of the maximum size, creating a naive approximation of the long links in the Kleinberg small-world model [**?**]. Long peers do not greatly contribute to maintenance overhead, so we chose 200 long peers as a default maximum.

5.3 Implementing other DHTs

5.3.1 Implementing Chord

Ring topologies are fairly straightforward since they are one dimensional Voronoi Tessellations, splitting up what is effectively a modular number line among multiple nodes.

Chord uses a unidirectional distance function. Given two integer keys a and b and a maximum value 2^m, the `distance` from a to b in Chord is:

$$distance(a,b) = \begin{cases} 2^m + b - a, & \text{if } b - a < 0 \\ b - a, & \text{otherwise} \end{cases}$$

Short peer selection is trivial in Chord, so rather than using DGVH for `getDelaunayPeers`, each node chooses from the list of candidates the candidate closest to it (predecessor) and the candidate to which it is closest (successor).

Chord's finger (long peer) selection strategy is emulated by `handleLongPeers`. For each of the ith bits in the hash function, we choose a long peer p_i from the candidates such that

$$p_i = getClosest\,(candidates, t_i)$$

where

$$t_i = (n + 2^i) \mod 2^m$$

for the current node n. The `getClosest` function in Chord should return the candidate with the shortest distance from the candidate to the point.

This differs slightly from how selects its long peers. In Chord, nodes actively seek out the appropriate long peer for each corresponding bit. In our emulation, this information is propagated

along the ring using short peer gossip.

5.3.2 Implementing Kademlia

Kademlia uses the exclusive or, or XOR, metric for distance. This metric, while non-euclidean, is perfectly acceptable for calculating distance. For two given keys a and b

$$distance(a, b) = a \oplus b$$

The `getDelaunayPeers` function uses DGVH as normal to choose the short peers for node n. We then used Kademlia's k-bucket strategy [**?**] for `handleLongPeers`. The remaining candidates are placed into buckets, each capable holding a maximum of k long peers.

To summarize briefly, node n starts with a single bucket containing itself, covering long peers for the entire range. When attempting to add a candidate to a bucket already containing k long peers, if the bucket contains node n, the bucket is split into two buckets, each covering half of that bucket's range. Further details of how Kademlia k-buckets work can be found in the Kademlia protocol paper [**?**].

5.3.3 ZHT

ZHT [**?**] leads to an extremely trivial implementation in UrDHT. Unlike other DHTs, ZHT assumes an extremely low rate of churn. It bases this rationale on the fact that tracking $O(n)$ peers in memory is trivial. This indicates the $O(\log n)$ memory requirement for other DHTs is overzealous and not based on a memory limitation. Rather, the primary motivation for keeping a number of peers in memory is more due to the cost of maintenance overhead. ZHT shows, that by assuming low rates of churn (and infrequent maintenance messages as a result), having $O(n)$ peers is a viable tactic for faster lookups.

As a result, the topology of ZHT is a clique, with each node having an edge to all other nodes. This yields $O(1)$ lookup times with an $O(n)$ memory cost. The only change that needs to be made to UrDHT is to accept all peer candidates as short peers.

5.3.4 Implementing a DHT in a non-contrived Metric Space

We used a Euclidean geometry as the default space when building UrDHT and DGVH [**?**]. For two vectors $\vec{a}$ and $\vec{b}$ in d dimensions:

$$distance\left(\vec{a},\vec{b}\right) = \sqrt{\sum_{i\in d}\left(a_i - b_i\right)^2}$$

We implement `getDelaunayPeers` using DGHV and set the minimum number of short peers to $3d+1$, a value we found through experimentation [**?**].

Long peers are randomly selected from the left-over candidates after DGVH is performed [**?**]. The maximum size of long peers is set to $(3d+1)^2$, but it can be lowered or eliminated if desired and maintain $O(\sqrt[d]{n})$ routing time.

Generalized spaces such as Euclidean space allow the assignment of meaning to arbitrary dimension and allow for the potential for efficient querying of a database stored in a DHT.

We have already shown with Kademlia that UrDHT can operate in a non-Euclidean geometry. Another non-euclidean geometry UrDHT can work in is a hyperbolic geometry.

We implemented a DHT within a hyperbolic geometry using a Poincarè disc model. To do this, we implemented `idToPoint` to create a random point in Euclidean space from a uniform distribution. This point is then mapped to a Poincarè disc model to determine the appropriate Delaunay peers. For any two given points a and b in a Euclidean vector space, the `distance` in the Poincarè disc is:

$$distance(a,b) = \operatorname{arcosh}\left(1 + 2\frac{\|a-b\|^2}{(1-\|a\|^2)(1-\|b\|^2)}\right)$$

Now that we have a `distance` function, DGVH can be used in `getDelaunayPeers` to generate an approximate Delaunay Triangulation for the space. The `getDelaunayPeers` and `handleLongPeers` functions are otherwise implemented exactly as they were for Euclidean spaces.

Implementing a DHT in hyperbolic geometry has many interesting implications. Of particular note, embedding into hyperbolic spaces allows us to explore accurate embeddings of internode latency into the metric space [**?**] [**?**]. This has the potential to allow for minimal latency DHTs.

5.4 Experiments

We use simulations to test our implementations of DHTs using UrDHT. Using simulations to test the correctness and relative performance of DHTs is standard practice for testing and analyzing DHTs [**?**] [**?**] [**?**] [**?**] [**?**] [**?**].

We tested four different topologies: Chord, Kademlia, a Euclidean geometry, and a Hyperbolic geometry. For Kademlia, the size of the k-buckets was 3. In the Euclidean and Hyperbolic geometries, we set a minimum of 7 short peers and a maximum of 49 long peers.

We created 500 node networks, starting with a single node and adding a node each maintenance cycle.[6]

For each topology, at each step, we measured:

- The average degree of the network. This is the number of outgoing links and includes both short and long peers.
- The worst case degree of the network.
- The average number of hops between nodes using greedy routing.
- The diameter of the network. This is the worst case distance between two nodes using greedy routing.

We also tested the reachability of nodes in the network. At every step, the network is fully reachable.

Results generated by the Chord and Kademlia simulations were in line with those from previous work [**?**] [**?**]. This demonstrates that UrDHT is capable of accurately emulating these topologies. We show these results in Figures **??** - **??**.

The results of our Euclidean and Hyperbolic geometries indicate similar asymptotic behavior: a higher degree produces a lower diameter and average routing. However, the ability to leverage this trade-off is limited by the necessity of maintaining an $O(\log n)$ degree. These results are shown in Figures **??** - **??**.

[6] We varied the amount of maintenance cycles between joins in our experiments, but found it had no effect upon our results.

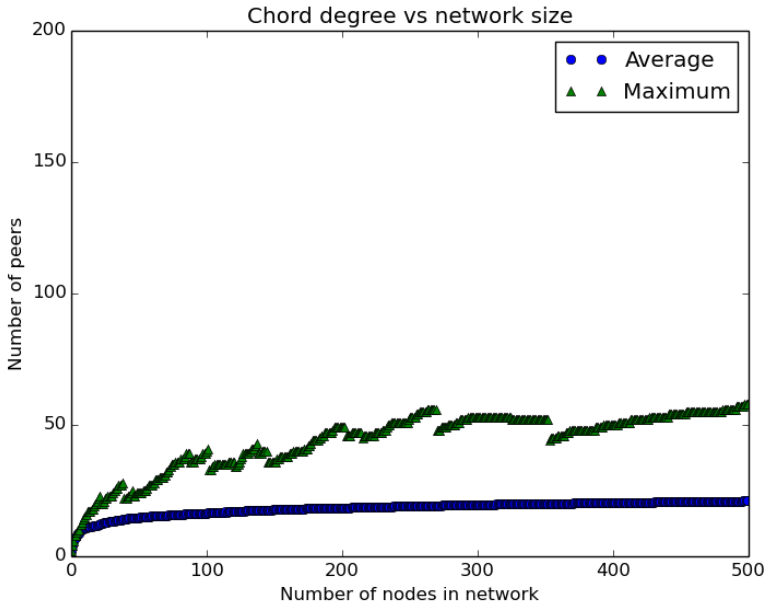


Figure 5.2: This is the average and maximum degree of nodes in the Chord network. This Chord network utilized a 120 bit hash and thus degree is bound at 122 (full fingers, predecessor and successor) when the network reaches 2^{120} nodes.

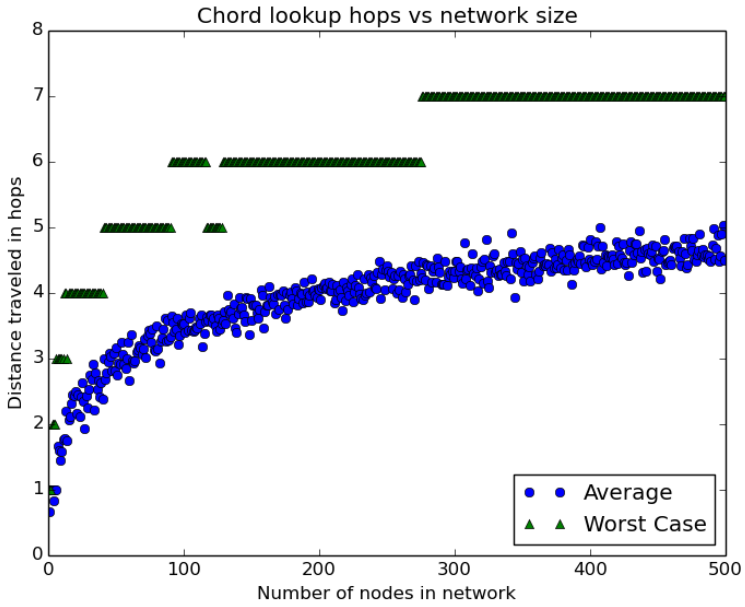


Figure 5.3: This is the number hops required for a greedy routed lookup in Chord. The average lookup between two nodes follows the expected logarithmic curve.

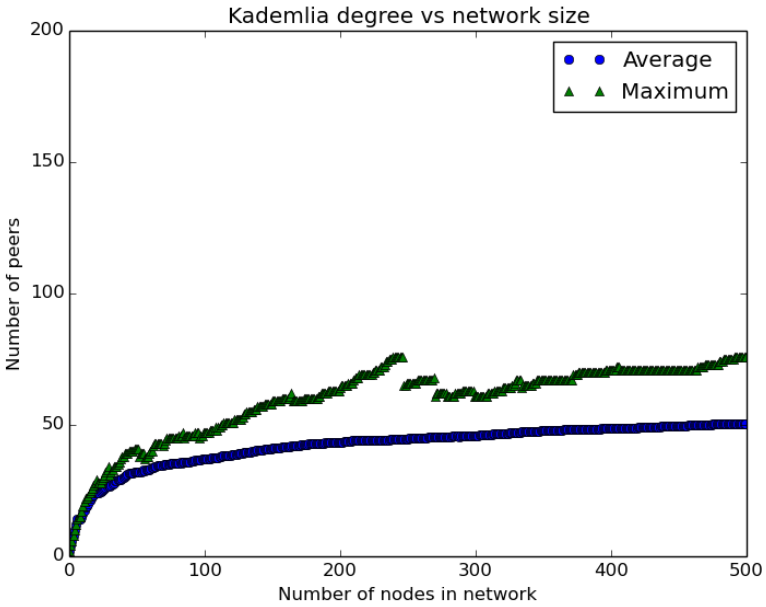


Figure 5.4: This is the average and maximum degree of nodes in the Kademlia network as new nodes are added. Both the maximum degree and average degree are $O(\log n)$.

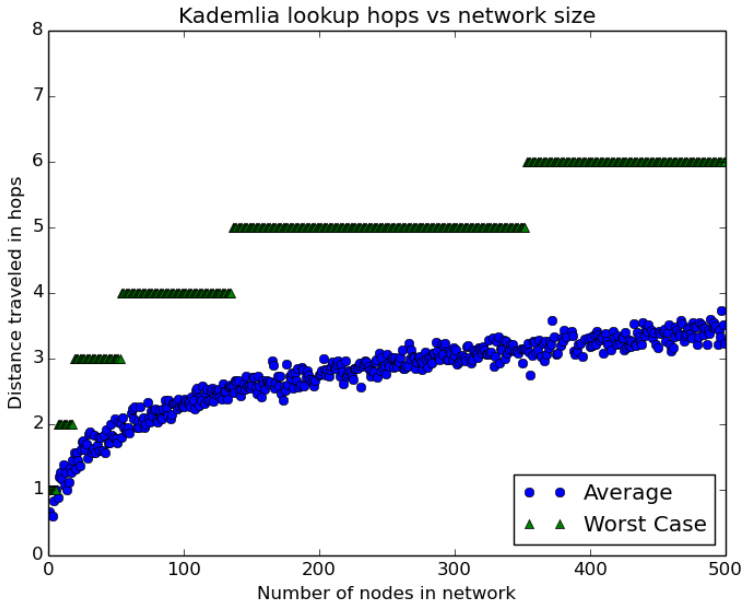


Figure 5.5: Much like Chord, the average degree follows a distinct logarithmic curve, reaching an average distance of approximately three hops when there are 500 nodes in the network.

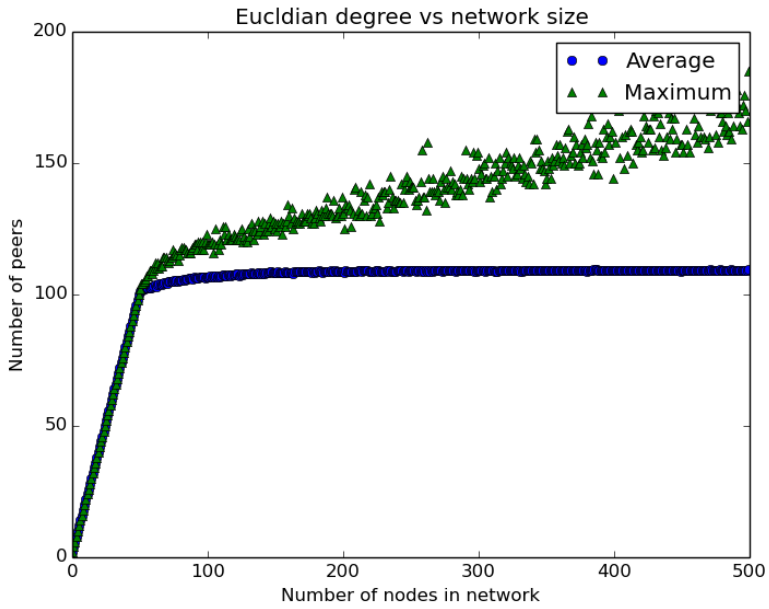


Figure 5.6: Because the long peers increase linearly to the maximum value (49), degree initially rises quickly and then grows more slowly as the number of long peers ceases to grow and the size short peers increases with network size.

While we maintain the number of links must be $O(\log n)$, all DHTs practically bound this number by a constant. For example, in Chord, this is the number of bits in the hash function plus the number of predecessors/successors. Chord and Kademlia fill this bound asymptotically. The long peer strategy used by the Euclidean and Hyperbolic metrics aggressively filled to this capacity, relying on the distribution of long peers to change as the network increased in size rather than increasing the number of utilized long peers. This explains why the Euclidean and Hyperbolic spaces have more peers (and thus lower diameter) for a given network size. This presents a strategy for trade-off of the network diameter vs. the overhead maintenance cost.

5.5 Related Work

There have been a number of efforts to either create abstractions of DHTs or ease the development of DHTs. One area of previous work focused on constructing overlay networks using system called P2 [**?**] [**?**]. P2 is a network engine for constructing overlays which uses the Overlog declarative logic language. Writing programs for P2 in Overlog yields extremely concise and modular implementations of for overlay networks.

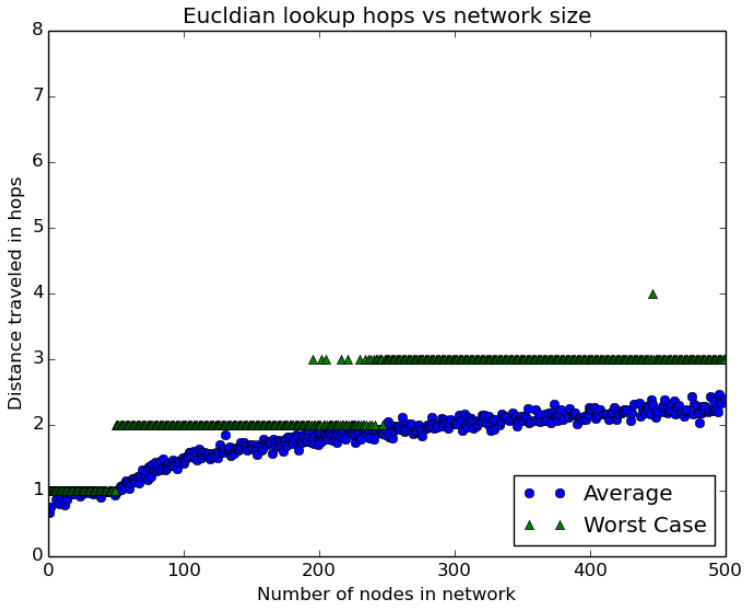


Figure 5.7: The inter-node distance stays constant at 1 until long peers are filled, then rises at the rate of a randomly connected network due to the distribution of long peers selected

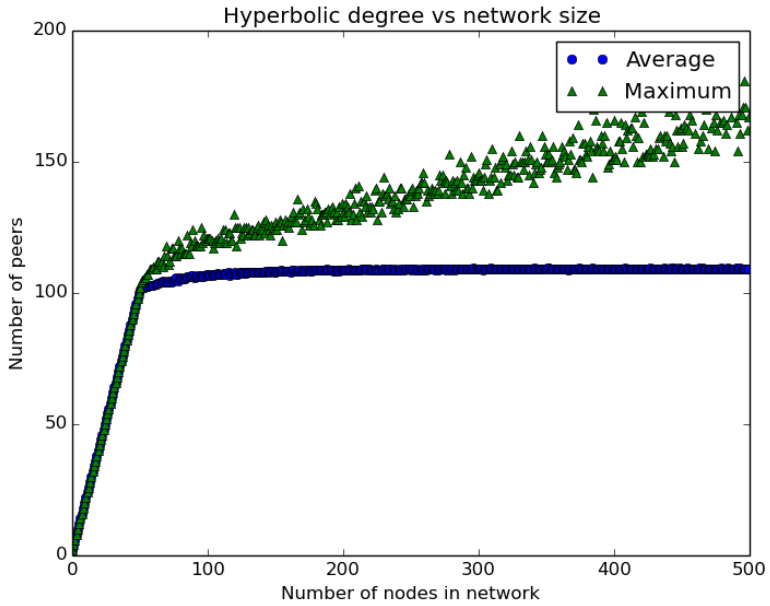


Figure 5.8: The Hyperbolic network uses the same long and short peer strategies to the Euclidean network, and thus shows similar results.

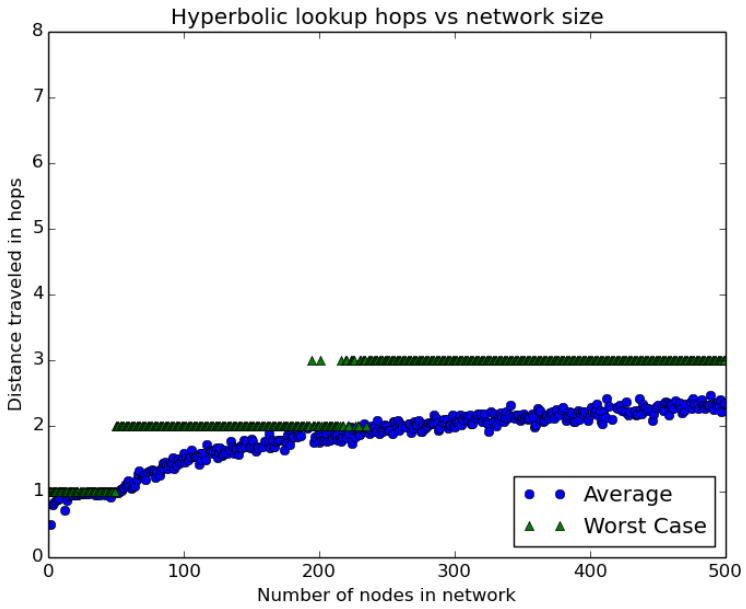


Figure 5.9: Like the Euclidean Geometry, our Poincarè disc based topology has much shorter maximum and average distances.

Our work differs in that P2 attempts to abstract overlays and ease construction by using a language and framework. while UrDHT focuses on abstracting the idea of a structured overlay into Voronoi Tessellations and Delaunay Triangulations. This allows developers to define the overlays they are building by mathematically defining a short number of functions.

Our use case is also subtly different. P2 focuses on overlays in general, all types of overlays. UrDHT concerns itself solely with distributed hash tables, specifically, overlays that rely on hash functions to distribute the load of the network and assign responsibility in an autonomous manner.

One difficulty in using P2 is that it is no longer supported as a project [**?**]. P2's concise Overlog statements also present a sharp learning curve for many developers. These present challenges not seen with UrDHT.

The T-Man[**?**] and Vicinity [**?**] protocols both present gossip-based methods for organizing overlay networks. The idea behind T-Man is similar to UrDHT, but again it focuses on overlays in general, while UrDHT applies specifically to DHTs. The ranking function is similar to the metrics used by UrDHT using DGVH, but DGVH guarantees full connectivity in all cases and is based on the inherent relationship between Voronoi Tessellations, Delaunay Triangulations, and DHTs.

UrDHT uses a gossiping protocol similar to the ones presented by T-Man and Vicinity due to

they gossip protocol's ability to rapidly adjust changes in the topology.

5.6 Applications and Future Work

We presented UrDHT, a unified model for DHTs and framework for building distributed applications. We have shown how it possible to use UrDHT to not only implement traditional DHTs such as Chord and Kademlia, but also in much more generalized spaces such as Euclidean and Hyperbolic geometries. The viability of UrDHT to utilize Euclidean and Hyperbolic metric spaces indicates that further research into potential topologies of DHTs and potential applications of these topologies is warranted.

There are numerous routes we can take with our model. Of particular interest are the applications of building a DHT overlay that operates in a hyperbolic geometry.

One of the other features shared by nearly every DHT is that routing works by minimizing the number of hops across the overlay network, with all hops treated as the same length. This is done because it is assumed that DHTs know nothing about the state of actual infrastructure the overlay is built upon.

However, this means that most DHTs could happily route a message from one continent to another and back. This is obviously undesirable, but it is the status quo in DHTs. The reason for this stems from the generation of node IDs in DHTs. Nodes are typically assigned a point in the range of a cryptographic hash function. The ID corresponds to the hash of some identifier or given a point randomly. This is done for purposes of load balancing and fault tolerance.

For future work, we want to see if there is a means of embedding latency into the DHT, while still maintaining the system's fault tolerance. Doing so would mean that the hops traversed to a destination are, in fact, the shortest path to the destination.

We believe we can embed a latency graph in a hyperbolic space and define UrDHT such that it operates within this space [**?**] [**?**]. The end result would be a DHT with latency embedded into the overlay. Nodes would respond to changes in latency and the network by rejoining the network at new positions. This approach would maintain the decentralized strengths of DHTs, while reducing overall delay and communication costs.

Chapter 6

D^3NS

The Domain Name System, commonly referred to as DNS [**?**] [**?**], is a fundamental component of the Internet. DNS maps memorable names to the numerical IP addresses used by computers to communicate over IP.

Two recent events in the United states have brought DNS to the forefront of networking and security research. First is recent legislation proposed in the US House of Representatives and US Senate. The Stop Online Piracy Act (SOPA) [**?**] and PROTECT IP Act (PIPA) [**?**] were both introduced in 2011. There were numerous aspects to both bills, but essential to both was that DNS servers located in the US would be required filter DNS records on demand, essentially fracturing the DNS system. There would be no guarantee that DNS could serve the same information to two different users.

More recent are the leaks of classified information elucidating the extent of the NSA's spying capabilities. These leaks have raised questions about the security of SSL and TLS, as well as the level of trust that users place in certificate authorities.

These types of threats to DNS, along with security concerns, were not considered when designing the protocol, but DNS is too widely used and too integrated with the Internet as a whole to be replaced. Extensions such as DNSSEC [**?**] add authentication and data integrity, but do not alter the fundamental architecture of the DNS network.

There have been many explorations and attempts [**?**] [**?**] [**?**] to propose a DNS system based on a distributed hash table (DHT) [**?**]. We extend on those papers by implementing a DHT which minimizes latency distance rather than hop distance and implementing a shared record of ownership

based on recent developments in cryptocurrency [**?**] [**?**].

This paper proposes the Distributed Decentralized Domain Name Service, or D^{3}NS. D^{3}NS is a completely decentralized Domain Name Service operating over a DHT. D^{3}NS does not replace the DNS protocol, but rather adds robustness to the architecture as a whole. Internally, D^{3}NS signs all DNS records using public/private keys, providing additional security internal to the DNS system.

We show that D^{3}NS addresses the objections to a decentralized DNS system posed by Cox *et al.* [**?**], specifically: dramatically reducing latency compared to other DHT systems, retaining the extensibility of the original DNS system, and changing the intended scope of use to address incentive issues. We show D^{3}NS allows for new authentication methods and a means of decentralized proof of ownership beyond that of Cox *et al.*'s work.

The rest of the paper is consists of the following sections. Section II gives an overview of DNS and identifies prior research in the area of distributed DNS. Section III defines the various components of D^{3}NS. Section IV covers the modified blockchain used for record authentication in D^{3}NS. Section V presents UrDHT [**?**], a DHT that we designed and used with D^{3}NS. Section VI details our implementation of D^{3}NS and we discuss our conclusions and future work in Section VIII.

6.1 Background

This paper is intended to address concerns raised by Cox *et al.* [**?**] and propose a viable decentralized DNS replacement utilizing a DHT. Our proposed improvements on the DNS alternative presented by Cox *et al.* are fully reverse compatible with the current hierarchical DNS system and provides a shared, authenticated public record that allows for DNSSEC style authentication.

6.1.1 DNS Overview

DNS queries proceed recursively through the DNS hierarchy, beginning with a query to a root server, which then yields a record for a server for the requested top level domain. This server then directs the request to another DNS server responsible for the domain under that, which yields an answer or another DNS server, which is queried in the same manner.

One of the key concepts of the DNS architecture is that no matter which servers end up being

queried, a user can expect to receive a record consistent with what the rest of the DNS system will serve for that particular request.

Recent legislative motions reflect DNS's weakness to be influenced by local government intervention [**?**] [**?**] [**?**].

These bills would have required that servers maintained in the US filter specified domain names, preventing users from obtaining the correct IP address for the domain name in question. Multiple governments have been noted to preform systematic attacks on DNS queries [**?**]. This filtering is incompatible with the DNS Security Extensions (DNSSEC) [**?**] and DNS's intended usage.

The mandated DNS filtering would possibly drive users to unregulated DNS servers, which would create more attack vectors.

6.1.2 Related Work

Cox *et al.* devised a distributed DNS using Chord [**?**] as the storage medium for DNS records, which they called Distributed DNS (DDNS). They examined the possibility of extending DNSSEC with new options for storing keys in the DHT. They encountered the then unsolved problem of proof-of-ownership [**?**] for domain names and found no means of enhancing security.

They noted that the overlay topology of a DHT such as Chord did not take into account latency optimization and thus DNS was not a viable application of a DHT due to significantly greater latency. They also pointed out several possible improvements as a result of using a DHT, namely increased robustness, an auto-balancing structure, resistance to both DDOS attacks and packet injection based DNS spoofing.

Cox *et al.* considered the optimization and security problems solvable, but they postulated that two issues rendered the system unviable. First, they intended that DDNS would replace all DNS servers and traffic, which removed extensibility and customizability of the original DNS protocol. Second, because they considered replacing the entire DNS system rather than a meaningful subset, they presented a question of incentive. What would incentivize companies to support the new system where their servers had to share the load of other companies traffic? What would stop them from holding only their content, while rejecting any additional responsibility assigned to it?

D^3NS addresses both of the raised issues. We utilize a side channel method of confirming domain named ownership via a blockchain [**?**] to enable DNSSEC style security at all layers of the network.

We propose a DHT structure which allows for minimum latency optimization. Our system aims only to replace authoritative Top Level Domain servers currently managed by registrars, where most records are simply a forward to an authoritative DNS server managed by the domain owner, rather than replacing all levels of DNS. This limiting of scope allows us to continue to take advantage of DNS extensions and as places responsibility of managing the network with those who have an incentive for its continued functioning.

6.2 D^{3}NS

D^{3}NS has logically discrete components which provide DNS efficient record storage, domain name ownership management and verification, and DNS backwards compatibility, all of which may be modularly replaced or have individual optimizations. D^{3}NS uses a DHT to store DNS records in a distributed fashion and a blockchain and Namecoin [**?**] analog to manage domain name ownership. D^{3}NS utilizes public and private key encryption for signing and verifying records.

6.2.1 Distributed Hash Table

Our implementation is not strictly specific to any particular distributed hash table. We examined using Chord [**?**] with DNS, similar to DDNS [**?**]. However, Chord's unidirectional ring overlay topology does not take actual network topology into account and using it for a global scale system is not viable because messages will be routed very inefficiently. D^{3}NS requires a DHT which allows the routing overlay to be optimized to the network topology and conditions in real time.

As a result we chose to develop a prototype DHT to meet this requirement to act as backend to our DNS system called UrDHT [**?**]. UrDHT is built on the idea of constructing the DHTs overlay by using Voronoi Tessellations and Delaunay Triangulation. Essentially, each node is at the center of Voronoi region and responsible for the records that fall in that region. The peers the node connects with correspond to that node's Delaunay neighbors. Because UrDHT works with the high level abstractions of Voronoi Tessellation and Delaunay Triangulation, UrDHT can easily be configured to work in any arbitrary metric space or imitate the overlay topology of any DHT, such as Chord.

For D^{3}NS, UrDHT uses a d-dimensional unit cube which wraps around the edges in a toroidal fashion as the space for the overlay. Each record in the DHT is assigned a location in that space.

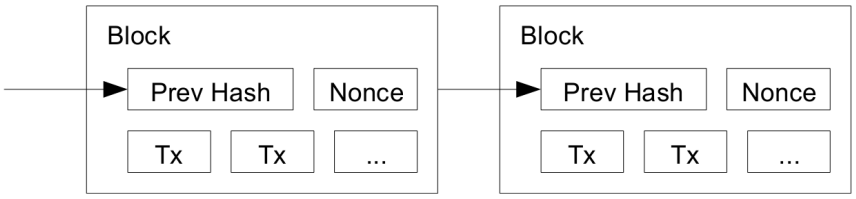


Figure 6.1: A section of the blockchain as defined by Bitcoin [**?**].

Each node is assigned a location and is responsible for records to which it is the closest node. The variable dimensionality is allowed so that problems can be embedded into the space with relative ease and records can be assigned locations which have meaning concerning the problem in which they are a part. This way, records that are close to each other in the problem formulation are close to each other in the DHT and are likely hosted on the same node. This offers speedup for many distributed algorithms which require traversal of data.

6.2.2 DNS Frontend

Because this system is intended to be reverse compatible with the existing DNS protocol, we serve the data provided by the DHT after it has been authenticated by the block chain to other DNS servers or clients. DNS nodes incorporated into the D^3NS system will not request data from other DNS servers and will only exchange data via the DHT.

6.3 Blockchain

We use a tool called a *blockchain* for maintaining and authenticating our DNS records. Blockchains have their roots in the cryptocurrency Bitcoin [**?**], where it is used to authenticate financial transactions and verify account balances. While there have been similar attempts to leverage Bitcoin's mechanisms extend DNS [**?**], they have been strictly tied to the concept of currency and not yet academically explored.

6.3.1 Blockchains in Bitcoin

Bitcoin is a decentralized electronic currency. Here we are particularly concerned with Bitcoin's blockchain. Bitcoin's blockchain consists of a shared authenticatable transaction record [**?**] [**?**] .

Bitcoin's blockchain is essentially a shared ledger. The blockchain (Figure **??**) is a record of every single transaction made using the Bitcoin. Each transaction refers to a previous transaction, indicating the funds handled by the new transaction are in fact owned by the user initiating the transaction. The record is validated by traversing the tree of transactions and marking the referenced transactions as used. A valid blockchain has all non-leaf node transactions marked as used only once.

Transactions are grouped together and verified in a *block*, which are linked together in a chain. Each block in the chain is a series of transactions published during the time it takes to generate that block. The process of authenticating these transactions and generating a new block is called mining (Algorithm **??**). Mining a block is analogous to the concept of gold mining, as the incentive for successfully mining a block is a large sum of new bitcoins.

A block is mined by generating a nonce field such that the hash of the entire block is less than a global difficulty value. This difficulty sets the rate at which new blocks are mined and is adjusted in reference to rate of mining [1]. When a block is mined, it is transmitted to the network and each transaction in it is validated by each peer. The network will then work on mining the next block.

Algorithm 6 Blockchain mining

Given previous Block B_{-1}
Given New Transaction Set T
Given Difficulty D
Given Reward destination R
New Block $B_0 = HASH(B_{-1})|T|R|Timestamp$
Block Attempt $b = B_0|Nonce$
while $HASH(b) > D$ **do**
    Block Attempt $b = B_0|Nonce$
end while
Propagate b as next block

6.3.2 Using the Blockchain to validate DNS records

We utilize the transaction record of Bitcoin to record ownership of domain names. Rather than rewarding miners with currency, the reward and incentive for mining is a record that allots the miner the right to claim a domain name.

[1] Bitcoin adjusts the difficulty rate every 2016 blocks, such that the network will then mine a block every ten minutes on average [**?**]

Algorithm 7 Blockchain Transaction Validation

```
1: A new transaction t consists of: Award domain D to user U with proof reference P and signature
   S
2: The transaction set T is the set of all transactions considered valid
3: if P is not marked used then
4:     if owner indicated in P matches signature S then
5:         if D matches domain referenced in P then
6:             Mark P as used
7:             Consider t valid
8:         else
9:             if P is a mining reward then
10:                P is an unclaimed mining reward
11:                if D is not yet claimed then
12:                    Mark P as used
13:                    Mark D as claimed
14:                    Consider t valid
15:                end if
16:            end if
17:        end if
18:    end if
19: end if
```

The transactions in each block indicate miners claiming a new domain or the transfer of domain ownership. Claims of new domains are validated by a reference to an unclaimed mining reward owned by the claiming user. Transfers are validated by a pointer to an unused previous transfer record or claim record indicating ownership by the transferring party. This way every domain name in the system can be associated with the owner's public key. New domains can be claimed and old domains can be transfered between owners. Algorithm **??** shows the process for validating transactions using the blockchain.

6.3.3 Using a Blockchain to Replace Certificate Authority

The shared record of the blockchain allows any participant in the mining network to act as a trusted third party to clients. This way, trust is not centralized at a single point of failure.

Internally, members of the DHT are also members of the blockchain network (as it is convenient to use the DHT overlay as the Blockchain network overlay) and thus all records pushed to the DHT and retrieved records can be confirmed as legitimate before transmission to the end user. This limits the viability of replay or injection based attacks.

6.4 UrDHT

One of the reasons we created UrDHT [**?**] was to allow for spacial representations to be mapped to hash locations, a feature lacking in many current distributed hash tables. In particular, we aimed to construct a mechanism for creating a more efficient global scale DHT built on a minimal latency overlay. Rather than focus on minimizing the amount of hops required to travel from point to point we wish to minimize the time required for a message to reach its recipient. UrDHT actually has a worse worst-case hop distance ($O(\sqrt[d]{n})$) than other comparable distributed hash tables ($O(lg(n))$). However, UrDHT can route messages as quickly as possible rather than traveling over a grand tour that an overlay network may describe in the real world.

The naive method of doing so is to assign coordinates to servers based on the geographic location of nodes. More complex approaches would approximate a minimum latency space based on inter-node latency. Algorithm **??** describes the process for performing a minimum latency embedding using UrDHT

Algorithm 8 UrDHT Minimum Latency Embedding

1: d is the dimensions of the hash space
2: seed the space with $d+1$ nodes at random locations
3: A node n wishes to join the network
4: n pings a random subset of peers to find latencies L
5: Normalize L onto (0.0,1.0) to yield L_N
6: Choose position p such that

$$\sum_{i \in peers} (L_N[i] - dist(p,i))^2$$

is minimized
7: Re-evaluate location periodically

6.4.1 Toroidal Distance Equation

Given two vector locations $\vec{a}$ and $\vec{b}$ on a d dimensional unit toroidal hypercube:

$$distance = \sqrt[|d|]{\sum_{i \in d} (\min(|\vec{a}_i - \vec{b}_i|, 1.0 - |\vec{a}_i - \vec{b}_i|))^2}$$

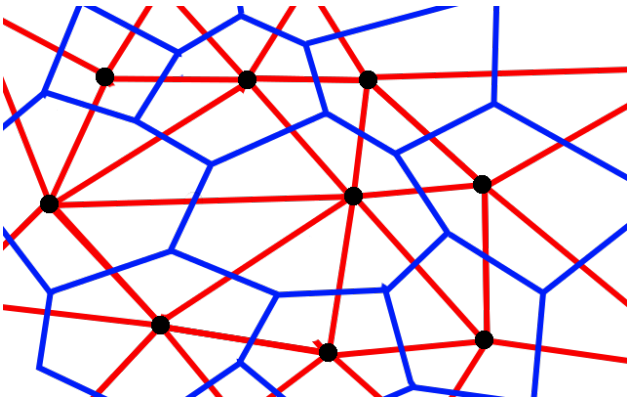


Figure 6.2: The starting network topology. The blue lines demarcate the Voronoi edges, while the red lines connecting the nodes correspond to the Delaunay Triangulation edges and one-hop connections.

6.4.2 Mechanism

UrDHT maps nodes to a d dimension toroidal unit space overlay. This is essentially a hypercube with wrapping edges. The toroidal property makes visualization difficult but allows for a space without a sparse edge, as all nodes can translate the space such that they are at the center of the space. In effect, each node views itself at the center of the graph.

Nodes in UrDHT are responsible for the address space defined by their Voronoi region. This region is defined by a list of peers maintained by the node. A minimum list of peers is maintained such that the node's Voronoi region is well defined. The links connecting the node to its peers correspond to the links of a Delaunay Triangulation. One such possible network is shown on Figure **??**.

6.4.3 Relation to Voronoi Diagrams and Delaunay Triangulation

UrDHT does not strictly solve Voronoi diagrams [**?**] for a number of reasons. DHTs are completed decentralized, with no single node having global knowledge of the topology. Many of the algorithms to compute Delaunay Triangulation and/or Voronoi Tessellation are unsuited to a distributed environment. In addition, the computational cost increases when we move into spaces with greater than two dimensions. In general, finding the Delaunay Triangulation of n points in a space with d dimensions takes $O(n^{\frac{2d-1}{d}})$ time [**?**].

UrDHT uses the Distributed Greedy Voronoi Heuristic [**?**], to create an approximation of Voronoi tessellation and Del. An online algorithm (Algorithm **??** maintains the set of peers defining

the node's Voronoi region. The set of peers required to define a node's Voronoi Region corresponds to a solution to the dual Delaunay Triangulation.

6.4.4 Messages

Maintenance and joining are handled by a simple periodic mechanism. A notification message consisting of a node's information and active peers is the only maintenance message. All messages have a destination hash location which is used to route them to the proper server. This destination can be the hash location of a particular node or the location of a desired record or service. The message is received by the node responsible for the location. Services running on the DHT define their own message contents, such as commands to store and retrieve data.

6.4.5 Message Routing

Messages are routed over the overlay network using a simple algorithm (Algorithm **??**). When routing a message to an arbitrary location, a node calculates which Voronoi region the message's destination is in amongst the itself and its peers. If the destination falls within its own region, then it is responsible and handles the message accordingly. Otherwise, the node forwards the message to the closest peer to the destination location. This process describes a precomputed and cached A* routing algorithm [**?**] .

6.4.6 Joining and Maintenance

Joining the network is a straightforward process. A new node first learns the location of at least one member of the network to join. The joining node then choses a location in the hash space either at random or based on a problem formulation (for example, based on geographic location or latency information).

After choosing a location, the joining node sends a *join* message to its own location via the known node. The message is forwarded to the current owner of that location who can be considered the "parent" node. The parent node immediately replies with a maintenance message containing its full peer list. This message is sent to the joining node, who then uses this to begin defining the space it is responsible for.

The joining node's initial peers are a subset of the parent and the parent's peers. The parent adds the new node to its own peer list and removes all his peers occluded by the new node. Then regular maintenance propagates the new node's information and repairs the overlay topology. This process is described by Algorithm **??**.

Algorithm 9 Join

1: new node N wishes to join and has location L
2: N knows node x to be a member of the network
3: N sends a request to join, addressed to L via x
4: node $Parent$ is responsible for location L and receives the join message
5: $Parent$ sends to N its own location and list of peers
6: $Parent$ integrates N into its peer set
7: N builds its peer list from N and its peers
8: regular maintenance updates other peers

Each node in the network performs maintenance periodically by a maintenance message to its peers. The maintenance message consists of the node's information and the information on that node's peer list. When a maintenance message is received, the receiving node considers the listed nodes as candidates for its own peer list and removes any occluded nodes (Algorithm **??**).

When messages sent to a peer fail, it is assumed the peer has left the network. The leaving peer is removed from the peer list and candidates from the set of 2-hop peers provided by other peers move in to replace it. Maintenance is described by Algorithms **??** and **??**. Figures **??**, **??**, and **??** illustrate the joining processing.

Algorithm 10 Maintenance Cycle

1: P_0 is this node's set of peers
2: T is the maintenance period
3: **while** Node is running **do**
4: **for all** node n in P_0 **do**
5: Send a Maintenance Message containing P_0 to n
6: **end for**
7: Wait T seconds
8: **end while**

There is no function for a "polite" exit from the network. UrDHT assumes nodes will fail and the difference between an intended failure and unintended failure is unnecessary. The only issue this causes is that node software should be designed to fail totally when issues arise rather then attempt to fulfill only part of its responsibilities.

Algorithm 11 Handle Maintenance Message

```
1: P_0 is this node's set of peers
2: Receive a Maintenance Message from peer n containing its set of peers:P_n
3: for all Peers p in P_n do
4:     Consider p as a member of P_0
5:     if p should join P_0 then
6:         Add p to P_0
7:         for all Other peers i in p do
8:             if i is occluded by p then
9:                 remove i from P_0
10:            end if
11:        end for
12:    end if
13: end for
```

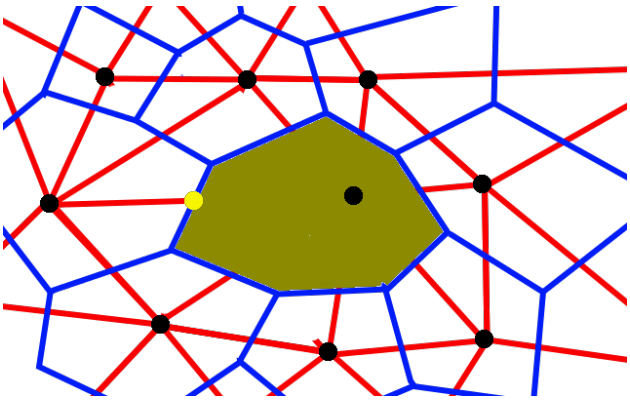


Figure 6.3: Here, a new node is joining the networks and has established that his position falls in the the yellow shaded Voronoi region.

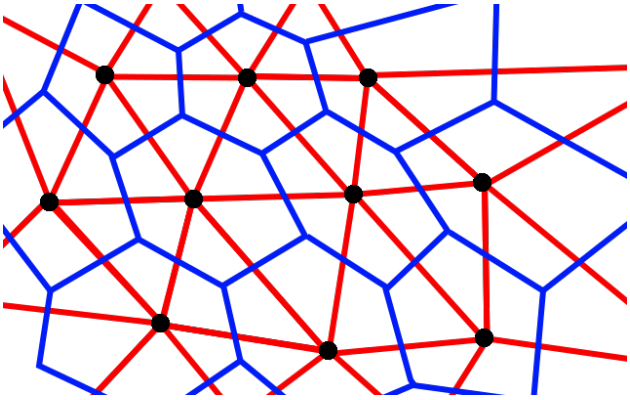


Figure 6.4: The network topology after the new node has finished joining.

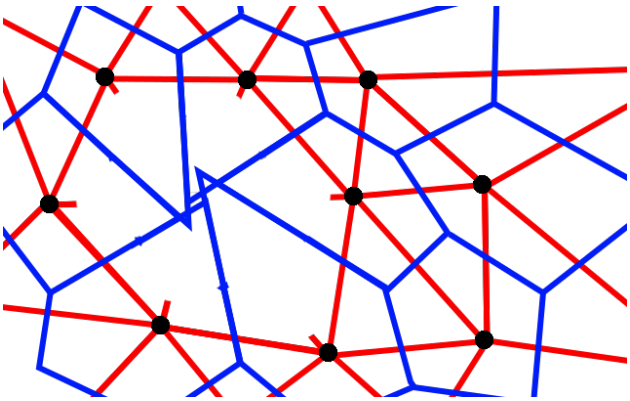


Figure 6.5: The topology immediately after the new node leaves the network. After maintenance takes place, the topology repairs itself back to the configuration shown in Figure **??**.

6.4.7 Data Storage and Backups

The primary goal of a DHT is to provide a distributed storage medium. We extend this idea to distribute work and information among nodes using the same paradigm. Resources in the network, be it raw data or assigned tasks, are assigned hash locations. The node responsible for a given hash location is responsible for the maintenance of that resource. When a node fails, its peers take responsibility of its space. Thus it is important to provide peers with frequent backups of a node's assigned resources. That way, when a node fails, its peers can immediately assume its responsibilities.

When a resource is to be stored on the network, it is assigned a hash location. The hash locations assigned could be random, a hash of an identifier, or have specific meaning for an embedding problem. The node responsible for that resource's hash location stores the resource.

A resource is accessed by contacting the node responsible for the resource. However, the requester generally has no idea which node is responsible for any particular resource. The data request messsage is addressed to the location corresponding to the resource, rather than the node responsible for that location. The message is forwarded over the overlay network, each hop bringing the node closer until it reaches the responsible node, who sends the resource or an error if the resource does not exist.

Some options are immediately apparent for dealing with wasted storage space. A system that is primarily read driven can record the time of the last read or a frequency of reads such that resources that are not read often enough are deleted after a certain period of time. If a system is

write driven, allow the resource to be assigned a time to live, which can be updated as needed.

A node periodically sends a message containing backups of the resources for which it became newly responsible for to each of its peers. To minimize bandwidth and time wasted by backups, the node should only send the records changed since last backup.

6.5 Implementation

This section describes how the components of the D^{3}NS system piece together as a coherent whole. We demonstrate how this system would be used in the real world to provide a better Domain Name Service.

6.5.1 Establishment of a New Domain

Under the current DNS system, a new domain name is purchased from a company registered with the Internet Corporation for Assigned Names and Numbers (ICANN). That company adds the domain name and a record provided by the owner to the TLD servers. The owner or management company then maintains a name server to answer DNS requests for the purchased domain. In D^{3}NS, new domain names are instead awarded as part of the blockchain mining process or purchased from a previous owner, then transferred to the new owner. These assignments and transfers are both recorded in the blockchain.

A prospective domain owner can use their own mining software and mine a domain name or purchase a domain name voucher from a miner and exchange it for a domain name. In the blockchain, domain name owners are referred to by their public key. The public key is used to authenticate both records and transfers of domains. Loss of the private key of an account will result in the loss of ability to update DNS records and the ability to transfer the domain.

6.5.2 Updating Records for a Domain

A domain name record in the current DNS system is used to indicate a record on your own Name Server or to configure the record held by the TLD server that contains the address record. Using D^{3}NS, all records must be signed using their owner's private key and confirmed with the public key.

A properly configured D^{3}NS server should not accept any DNS records which have not been signed by their owner or accept a record with an older version number. To push a new DNS record for a domain, the owner must create the record set for the domain and then sign and submit it to a node on the DHT. The DHT will forward the record to the responsible party and store it after confirming its validation. The new record will begin to be broadcast to clients after old records begin to expire and caches seek new records.

6.5.3 Looking up a DNS record

In the current DNS configuration, a record is looked up using a UDP system that queries a tree of servers. clients send queries to a local DNS server which acts as a DNS resolver and cache. If a portion of the domain name is unknown, the resolver sends a request to the responsible server and looks the record up recursively.

This system is largely unchanged under D^{3}NS from the point of view of the DNS resolver and client. Ideally, the resolver or client has chosen a nearby member of the D^{3}NS network as its root domain name server (it can also maintain a large list of backup servers, should the current one fail). The resolver requests a domain's record from the D^{3}NS node. The node then forwards the request to the responsible party. If any node along the route has a valid cache of the required record, then that server responds and routes the message back to the entry node. All nodes along the route cache the response to aid future queries.

6.5.4 Caching

DNS needs to aggressively cache lookups. Previous investigations into optimizing caching on a DHT saw favorable results [**?**]. However, with the specific application of DNS in mind, the time-to-live field on DNS records defer the caching optimization problem onto users. While it may be tempting to utilize the built in time-to-live field for caching on the DHT, the possible cyclical nature of cache passing may result in difficulty in propagating new records.

Integrated File Replication and Consistency Maintenance (IRM) [**?**] views the process of caching and keeping the cache up to date as components of larger problem. Nodes in the DHT keep track of how often records are requested and cache those records once a defined rate is passed. Nodes then request an update for the cache based on how often the record is requested and how often

that request is expected to be changed by the owner.

In the current implementation of DNS, caching involves a time-to-live field defined by the domain owner. This means that no effective cache optimization done by the server; rather the server that trusts records to have a sensible time-to-live value. IRM [**?**] can be used to approximate the correct time-to-live value for a record.

6.6 Conclusion and Future Work

D^{3}NS was successfully implemented to act as a DNS server. A user would query the a computer we set up as a DNS gateway which was a member of the DHT and mining network. If the queried domain had a record stored in the DHT and an owner established in the blockchain, the server would reply with the stored DNS records. Otherwise the server would reply with a DNS failure. We ran the DHT and mining network on a cluster of computers and an artificially low difficulty such that a live demo of mining would be viable.

Using all of these components together allowed us to create a system with the following features:

- Robustness - The DHT and Blockchain are both robust to failures and attacks.
- Extensibility - The DNS reverse compatibility allows any DNS extension to be utilized, if dynamic resolution is required a name server record can be stored in the DHT to point to a user's specialized DNS servers.
- Decentralization - Both the DHT and Blockchain can operate without the support of any controlling organization, this offers security against corruption and abuse.

D^{3}NS successfully addresses the challenges laid down by Cox *et al.* [**?**] in regards to designing a DNS replacement running over a DHT. We encourage criticism, revision, and adoption of this new system.

6.6.1 Unaddressed Issues and Future Work

The Blockchain does not solve all security issues relevant to DNS authentication and security. Exit nodes could lie or have packets inject to clients until the protocol from DNS server to client is improved. The DHT structure opens up unexplored disruption attacks on the overlay topology.

A series of issues relevant to UrDHT are not addressed here due to limiting of scope, space, time, and a lack of actual solutions to the problems: The exact method of caching to optimize lookup time under real world usage. The overlay network being mapped onto latency results in nodes whose failure due to natural disaster to be comorbid with it's neighbors resulting to data loss. Comorbidity could be counteracted by more complex backup schemes.

Future work will explore various solutions to theses issues, as well as generalized improvements to D^3NS as whole. In particular, the technique of allying a DHT value store for real-time data and a Blockchain for ownership verification may prove a viable technique for decentralizing other web services and enabling new shared storage and computation mediums.

However, D^3NS served as our first real application built with the concepts of DGVH, VHash, and UrDHT. It served as a successful prototype for and demonstrated the viability of those ideas.

Chapter 7

Analysis of The Sybil Attack

7.1 Introduction

One of the key properties of structured peer-to-peer (P2P) systems is the lack of a centralized coordinator or authority. P2P systems remove the vulnerability of a single point of failure and the susceptibility to a denial of service attack [**?**], but in doing so, open themselves up to new attacks.

Completely decentralized P2P systems are vulnerable to *Eclipse attacks*, whereby an attacker completely occludes healthy nodes from one another. This prevents them from communicating without being intercepted by the adversary. Once an Eclipse attack has taken place, the adversary can launch a variety of crippling attacks, such as incorrectly routing messages or returning malicious data [**?**].

One way to accomplish an Eclipse attack is to perform a *Sybil attack* [**?**]. In a Sybil attack, the attacker masquerades as multiple nodes, effectively over-representing the attacker's presence in the network to maximize the number of links that can be established with healthy nodes. If enough malicious nodes are injected into the system, the majority of the nodes will be occluded from one another, successfully performing an Eclipse attack.

This vulnerability is well known in the security community [**?**]. Extensive research has been done assessing the damage an attacker can do after establishing themselves [**?**]. Little focus has been done on examining how the attacker can establish himself in the first place and precisely how easily the Sybil attack can be accomplished.

A simple method to generate node locations is to assign them at random. A Sybil attack

against this method is fairly straightforward; the attacker just assigns their own nodes at "random" locations. A more sophisticated method to generate node locations would use a hash function of some unique characteristic of the node. For example, a Distributed Hash Table could use a hash of the node's IP address and port number. In this paper, we show that using a hash function provides no protection against a Sybil attack.

Our goal is to look at the Sybil attack from the perspective of an adversary executing the Sybil attack. We did a formal analysis on the breadth and depth of the presence an adversary could establish on a structured P2P network. We also constructed simulations demonstrating the steps an attacker could follow to perform a Sybil attack. Once the attacker has joined the network, they can proceed to incrementally inject malicious nodes directly in between members of the network, a process we call *mashing*.

Sybil attacks represent a significant threat to the security of any distributed system. Many of the analyses on Tor [**?**] emphasize the vulnerability of Tor to the Sybil attack [**?**]. This threatens the anonymity of Tor users.

Sybil attacks are also a threat to P2P systems such as BitTorrent, which is essential to a wide variety of users. BitTorrent is currently the *de facto* platform for distributing large files scalably among tens of thousands of clients. Many implementations rely on Mainline DHT (MLDHT) [**?**] to connect users to other peers. The number of users on Mainline DHT ranges from 15 million to 27 million users daily, with a turnover of 10 million users a day [**?**]. Current research demonstrates BitTorrent is vulnerable to Sybil attacks and a persistent attack disabling BitTorrent would be highly detrimental to many users, especially developers and system administrators [**?**]. BitTorrent is currently under an active Sybil attack [**?**], although the attackers are apparently not trying to destroy the network.

There have been many suggestions on how to defend against Sybil attack, but there is no agreed upon "silver bullet" among researchers that should be implemented for every distributed application [**?**] [**?**]. Urdaneta *et al* find that in DHT security, a centralized, trusted authority which certifies or binds identities is the most effective strategy [**?**]. This solution potentially removes the Sybil attack, but reintroduces vulnerabilities to denial of service attacks and is contrary to the objective of creating fully decentralized systems. Other techniques such as proof-of-work [**?**] may provide a defense against Sybil attacks, but proof-of-work systems must set their computational puzzles to

be simple enough for the weakest member of the network to participate. However, the attacker can reasonably obtain computational power that is orders of magnitude greater than those weakest nodes and overcome the puzzle with brute force [**?**].

Our work presents the following contributions:

- We first discuss the assumptions behind performing a Sybil attack on a structured P2P network and analyze how effective a Sybil attack is based on the resources available to the attacker. We show that in a size n network being attacked by an adversary with s distinct identities that the probability that *any* given link leads to a Sybil is $P_{bad\_neighbor} = \frac{s}{s+n-1}$ (Section **??**).

- We present our simulations that show how quickly even a naive Sybil attack can compromise a system. We validate our experimental results by comparing them with the equations we specify in our analysis (Section **??**).

- We discuss the broader implications of our work, including how mashing can be used for automatic load balancing and disrupting P2P botnets (Section **??**).

7.2 Analysis

We make a few assumptions for our analysis; some apply to the P2P network we are analyzing and some create rules that restrict the adversary. Without these assumptions, the Sybil attack becomes trivial to perform.

7.2.1 Assumptions

Our first assumption is that the systems we analyze are fully distributed and assign identities to nodes and data using a cryptographic hash function. These systems are called distributed hash tables (DHTs).

Cryptographic hash functions work by mapping some input value to an m-bit key or identifier. Well-known hash functions for performing this task include MD5 [**?**] and SHA1 [**?**]. Keys generated by the hash function in our analysis are assumed to be uniformly distributed and random [**?**], which

we will see in the next chapter is not completely true. These hash functions are designed to make the intentional discovery of collisions computationally difficult.

In distributed hash tables, m is a large value in order to avoid collisions between mapped inputs, unintentional or otherwise. An $m \geq 128$ is typical, with $m = 160$ being the most popular choice.

Our second assumption is that node IDs are generated by hashing their IP address and port. If the choice of ports are restricted, the attacker would have to obtain more IP addresses. This is a form of very weak security that binds a particular hash key to a specific IP/port combination [**?**] [**?**]. This method is often used as a means of generating node IDs.

Although other methods do exist, the only other one that is mentioned as often is to let nodes choose their own m-bit ID at random.[1] This is notably done in Mainline DHT, and makes the system extremely vulnerable to a Sybil attack. Since there is no way to verify that a node chose the m-bit ID at random, nodes in the network accept advertised keys at face value. This allows a prospective attacker to choose any specific key they want.

We also assume that nodes verify that a peer's advertised IP/port combination exists and that the hash function of these IP/port generates the correct node ID. This verification is not explicitly used or implemented in any DHT. Failure to validate advertised values results in a trivial security flaw.

Consider an attacker operating under these assumptions who wants to inject a malicious node in between two victims which have no other nodes in between them. The attacker must search for a valid IP and port combination under their control that generates a hash key that lies between the two victims' ID, a process we call *mashing*. The attacker's ability to compromise the network depends on what IP addresses and ports are available.

The process for mashing is similar to searching for a hash collision, but much easier. Rather than searching for two inputs to a function that produce the same m-bit output, the attacker searches for a single input and corresponding m-bit hash that falls between two given m-bit IDs. We assume the IDs are evenly distributed [**?**], so in a size n network there would be $\approx \frac{2^m}{n}$ unused IDs between each pair of nodes. This means the attacker is actually searching for a collision with one of $\approx \frac{2^m}{n}$ m-bit hashes, which is a much simpler problem.

[1] Another commonly mentioned method is hash public keys [**?**] [**?**] [**?**] [**?**]. If the keys are certified or signed by an centralized source, we no longer have a completely decentralized network. If the nodes are generating the keys themselves, then we have essentially the same problem as letting nodes choose keys at random.

7.2.2 Analysis

Suppose we have a DHT with n members in it, with m-bit node IDs between $[0, 2^m)$. Consider two victim nodes with IDs a and b, with no others nodes with an ID in the range (a, b).

The probability that a single mash key lies in the range of (a, b) is $\frac{|b-a|}{2^m}$, which is the fraction of the network that lies between a and b. Thus the probability that the mash key does not lie in that range is $1 - \frac{|b-a|}{2^m}$. Assuming that the individual mash keys are statistically independent yields the expression:

$$(1 - \frac{|b-a|}{2^m})^{num\_ips \cdot num\_ports}$$

for the probability that no mash key lands in the range.

Thus the probability P that an attacker can mash a hash key that lands in the range (a, b) is:

$$P \approx 1 - (1 - \frac{|b-a|}{2^m})^{num\_ips \cdot num\_ports}$$

where num_ip is the number of IP addresses the attacker has under thier control and num_ports is the number of ports the attacker can try for each IP address.

If the ports the attacker can utilize are limited to the ephemeral ports,[2] the attacker has 16383 ports to use for each IP address. As previously noted, we assume that for a large enough n, node IDs will be close to evenly distributed across the keyspace. This means $|b - a| \approx \frac{2^m}{n}$. Therefore, the earlier probability is equivalent to:

$$P \approx 1 - (1 - \frac{1}{n})^{num\_ips \cdot num\_ports}$$

This indicates that the statistical ease of mashing is independent of m.

Given a healthy node, the probability $P_{bad\_neighbor}$ that a Sybil is its closest neighbor is:

$$P_{bad\_neighbor} = \frac{num\_ips \cdot num\_ports}{num\_ips \cdot num\_ports + n - 1} \tag{7.1}$$

This is effectively the number of malicous identities in the network ($num\_ips \cdot num\_ports$) over the total number of identities in the network. Our experiments in Section **??** show that $P_{bad\_neighbor}$ is

[2] Also known as private or dynamic ports. These ports are never assigned a specific use by the Internet Assigned Numbers Authority and are available for applications to use as needed [**?**].

actually the probability that *any* of a nodes links connect to a Sybil.

From the previous equation, the adversary can compute how many unique IP/port combinations they need if they wish to obtain a desired probability $P_{bad\_neighbor}$:

$$num\_ips \cdot num\_ports = P_{bad\_neighbor} \cdot \frac{n-1}{1 - P_{bad\_neighbor}}$$

Using our previous assumption that the adversary is limited to the 16383 ephemeral ports, the attacker can computer the number of unique IP addresses needed:

$$num\_ips = P_{bad\_neighbor} \cdot \frac{n-1}{1 - P_{bad\_neighbor}} \cdot \frac{1}{16383}$$

We verify these equations with our simulations.

7.3 Simulations

An essential part of our analysis was demonstrating just how fast an adversary can compromise a system. We performed four experiments to accomplish this task. These experiments were designed to analyze increasing levels of difficulty. The first experiment demonstrates a hash attack is possible and later experiments verify the feasibility on larger and more complicated networks. Our simulations were written in Python 2.7 and performed on an AMD Phenom II 965 processor.

We used SHA1 as our cryptographic function, which yields 160-bit hash keys. Again, we use the constraint that victim nodes do an absolute minimum verification which forces an attacker to only present Sybils with hash keys that they can generate with valid IP and port combinations.

We assume that the attacker has no resource limitations. Previous research [**?**] shows that an adversary performing a Sybil attack does not need to maintain the state information of other nodes and can leverage the healthy nodes to perform any needed routing. Nor does the adversary necessarily need to create a new running copy for every Sybil created, but doing so is quite feasible.

7.3.1 Experiment 0: Mashing 2 random nodes

Our initial experiment was designed to establish the feasibility of joining the network in between two random nodes. Each trial, we generated two victims with random IP addresses and ports,

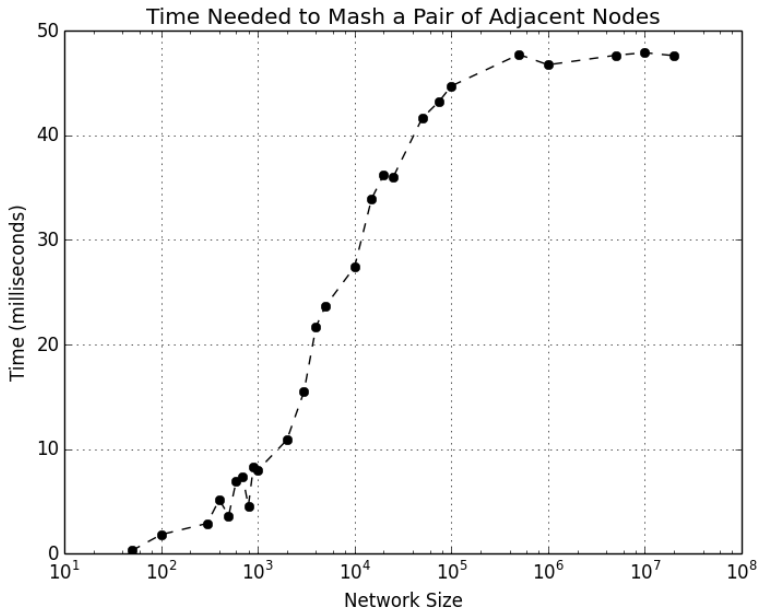


Figure 7.1: This figure shows the amount of time needed for an adversary with a single IP address to mash a pair of adjacent nodes. The time it takes to mash a pair of nodes begins to markedly increase once the network size gets above 1000 until it asymptotes at 48 ms. For larger networks, more IP addresses are needed and precomputing becomes necessary.

and an attacker with a random IP address. The experiment was for the attacker to find a key in between the two victims' keys, going clockwise. The average amount of time over 10,000 trials to mash two random keys was 29.6218 microseconds, and was achievable 99.996% of the time.

This test shows that the hashing operation is extremely quick. However, two arbitrary nodes in a network can be and often are quite distant, in which case the mashing can be done quickly. Our next experiment studies a more realistic condition.

7.3.2 Experiment 1: Time Needed to Mash a Region

After showing that mashing two arbitrary nodes takes a minuscule amount of time, the next step is to demonstrate that mashing the region between two adjacent nodes in a network of size n also takes an inconsequential amount of time. We simulate this by creating a sorted list of node IDs for n random IP/port combinations and pick a random adjacent pair of numbers from the list. The adversary then hashes their IP with their ports until they find an IP/port combination that results in a hash key falling in between the given pair. Our results averaged 100 trials for each network size are shown in Figure **??** and Table **??**.

Table 7.1: Times and success rate for mashing adjacent nodes for a single IP.

Network Size	Success Rate	Avg Time to Mash (ms)
50	1.0	0.29
100	1.0	1.82
300	0.99	2.89
400	0.98	5.16999
500	1.0	3.62999
600	0.98	6.97
700	0.94	7.32
800	0.99	4.54999
900	0.92	8.28
1000	0.92	7.96999
2000	0.95	10.88
3000	0.88	15.47999
4000	0.74	21.7
5000	0.71	23.68
10000	0.67	27.41
15000	0.5	33.93
20000	0.37	36.24999
25000	0.39	35.98
50000	0.23	41.64999
75000	0.2	43.25999
100000	0.13	44.71999
500000	0.04	47.73999
1000000	0.03	46.75
5000000	0.0	47.65999
10000000	0.0	47.90999
20000000	0.0	47.62

These figures show that the larger the network size, the longer it takes for the adversary to mash a given pair of adjacent nodes. Eventually, the time it takes to mash a region asymptotes to about 48 milliseconds. This is the amount of time it takes for the adversary with a single IP to generate all 16383 hash combinations. While this is a short time to mash a single region, an adversary following the attack specified in our next experiment will want to mash $n-1$ regions. If the network size is 1 million, this process can take upwards of 13 hours in computational time.

Since the attacker's IP addresses and ports do not change over the course of the attack, the attacker would waste time by generating the same keys over and over. The mashing process could also take substantially longer if the network a hash function that produces numbers larger than 160 bits or if the network uses a more expensive function such as scrypt [**?**].

The attacker can instead perform all the work needed to mash a network upfront, precomputing all possible valid hash keys. We have shown this takes about 48 milliseconds for 16383 keys. Storing these values in a sorted list costs 160 bits for each SHA1 key and 16 bits for each port, for a total of $176 \cdot 16383 = 2,883,408$ bits, or roughly 352 kilobytes for each IP address the attacker has.[3]

7.3.3 Experiment 2: Nearest Neighbor Eclipse via Sybil

The objective of this experiment is to completely eclipse a network using a Sybil attack, starting with a single malicious node. We simulate this by creating a network of n nodes. Each node is represented by a key generated by taking the SHA1 of a random IP/port combination.

The goal of the attacker is to mash as many pairs of adjacent nodes as possible. We call this the *Nearest Neighbor Eclipse* since the attacker seeks to become the nearest neighbors of each node.

The attacker is given *num_ips* randomly generated IP addresses, but can use any port between 49152 and 65535. This gives the attacker $16383 \cdot num\_ips$ possible hash keys to use for Sybils. As mentioned previously in Section **??**, the attacker can easily precompute all of theses hash keys and store them in a sorted list to be used as needed, requiring only 352 kilobytes per IP. Since this list is sorted and this attack will go in order through the network, searching for a key that mashes a pair of nodes takes constant time.

To perform the attack, an adversary choses any random hash key as a starting point to "join" the network. This is their first Sybil and the join process provides information about a number

[3]Storing the IP address is unnecessary since it is always the same.

of other nodes. Most importantly, nodes provide information about other nodes that are close to it, which are provided to ensure fault tolerance between immediate neighbors. The adversary uses this information to inject Sybils in between successive healthy nodes. For example, in Pastry, a joining node typically learns about the 16 nodes closest to it for fault tolerance, in addition to all the other nodes it learns about [**?**]. In Chord, this number is a system configuration value r [**?**].

For clarity we present this example. Consider the small segment of the network made up of adjacent nodes a, b, c, and d. The Sybil joins between nodes a and b, and the joining process informs the adversary about node c, possibly node d, and a handful of other nodes in the network. The adversary will always learn about node c because a node between a and b would need to know about node c for fault tolerance.

The adversary's next move would be to inject a node between nodes b and c. This is done by selecting a hash key k. The adversary injects a Sybil node with key k, which joins in between b and c, and the joining process informs the adversary about node d and several other nodes, including many close nodes. The adversary then aims to inject a node in between c and d, and continues *ad nauseam*.

Depending on the network size and the number of keys available to the adversary, it is entirely possible the adversary will not have a key to inject between a pair of successive nodes. In this case, the adversary moves on to the next successive pair that the adversary has learned about. In the extremely unlikely event this information is not already known, the adversary can look it up using the DHT's lookup function.

We simulated this attack on networks of up to 20 million nodes. We chose 20 million since it falls neatly into the 15-27 million user range seen on Mainline DHT [**?**]. We gave the attacker access to up to 19 IP addresses. Our results are in Figures **??** and **??** and Table **??**. For Table **??**, we have included only the results for larger sized networks, as the smaller sized networks were completely occluded.

Our results show that an adversary, given only modest resources, can inject a Sybil in between the vast majority of successive nodes in moderately sized networks. In a large network, modest resources still can be used to compromise more that a third of the network, an important goal if the adversary wishes to launch a Byzantine attack.

Our results match values predicted by Equation **??**. However, this experiment only covers the

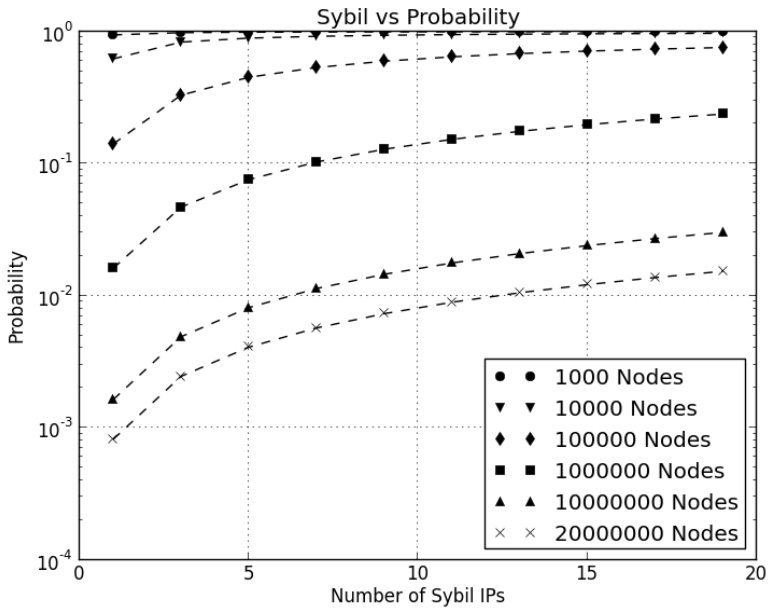


Figure 7.2: Our simulation results. The x-axis corresponds to the number of IP addresses the adversary can bring to bear. The y-axis is the probability that any chosen region has been mashed. Each line maps to a different network size of n. The dashed line corresponds to values from Equation **??**: $P_{bad\_neighbor} = \frac{num\_ips \cdot 16383}{num\_ips \cdot 16383 + n - 1}$

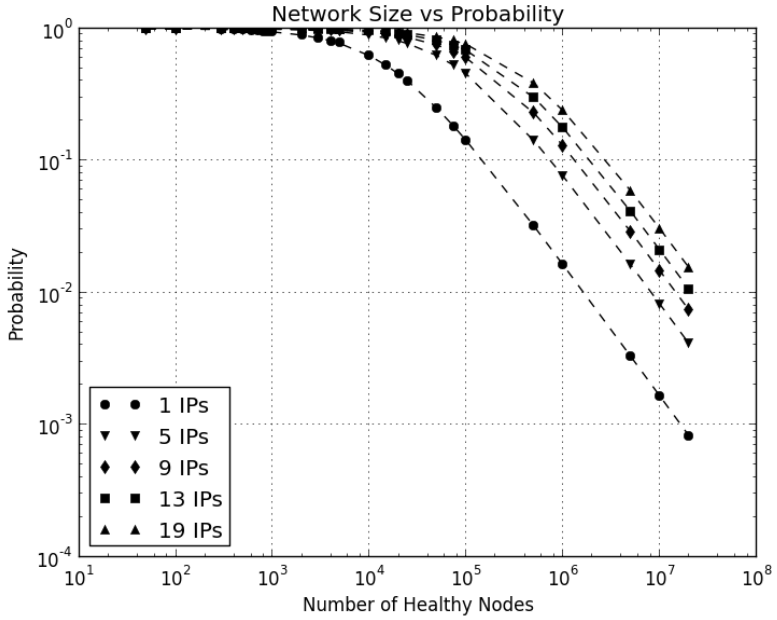


Figure 7.3: These are the same as results shown in Figure **??**, but our x-axis is the network size n in this case. Here, each line corresponds to a different number of unique IP addresses the adversary has at their disposal.

Table 7.2: Selection of results for Nearest Neighbor Eclipse.

IPs	Network Size	Success Rate	Sybils/Region
1	5000	0.7748	3.2762
1	5000000	0.0032654	0.0032768
1	10000000	0.0016364	0.0016384
1	20000000	0.00081865	0.0008192
5	5000	0.9444	16.381
5	5000000	0.0161208	0.016384
5	10000000	0.0081223	0.008192
5	20000000	0.0040801	0.004096
11	5000	0.9708	36.0428
11	5000000	0.0347646	0.0360448
11	10000000	0.0177117	0.0180224
11	20000000	0.008932	0.0090112
19	5000	0.9834	62.2452
19	5000000	0.058562	0.0622592
19	10000000	0.0301911	0.0311296
19	20000000	0.01532465	0.0155648

short links of the network, but not the long distance links.

7.3.4 Experiment 3: Complete Eclipse via Sybil on Chord

We extended the previous experiment by considering the long-distance hops of each node in addition to the short-range links of the DHT. We choose to model an attack on a P2P system built using Chord [**?**].

We chose to model Chord for a number of reasons. Chord is an extremely well understood DHT and is very simple to evaluate using simulations. Nodes in Chord generates long distance links independent of information provided by other nodes, rather than directly querying neighbors. This minimizes the opportunities adversaries have to poison the node's routing table via false advertisements, which can be on other DHTs such as Pastry [**?**]. This makes the Sybil attack the most straightforward means of effecting an Eclipse attack on a Chord network.

Nodes in Chord have m long-range links, one for each of the bits in the keys, which is 160 in our experiments. Each of node a's long-range links points to the node with the lowest key $\geq a + 2^i \mod 2^m, 0 \leq i \leq 160$.

However, many of the fingers are redundant and point to the nearest neighbor. As we have mentioned, on average, nodes are $\frac{2^m}{n}$ distance apart. The smaller the network, the further apart nodes are, and therefore each node has more redundant fingers and is easier to attack.

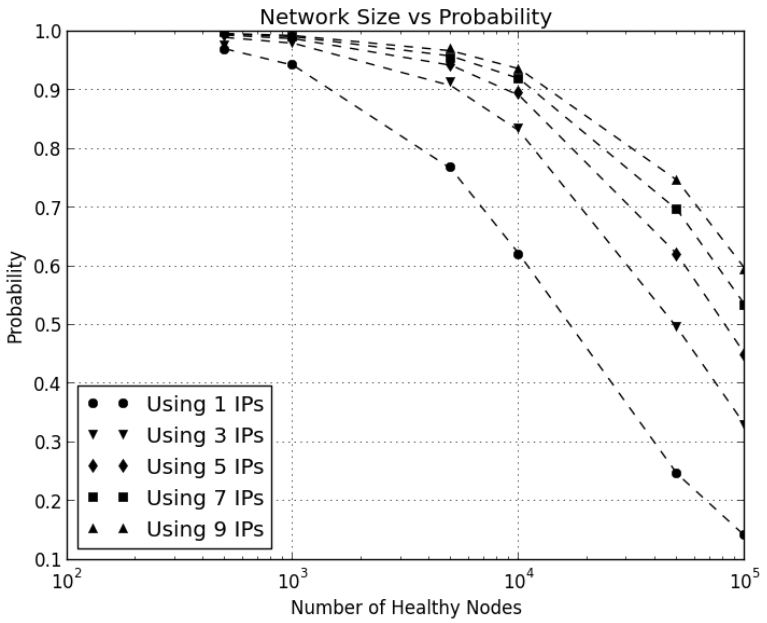


Figure 7.4: This graph shows the relationship between the network size and the probability a particular link in Chord, adjacent or not, can be mashed. The dotted line traces the line corresponding to the Equation **??**: $P_{bad\_neighbor} = \frac{num\_ips \cdot 16383}{num\_ips \cdot 16383 + n - 1}$

The attack is very similar to the Nearest Neighbor attack demonstrated above. Beside injecting a node in between successive nodes, the attacker also attempts to place a Sybil in between each of the long-range links. We simulated this attack under the same parameters as above and are presented in Table **??**.

Surprisingly, the percentage of links from healthy nodes that connect to Sybil nodes follows Equation **??** and the results from **??**. This means performing a Nearest Neighbor Eclipse provides the same results as actively blocking all the long range links in the network.

Our results show that an attacker needs only to focus their efforts on compromising the links between adjacent nodes to attack all the links in the network.

We can calculate that the number of IP addresses needed to compromise half the links in a 20,000,000 node network is 1221 IP addresses. While this seems like a daunting number of IP addresses, cloud computing has made solutions for an attacker much more accessible and affordable to attackers. At the time of writing, it would cost $43.26 USD to use 1221 instances for an hour on Amazon's Elastic Cloud Compute service. In fact, one of the attacker launching a Sybil attack was identified as having an IP address associated with Amazon's Elastic Cloud Compute [**?**].

Table 7.3: Selection of results for a Sybil attack on Chord.

IPs	Network Size	Success Rate	Occlusions/Node
1	1000	0.94186875	150.699
1	10000	0.618480625	98.9569
1	100000	0.141753625	22.68058
3	1000	0.97915625	156.665
3	10000	0.83425	133.48
3	100000	0.3286290625	52.58065
5	1000	0.988725	158.196
5	10000	0.894415	143.1064
5	100000	0.4488916875	71.82267
7	1000	0.99091875	158.547
7	10000	0.919071875	147.0515
7	100000	0.5337635625	85.40217
9	1000	0.9948125	159.17
9	10000	0.935495625	149.6793
9	100000	0.5936118125	94.97789

7.4 Conclusions and Future Work

Our analysis and experiments show that an adversary with limited resources can easily compromise a P2P system and occlude the majority of the paths between nodes. All that is required is a small number of IP addresses and the unassigned ports. This implies system privileges are not required. A successful attack effectively prevents nodes from talking to one another without sending messages through Sybils. The Sybils can eavesdrop on the messages, actively reroute them, or substitute malicious data. Mashing can also be used prevent malicious behavior. Sybils inserted in a P2P botnet by this approach could effectively interfere with command and control functions to shut down the botnet [**?**]. Future research would involve developing an appropriate mashing algorithm for a given botnet.

Our discussion has primarily concerned Chord. We did not simulate an attack on Mainline DHT [**?**], the Kademlia [**?**] based DHT used as the backend of BitTorrent, because it is completely unnecessary to perform any mashing. In MLDHT, a node ID is not chosen by hashing an IP and port combination, but by picking an address uniformly at random between 0 and $2^{160} - 1$. Since the choice of node ID in MLDHT is left to the client, there is no impediment to a Sybil attack. Research has examined MLDHT's vulnerability to Sybil attacks [**?**] and detected entities performing the attack on MLDHT.

A hash function over a unique identifier might seem to provide a level of protection against

a Sybil attack. Our research demonstrates that using a SHA1 hash of the IP address and port number is no defense against a Sybil attack. We show that the adversary can easily mash Sybil into desirable locations.

However, the mashing process can be used in non-malicious purposes to benefit a DHT. The SHA1 hash has an evenly distributed output. Most sets of meaningful keys will not have a uniform distribution [**?**] Some nodes will be responsible for larger regions than others and therefore will be responsible for a larger portion of the data. If a node can detect when a peer is overloaded, the node can inject a virtual node into the region to shoulder some of the load. The load could be defined by the size of the region or by the volume of traffic.

A network implementing this load-balancing strategy would be self-adaptive. Nodes in this type of self-adaptive network would have a limited number of virtual nodes to mash. This limit would protect nodes from becoming overloaded themselves and ensure network stability. We discuss how we can implement this in Chapter **??**.

Chapter 8

Autonomous Load Balancing in a Distributed Hash Table

One of key components of a Distributed Hash Table is a cryptographic hash function, most commonly SHA1 [**?**]. Distributed Hash Tables rely on this cryptographic hash function to generate identifiers for data stored on the network. The cryptographic hash of the filename or other identifier for the data is used as the location of the file or data in the network. It can also be used to generate the identifiers for nodes in the network.

Ideally, inputing random numbers into a cryptographic hash function should produce a uniformly distributed output. However, this is impossible in practice [**?**] [**?**].

In practice, that means given any DHT with files and nodes, there will be an inherent imbalance in the network. Some nodes will end up with a lion's share of the keys, while other will have few responsibilities (Table **??**).

This makes it especially disheartening to try and ensure as even a load as possible. We cannot rely on a centralized strategy to fix this imbalance, since that would violate the principles and objects behind creating a fully decentralized and distributed system.

Therefore, if we want to create strategies to act against the inequity of the load distribution, we need a strategy that individual nodes can act upon autonomously. These strategies need to make decisions that a node can make at a local level, using only information about their own load and the topology they can see.

8.0.1 Motivation

The primary motivation for us is creating a new viable type of platform for distributed computing. Most distributed computing paradigms, such as Hadoop [**?**], assume that the computations occur in a centralized environments. One enormous benefit is a centralized system has much greater control in ensuring load-balancing.

However, in an increasingly global world where computation is king and the Internet is increasingly an integral part of everyday life, single points of failure failures quickly become more and more risky. Users expect their apps to work regardless of any power outage affecting an entire region. Customers expect their services to still be provided regardless of any. The next big quake affecting the the San Andreas fault line is a matter of when, not if. Thus, centralized systems with single points of failure become a riskier option and decentralized, distributed systems the safer choice.

Our previous work in ChordReduce [**?**] focused on creating a decentralized distributed computing framework based off of the Chord Distributed Hash Table (DHT) and MapReduce. ChordReduce can be thought of a more generalized implementation of the concepts of MapReduce. One of the advantages of ChordReduce can be used in either a traditional datacenter or P2P environment.[1] Chord (and all DHTs) have the qualities we desire for distributed computing: scalability, fault tolerance, and load-balancing.

Fault tolerance is of particular importance to DHTs, since their primary use case is P2P file-sharing, such as BitTorrent [**?**]. These systems experience high levels of churn– disruptions to the network topology as a result of nodes entering and leaving the network. ChordReduce had to have the same level of robustness against churn that Chord did, if not better.

During our experiments with ChordReduce, we found that high levels of churn actually made our computations run *faster*. We hypothesized that the churn was effectively load-balancing the network.

8.0.2 Objectives

This paper serves to prove our hypothesis that churn can load balance a Distributed Hash Table. We also set out to show that we can use this in a highly controlled manner to greater effect.

[1] The other one being that new nodes could join during runtime and receive work from nodes doing computations.

Table 8.1: The median distribution of tasks (or files) among nodes. We can see the standard deviation is fairly close to the expected mean workload ($\frac{tasks}{nodes}$). Each row is the average of 100 trials. Experiments show there is practically little deviation in the median load of the network.

Nodes	Tasks	Median Workload	σ
1000	100000	69.410	137.27
1000	500000	346.570	499.169
1000	1000000	692.300	996.982
5000	100000	13.810	20.477
5000	500000	69.280	100.344
5000	1000000	138.360	200.564
10000	100000	7.000	10.492
10000	500000	34.550	50.366
10000	1000000	69.180	100.319

We present three additional strategies that nodes can use to redistribute the workload in the network. Each of these three strategies relies on nodes creating virtual nodes, and so that they are represented multiple times in the network. The idea behind this is that a node with low work can create virtual nodes to seek out and acquire work from other nodes.

This tactic is the same one used in the Sybil [**?**] attack, but limited in scope and performed for altruistic and beneficent reasons, rather than malicious ones. Consequently, we'll call our virtual nodes in this scenario Sybils for clarity and brevity. None of the strategies require a centralized organizer, merely a way for a node to check the amount of files or tasks it and its Sybils are responsible for.

We also want to show how distributed computing can be performed in a heterogeneous environment. We want to see if our strategies result in similar speedups in both homogeneous and heterogeneous environments.

8.1 How Work Is Distributed in DHTs: A Visual Guide

As we have previously mentioned, many DHTs use a cryptographic hash function to choose keys for nodes and data. However, no cryptographic hash function can uniformly distribute it's outputs across its range. Table **??** shows the median workload for networks of different numbers of nodes and tasks. In this context, tasks and nodes are interchangeable, as each node in a DHT performing a distributed computation would receive one task per file or chunk of file. The exact mechanics of this were discussed in Chapter **??**.

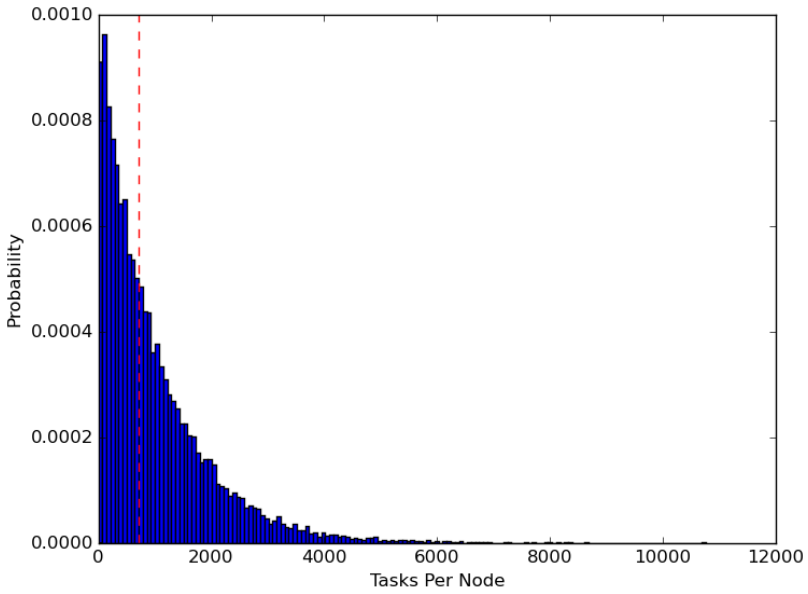


Figure 8.1: The probability distribution of workload in a DHT with 1000 nodes and 1,000,000 tasks or files. The vertical dashed line designates the median. Keys were generated by feeding random numbers into the SHA1 hash function [**?**], a favorite for many distributed hash tables.

We can see that in a 1000 node/1,000,000 tasks network, the average median workload of a node is 692.3 tasks. If work were distributed equally among all nodes in this network, each node would have 1000 tasks. This means that 50% if of the network has less significantly less tasks than the average number of tasks per node.

If we plot a histogram of how work is distributed in this network, we gain a clearer picture (Figure **??**). We see the bulk of the nodes have less than 1000 tasks and a few unfortunate nodes end up with more than 10,000 tasks.

Our final example is on a much smaller scale, but provides an excellent visual representation of a network. Figure **??** shows a visualization of 10 nodes and 100 tasks in a Chord overlay network.

Each node and task is given a 160-bit identifier `id` that is mapped to location (x, y) on the perimeter of the unit circle via the equations $x = \sin\left(\frac{2\pi \cdot id}{2^{160}}\right)$ and $y = \cos\left(\frac{2\pi \cdot id}{2^{160}}\right)$. Note that some of the nodes cluster right next to each other, while other nodes have a relatively long distance between each other along the perimeter. The most blatant example of this is the node located at approximately $(-0.67, 0.75)$, which would be responsible for all the tasks between that and the next node located counterclockwise. That node and the node located at about $(-0.1, -1)$ are responsible

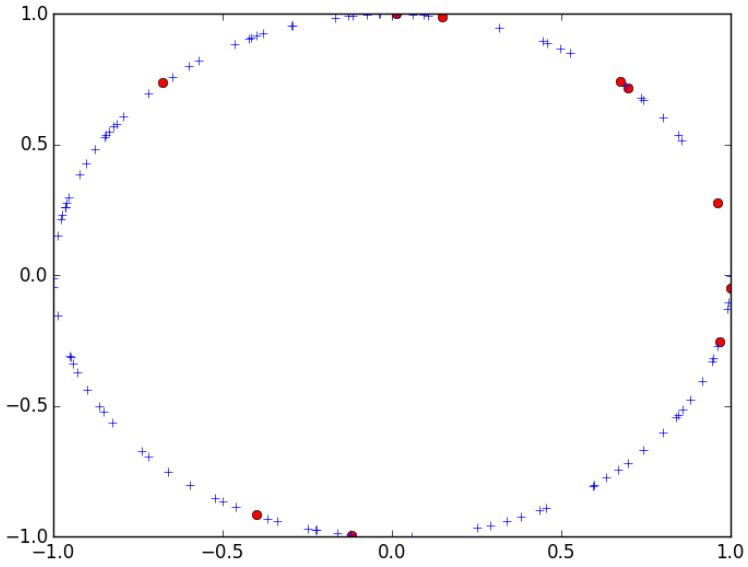


Figure 8.2: A visual example of data and nodes in a Chord DHT with 10 nodes (represented by red circles) and 100 tasks (blue pluses). Nodes are responsible for all the tasks that fall along the perimeter between themselves and their predecessor, which is the closest node counterclockwise.

for approximately half the tasks in the network.

Figure **??** shows the same network, but the nodes are evenly distributed, rather than generated but the SHA1 hash function. We see that while the network is better balanced, the files cluster and some nodes still end up with noticeably more work than others. It is possible for nodes to choose their own IDs in some DHTs [**?**], but the files will still be distributed according to a cryptographic hash function. In addition, it would require some additional centralization to make sure every single node covered the same range and may be impossible to coordinate such an effort in a constantly changing network.

From these examples, we can see that nodes and data in a DHT are not distributed uniformly at random, but rather their distribution is better represented by an exponential distribution. In this setting, a few nodes are responsible for the bulk of the work, and in a distributed computation, it is these nodes that will account for the majority of the runtime in the network. As we will see in our simulations, if nodes with little or no work can acquire some of this work, this has a significant impact on the networks's runtime.

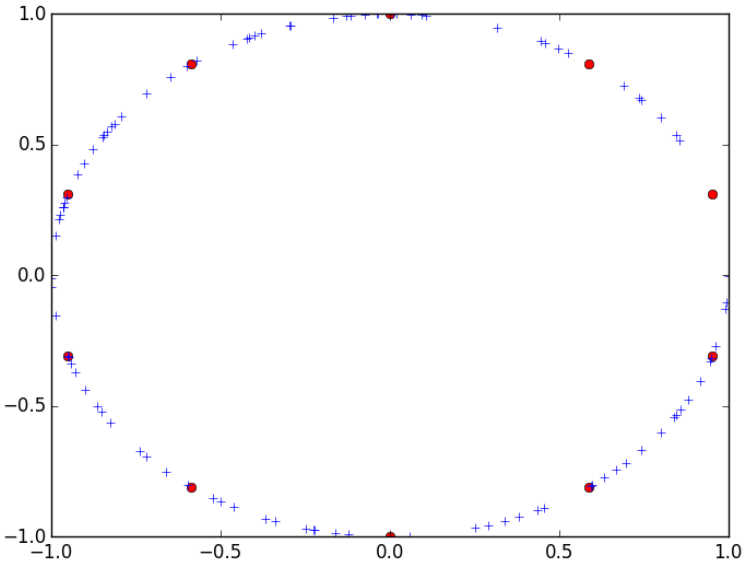


Figure 8.3: A visual example of data and nodes in a Chord DHT with 10 evenly distributed nodes (represented by red circles) and 100 tasks (blue pluses).

8.2 Simulation

We will be simulating our strategies on a Chord distributed hash table [**?**], although it is fairly straightforward to implement our strategies for other, more complex DHTs. Nodes in a Chord ring are given an ID, drawn from a cryptographic hash function, typically SHA1 [**?**]. Any data in the network is given a key in a similar manner. Nodes are responsible for all the keys between their predecessor's ID and their own.

We assume that the network starts our experiments stable and the data necessary already present on the nodes and backed-up. The following analysis and simulation relies on an important assumption about DHT behavior often assumed but not necessarily implemented.

We assume that nodes are active and aggressive in creating and monitoring the backups and the data they are responsible for. We have demonstrated the effectiveness and viability of implementing an active backup strategy in other work [**?**] [**?**]. As previously mentioned, we also assume nodes have the ability to examine the amount of work they have and know how many tasks or pieces of data exist for a particular job.

Another assumption is that nodes do not have control in choosing their IDs from the range of

hash values. This means that nodes cannot automatically change their spacing to ensure they are all evenly spread out across the network. Likewise, nodes cannot create necessarily create Sybils exactly where they would like, but would have to search for an appropriate ID in between two other nodes. We discussed this process in previous work and showed that it is extremely quick for a node to do so [**?**].

8.2.1 The Parameters

Our simulations relied on a great number of parameters and variables. We present each of them below.

Constants and Terminology

First, we'll define informally define the vocabulary we use to discuss our simulations.

Tick In a simulation, normal measurements of time such as a second are completely arbitrary. We will be using an abstract *tick* to measure time. We consider the tick the amount of time it takes a node to complete one task (or more depending on our variables, see below) and perform the appropriate maintenance to keep the network consistent and healthy.[2]

Maintenance We assume nodes use the active, aggressive strategy from ChordReduce and UrDHT [**?**] [**?**]. Every maintenance cycle, each node checks and updates its list of neighbors (successors and predecessors in Chord) and responds appropriately. We assume that a tick is enough time to accomplish at least one maintenance cycle.

Task We measure the size of a distributed computing job in tasks. Each task has a key that corresponds to the key of a file or chunk of a file stored on the network. We assume that it takes a tick for a node to consume at least one task.

IDs and Keys We will be using SHA-1 [**?**], a 160-bit hash function, to generate node IDs and keys for tasks. We assume each task's key corresponds to some piece of data with the same key, a scheme we used in our previous work on ChordReduce [**?**].

[2]If we need to be more concrete, define a tick as a New York Second, which is "the period of time between the traffic lights turning green and the cab behind you honking."
– Terry Pratchett

Experimental Variables

We tested a number of strategies and variables that could affect each strategy. While we believed the overall strategy would result in largest differences in runtime, we wanted to see what effects, if any, each of the variables would have on a particular strategy.

Strategy We use several different strategies, each discussed in Section **??**: churn, random injection, neighbor injection, and invitation. Each of these strategies differs in how nodes attempt to autonomous balance the workload of the network. None of the strategies require centralized organization.

Homogeneity This variable controls whether the network is homogeneous or not. In a homogeneous network, each node has the same strength, which dictates how much work is consumed per a tick and how many Sybils it can create. In a heterogeneous network, each node has a strength chosen uniformly at random from 1 to `maxSybils`. The default value is homogeneous.

Work Measurement This variable dictates how much work is consumed in a tick. Each node can either consume a single task per a tick or their strength's worth of tasks per a tick, with the former being the default.

Network Size How many nodes start in the network. We assume that this can grow during the experiment, either via churn or by creating Sybils. We discuss how this works in Sections **??** and **??**.

Number of Tasks We measure the size of of a job in tasks. This number is typically a few orders of magnitude greater than the network size.

Churn Rate The churn rate is a float between 0 and 1. This represents both the chance each individual node has of leaving (or joining) the network each tick. It also corresponded to the fraction of nodes we expect to leave the network each tick. Churn can be self induced or a result of actual turbulence in the network. Like most analyses of churn [**?**], we assume churn is constant throughout the experiment and that the joining and leaving rate are equal. The default value is 0.

Max Sybils `maxSybils` is the maximum number of Sybils a node can have at once. We tested 5, the default, and 10.

Sybil Threshold The `sybilThreshold` dictates the number of tasks a node must have before it can create a Sybil. The default setting is having no work (0 tasks).

Successors The number of successors each node keeps track of, either 5 or 10, with 5 being the default. Nodes also keep track of the same number of predecessors.

We also considered using a variable noted as the `AdaptationRate`, which was the interval at which nodes decided whether or not to create a Sybil. Preliminary experiments showed `AdaptationRate` to have a minimal effect on the runtime, so it was removed.

Outputs

The most important output was the number of ticks it took for the experiment to complete. We compared this runtime to the what we call the "ideal runtime," which is our expected runtime if the every node in the network was given an equal number of tasks and performed them without any churn or creating any Sybils. For example, consider a network with 1,000 nodes and 100,000 tasks, where each node consumes a single task each tick. This network has an ideal runtime of 100 ticks ($\frac{100000}{1000} = 100$).[3]

We used these to calculate a "runtime factor," the ratio of the experimental runtime compared to the ideal runtime. For example, in the network from our previous example took 852 ticks to finish, its factor is 8.52. We prefer to use this runtime factor for comparisons since it allows us to compare networks of different compositions, task assignments, and other variables.

We also collected data on the average work per tick and statistical information about how the tasks are distributed throughout the network. We additionally performed detailed observations of how the workload is distributed and redistributed throughout the network during the first 50 ticks.

[3]The ideal runtime also happens to be the average number of tasks per node. An interesting, but mathematically unsurprising, coincidence with a few consequences for our data collection.

8.3 Strategies

For our analysis, we examined four different strategies for nodes to perform autonomous load balancing. We first show the effects of churn on the speed of a distributed computation. We then look a three different strategies for in which nodes take a more tactical approach for creating churn and affecting the runtime.

Specifically, nodes perform a limited and controlled Sybil attack [**?**] on their own network in an effort to acquire work with their virtual nodes. Our strategies dictate when and where these Sybil nodes are created.

We discuss the effectiveness of each of the strategies and present the results of our simulations in Section **??**.

8.3.1 Induced Churn

Our first strategy, *Induced Churn*, relies solely on churn to perform load balancing. This churn can either be a product of normal network activity or self-induced.[4] By self-induced churn, we mean that each node generates a random floating point number between 0 and 1. If the number is $\leq churnRate$, the node shuts down and leaves the network and gets added to the pool of nodes waiting to join.

Similarly, we have a pool of waiting nodes that begins the same initial size as the network. When they generate an appropriate random number, they join the network and leave the waiting pool. We assume that nodes enter and leave the network at the same rate. Because the initial size of the network and the pool of waiting nodes is the same and nodes move between one another at the same random rate, the size of either does not fluctuate wildly.

As we have previously discussed, nodes in our network model actively back up their data and tasks to the a number of successors in case of failure. In addition, when a node joins, it acquires all the work it is responsible for. While this model is rarely implemented for DHTs, it is discussed [**?**] and often assumed to be the way DHTs operate. We have implemented it in ChordReduce[**?**] and UrDHT[**?**] and demonstrated that the network is capable from recovering from quite catastrophic failures and handling ludicrous amounts of churn.

[4] All distributed systems experience churn, even if only as hardware failures.

The consequences of this are that a node suddenly dying is of minimal impact to the network. This is because a node's successor will quickly detect the loss of the node and know to be responsible for the node's work. Conversely, a node joining in this model can be a potential boon to the network by joining a portion of the network with a lot of tasks and immediately acquiring work.

This strategy acts as a baseline with which to compare the other strategies, as it is no more than a overcomplicated way of turning machines off and on again. All strategies below are attempts to do better than random chance. However, this strategy also serves to confirm the speedup phenomenon we observed in our previous work on a distributed, decentralized MapReduce framework [**?**].

8.3.2 Random Injection

Our second strategy we dubbed *Random Injection*. In this strategy, once a node's workload was at or below the `sybilThreshold`, the node would attempt to acquire more work by creating a Sybil node at a random address.

A node compares its workload to the `sybilThreshold` and decides whether or not to make a Sybil. This check occurs every 5 ticks. A node cam also have multiple Sybils, up to `maxSybils` in a homogeneous network or the node's `strength` in a heterogeneous network.[5] If a node has at least one Sybil, but no work, it has its Sybils quit the network. We limit each node to creating a single Sybil during this decision to avoid overwhelming the network.

8.3.3 Neighbor Injection

Neighbor Injection also creates Sybils, but in this case, nodes act on a more restricted range in an attempt to limit the network traffic. Nodes with `sybilThreshold` or less tasks attempt to acquire more work by placing a Sybil among it's successors. Specifically, it looks for the biggest range among it's successors and creates a Sybil in that range.

This range strategy of finding the largest range and injecting assumes that the node with the largest range of responsibility will have been allocated the most work. This is a sensible assumption since the larger the range of a node's responsibility, the more *potential* tasks it can receive. We compare this estimation strategy to actually querying the neighbor and asking how many tasks

[5] No benefit was shown by increasing `maxSybils` beyond 10.

they have. An estimation, if accurate, would be preferable to querying the nodes as an estimation can be done without any communication with the successor nodes.

To avoid constant spamming of a range, once a node creates a Sybil, but does not acquire work, it may be advisable to mark that range as invalid for Sybil nodes so nodes don't keep trying the same range repeatedly.

8.3.4 Invitation

The *Invitation* strategy is the reverse of the Sybil injection strategies. In this strategy, nodes with a higher than desired level of work announces it needs help to its predecessors. The predecessor with least amount of tasks less than or equal to the `sybilThreshold` creates a Sybil to acquire work from the node. It is possible for an invitation to get more work to be refused by anyone if no predecessor is at the `sybilThreshold` or each predecessor has too many Sybils. Nodes determine whether or not they are overburdened using the `sybilThreshold`.

8.4 Results Of Experiments

We now briefly summarize the results of our simulation before discussing each more in depth below. First, we confirmed that churn, even at low levels, can speed up the execution of a distributed computation by dynamically load balancing the network. However, our best strategy was random injection, which managed to have a runtime factor which approached close to 1.

All examples are compared against against a baseline network of the same size and initial configuration of nodes. The only difference is that the baseline never uses a strategy or experiences any churn.

All the raw data can be found online [**?**]. Files are sorted by the strategy used, the network size, and number of tasks and include the both the results of each individual run and the averages of each 100 trials for a particular set of variables. Each trial is linked with a seed for the pseudorandom number generator and can be fully reproduced.

We will be referring to a **base** runtime factor. This means the network had the defaults for variable. We suspect the worse runtime factors in homogeneous networks don't necessarily imply the method is weaker. It may imply that runtime factor is not the best metric, but it is the best

simple one we have.

8.4.1 Churn

Our results confirmed our hypothesis from ChordReduce [**?**]. Churn has a profound and significant impact on the network's computation, and this effect is more pronounced with higher rates of churn. Our results in Table **??** show the effects of churn in networks of varying sizes and loads on the runtime factor.

Table 8.2: Runtime factor of networks of varying sizes and number of tasks, each using the Churn strategy to load-balance. Each result is the average of 100 trials. The networks are homogeneous and each node consumes one task per tick. A runtime of 1 is the ideal and target.

Churn Rate	10^3 nodes, 10^5 tasks	10^3 nodes, 10^6 tasks	100 nodes, 10^4 tasks	100 nodes, 10^5 tasks	100 nodes, 10^6 tasks
0	7.476	7.467	5.043	5.022	5.016
0.0001	7.122	5.732	4.934	4.362	3.077
0.001	6.047	3.674	4.391	3.019	1.863
0.01	3.721	2.104	3.076	1.873	1.309

We see that for each network size and load, even small amounts of churn have a noticeable impact on churn. The magnitude of churn's effect varies based on the size of the network and the number of tasks. In networks where there are fewer nodes, we see the base runtime factor is smaller. The gains from churn are most strongly related the number of tasks the network has, with the more tasks there are, the greater the gains of churn. A network 100 nodes and 1 million tasks, on average, has a runtime factor only 30% higher than ideal when churn is 0.01 per tick. The runtime for heterogeneous versus homogeneous networks had no significant differences.

We ran additional experiments on rates of churn for a 1000 node network and 100,000 tasks, in order to give a fuller picture of the effects of churn. We tested this network with a wider variety of churn rates. The results of this are shown on Figure **??**, which plots the runtime of the distributed computation against the level of churn in the network.

We note the significantly diminishing returns that occur after a churn rate of 0.01. One facet not captured by our simulations, but is significant, is the rising maintenance costs after that point. The makes any amount of churn after a certain point prohibitively expensive. What this point is requires implementation on a real network.

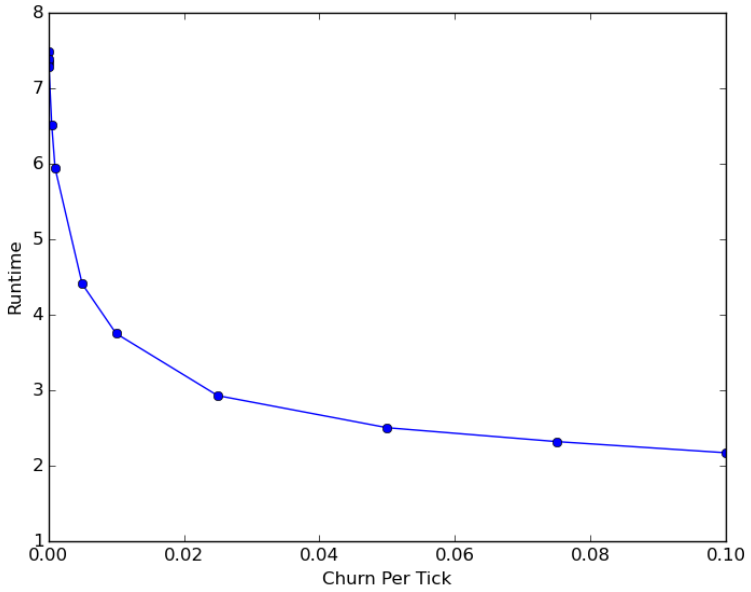


Figure 8.4: This graph shows the effect churn has on runtime in a distributed computation. Runtime is measured as how many times slower the computation runs than an ideal computation, where each node receives an equal number of tasks. The lower the runtime factor, the closer it is to an ideal of 1. Neither the homogeneity of the network nor work measurement had a significant effect on the runtime.

This speedup is reflected in the average number of tasks consumed in a tick, shown in Figure **??**. In a stable network with no churn, we would expect a good portion of the network to end up with little work, which is quickly consumed. These nodes must then idle, waiting for the few nodes which received a large number of tasks to finish. When there is churn, however, nodes have a chance of joining the network and acquiring more work, thus making it possible for more work to be done per a tick. The higher the rate of churn, the more this happens.

A more detailed view of how this happens is shown in Figures **??**, **??**, and **??**. These figures show histograms of workload distribution for two networks at different ticks. One network uses 0.01 churn per tick to autonomously load balance the workload, the other uses no strategy at all.

Both networks [6] start with the 1000 nodes and 100,000 tasks distributed identically throughout the network. Figure **??** shows the distribution of the workload for this initial configuration.

As the network begins to work, we see the distributions diverge from one another. Figure **??** shows that after merely 5 ticks, the network using the churn strategy has noticeably fewer nodes that have smaller workloads. We also see more nodes with greater workloads. The effect becomes

[6] Indeed, all networks we do this assessment for start with the same initial configuration

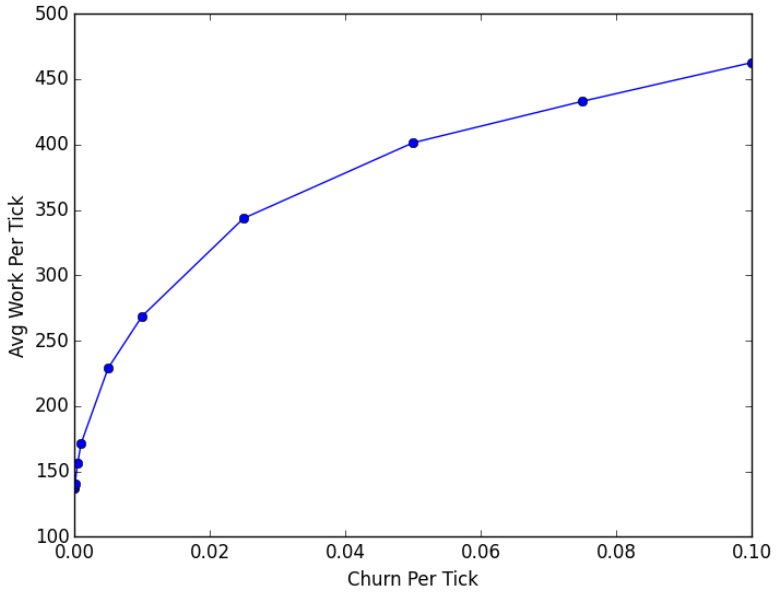


Figure 8.5: With more and more churn in the network, new nodes have a higher chance of joining the network and acquiring work from overloaded nodes. This results in more average work being done each tick, as there are less nodes simply idling.

even more pronounced after 35 ticks, shown in Figure **??**, where more have had a chance to finish their work and more churn has had the opportunity to occur.

8.4.2 Random Injection

The goal behind the churn strategy was to effectively have nodes join in the proper place with random insertions. However, churn relies on two factors that are completely random. The network nor it's members have any control over when node joins happen or where these joins occur. In addition, churn removes nodes, which can be detrimental to the network.

The random injection strategy removes some of the randomization that the churn churn strategy deals with, namely *when* new nodes join, albeit not where. As we discussed earlier, random injection does this by means of the Sybil Attack [**?**], with nodes creating virtual Sybil nodes when they are underutilized.

We found that the strategy of having under-utilized nodes randomly create Sybil nodes works phenomenally well, approaching very close to the ideal time. Figures **??** and **??** compare two networks with identical starting configurations as the network preforms the computations.[7] These

[7]We omit a figure comparing the two networks at tick 0, since it identical to Figure **??**.

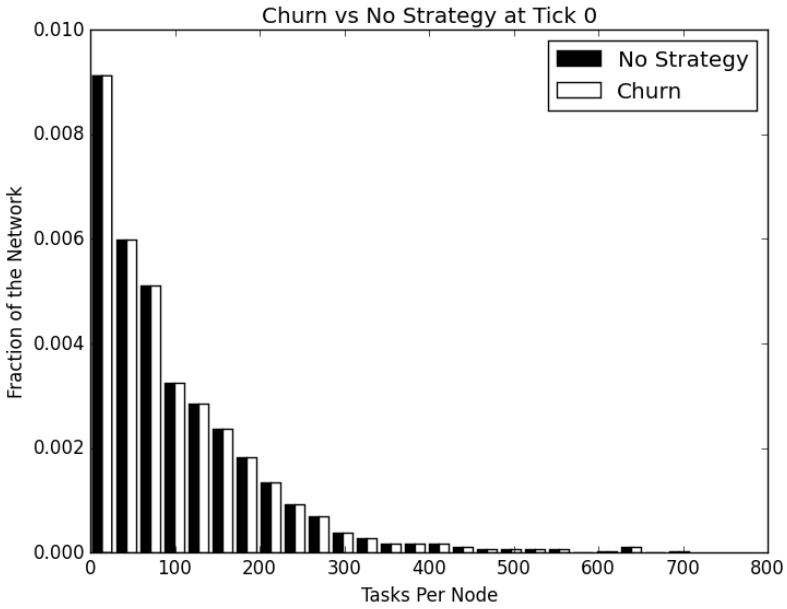


Figure 8.6: The initial distribution of the workload in both networks. As both networks start with same initial configuration, the distribution is currently identical. This greatly resembles the distribution we saw in Figure **??**.

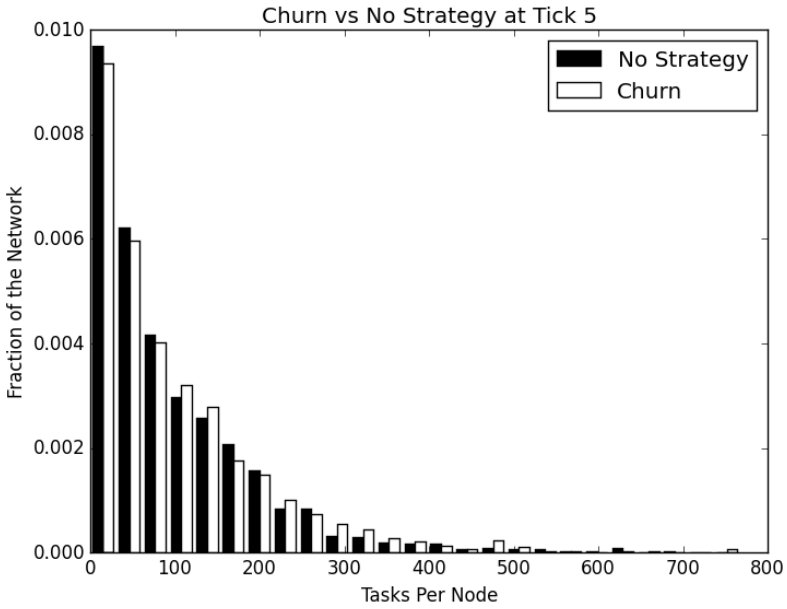


Figure 8.7: This is the distribution of the workloads at the beginning of tick 5. We can see the network using 0.01 churn has fewer nodes with less work and more nodes with a greater workload.

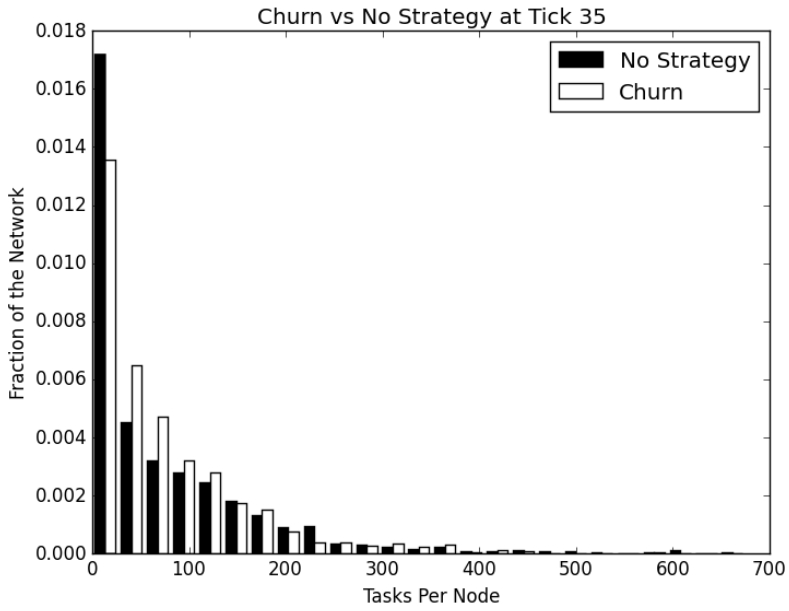


Figure 8.8: After 35 ticks, the effects of churn on the workload distribution become more pronounced. More nodes have consumed all their tasks and are simply idling, but significantly less in the network using churn.

networks have 1000 nodes and 100,000 tasks. The network using random injection fared significantly better than those using no strategy.

We can see in Figure **??**, the results of a single load balancing operation. Each node has checked its workload, and if it was too low, created a single Sybil. If we compare this to Figure **??**, we see that this single operation has a better workload distribution than what we had started with and is substantially better than using no strategy.

We can see these effects become even more pronounced at tick 35 (Figure **??**), where seven load balancing operations have taken place. The network using random injection has many fewer nodes with little or no work and many more nodes with some work. Furthermore, we see a huge difference between the effectiveness of random injection versus churn (Figure **??**).

We found that a homogeneous, 1000 node/100,000 task network, where each node consumed a single task each tick would never have an average runtime factor greater than 1.7 and the average runtime was as fast as 1.36. In the same network with 1,000,000 tasks, these runtimes were 1.25 and 1.12 respectively. On average, the 1,000,000 task network had a runtime factor 0.82 less than the 100,000 task network. This huge jump is the result of how the network is impacted by heterogeneous nodes, explained further below.

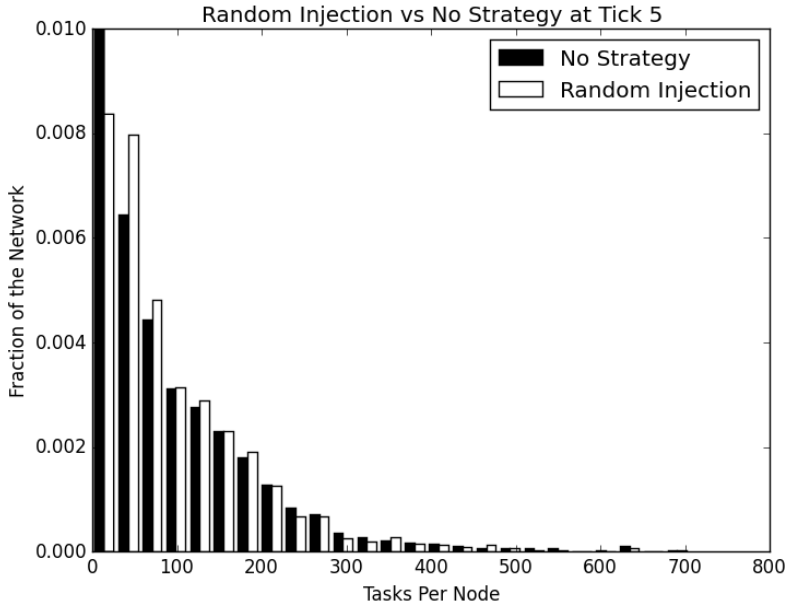


Figure 8.9: The networks after 5 ticks. The network using random injection has significantly less underutilized nodes, even after only 5 ticks.

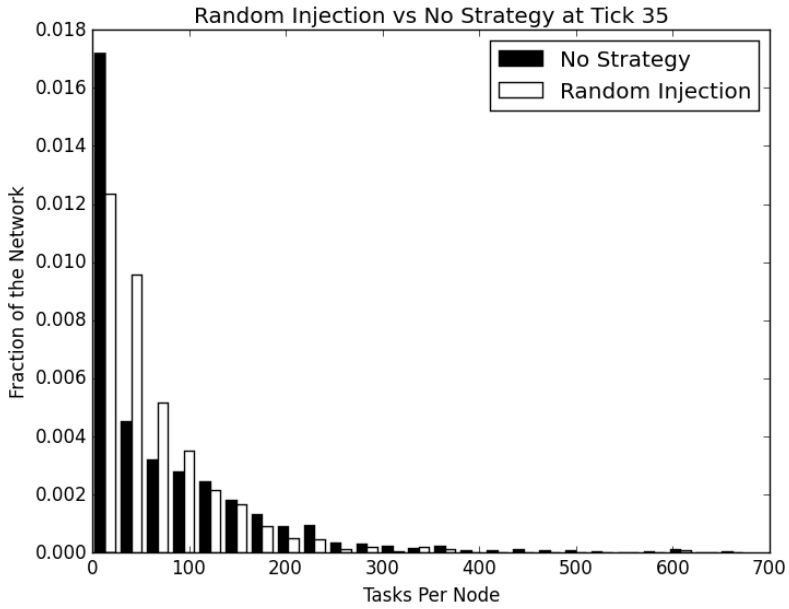


Figure 8.10: The networks after 35 ticks. The network using random injection has significantly less underutilized nodes and substantially more notes with some or lots of work.

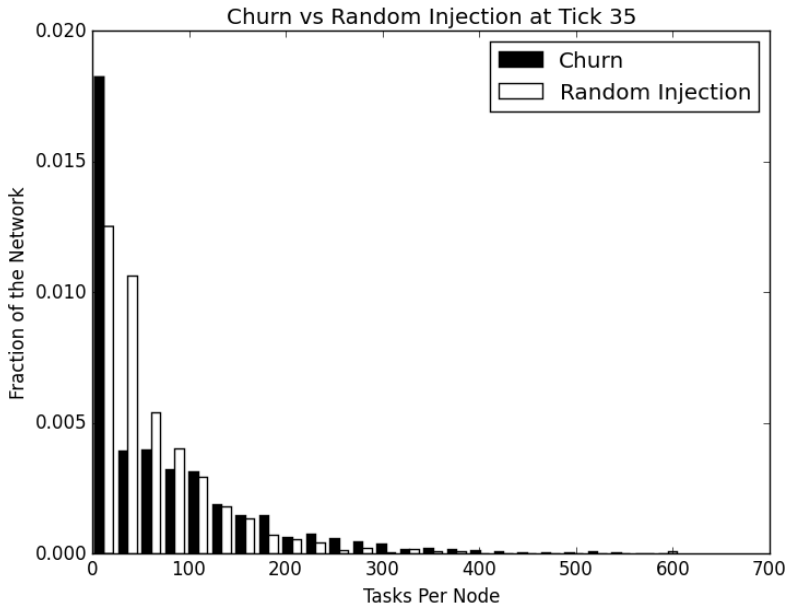


Figure 8.11: The networks after 35 ticks. The network using random injection load-balances significantly better than the network using Churn.

Overall we found that networks with the same ratio of tasks to nodes would have relatively the same runtimes, but the smaller network would run slightly faster. For example, we compared two networks with 100 tasks per a node: a network with 100 nodes and 100,000 tasks and one with 1,000 nodes and 1,000,000 tasks. The smaller network had, on average, a mean runtime factor 0.086 less.

Heterogeneous networks also saw significantly better performance (Figure **??**), but the gains were not as great as in homogeneous networks. However, the larger ratio networks handled heterogeneity much better, with the worst average heterogeneous run time being 1.955 in networks with 1000 tasks per node, compared to 4.052 on the smaller ratio networks with 100 tasks per node. However, most trials did not have a runtime factor greater than 3.

The Effects of Other Variables

The `sybilThreshold` had an effect in homogeneous networks but no effect in heterogeneous networks. In 1000 node/100,000 task and 100 node/10,000 experiment, a homogeneous network where each node completed one task per a tick, this amounted to an reduction of at least 0.1 runtime factor. The effect was more pronounced when networks could complete a number of tasks equal to

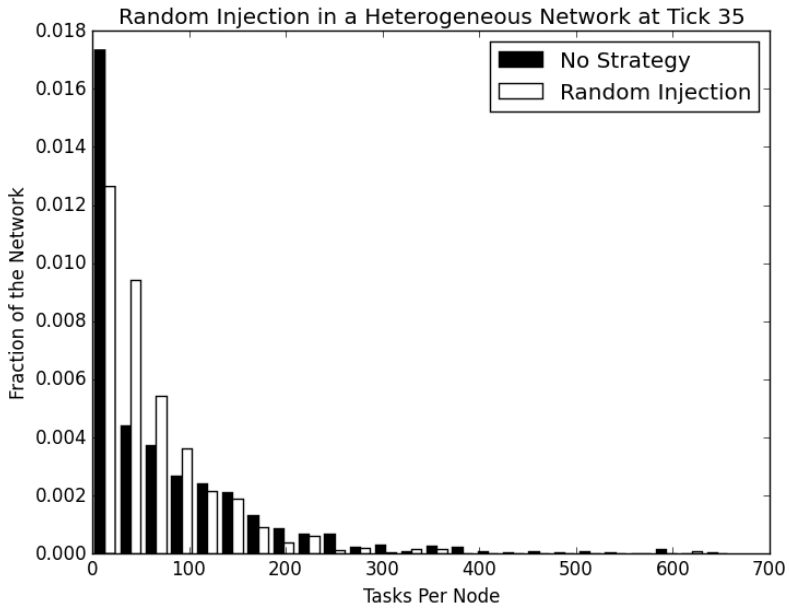


Figure 8.12: The workload distribution of heterogenous networks after 35 ticks. We can see the network using the random injection strategy is experiencing a better distribution of work.

their strength each tick, reducing the runtime factor by at least 0.2.

However, we saw no corresponding speedup in the 1000 node/1,000,000 task and 100 node/100,000 task networks. We also found the `sybilThreshold` had no discernible effect on the runtime of heterogeneous networks. This suggests the effect of a particular `sybilThreshold` is tied to the ratio of nodes to tasks and that the larger the ratio, the less room there is to improve.

Churn had no positive impact on the runtime factor. At higher levels, churn could begin having an extremely minor impact when churn is at 0.01 per tick, increasing the average runtime factor by approximately 0.06, not to mention any maintenance costs incurred by handling churn.

Our `maxSybils` variable had no noticeable effect on runtime in a heterogeneous network. `maxSybils` controlled both the number of tasks a node could consume and the maximum number of Sybils that node could make. Surprisingly, larger values for `maxSybils` had a negative impact on runtime in heterogeneous networks. Networks where nodes strength ranged 1 to 5 performed better than those where the range of `maxSybils` was 1 to 10. In other words, the greater the disparity between node strength in the network, the greater the detrimental effect to the heterogeneous network.

This impact was felt stronger in nodes with a lower node to task ratio. The runtime factor saw

a 0.3 to 0.4 increase in the 1000 node/1,000,000 task and 100 node/100,000 task networks (1000 tasks per node). On the other hand, the 100 node/10000 task and 1000 node/100000 task networks saw an increase of about 1.

8.4.3 Neighbor Injection

The neighbor injection strategy was also effective at reducing the overall runtime factor, albeit not as greatly as the random injection strategy. Figures **??** and **??** show the workload distribution of the neighbor injection strategy in a 1000 node/100,000 task network. At the first glance, neighbor injection does not seem to be doing worse than no strategy; there are more nodes with less work than no strategy. However, if we look at the whole histogram, we see there are less nodes that have a huge amount of work and noticeably more nodes with a small number of tasks. In fact, at tick 35, we see that the network with no strategy has a node with approximately 650 tasks, while the most the network using the neighbors strategy has is 450 tasks.

This is because the network is finishing off the tasks with small amounts of work quicker. However, nodes are not able to acquire work outside their immediate vicinity and must idle. In addition, nodes always inject Sybils into the largest gap between their successors that they see, but if they acquire no work. That means in the simulation, it is possible for nodes to get into a loop of constantly checking the largest gap and miss other neighbors that do have work to acquire.[8]

The base runtime factor of the neighbor strategy in a 1000 node/100,000 task homogeneous network was 5.033, which is 2.4 lower than no strategy. In a 100 node/10,000 task network, this was lower – a runtime factor of 3.006, which was 2 lower than no strategy. However, the base runtime in a heterogeneous network was **worse** and, like in random injection, is exacerbated by a higher `maxSybil`.[9] We suspect this is because weaker nodes are acquiring work away from stronger nodes and then taking longer to finish.

Unsurprisingly, a larger `numSuccessors` improves the runtime factor. Our example 1000 node/100,000 task network experienced a decrease of about 0.3 to the runtime factor. However, `sybilThreshold` had no significant effect, nor did `maxSybil` for homogeneous networks.

To fully evaluate the effectiveness of the strategy, we compared the neighbor injection strategy,

[8] We suggest how to avoid this in a real implementation in Section **??**

[9] Runtime was fine in the heterogeneous networks where each node could create a different number of Sybils, but still only complete one task per tick.

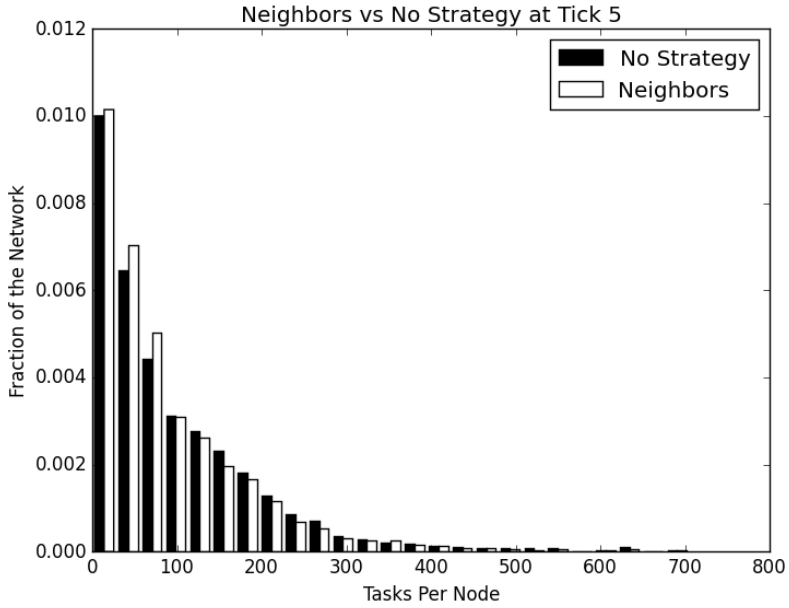


Figure 8.13: While the network no strategy appears to have less nodes idling, the active nodes in the network using neighbors are being better utilized.

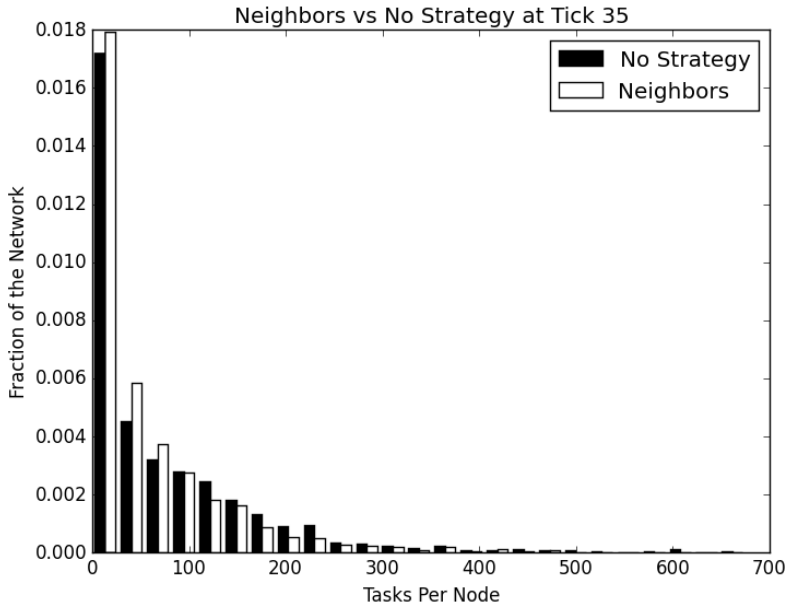


Figure 8.14: Despite have more idling nodes, we see that the nodes using the neighbor injection strategy have acquired smaller workloads and have effectively shifted part of the histogram left.

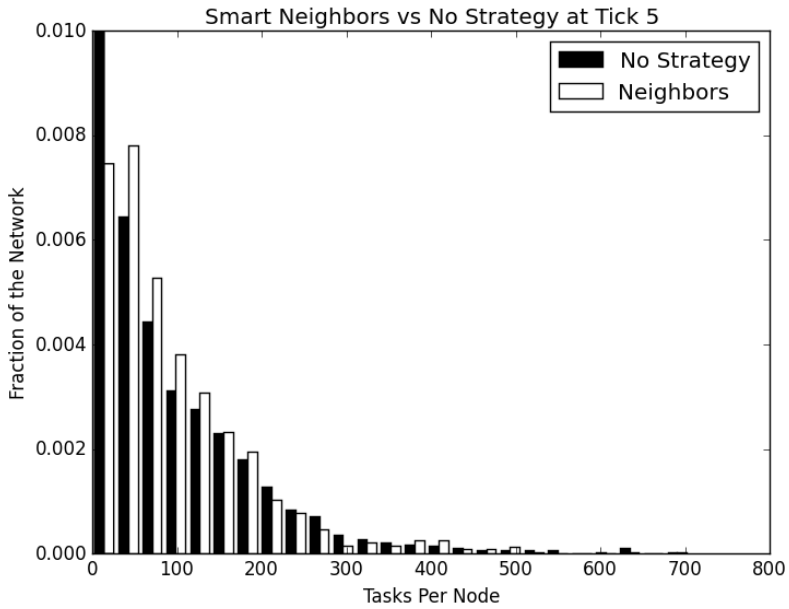


Figure 8.15: The workload in the networks after 5 ticks. We can that the network using neighbor injection has directed more nodes that would be idling to perform work. This is especially apparent in comparison to Figure **??**.

which estimates the node with the largest workload, to what we call smart neighbor injection. Smart neighbor injection actually queries the neighbors to find out their workload and injects a Sybil to take work away from the node with the most amount of work, not merely the node with the largest space of responsibility. The workload distributions of smart injection are shown in Figures **??** and **??**. Both graphs show the same reduction in high amounts of workload that the base neighbor strategy provided, but with fewer idling nodes.

The strategy of probing each of the neighbors before inserting, rather than estimating, improved the runtime factor by 1.2 on average in when we compare each strategies mean homogeneous and heterogeneous runtimes. However, the estimation based neighbor injection requires fewer messages in an actual implementation. Overall, either neighbor injection strategy did not perform as well as the random injection strategy, but generates much less churn from joining nodes, since nodes can create their Sybils in a greatly reduced range.

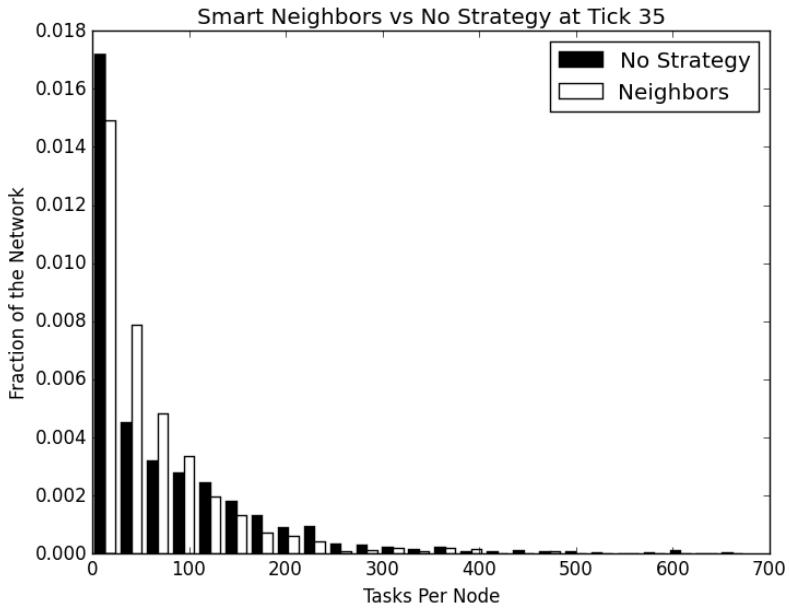


Figure 8.16: After 35 ticks, we see the network using the smart neighbor injection strategy has significantly less nodes with little or no work, more nodes with smaller amounts of work, and less nodes with large amounts of tasks.

8.4.4 Invitation

Our final strategy is invitation based injection. What differentiates invitation based injection from the neighbor injection or random injection strategy is that the latter two are proactive strategies, while the former is reactive.

The proactive strategies work by having nodes with low work loads seek out acquire work from other nodes. This is good because less nodes become idle. However, nodes acquire work from other workers, even if that other worker needed no help. In addition, nodes can spend many cycles trying to acquire work that may or may not exist, which significantly

Invitation, however, is reactive. Nodes react to having too much work and ask the predecessors (the same nodes who would be injecting Sybils in the neighbor injection strategy) with the lest work to come and help. This means queries of other nodes and Sybil injections only occur when they need to, greatly reducing the maintenance costs in an actual implementation.

Figures **??** and **??** show the work distribution of a network using the invitation based strategy. When we compare this strategy to the smart neighbor injection strategy (Figures **??** and **??**), we see that invitation does a much better job of distributing the work.

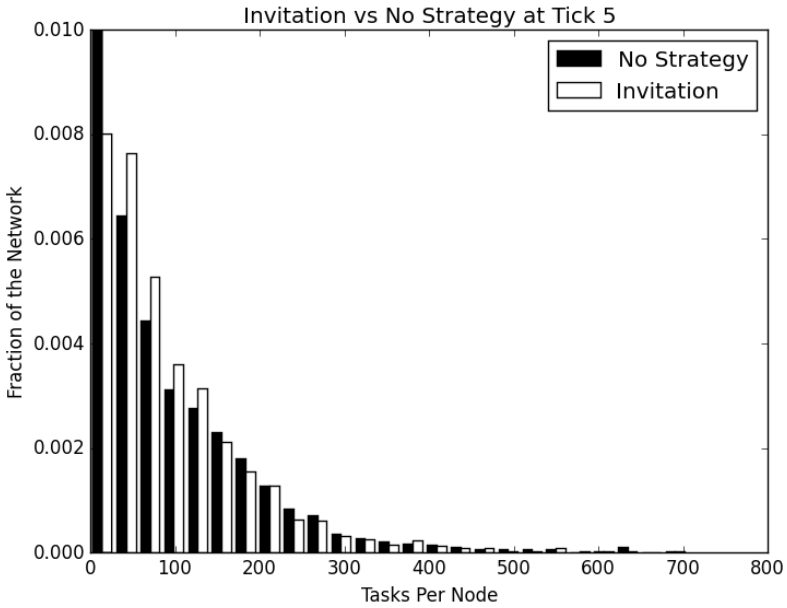


Figure 8.17: Here, we see that the invitation strategy performs markedly better at distributing the work than no strategy. At tick 5, there are many more nodes with small work loads. There are also few nodes with large amounts of work.

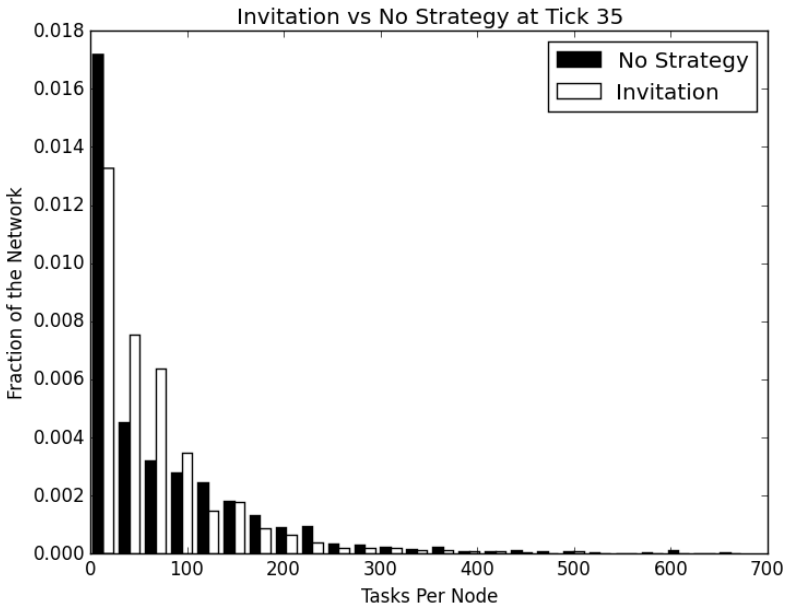


Figure 8.18: At 35 ticks, we can see the network using the invitation strategy perform markedly better than the network using no strategy. The highest load is around 500 tasks in the network using invitation, compared to approximately 650 tasks in the network using no strategy.

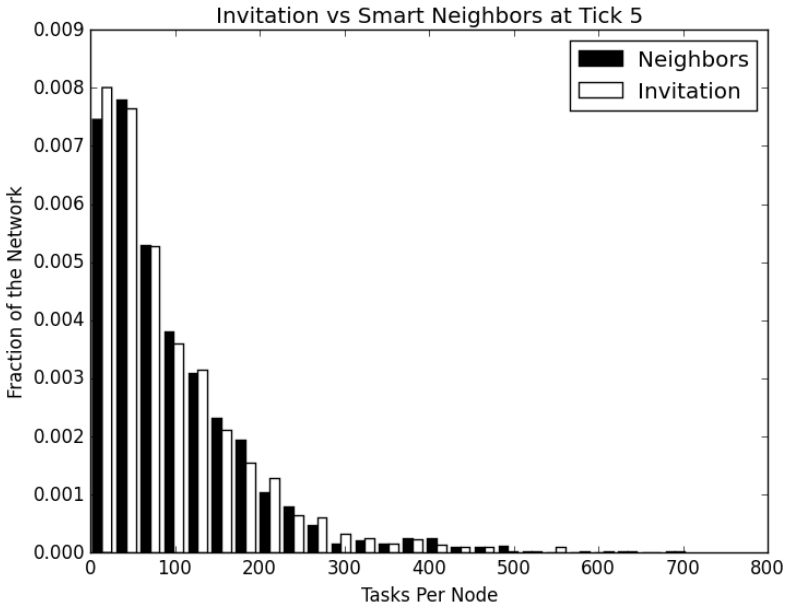


Figure 8.19: A comparison of a network using the smart neighbors strategy and a network using the invitation strategy. Invitation has slightly more nodes on the performing less work, but no significant differences have emerged.

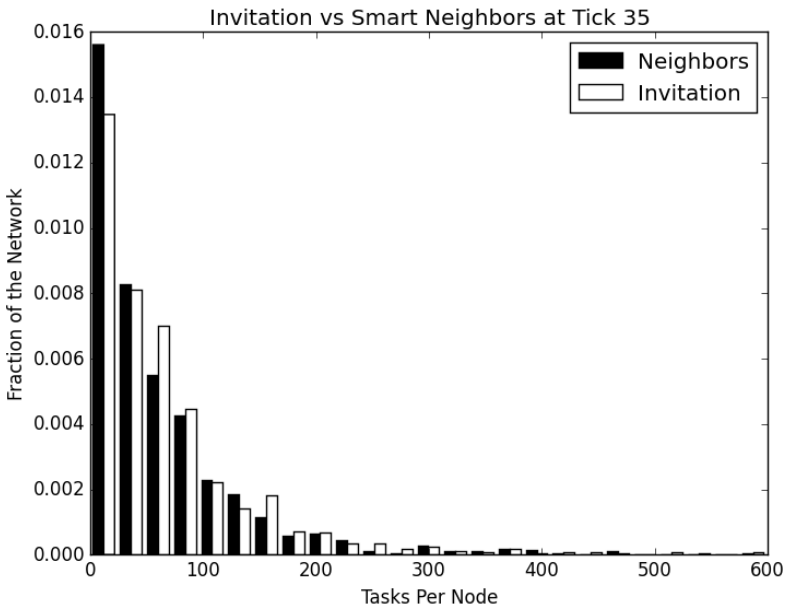


Figure 8.20: After 35 ticks, differences between the two strategies have emerged. The network using the invitation strategy has significantly less nodes with a small work load and many more with large work loads.

The impact of the invitation strategy on the runtime factor was closely tied to the number of nodes in the network. For example, in a 100 node/ 100,000 task network (1000 tasks per node), the base average runtime factor was 3.749. However, a 1000 node/ 100,000 task network had a base average runtime of 5.673.

Other variables and the ratio of tasks to nodes appeared to have no effect on the runtime factor.[10] The single exception was when the network was heterogeneous and each node could complete a number of tasks equal to it's strength. Like the neighbor injection strategy, networks under these conditions faired much worse, with our 1000 node/ 100000 tasks networks base average runtime factor being 6.097.

The invitation strategy load balances better than smart neighbors and uses less bandwidth than it and neighbor injection, since this strategy is reactive, rather than proactive, like random injection or neighbor injection.

8.5 Remarks and Future Work

Our simulation results are notable for a number reasons. First, as we have previously mentioned, is the confirmation that churn can have a net positive effect on the runtime of the network. Second, we presented strategies based on the Sybil attack that performed significantly better than churn and would have a much less disruptive impact on the network's structure. We found that our random injection strategy performed exceptionally well, approaching as closer to ideal times as we could hope.

The fact that these strategies can be used as new nodes join the network can not be understated. Each joining node is another member of the network that can fully participate in the computation, despite not being present at the beginning of the computation.

However, our strategies were not nearly as successful in a heterogeneous network, even though the work was better distributed throughout the network. We suspect this is the result of weaker nodes acquiring more work from stronger nodes, leading to an overall longer runtime, despite the workload being better balanced. In other words, the workload is balanced in the heterogeneous network, but the efficiency is not improved. An avenue for future work can take the node strength

[10] Churn was not tested on the invitation strategy, but we suspect it has the same effect as in the neighbor strategy.

into account or use another, smarter strategy.

As mentioned in Section **??**, we made the assumption that nodes cannot choose their own ID and must rely on the strategies described in Chapter **??** [**?**] for creating a Sybil with the appropriate ID. However, if this assumption was removed, this presents even more strategies for nodes to autonomously load-balance.

Chapter 9

Conclusion

Distributed Hash Tables (DHTs) are extremely powerful frameworks for distributed applications that are based off the simple and powerful hash tables. Because DHTs were designed with P2P applications in mind, DHTs are scalable, fault-tolerant, and load-balancing. These are exactly the qualities needed in a distributed computing framework.

We created a new DHT called VHash, which was based off the relationship we discovered between the DHTs and Voronoi tessellation. VHash is a DHT that operates over a multidimensional space, which allows the embedding of arbitrary metrics into this space. We showed that we can optimize latency in VHash to obtain faster lookup speeds than a traditional DHT, such as Chord. The key to VHash is our Distributed Greedy Voronoi Heuristic (DGVH). DGVH is a sufficiently accurate and fast approximation of Delaunay triangulations. Aside from its application in VHash, DGVH's applications extend to other areas, such as wireless sensor networks.

We have also shown in the previous chapters that we were able to create a prototype distributed computing application [**?**] based on the Chord DHT [**?**]. ChordReduce, as we named it, demonstrated how MapReduce could be performed on the Chord distributed hash table. As a DHT, ChordReduce is completely decentralized and fault-tolerant, able to handle nodes entering and leaving the network during churn. We demonstrated that ChordReduce can efficiently distribute a problem whilst undergoing significant churn and achieve a significant speedup.

During our experiments with ChordReduce, we found an anomaly in which a computation undergoing a significantly high level of churn finished twice as fast than when no churn was involved. This implied to us that there the churn was effectively shuffling around the nodes such that nodes

with no work were taking work from nodes with large amounts of work. We want to use this implication develop a more intelligent autonomous load-balancing mechanism. Such a mechanism would allow underworked nodes to steal work from overworked nodes in the network.

Part of autonomous load-balancing will involve exploiting heterogeneity in the network. We can do this by having more powerful nodes take a proportionally higher amount of work. This involves a process we dubbed *mashing*, which we originally used to analyze the Sybil attack on DHTs [**?**].

Based on the work we have completed, we proposed creating a framework, called UrDHT, and use it to create a distributed computing. As the name implies, UrDHT is meant to be the prototypical DHT, from which we can derive all other DHTs. This framework would make it easy for developers to create not only new DHTs, but new distributed and P2P applications. The application that we plan on creating with UrDHT is a Distributed Computing framework based on ChordReduce.

Our new framework will be able to handle more than just MapReduce problems and incorporate an autonomous load-balancing mechanism, Developers could use our framework to effortlessly organize a disparate set of nodes into a functional distributed computing system and run their own applications. Our framework could be used in numerous contexts, be it P2P or a data center.

Finally, we developed strategies that are effective at load balancing the networks in a DHT. Our random injection strategy, based off the Sybil attack, approaches close to ideal time in a homogeneous network and shows a substantial speedup in a heterogeneous network.