Storj
A Decentralized Cloud Storage Network Framework

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`https://github.com/storj/whitepaper`

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Abstract

Decentralized cloud storage is attractive for a number of reasons. Eliminating central control allows users to store and share data without reliance on a third-party storage provider. Decentralization mitigates many traditional data failures and outages while simultaneously increasing security and privacy. At a greater rate than any single entity can afford, it allows market forces to innovate on cheaper ways to provide storage. While there are many ways to build such a system, there are some specific responsibilities any given system should address. Based on our experience with petabyte-scale storage systems, we introduce a modular framework for considering these responsibilities and building such a system. Additionally, we describe initial concrete implementations for each responsibility of the framework.

TODO Remaining big todo items:

- Datascience: write an appendix about repair bandwidth based on node churn and uptime
- Datascience: Write an appendix about how we select RS numbers
- Eng/marketing: Quality control/branding section - talk about how we plan to ensure heavy client quality by quality control evaluations, formal partnerships, relationships, and not letting poor quality heavy clients use the brand.
- Eng: Walkthroughs - highly detailed walkthroughs of how each op works
  - Upload walkthrough
  - Download walkthrough
  - Delete walkthrough
  - List walkthrough
  - Repair walkthrough
  - Payment walkthrough
  - Export/import walkthrough
- Alex/JT: Bandwidth allocation protocol

Remaining medium todo items:

- Anyone: Make sure this paper explains conclusively why we're doing v3 and why we won't have to do a v4 - difference between framework vs concrete sections
- Anyone: Clean up distributed consensus positioning in the Metadata section.
- JT: Move merkle-tree-based-filesystem idea to future work section
- Eng: Describe how path encryption works
- Eng: Describe payer (heavy client) ids and why they're needed
- Eng: General data repair framework description
- Anyone: Clean up attacks section
- Anyone: Clean up selected calculations section

- Eng: more macaroon details

Remaining little todo items:

- Anyone: Write the security and privacy requirements section
- Eng: Write a future work section about eliminating TLS handshakes
- Anyone: Clean up the pacing for the structured file storage section
- Eng: Write about how piece ids are generated
- Eng: Describe pointers
- Eng: Future work section about reputation sharing
- Eng: Future work section about finding a better data structure than a bloom filter for gc

1 Introduction

Storj is a protocol that creates a distributed network for the reliable storage of data and facilitates payment for successful data storage and transfer between peers. The Storj protocol enables peers on the network to transfer and receive data, verify the integrity and availability of remote data, and pay other nodes for storing data. While not all peers in the network have the same responsibilities, every peer is an autonomous agent, capable of performing these actions without significant human interaction.

Many storage products have been created based on distributed storage techniques. Products such as Wuala, Allmydata, Tahoe-LAFS, Space Monkey, Sia, Maidsafe, Filecoin, Crashplan, Mozy, HDFS, Storj, S3, GFS, all share one thing in common: a single computer is not as powerful or as robust as a network. These products and others attempt to solve a variety of use cases and have many different requirements, but at a high level, they all operate on the same principles. They generate redundancy for data in case of failure, store this redundancy in locations with varying degrees of failure isolation, then keep track of where the data was placed.

There are a multitude of optimization focuses one could target when creating a distributed storage system. Speed, capacity, simplicity, trustlessness, byzantine fault tolerance, security, cost, etc., are all desirable traits in a storage system. However, independently of anything else, data must be maintained to prevent data loss, nodes in the system must be able to be communicated with, and metadata must be kept track of.

We propose a framework that will allow us to choose some reasonable trade-offs and then iterate on improvements to components of the system without changing the overall system. We accomplish this by breaking the design up into a collection of relatively independent concerns, and then bring them together to form the final protocol.

After this first introduction section, the rest of the paper is divided into 4 sections. In Section 2 we discuss the design space in which Storj operates in and elaborate on specific design constraints that focus what we plan to optimize for. Section 3 covers our framework and proposes a simple concrete implementation of each component. Section 4 covers specific details about how we will deliver this implementation to users. Section 5 covers future areas of research.

2 Storj design constraints and considerations

Before designing a system, it's important to understand its requirements. We will begin with a discussion of Storj's design constraints.

2.1 S3 compatibility

The flagship cloud storage product is Amazon's Simple Storage Service, or S3 for short. Most cloud storage products provide some form of compatibility with the S3 API.

Until a decentralized cloud storage protocol is the *lingua franca* of storage protocols, we must create a graceful transition from centralized providers. For users with data currently stored on a centralized provider, this will alleviate any switching costs.

Our objective is for Storj to compete successfully in the wider cloud storage industry and bring decentralized cloud storage to the mainstream – thus enabling more people greater security and less centralized control. To achieve this goal, applications built against S3 should be able to be configured to work with Storj with minimal friction and changes. Imagine if 90% of existing application services could switch to Storj with a single configuration change. TODO maybe talk about s3 market penetration? This adds strong requirements on feature set, performance, and durability.

2.2 Device failure and churn

For any storage system, but especially a distributed storage system, component failure is a guarantee. All hard drives fail after enough wear [1], and the servers providing the network access to these hard drives will eventually fail, too. Network links die, power is lost, and storage mediums become unreliable. For data to outlast individual component failure, data must be stored with enough redundancy to recover from failure. Perhaps more importantly, no data should be assumed to be stationary and all data must eventually be moved. In such an environment, redundancy, data maintanance, repair, and replacement of lost redundancy are facts of life, and the system must account for these issues.

Decentralized systems are additionally susceptible to high churn rates, where potential participants join the network and then leave for various reasons, well before their hardware has actually failed. A network with a high churn rate will use a large amount of bandwidth just to ensure durability of the data, and such a network will fail to scale. As a result, a scalable, highly durable storage system must prefer stable nodes and endeavor to keep the churn rate as low as possible.

Despite the chance of hardware failure, Maymounkov et al. found that in decentralized systems, due to churn rates the probability of a node staying on for an additional hour as a member of the network is an *increasing* function of uptime [2]. In other words, the longer a node is a participant in the network, in general the more likely it is to continue participating. This gives our system a strong incentive to prefer long-lived, stable nodes.

See Appendix TODO for a discussion about how repair bandwidth varies as a function of node churn and uptime.

2.3 Latency

Decentralized, distributed storage has massive opportunities for parallelism with transfer rates, processing, and a number of other factors. Parallelism by itself is a great way to increase overall throughput even when individual network links are slow. However, parallelism cannot by itself improve *latency.* If an individual network link has fixed latency and is a required part of an operation, the latency of the overall operation will be bound from below by the latency of the required network link. Therefore, a distributed system intended for high performance applications must aggressively optimize for low latency, both at the individual process scale and at the overall architecture scale.

We emphasize an architectural strategy aimed at achieving low latency by focusing on eliminating the need to wait for long tails [3]. What are long tails? The goal is a protocol that allows for every request to be satisfiable by the fastest nodes participating in any given transaction, without waiting for a slow subset. Focusing on operations where the result is only dependent on the fastest nodes turns what could be a potential liability (highly variable performance from individual actors) into a great source of strength for a distributed storage network.

2.4 Bandwidth

Global bandwidth availability is increasing year over year; however, access to high-bandwidth internet connections is unevenly distributed. While users in some countries can easily access symmetric, high-speed, unlimited bandwidth, users in other countries may have significant difficulty in obtaining access to the same. In the United States, the way many residential internet service providers provide internet presents two specific challenges for designers of a decentralized network protocol. The first challenge is that the internet connection is often asymmetric. Customers subscribe to internet service based on an advertised download speed, but the upload speed is potentially an order of magnitude or two slower. The second challenge is that bandwidth is sometimes "capped" at a fixed amount of traffic per month. For example, in many markets, Comcast poses a one terabyte per month bandwidth cap with stiff fines for customers who go over. Such caps impose significant limitations on the bandwidth available at any given moment. An internet connection with a throughput of 10 MB/s and a cap of 1 TB/month may not average more than 385 KB/s over the month without going over the monthly bandwidth cap.

With device failure and churn guaranteed, any decentralized system will have a corresponding amount of repair traffic. It is therefore important to make sure there is enough headroom for the bandwidth required by data maintenance, over and above that required for data storage and retrieval. Designing a storage system that is careless with bandwidth usage would be to relegate that system below storage providers with access to unlimited high-speed bandwidth, recentralizing the system to some degree. To keep the storage system as decentralized as possible and for it to work in as many environments as possible, bandwidth usage must be aggressively minimized.

Please see Appendix TODO for a discussion on how available bandwidth, combined with required repair traffic, limits usable space.

2.5 Security and privacy

TODO we want to make sure users' data privacy is protected

2.6 Object size

Broadly, large storage systems can be classified into two groups by average object size. When storing lots of small bits of information, generally a database is the preferred route. On the other hand, when storing lots of large files, an object store or filesystem is ideal. We classify a "large" file as a few megabytes or greater.

The initial product offering by Storj Labs is designed to function primarily as an object store for larger files. While future improvements may enable database-like use cases, the predominant use case described by this paper is object storage. Protocol design decisions are made with the assumption that the vast majority of objects stored will be a couple of megabytes or more. It is worth pointing out that this will not negatively impact use cases that require lots of files smaller than a megabyte. Such cases can admit a packing strategy, where many small files are aggregated and stored together as one large file. As the protocol has streaming support, small files can be retrieved without requiring full retrieval of any aggregated object they were packed into.

2.7 Byzantine Fault Tolerance

Unlike datacenter-based solutions like Amazon S3, Storj operates in an untrusted environment, where individual storage nodes are not necessarily assumed to be trustworthy. Storj operates over the public internet, and allows anyone to sign up to become a storage node.

We adopt the BAR (Byzantine, Altruistic, Rational) model [4] to discuss participants in the network. *Byzantine* nodes may deviate arbitrarily from the suggested protocol for any reason. Some examples include nodes that are broken, nodes that are trying to cheat the suggested protocol to their advantage, or nodes that are actively trying to sabotage the protocol. In general, a Byzantine node is one that optimizes for a utility function that is independent of the one given for the suggested protocol. Inevitable hardware failure aside, *Altruistic* nodes participate in a proposed protocol even if the rational choice is to deviate. *Rational* nodes participate exactly when it is in their net benefit to do so, and may depart for the same reason.

Some distributed storage systems (e.g., Amazon S3) operate in an environment where all nodes are altruistic add citation?. Storj operates in an environment where a majority of storage nodes are rational and a minority are byzantine. Storj assumes no altruistic nodes. Any potential design must account for this distinction.

3 Framework and concrete implementation

At a high level, there are three major operations in the system: storing data, retrieving data, and maintaining data.

Storing data When data is stored with the network, the client encrypts it and breaks it up into multiple little pieces. It then distributes the pieces to peers in the network then generates and stores some metadata about where to find the data again.

Retrieving data When data is retrieved from the network, it first recovers the metadata about where to find the pieces. Then the pieces are retrieved and the original data is reconstructed on the client's local machine.

Maintaining data Data is maintained in the network with nodes replacing missing pieces when the amount of redundancy drops below a certain threshold. The data is reconstructed and the missing pieces are regenerated and replaced.

To make this system feasible while satisfying our design constraints, we will need to solve a number of complex challenges. Inspired by Raft [5], we break up the design into a collection of relatively independent concerns and then combine them to form the desired protocol. One important benefit is it makes updating individual components much easier without having to rearchitect the rest of the network. The individual components are:

1. Storage nodes
2. Peer-to-peer communication

3. Overlay network
4. Redundancy
5. Structured file storage
6. Metadata
7. Encryption
8. Authorization
9. Audits
10. Data repair
11. Storage node reputation
12. Payments
13. Payer reputation
14. Garbage collection

3.1 Storage nodes

The most basic building block is the storage node. The storage node stores and returns data provided to it. Nodes should provide reliable storage space, network bandwidth, and appropriate responsiveness. In return, nodes are rewarded for their participation. Storage nodes will be selected based on a number of different criteria. Ping time, latency, throughput, disk space, geographic location, legal restrictions, etc., are all important factors that may need to be considered. This means that node selection almost certainly must be an explicit process.

3.1.1 Concrete implementation

Storage nodes will support three methods: `get`, `put`, and `delete`. Storage nodes store *pieces* (to be described in more detail later). Each method will take a *piece ID*, a *payer ID* and signature by the payer, an optional TTL, and the other metadata required by the bandwidth allocation protocol (also to be described later).

The `put` operation will take a stream of bytes and store the bytes such that any subrange of bytes can be retrieved again via a `get` operation. `get` operations are expected to work until the TTL expires (if a TTL was provided), or until a `delete` operation is received, whichever comes first.

The *payer ID* forms a namespace. An identical *piece ID* with a different *payer ID* refers to a different *piece*.

Storage nodes should allow administrators to configure maximum allowed disk space usage and maximum allowed bandwidth usage over the last rolling 30 days. Storage nodes should keep track of how much is remaining of both. Storage nodes should reject operations that do not have a valid signature from the appropriate payer.

3.2 Peer-to-peer communication

All peers on the network will need to communicate. The framework requires a reliable and ubiquitous protocol that all peers speak that:

- provides peer reachability, even in the face of firewalls and NATs. This may require techniques like STUN, relays, etc.
- provides authentication, where each participant knows exactly the identity of the peer with whom they are speaking.
- provides privacy, where only the two peers know what transfers between them.

3.2.1 Concrete implementation

Initially, we'll be using gRPC [6] on top of TLS on top of μTP [7] with added STUN functionality. Over time, we'll be replacing TLS to reduce round trips due to connection handshakes in situations where the data is already encrypted and forward secrecy isn't necessary. TODO See the Future Work section for more details. Gateways will be provided that allow for more standard protocols such as HTTPS.

As in S/Kademlia [8], the *node ID* will be the hash of a public key and will serve as a proof of work for joining the network. Unlike Bitcoin proof of work [9], the work will be dependent on how many *trailing* zero bits one can find in the hash output. This means that the node ID will still be usable in a balanced Kademlia [2] tree.

Each node will operate its own certificate authority, which requires a public/private keypair and a self-signed certificate. The certificate authority should ordinarily be kept in cold storage to prevent key loss.

Each node will also have revokable leaf key pair and certificate, signed by the node's certificate authority. Nodes will use this leaf keypair for actual communication. Should the leaf become compromised, the node can issue a new leaf and a new entry in a certificate revocation list.

The *node ID* will be determined from the certificate authority by hashing the DER-encoded public key.

$$\text{NodeID} = \text{SHA256}(\text{Pu}) \tag{1}$$

It's important that the certificate authority private key be managed with good operational security as key rotation for the certificate authority will require a brand new node ID.

When using TLS, every peer can ascertain the ID of the node with which it is speaking by validating the certificate chain and hashing its peer's certificate authority's public key. It can then be estimated how much work went into constructing the node ID by considering the number of 0 bits at the end of the ID.

For the few cases where a node cannot achieve a successful hole punch through a NAT or firewall via STUN, uPnP, NATPmP, or a similar technique, manual intervention and port forwarding will be required.

3.3 Overlay network

If, given a peer's network address, any other peer can connect to it, the framework requires a system to look up peer network addresses by node ID in the first place. An *overlay network* can be built on top of our peer-to-peer communication component that provides functionality similar to DNS, where a node's ID can be resolved to an ephemeral network address for communication.

3.3.1 Concrete implementation

The Kademlia DHT serves as a key-value store with a built-in node lookup protocol. We utilize this protocol to achieve DNS-like functionality for node lookup, while ignoring the storage aspects of the Kademlia protocol due to some issues around value republishing, limits to network growth rate, and so on. However, using a DHT will make it difficult to achieve millisecond-level response times when multiple DHT lookups must happen for every operation, so more work is necessary to achieve our performance goals. Fortunately, caching address information for an entire network of 80k nodes (for example) can be done with 3MB of memory, so the DHT can be sped up with some simple, optional caching.

Because a cache of the DHT can be untrusted (and peer-to-peer communication is authenticated to avoid man-in-the-middle-attacks anyway), some well-known community-run DHT caches can be provided that simply attempt to talk to every storage node every so often, such as every hour, evicting nodes from their cache that have not been seen recently. Since nodes are expected to be long lived with good uptime, they are expected to have stable addresses that don't change often on the order of more than once an hour. Thus, such a cache will add a massive performance boost, even when slightly stale. In addition, the protocol will be resilient against an expected degree of node churn, so having a small number of stale addresses in a DHT cache will not alter the expected performance of the network. Furthermore, we avoid a number of known attacks by using the S/Kademlia extensions. [8]

TODO talk about how we're using kademlia to advertise disk space and bandwidth availability, and then storing that information in the cache

3.4 Redundancy

At any moment, any storage node could go offline permanently. Our redundancy strategy must store data in a way that provides access to the data with high probability, even though any given number of individual nodes may be offline. To achieve a certain level of *durability* (the probability that data will remain available in the face of failures), many products in this space use simple replication. Unfortunately, this ties durability to the network *expansion factor*, which is the storage overhead for reliably storing data.

As an example, suppose a certain desired level of durability requires a replication strategy that makes eight copies of the data. This yields an expansion factor of 8x, or 800%. This data then needs to be stored on the network, using bandwidth in the process. Thus, more replication results in more bandwidth usage for a fixed amount of data. As discussed in the protocol design constraints, high bandwidth usage prevents scaling, so this is an undesireable strategy for ensuring a high degree of file durability. Instead, *erasure codes* are a more general and more flexible scheme for manipulating data durability without tying it to bandwidth usage. Importantly, erasure codes allow changes in durability without changes in expansion factor!

An erasure code is often described by two numbers, k and n. If a block of data is encoded with a (k, n) erasure code, there are n total generated *erasure shares*, where only any k of them are required to recover the original block of data. If a block of data is s bytes, each of the n erasure shares is roughly s/k bytes. Besides the case when $k = 1$ (replication), all erasure shares are unique. Interestingly, the durability of a $(k = 20, n = 40)$ erasure code is better than a $(k = 10, n = 20)$ erasure code, even though the expansion factor (2x) is the same for both! Intuitively, this is because the risk is spread across more nodes in the $(k = 20, n = 40)$ case. These considerations make erasure codes an important part of our general framework.

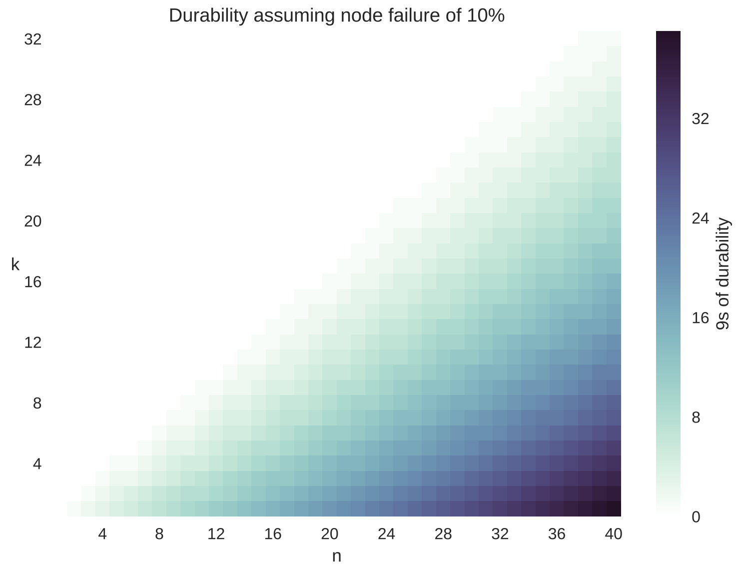
With the simplifying assumption that every node has an equal probability of failure p, one can gain more intuition by modeling file durability as the CDF of the binomial distribution, as seen in Equation (2). In this case, $P(D)$ represents the probability that at most $n-k$ erasure shares are lost for a given file, so that $n-(n-k) = k$ erasure shares of the file remain; i.e. the file can still be rebuilt. The CDF of the binomial distribution is given by:

$$P(D) = \sum_{i=0}^{n-k} \binom{n}{i} p^i (1-p)^{n-i} \tag{2}$$

By being able to tweak the durability independently of the expansion factor, very high durabilities can be achieved with surprisingly low expansion factors. Because of how limited bandwidth is as a resource, eliminating replication as a strategy entirely and using erasure codes only for redundancy causes a drastic decrease in bandwidth footprint and a drastic increase in the funds available per byte on storage nodes.

k	n	Exp. factor	P(D)
2	4	2	99.629999999999996341%
4	8	2	99.956834999999999436%
8	16	2	99.999407567699549748%
16	32	2	99.999999871786737771%
32	64	2	99.999999999999988898%

Table 1: $P(D)$ for various choices of k and n, assuming $p = 0.9$.



3.4.1 Streaming

Erasure codes are used in many streaming contexts such as audio CDs and satellite communications, so it's important to point out that using erasure coding in general does not make our streaming design requirement more challenging. Whatever erasure code is chosen for our framework, streaming can be added on top by encoding small portions at a time, instead of attempting to encode a file all at once. See the structured file storage section for more details.

3.4.2 Long tails

Erasure codes enable an enormous performance benefit, which is the ability to avoid waiting for long-tail response times [3]. For uploads, a file can be encoded to a higher (k, n) ratio than necessary for durability guarantees. During an upload, after enough pieces have uploaded to gain required redundancy, the remaining additional uploads can be canceled, allowing the upload to be blocked by the fastest nodes in a set, instead of waiting for the slowest nodes. Downloads are similarly improved. Since more redundancy exists than is needed, downloads can be served from the fastest peers, eliminating a wait for temporarily slow or offline peers.

3.4.3 Concrete implementation

We use the Reed-Solomon erasure code [10]. For each object that we store we choose 4 numbers, k, m, o, and n, such that $k \leq m \leq o \leq n$. k and n are the standard Reed Solomon numbers, where k is the minimum required number of pieces for reconstruction, and n is the total number of pieces generated during creation.

m and o are the *minimum safe* and *optimal* values, respectively. m is chosen such that if the amount of available pieces falls below m, a repair is triggered immediately in an attempt to make sure we always maintain k or more pieces. o is chosen such that during uploads, as soon as o pieces have finished uploading, remaining pieces up to n are canceled as described above. o is chosen such that storing o pieces is all that is needed to achieve the desired durability goals; n is thus chosen such that storing n pieces would be excess durability.

Our durability story does not end with our selection of these numbers. Please see section 3.10 for a discussion about how we repair data as its durability drops over time.

See TODO data science: Appendix for how we select our Reed-Solomon numbers.

3.5 Structured file storage

Our design constraints include S3 compatibility. This means we should support hierarchical objects (paths with prefixes), object metadata, arbitrarily large files, arbitrarily large amounts of files, and so on. Similarly, our design constraints require security, so any such metadata must be encrypted.

Provided we have an efficient way to store data, we can build many of these features on top by means of an *injective embedding* (here used in the mathematical sense). In other words, adding this functionality can be done by building on top of the basic components we have already created without loss of generality.

Because so much here depends on concrete implementation details, our framework is loose in specificity, while our concrete implementation has significant detail.

3.5.1 Concrete implementation

TODO an introduction before diving into a list of definitions

Bucket A `bucket` is an unbounded but named collection of `file`s identified by `path`s. Each `path` represents one `file`, and every `file` has a unique `path`.

Path A `path` is a unique identifier for a `file` within a `bucket`. A `path` is a string of UTF8 codepoints that begins with a forward slash and ends with something besides a forward slash. More than one forward slash (referred to as the `path separator`) separate `path components`.

An example path might be `/etc/hosts`, where the `path components` are `etc` and `hosts`.

We encrypt `paths` before they ever leave the customer's application's computer.

File A `file` is a collection of `streams`. Every `file` has exactly one default `stream` and may have 0 or more named `streams`. Multiple `streams` allow flexible support of extended attributes, alternate data streams, resource forks, and other slightly more esoteric filesystem features.

Like `paths`, the data contained in a `file` is encrypted before it ever leaves the client computer.

Stream A `stream` is an ordered collection of 0 or more `segments`. `segments` have a fixed maximum size, and so the more bytes the `stream` represents through `segments`, the more `segments` there are.

Segment A `segment` represents a single array of bytes, between 0 and a user-configurable maximum `segment` size. Breaking large `files` into multiple `segments` provides a number of security and scalability advantages.

Inline Segment An `inline segment` is a `segment` that is small enough it makes sense to store it "inline" with the metadata that keeps track of it, such as a `pointer`.

Remote Segment A `remote segment` is a larger `segment` that will be encoded and distributed across the network. A `remote segment` is larger than the metadata required to keep track of its book keeping.

Stripe A `stripe` is a further subdivision of a `segment`. A `stripe` is a fixed amount of bytes that is used as an encryption and erasure encoding boundary size. Erasure encoding happen on `stripes` individually, whereas encryption may happen on a small multiple of stripes at a time. All `segments` are encrypted, but only `remote segments` are erasure encoded.

Erasure Share When a `segment` is a `remote segment`, its `stripe`s will get erasure encoded. When a `stripe` is erasure encoded, it generates multiple pieces called `erasure share`s. Only a subset of the `erasure share`s are needed to recover the original `stripe`, but each `erasure share` has an index identifying which `erasure share` it is (e.g., the first, the second, etc.).

Piece When a `remote segment`'s `stripe`s are erasure encoded into `erasure share`s, the `erasure share`s for that `remote segment` with the same index are concatenated together, and that concatenated group of `erasure share`s is called a `piece`. If there are n `erasure share`s after erasure encoding a `stripe`, there are n `piece`s after processing a `remote segment`. The ith `piece` is the concatenation of all of the ith `erasure shares` from that `segment`'s `stripe`s.

Piece Storage Node A node in the network that is responsible for storing `piece`s. These are operated by `farmer`s.

Farmer A person or group that is responsible for running and maintaining `piece storage node`s.

Pointer A `pointer` is a data structure that keeps track of which `piece storage node`s a `remote segment` was stored on, or the `inline segment` data directly if applicable.

3.5.2 Files as Streams

Many applications benefit from being able to keep metadata alongside files. For example, NTFS supports "alternate data streams" for each file, HFS supports resource forks, EXT4 supports "extended attributes," and more importantly for our purposes, AWS S3 supports "object metadata" [11]. Being able to support arbitrarily named sets of keys/values dramatically improves compatibility with other storage platforms. Every `file` will have at least one `stream` (the default `stream`) and many files may never have another `stream`.

3.5.3 Streams as Segments

Because `stream`s are used for data (the default `stream`) and metadata (extended attributes, etc.), `stream`s should be designed both for small data and large data. If a `stream` only has very little data, it will have one small `segment`. If that `segment` is smaller than the metadata it would require to be stored on the network, the `segment` will be an `inline segment` and the data will be stored directly inline with the metadata.

For larger `stream`s past a certain size, the data will be broken into multiple large `remote segment`s. Segmenting in this manner has a number of advantages to security, privacy, performance, and availability.

Maximum `segment` size is a configurable parameter. To preserve privacy, it is recommended that `segment` sizes be standardized as a byte multiple, such as 8 or 32 MB. Smaller `segment`s may be padded with zeroes or random data. Standardized sizes help frustrate attempts to determine the content of a given `segment` and can help obscure the flow of data through the network.

Segmenting large files like video content and distributing the `segment`s across the network separately reduces the impact of content delivery on any given node. Bandwidth demands are distributed more evenly across the network. In addition, the end-user can take advantage of parallel transfer, similar to BitTorrent or other peer-to-peer networks.

3.5.4 Segments as Stripes

In many situations it's important to be able to access just a portion of some data. Some large file formats such as large video files, disk images, or file archives support the concept of seeking, where only a partial subset of the data is needed for correct operation. In these cases it's useful to be able to decode and decrypt only parts of a file.

A `stripe` is no more than a couple of kilobytes, and encoding a single `stripe` at a time allows us to read portions of a large `segment` without retrieving the entire `segment`, allows us to stream data into the network without staging it beforehand, and enables a number of other useful features.

Depending on the sizes, `stripes` are either encrypted individually or in small batches. Only a few stripes should be needed for successful decryption. In either case, `stripes` should be encrypted client-side before being erasure encoded. The reference implementation uses AES256-GCM by default, but XSalsa20+Poly1305 is also provided. This protects the content of the data from the `farmer` housing the data. The data owner retains complete control over the encryption key, and thus over access to the data.

It's important to use authenticated encryption to defend against data corruption (willful or negligent) with a monotonically increasing nonce to defeat reordering attacks. The nonce should be monotonically increasing throughout the entire `stream`. If `stripe` batch i is encrypted with nonce j, stripe batch $i+1$ should be encrypted with nonce $j+1$. Each `segment` should get a new encryption key whenever the content in the `segment` changes to avoid nonce reuse. TODO jt: fix this

3.5.5 Stripes as Erasure Shares

Erasure encoding gives us the chance to control network durability in the face of unreliable `piece storage nodes`. Erasure encoding schemes often are described as (k, n) schemes, where k `erasure shares` are needed for reconstruction out of n total. For every `stripe`, n `erasure shares` are generated, where the network has an expansion factor of $\frac{n}{k}$.

For example, let's say a `stripe` is broken into 40 `erasure shares` ($n = 40$), where any 20 ($k = 20$) are needed to reconstruct the `stripe`. Each of the 40 `erasure shares` will be $\frac{1}{20}$th the size of the original `stripe`. All n `erasure shares` have a well defined index associated with them. The ith share will always be the same, given the same input parameters.

Because peers generally rely on separate hardware and infrastructure, data failure is not correlated. This implies that erasure codes are an extremely effective method of securing availability. Availability is proportional to the number of nodes storing the data.

See section TODO for a breakdown of how varying the erasure code parameters affects availability and redundancy.

3.5.6 Erasure Shares as Pieces

Because `stripes` are already small, `erasure shares` are often much smaller, and the metadata to keep track of all of them separately would be immense relative to their size. Instead of keeping track of all of the shares separately, we pack all of the `erasure shares` together into a few `pieces`. In a (k, n) scheme, there are n `pieces`, where each `piece` i is the ordered concatenation of all of the `erasure shares` with index i. As a result, where each `erasure share` is $\frac{1}{k}$th of a `stripe`, each `piece` is $\frac{1}{k}$th of a `segment`, and only k `pieces` are needed to recover the full `segment`.

TODO piece ids are generated as the hmac of a root piece id and the storing node id

3.5.7 Pointers

TODO

3.6 Metadata

In the previous section, we discussed how we will break up files, encode them for redundancy, and then store them in the network. Independently of the concrete organization and structure of this scheme, there are two types of metadata that are important to store somewhere for recovery: paths and what storage nodes received pieces (pointers).

Our framework requires a relatively performant system that can store pointers by path in a way that supports ordered iteration over those paths. Every time an object is added, edited, or removed, one or more entries in this metadata storage system will need to be adjusted. As a result, there could be heavy churn in this metadata system, and across the entire userbase the metadata itself could end up being a sizeable amount of data.

To talk more about the scope and scale we expect with some examples, suppose in a few years this system stores 1 total exabyte of data, where the average object size is 50MB and our erasure code is such that $n = 40$. Each object will use just one segment, and thus have one pointer each. The pointer will contain information about the segment encoding, including what n nodes the segment pieces are stored on. 1 exabyte of 50MB objects is 20 billion objects. If each pointer is roughly 40*64+192 bytes (info for each node plus the path and some general overhead), there are over 55 terabytes of metadata to keep track of (which is still 18,181 times less data to keep track of than an exabyte). Fortunately, this metadata can be heavily partitioned by user. A user storing a 100 terabytes of 50MB objects will only incur an overhead of 5.5 gigabytes, once again 18,181 times less data. It's worth pointing out that these numbers vary heavily with average object size (the larger the object size, the less the metadata overhead).

One of our framework's primary focuses is making sure this component – metadata storage – is interchangeable per user. Specifically, we expect to ship with multiple implementations of metadata storage that we will allow users to choose between. Other systems have spent an enormous amount of time attempting to solve this problem. We've concluded that multiple *good enough* solutions already exist, and propose using them.

Aside from scale requirements, the desired API is straightforward and simple: Put (store a pointer given a path), Get (retrieve a pointer given a path), List (paginated, ordered listing of existing paths), and Delete (remove a path).

3.6.1 Aside about distributed consensus

A long and challenging area of research has been directed toward getting a group of computers to agree on a set of values, with the goal of constructing a horizontally-scalable database that works in the face of expected failures (crash failures, for example: failures where a server simply shuts down). Fortunately, this research has led to some really exciting technology.

The biggest issue with getting a group of computers to agree is that messages can be lost. How this impacts decision making is succinctly described by the "Two Generals' Problem" [12] (earlier described as a problem between groups of gangsters [13]), in which two armies try to communicate in the face of potentially lost messages. Both armies have already agreed to attack a shared enemy, but have yet to decide on a time. Both armies must attack at the same time or else failure is assured. Both armies can send messengers, but the messengers are often captured by the enemy. Both armies must know what time to attack and that the other army has also agreed to this time.

Ultimately, a solution to the two generals' problem with a finite number of messages has been proven to be impossible, so engineering approaches have had to brace uncertainty by necessity. Many distributed systems make tradeoffs to deal with this uncertainty. Some systems embrace *consistency*, which means that the system will choose downtime over inconsistent answers. Other systems embrace *availability*, which means that the system chooses potentially inconsistent answers over downtime. The widely-cited CAP theorem [14] states that every system must choose only two of consistency, availability, and partition tolerance. Due to the inevitability of network failures, partition tolerance is non-negotiable, and when a partition happens, every system must choose to sacrifice either consistency or availability. Many systems sacrifice both (sometimes by accident).

In the CAP theorem, consistency means that every read receives the most recent write or an error, so an inconsistent answer means the system returned something besides the most recent write without obviously failing. More generally, there are a number of *consistency models* that may be acceptable by making various tradeoffs. Linearizability, sequential consistency, causal consistency, PRAM consistency, eventual consistency, read-after-write consistency, etc., are all models for discussing how a history of events appears to various participants in a distributed system.[1]

Amazon S3 generally provides *read-after-write consistency*, though in some cases will provide *eventual consistency* instead [17]. Arguably, there may be some flexibility here for the selection of alternate consistency models that suit us better while still broadly providing S3 compatibility. Many distributed databases provide eventual consistency by default, such as Dynamo [18] and Cassandra [19].

Linearizability in a distributed system is often much more desirable, as it is useful as a building block for many higher level data structures and operations such as distributed locks and other coordination techniques. Initially, early efforts centered around two-phase commit, then three-phase commit, which both suffered due to issues similar to the two generals' problem. Things were looking bad in 1985 when the FLP-impossibility paper [20] proved that no algorithm could reach linearizable consensus in bounded time. Then in 1988, Barbara Liskov and Brian Oki published the Viewstamped Replication algorithm [21] which was the first linearizable distributed consensus algorithm. Unaware of the VR publication, Leslie Lamport set out to prove linearizable distributed consensus was impossible [22], but instead in 1989 proved it was possible by publishing his own Paxos algorithm [23], which for some reason became significantly more popular. Ultimately both algorithms have a large amount in common.

Despite Lamport's claims that Paxos is actually simple [24], many papers have been published since then challenging that assertion. Google's description of their attempts to implement Paxos landed in Paxos Made Live [25], and Paxos Made Moderately Complex [26] is an attempt to try and fill in all the details of the protocol. The entire basis of the Raft algorithm is rooted in trying to wrangle and simplify the complexity of Paxos [5]. Ultimately, after an upsetting few decades, reliable implementations of Paxos, Raft, Viewstamped Replication [27], Chain Replication [28], and Zab [29] now exist, with ongoing work to improve the situation further [30, 31]. Arguably, part of Google's early success was in spending the time to build their internal Paxos-as-a-service distributed lock system, Chubby [32]. Most of Google's most famous internal data storage tools such as Bigtable [33] depend on Chubby for correctness. Spanner [34] – perhaps one of the most incredible distributed databases in the world – is mainly just two-phase commit on top of multiple Paxos groups.

[1] If differing consistency models are new to you, it may be worth reading about them in Kyle Kingbury's excellent tutorial [15]. If you're wondering why computers can't just use the current time to order events, keep in mind it is exceedingly difficult to get computers to even agree on that [16].

Reliable distributed consensus algorithms have been game-changing for many applications needing fault-tolerant storage.

3.6.2 Aside about Byzantine distributed consensus

As mentioned in our design constraints, we expect most nodes to be *rational* and some to be *byzantine*, but few-to-none to be *altruistic*. Unfortunately, all of the previous algorithms we discussed assume a collection of altruistic nodes.

There have been a number of attempts to solve the Byzantine fault tolerant distributed consensus problem [9, 35–51]. Each of these algorithms make some additional tradeoffs the non-Byzantine distributed consensus algorithms don't require to deal with the potential for uncooperative nodes. For example, PBFT [35] causes a significant amount of network overhead. Bitcoin [9] intentionally limits the transaction rate with changing proof-of-work difficulty, in addition to requiring all participants to keep a full copy of all change histories (like other blockchain-based solutions).

TODO talk about merkle-dag, git-inspired approaches to metadata, potentially built on kademlia, potentially reworking this entire section because ugh

3.6.3 Concrete implementation

Given the situation described in the asides about distributed consensus, we have decided that good-enough solutions already exist, so we will revisit the problem of solving Byzantine distributed consensus for our use case to a later release. We believe that a great distributed algorithm here is possible, all of the necessary building blocks are likely described above, and we expect to invest heavily in research to find it after we have a thriving user base with our solution based on good-enough approaches.

The most trivial implementation for the metadata storage functionality we require would be to simply have each user use their preferred trusted database such as PostgreSQL, SQLite, MongoDB, Cassandra [19], Spanner [34], CockroachDB, or something else. In many cases, this will be acceptable for specific users, provided those users were managing appropriate backups of their metadata. Indeed, the types of users who have petabytes of data to store probably can manage reliable backups of a single relational database storing only metadata.

There are a few downsides with this punt-to-the-user approach, however, such as:

- **Availability** - the availability of the user's data is tied entirely to the availability of their metadata server. The counterpoint here is that the availability can be made arbitrarily good with existing trusted distributed solutions such as Cassandra, Spanner, or CockroachDB. Further, any individual metadata service downtime does not affect the entire network. In fact, the network as a whole can still never go down.
- **Durability** - if the metadata server suffers a catastrophic failure without backups, all of the user's data is gone. This is already true with encryption keys, but a punt-to-the-user solution increases the risk area from just encryption keys considerably. Fortunately, the metadata itself can be periodically backed up into the Storj system, such that only needing to keep track of metadata-metadata further decreases the amount of critical information that must be stored elsewhere.
- **Trust** - the user has to trust the metadata server.

On the other hand, there are a few upsides:

- **Use cases** - in a catastrophic scenario, this design still covers all required use cases.
- **Control** - the user is in complete control of all of their data. There is still no organizational single point of failure. The user is free to choose whatever metadata store with whatever tradeoffs they like. Like Mastodon [52], this solution is still decentralized. Further, in a catastrophic scenario, this design is no worse than most other technologies or techniques application developers frequently use (databases).
- **Simplicity** - other projects have spent multiple years on shaky implementations. We can get a useful product to market without doing this work at all. This is a considerable advantage.

Our launch goal is to allow customers to store their metadata in a database of their choosing. We expect and look forward to new systems and improvements specifically in this component of our framework.

3.7 Encryption

Data should be encrypted as early as possible in the data storage pipeline, ideally before the data ever leaves the source computer. This means that the S3-compatible gateway or appropriate similar client library should run colocated on the same computer as the user's application.

Ideally encryption uses a pluggable mechanism that allows users to choose their desired encryption scheme as well as store metadata about that encryption scheme to allow them to recover their data using the appropriate decryption mechanism.

To support rich access management features, the same encryption key should not be used for every file, as having access to one file would result in access to decryption keys for all files. Instead, each file should be encrypted with a unique key, such that users can share access to certain selected files without giving up encryption details for others.

Because each file should be encrypted differently with different keys and potentially different algorithms, the metadata about that encryption must be stored somewhere in a way that is secure and reliable. This metadata will be stored in appropriate `pointers`, itself encrypted by a deterministic, hierarchical encryption scheme. A hierarchical encryption scheme similar to BIP32 [53] will allow subtrees to be shared without sharing their parents, and will allow some files to be shared without sharing other files.

Like all other metadata, paths themselves can be encrypted using a hierarchical encryption scheme.

3.7.1 Concrete implementation

Encryption is authenticated encryption, with support for the AES-GCM cipher and the Salsa20 and Poly1305 combination NaCl calls "Secretbox" [54]. Authenticated encryption is used so that the user can know if the data has been tampered with. Encryption keys are chosen randomly.

Data is encrypted in small batches of `stripes`, recommended to be 4KB or less [55]. While the same encryption key is used for every `stripe` in a `segment`, `segments` may have different encryption keys. On the other hand, the nonce for each `stripe` batch must be monotonically increasing from the previous batch throughout the entire `stream`. The nonce wraps around to 0 if the counter reaches the maximum representable nonce. The first nonce is chosen at random and is stored with the `stream`'s metadata.

Paths are also encrypted with authenticated encryption, but the nonce and key must be deterministic, determined entirely from a root secret combined with the unencrypted path.

TODO describe path encryption

Path encryption is optional, as encrypted paths make efficient sorted path listing challenging. When path encryption is enabled (a per-bucket feature), objects are sorted by their encrypted path name, which is relatively unhelpful when interested in unencrypted paths. For this reason, users can opt in to disabling path encryption. When path encryption is disabled, unencrypted paths are only revealed to the user's chosen metadata storage system.

3.8 Authorization

Encryption protects the privacy of data while allowing for the identification of tampering, but authorization allows for the prevention of tampering by disallowed clients. Users who are authorized should be able to add, remove, and edit files, while users who are not authorized should not be able to.

First, metadata operations should be authorized. Users should authenticate with their chosen metadata service, which should allow them given their authorization configuration access to various operations.

Once authorized with a metadata service, that metadata service has an associated *payer ID* TODO discuss payer IDs and is able to sign operations. All operations with storage nodes require a specific payer ID and associated signature. A storage node should reject operations not signed by the appropriate payer ID. The client must retrieve valid signatures from the metadata service prior to operations with storage nodes.

3.8.1 Concrete implementation

Our initial metadata authorization scheme uses macaroons [56]. Each account has a root macaroon and operations are validated against a supplied macaroon's set of caveats.

3.9 Audits

Incentivizing farmers to accurately store data is of paramount importance to the viability of this whole system. As such, it is important to be able to validate and verify that farmers are accurately storing what they have been asked to store.

Many storage systems use audits as a way of determining when to do repair and which files to repair. Our storage system does not. In our storage system, audits are simply a mechanism by which a node's degree of stability is determined. Failed audits will result in marking a storage node as bad, which could result in shuffling data to new nodes and avoiding that node altogether in the future. File repair needs are detected via another mechanism.

Audits in this case are probabilistic challenges that confirm with a high degree of certainty and a low amount of overhead that a storage node is well behaved, is keeping the data it claims, and is not susceptible to hardware failure or malintent. An audit functions as a spot check to help calculate a storage node's future usefulness.

This partial auditing mechanism does not audit all bytes in all files and leaves room for false positives, where the verifier believes the storage node retains the intact `piece`, when it has actually been modified or partially deleted. Fortunately, the probability of a false positive on an individual partial audit is easily calculable (see Section TODO). When applied iteratively to a storage node as a whole, detection of unexpected behavior becomes practically certain.

3.9.1 Concrete implementation

Some distributed storage systems (including the previous release of Storj [57]) discuss *Merkle tree proofs*, in which audit challenges and expected responses are generated ahead of time, as a form of compact proof of retrievability [58]. By using a Merkle tree [59], the amount of metadata needed to store these pregenerated challenges and responses can be made to be negligible.

Unfortunately, in such a scheme, the challenges and responses must be pregenerated, and without a periodic regeneration of these challenges, a storage node can begin to pass most audits without storing all of the requested data.

We do something else. A central assumption in our storage system is that most storage nodes are reasonably well-behaved, and most data is stored faithfully. As long as that assumption holds, Reed-Solomon is able to detect errors and even correct them, via mechanisms such as the Berlekamp-Welch error correction algorithm [60]. We are already using Reed-Solomon erasure coding [10] on small ranges (`stripes`), so we use it to issue challenges and verify responses as well. This feature can be used for arbitrary audits without pregenerated challenges.

To perform an audit, we first choose a `stripe` to audit. We request that `stripe`'s `erasure shares` from all storage nodes responsible. We then run the Berlekamp-Welch algorithm [60] across all the `erasure shares`. When enough storage nodes return correct information, any faulty or missing response can easily be identified. These audit failures will be stored and saved in the reputation system.

It is important that every storage node has a frequent set of random audits to gain statistical power on how well-behaved that storage node is, but it is not a requirement that audits are performed on every byte, or even on every file. Additionally, it is important that every byte stored in the system has an equal probability of being checked for a future audit to every other byte in the system. Audits should happen uniformly at random by byte with replacement.

3.10 Data repair

TODO general framework repair - should work with any version of our framework. goal is to replace missing pieces

3.10.1 Concrete implementation

An ever-present risk in any distributed storage system is file loss. While there are many potential causes for file loss, storage node churn is the leading cause by far TODO citation needed . Storage nodes may go offline due to hardware failure, intermittent internet connectivity, or operator choices. Because audits are validating that conforming nodes store data correctly, all that remains is to detect when a storage node goes offline and repair at-risk data.

We're taking a huge shortcut with this assumption. We're assuming that probabilistic audits are enough for us to estimate the likelihood that a node will have the data it should have, and then using that along with node uptime (which is much more efficient than audits) to calculate when a file is at risk. We *only* consider *node* availability and configured repair thresholds when determining which *files* to repair.

There are many other ways data might get lost in the network besides node churn: corruption, malicious behavior, bad hardware, software error, user space reclaimation, but these issues are less serious than full node churn (power loss, internet connectivity intermittency, software shutdown or removal). Our spot-check-based audits will incentivize farmers to reliabily store data while estimating the rate at which data is actually stored reliably. Therefore, our repair system only seeks to solve the node churn problem, and we expect to make up the difference via configuring Reed-Solomon erasure code parameters to match.

The Overlay Network already has caches in place that have accurate and up-to-date information about which storage nodes have been online recently. When a storage node changes state from recently online to offline, this can trigger a lookup in a reverse index in a user's metadata database, identifying all `segment pointers` that were stored in part on that storage node. For every `segment` that drops below the appropriate minimum safety threshold, the segment should be downloaded and reconstructed and the missing pieces should be regenerated and uploaded to new nodes. Finally, the `pointer` should be updated to include the new information.

As farmer nodes go offline, taking their file pieces with them, it will be necessary for the missing pieces to be rebuilt once the entire file's pieces fall below a certain, predetermined threshold. If a node goes offline, the heavy client will mark that nodes' file pieces as missing. Once enough correlating file pieces are lost, the heavy client will download the remaining file pieces from their corresponding farmers. Those pieces will be used to rebuild the file's missing, encrypted, erasure encoded pieces. Once the repair process is complete, the heavy client will send the recovered pieces to new farmers.

Users will choose their desired durability when they sign up for an account (which may impact price among other things). This desired durability, along with statistics from ongoing audits, will directly inform what Reed-Solomon erasure code choices should be made for new and repaired files, and what thresholds should be set for when uploads are successful and when repair is needed. See Appendex TODO for how we calculate these things given user inputs.

A practical upshot of this design is that for now, the heavy client must constantly stay running. If the user's heavy client stops running, repairs will stop, and data will eventually fall out of the network due to node churn. This is similar to the design of how value storing and republishing works in Kademlia [2].

The ingress bandwidth demands of the audit and repair system are large, but the egress demands are relatively small. A large amount of data comes in to the system for audits and repairs, but just the formerly missing pieces get sent back out. While the repair and audit system can run anywhere, the bandwidth usage asymmetry means that hosting providers that offer free ingress TODO should we mention specific hosts? (e.g., Google Cloud Platform, Amazon AWS, and Microsoft Azure) make for an especially attractive hosting location for users of this system.

3.10.2 Merkle trees

Repairs are one of the few places latency doesn't matter. The data repair system just needs to get through as many files as possible, but it doesn't matter if a specific file takes longer. Throughput is much more important than latency during repair. Further, while potentially using cheap bandwidth, repair is still a costly operation that costs a single operator, so work should be minimal.

As a result, when repairing a segment, the minimum number of pieces required should be all that are needed for download. Unfortunately, this means that with little redundancy, erasure codes will be less effective at catching errors. Further, the fallback safety mechanism that the user has for detecting errors (authenticated encryption) is unavailable to the repair system (no decryption keys).

Because full segments are repaired at a time from minimal pieces, hashes of each `piece` should be stored in the system via a Merkle tree [59], storing the root of the tree in the `pointer`. This allows the repair system to correctly assess whether or not repair has completed successfully without using extra redundancy for the same task.

A full copy of the leaves of the Merkle tree of `pieces` (enough to generate the full tree) should be stored alongside each `piece` on each storage node, with the root in the `pointer`, such that the only additional central metadata storage required is just for the root.

Repair should validate the tree after each repair before updating the `pointer` to point to new locations.

3.11 Storage node reputation

Reputation inside of decentralized networks is a critical part of creating trust between nodes where there would otherwise be none. Reputation ensures bad actors within the network are eliminated as participants, improving security, reliability and durability.

Storage node reputation can be divided into three subsystems. The first subsystem is the initial vetting process, the second subsystem is a filtering system, and the third system is a preference system.

When storage nodes first join the network, their quality is unknown. As a result, storage nodes with unknown reputation will be placed into a vetting process until enough data is known about that storage node. Every time a file is uploaded, the system will select some small amount of unvetted storage nodes to include in the list of target nodes. The Reed-Solomon parameters will be chosen such that these unvetted storage nodes will not affect the durability of the file, but allow the network to test the node with a small fraction of data until we are sure the node is reliable. After the storage node has successfully stored enough data for a long enough period (potentially months), the system will then start selecting that storage node for general uploads. Importantly, storage nodes get paid during this vetting period, but simply don't receive as much data.

While new nodes require a proof of work to avoid some Sybil attacks [61], additional effort may be required to prevent malicious and determined new nodes from overwhelming the vetting process and preventing well-behaved new nodes from getting enough data to progress past it. As a result, users will be able to choose as a configuration parameter the minimum proof of work required from storage nodes for new data. Additionally, other schemes are possible, such as a form of proof of stake as we proposed in our previous work [62].

The filtering system is the second subsystem and blocks bad storage nodes from participating. Certain actions a storage node can take are disqualifying events, and the reputation system will be used to filter these nodes out from future uploads, regardless of where the node is in the vetting process. What these events are will require careful selection and tuning to make sure that incentives are correct, but will at least include failing too many audits, failing to return data (with reasonable speed), and failing too many uptime checks. If a storage node is disqualified by failing too many audits, that node will no longer be selected for future data storage and the data that node stores will be moved to new storage nodes. Likewise, if a client attempts to download a piece from a storage node that the node should have and the node fails to return it too many times, the node will be disqualified. Importantly, storage nodes will be allowed to reject and fail uploads without penalty, as we want to allow nodes to choose which data to store.

It's worth reiterating that failing too many uptime checks is a disqualifying event. Storage nodes can be taken down for maintenance, but if a storage node is offline too much, it can have an adverse impact on the network. See Appendix

TODO for why uptime is so important in our storage system.

After a storage node is disqualified, the node must go back through the vetting process again, potentially with a minor headstart. If the node decides to start over with a brand new identity, the node must restart the vetting process from the beginning (in addition to generating a new node ID via the proof-of-work system). This strongly disincentivizes storage nodes from being cavalier with their reputation.

The third subsystem is a preference system. After disqualified storage nodes have been eliminated, remaining statistics collected during audits will be used to prefer better storage nodes during uploads. These statistics include performance characteristics such as throughput and latency, history of reliability and uptime, geographic location, and other desirable qualities. These statistics will be combined into a load-balancing selection process, such that all uploads are sent to qualified nodes, with a higher likelihood of uploads to preferred nodes, but with a non-zero chance for any qualified node. Initially, we'll be load balancing with these preferences via a randomized scheme such as the Power of Two Choices [63], which selects two options entirely at random, and then chooses the more qualified between those two.

On the Storj network, preferential storage node reputation is only used to select where new data should be stored - both during repair and during the upload of new files. If a storage node's preferential reputation decreases, its file pieces will not be moved or repaired to other nodes. However, data stored on disqualified nodes may be moved to qualified nodes.

There is not a facility planned in our system for storage nodes to contest their reputation scores. It is in the best interest of storage nodes to have good uptime, pass audits, and return data. Storage nodes that don't do these things are not useful to the network. Storage nodes that are treated by payers unfairly should not accept future data from those payers. See the section TODO about quality control on how we plan to ensure payers are incentivized to treat farmers fairly.

3.11.1 Concrete implementation

Initially, storage node reputation will be individually determined by each heavy client. If a node is disqualified by one heavy client, it could still store data for other heavy clients. Reputation will not be shared between heavy clients initially. Over time, as we plan to eliminate heavy clients, reputation would then be determined globally.

TODO future work section about reputation sharing

3.12 Payments

Payments in decentralized networks are a critical part of maintaining a healthy ecosystem of both supply and demand. In the Storj network, payments are made by gateway users who store data on the platform to the heavy client they utilize. The heavy client then pays farmers for the amount of storage and bandwidth they provide on the network.

The Storj network is payment agnostic. Neither the protocol nor the contract requires a specific payment type. The network assumes STORJ as the default payment medium, but many other payment types could be implemented, including Bitcoin, Ether, ACH transfer, or physical transfer of live goats. Currently, the platform supports STORJ as payment (providing a discount for using this method), Bitcoin, Ether and credit card.

Previous distributed systems have handled payments as hard-coded contracts. For example, the previous Storj network utilized 90-day contracts to maintain data on the network. After that period of time, the file would be deleted. Other distributed storage platforms use 15-day renewable contracts that delete data if the user does not login every 15 days. Others use 30-day contracts. Moving forward, the network will not use contracts to manage payments and file storage durations.

Heavy clients will pay farmers for the data they store long-term, audits and downloads. Farmers will not be paid for the initial storage of data, but they will be paid for storing the data month-by-month. At the end of the payment period, heavy clients will calculate earnings for each farmer. Provided the farmer node hasn't been blacklisted, the farmer will be paid by the heavy client for the data the heavy client thinks it has stored over the course of the month. If a farmer misses a delete file command due to the node being offline, it will be storing more data than the heavy client credits it for. In this case, the farmer would not be paid for storing those file pieces and they would eventually be cleaned up through the garbage collection process.

The payment system is focused on simplicity and efficiency to minimize the amount of resources needed to properly execute monthly payments. Because of the way delete commands are issued, and because farmers are not expected to be online at all times, farmers may be storing file pieces that should have been deleted because they missed the delete command. This scenario is factored into the farmer payment amounts, meaning farmers are paid slightly more than they should for the file pieces they store, offsetting any lost revenue due to garbage data. In theory, this means farmers that maintain higher availability can maximize their profits by properly deleting files and minimizing the amount of garbage data on their nodes.

The heavy client maintains a database of all file pieces it is responsible for and the farmers it believes are storing these pieces. Each day, the heavy client adds another day's worth of credits to that farmer for each file piece it should be storing. As files are downloaded from the farmer, the heavy client also tracks this in the database. At the end of the month, the heavy client adds up all the bandwidth and storage payments its farmer has earned and makes the payments to the farmer nodes.

Heavy clients will track utilized bandwidth through a bandwidth allocation protocol. To download a file, the gateway user connects to the heavy client to identify where its file pieces are stored and to provide a promise to pay for the file download. The heavy clients sends a confirmation of this promise to pay back to the gateway along with the location of the file pieces the gateway needs to download the file. The gateway then sends the promise to pay directly to the farmer nodes along with the details on the file pieces it needs. The farmer then accepts or rejects this operation. If the farmer accepts this operation, it confirms and retains a copy of this promise to pay and sends the farmer the file piece it needs. Later, the farmer sends the promise to pay to the heavy client, and the heavy client credits that farmer node as having successfully delivered the file piece.

Heavy clients will also earn revenue from farmers for executing audits, repairing files and storing metadata. Every day, each heavy client will execute a number of audits across all of its farmers on the network. During an audit, if a farmer does not have the file it should be storing, it will be immediately blacklisted and the heavy client will flag that farmer's file pieces for repair in the system. The heavy client will be paid for both completing the audit and for the repair, once that file falls below the file piece threshold needed for repair.

If a heavy client is not executing payments properly, farmers can report them to the Storj network clearing houses, where all heavy clients' reputations are tracked. By default, the farmer node will only trust a whitelist of heavy clients, however, during the farmer setup phase, the farmer operator can choose to work with non-whitelisted heavy clients. If a heavy client has a low reputation score, farmers should always forgo utilizing that particular heavy client.

If a heavy client would like to become a Storj Approved Heavy Client, they will be required to have insurance with Storj. This guarantees that if a heavy client does act maliciously, they have some proof of stake, which would be lost and would help compensate network participants for the missing payments and service interruption. The Storj Labs team will always run and maintain a certain number of heavy clients to ensure gateway users have sufficient availability across the network.

TODO users pay heavy clients TODO list what farmers are paid for: returning data and keeping data, but NOT the initial store of data. no ingress payment to farmers, just egress. farmers should be incentivized to hang on to data they already have instead of replacing it with something new. TODO payers roll up payments every day, but pay every month

TODO Payment automation?

TODO Payment wallets vs payment addresses.

3.12.1 Bandwidth allocation protocol

TODO

3.12.2 Concrete implementation

At launch, reputable heavy clients will be identified through a Storj-maintained whitelist and blacklist. As more heavy clients emerge, Storj will launch the heavy client clearing house where farmers can review specific heavy clients and see which heavy clients are Storj-approved.

Payments to farmers will be calculated on a daily basis, based on the bandwidth utilized and files stored, and paid at the end of the month. If a farmer acts maliciously and does not store files properly or maintain sufficient availability, they will not be paid for the services rendered, and the funds allocated to their farmer node will instead be used to repair their missing file pieces and pay new farmers to store the data long-term.

3.13 Payer reputation

Storage nodes have a strong incentive to avoid accepting data assigned to payers that don't have a good history of paying their bills.

3.13.1 Concrete implementation

Initially, storage nodes will put payers through a vetting process where storage nodes limit their exposure to unknown payers and build up trust over time that specific payers are likely to pay their bills. Storage nodes will have a configurable maximum amount of data that they will store for an unknown payer, and use whether or not they get paid for that data as input into whether or not that payer should be trusted for more data in the future.

Storage nodes will also feature a whitelist, where storage node operators can input a list of payers they already trust. Storj Labs will ship a prefilled whitelist with guaranteed and insured payers (see payments).

TODO future work - shared reputation

3.14 Garbage collection

When data is moved or deleted, it's important to inform impacted storage nodes that they are no longer required to store that data. Unfortunately, sometimes storage nodes will be temporarily unavailable and delete messages will be missed. In these cases, data that is no longer needed is considered *garbage*. Payers only pay for data they expect to be stored, so storage nodes with lots of garbage will be sad to find less earnings than they would otherwise be entitled to unless a garbage collection system is employed.

A garbage collection algorithm is a method for freeing no-longer used resources. A *precise* garbage collector collects all garbage exactly and leaves no additional garbage, whereas a *conservative* garbage collector may leave some small proportion of garbage around given some other tradeoffs, often performance. As long as a conservative garbage collector is used, it should be assumed that the cost of storage owed to a storage node is high enough to amortize the cost of storing the garbage.

3.14.1 Concrete implementation

When data is deleted through the client, the metadata system (and thus a payer, with payer reputation on the line) will require proof that deletes were issued to a configurable minimum number of storage nodes. This means that every time data is deleted, storage nodes that are online and reachable will get notification right away.

For the nodes that miss initial delete messages, we propose a conservative garbage collection strategy. Periodically, a payer will send out a highly-compressible data structure such as a *Bloom filter* [64] that contains hints about what pieces a node is expected to continue storing. A Bloom filter is like a set that can answer set membership questions with the answers *isn't contained* or *maybe contained*, but not *is contained*. By sending a data structure tailored to each node on a periodic schedule, a payer can give a storage node the ability to clean up garbage to a configurable tolerance.

Because Bloom filters are probabilistic and their collision risk is configurable, the conservative garbage collector can be tuned to eliminate garbage down to an acceptable tolerance, given the tradeoff of additional bandwidth for these larger, more exact cleanup messages. Further, each time a Bloom filter is generated, it can be generated with a new hashing seed, making the probability that a specific piece of garbage is continually missed by the garbage collector lower over time.

Because this garbage collection system is not precise, storage nodes have a strong incentive to stay online to witness all delete messages if possible. If a storage node misses a handful of delete messages due to an outage, the garbage with almost guaranteed certainty will eventually get cleaned up with enough Bloom filter based cleanups. On the other hand, because this garbage collection system is not precise, bandwidth overhead for negotiating the list of pieces a storage node must store will be efficient and small.

TODO future work: is a bloom filter the best data structure?

4 Product details

4.1 Overview of components

Our concrete implementation is currently subdivided into three major peer classes. This may change as responsibilities in the framework are improved or upgraded, but for our initial release, these three classes of node on the network work together to provide a cohesive product experience.

- **Farmer** - This peer class participates in the DHT, stores data for others, and gets paid for storage and bandwidth (via a bandwidth allocation protocol).
- **Heavy Client** - This peer class participates in the DHT, caches DHT lookups, stores per-object metadata, stores farmer reputation, pays farm-

ers, performs audits and repair, and manages authorization and user accounts. Any user can run their own heavy client, but we expect many users will elect to avoid the operational complexity and create an account on another heavy client hosted by a trusted party like a friend, group, or workplace.

- **Gateway/libstorj** - This peer class represents any application or service that wants to store data. Applications can store data via the S3-compatible gateway, or through our libstorj C-bindings. This peer class is not expected to remain online like the other two classes and is otherwise relatively lightweight. This peer class performs encryption, erasure encoding, and coordinates between the other peer classes on behalf of the customer.

We'll dive into more details about each of these components.

4.2 Farmer

The main duty of a farmer is to reliably store and return data. Farmer operators are individuals or entities that have excess hard drive space and want to earn compensation for lending their space to others. Farmer operators will download, install, and configure Storj software locally, with no account required anywhere. Farmer operators will select what disk space and bandwidth usage is allowed during configuration. Farmers will advertise during DHT communications what hard drive space is still available, how much bandwidth is available, and what their desired STORJ token wallet address is.

Because Storj is optimized for larger files, farmers have no reason to do anything more complex than store `pieces` directly on disk. As a result, unlike the previous release of Storj that used KFS [57], Storj no longer has a restriction on the maximum amount of data a farmer can store.

Farmers also keep track of optional per-`piece` time-to-live, or TTL. `Pieces` may be stored with a specific TTL expiry where data is expected to be deleted after the expiration date. If no TTL was provided, data is expected to be stored indefinitely. This means farmers have a database of expiration times and must occasionally clear out old data.

Farmers must additionally keep track of signed bandwidth allocations to send to heavy clients for later settlement and payment. This also requires a small database. Both TTL and bandwidth allocations are stored in a SQLite [65] database.

Farmers can choose what heavy clients to work with. If farmers work with multiple heavy clients (the default behavior), then payment may come from multiple sources at varying payment schedules. Farmers are paid by specific heavy clients for returning data when requested in the form of egress bandwidth payment. Bandwidth payment is made payable after the farmer sends in signed bandwidth allocation messages. Farmers are also paid for data at rest. Farmers are expected to reliably store all data ever sent to them and are paid with the assumption that they are faithfully doing so. Farmers that fail random audits will be removed from the pool and will receive limited to no future payments. Farmers are *not* paid for the initial transfer of data to store (ingress bandwidth). This is to discourage farmers from deleting data only to be paid for storing more. Farmers are not paid for specific audits. Farmers are likewise not paid for DHT or other maintenance traffic.

4.3 Heavy client

As should be apparent, the data owner has to shoulder significant burdens to maintain availability and integrity of data on the Storj network. Because nodes cannot be trusted, data owners are responsible for selecting good farmers, issuing and verifying audits, providing payments, managing file state and object metadata, etc. Many of these functions require high uptime and significant infrastructure, especially for an active set of files. User run applications, like a file syncing application, cannot be expected to efficiently manage files on the network.

To enable simple access to the network from the widest possible array of client applications, Storj implements a thin-client model that delegates trust to a dedicated server that manages data ownership. The burdens of the data owner can be split across the client and the server in a variety of ways. This sort of dedicated server, called the heavy client, has been developed and released as Free Software. Any individual or organization can run their own heavy client to facilitate network access.

With respect to customer data, the heavy client is designed to store only metadata. It is never given data unencrypted and does not hold encryption keys. The only knowledge of an object that the heavy client is able to share with third parties is metadata such as access patterns. This system protects the client's privacy and gives the client complete control over access to the data, while delegating the responsibility of keeping files available on the network to the heavy client.

In cases where the cost of delegating trust is not excessively high, clients may use third-party heavy clients. Because heavy clients do not store data and have no access to keys, this is still a large improvement over the traditional data-center model. Many of the features heavy clients provide, like farmer selection and reputation, leverage considerable network effects. Data sets grow more useful as they increase in size, indicating that there are strong economic incentives to share infrastructure and information in a heavy client.

Applications using object stores delegate significant amounts of trust to the storage providers. Providers may choose to operate public heavy clients as a service. Application developers then delegate trust to a specific heavy client, as they would to a traditional object store, but to a lesser degree. Future updates will allow for various distributions of responsibilities (and thus levels of trust) between customer applications and heavy clients. This shifts significant operational burdens from the application developer to the service-provider. This would also allow developers to pay for storage with standard payment mechanisms, like credit cards, rather than managing a cryptocurrency wallet. Storj Labs Inc. currently provides this service.

A specific heavy client *instance* does not necessarily constitute one server. A heavy client may be run by a collection of servers and be backed by a horizontally scalable trusted database for higher uptime.

The heavy client is, at its core, one of the most complex and yet straightforward components of our initial release that fulfills our framework. Future framework-conforming releases nonwithstanding, the initial heavy client is a standard application server that wraps a trusted database such as PostgreSQL, Cassandra, or something else. Users sign in to a specific heavy client with account credentials. The heavy client is responsible for keeping track of accounts and authorization, farmer contact information and reputation, and object metadata. The heavy client is also responsible for payments and data repair. Data available through one heavy client instance is not available through another heavy client instance, though various levels of export and import are planned.

The heavy client is made up of components discussed earlier

- A full DHT cache.
- An account management and authorization system
- A per-object metadata database indexed by encrypted path
- A reputation and farmer statistics database
- A farmer payment service

- A data audit and data repair service

4.4 Gateway/libstorj

The gateway provides an S3-compatible drop-in interface for applications that need to store data but don't want to bother with the complexities of distributed storage directly. The gateway is a simple service layer on top of libstorj, which is a library that provides access to storing and retrieving data in the Storj network.

The gateway (via libstorj) first encrypts data, then erasure encodes it, then streams it out to farmers, all while coordinating with a chosen heavy client for metadata and tracking.

The gateway should run co-located with wherever data is generated, and will communicate directly with storage nodes so as to avoid central bandwidth costs.

4.5 Quality control and branding

TODO discuss quality control and branding TODO insurance

4.6 Detailed walkthroughs

4.6.1 Detailed walkthrough: upload

In order to upload a file, the light client will log in and ask the overlay network for a set of farmers that fulfill a criteria, i.e. storage availability and bandwidth to potentially store files. The overlay network will have a list of nodes that meet those criteria and use the reputation network to filter out reputable farmers. The overlay network then sends a refined list of farmers to the light client, which is then used to directly upload data. Finally, the light client sends a request to the network state in order to store the IDs of the piece storage nodes holding the segments and other related metadata in pointers.

Technical Dive into how Upload Works TODO

TODO First thing, at some point prior, the gateway is going to talk to the heavy client and authorize itself as having an account. The heavy client won't talk to any gateway; the gateway needs an account on the heavy client.

Next, the gateway is going to talk to the heavy client and try and get a bunch of things all at once. Make sure it can upload data. Does this heavy client have funds for this gateway? Is the gateway out of funds? Gateway: "I'm about to do an upload, it's for this much data, I'd like to store it" Heavy client: chosen piece id, signatures to authorize gateway communication to storage nodes on heavy client's behalf, what nodes to talk to, how to talk to them (ips, port) Gateway starts upload with those farmers using bandwidth allocation protocol. Gateway breaks encrypts object, breaks object into segments, erasure encodes, uploads. At any point the storage node can stop upload due to bandwidth allocation protocol failure. At the end, storage node has data and signed document about how much bandwidth was used, approved by the gateway and heavy client. Storage node stores data, signed check, ttl. Gateway keeps track of which storage nodes succeed. Gateway sends back which nodes successfully uploaded to heavy client, along with encrypted path, what nodes were selected, encryption, encoding metadata (which algorithms were used).

TODO gateways must send data to heavy client and can't cache it locally because heavy clients won't authorize gets for data that doesn't exist

TODO discuss long tail elimination via overencoding TODO Deep dive into example upload steps

4.6.2 Detailed walkthrough: download

In order to download a file, the light client will login and send a request to the network state to get pointers to the stored segments and other metadata. The light client extracts the node IDs that are storing the data and sends a request to the overlay network with those IDs. The overlay network responds with an object containing the nodes' IP addresses. Finally, the light client sends a request to farmers in order to receive pieces using those IP addresses.

Technical Dive into how Download Works TODO

TODO for every segment, gateway will ask heavy client for a big chunk of information given an encrypted path.

heavy client: returns what nodes the segment is on, what ip addresses those nodes have, check authorizing request for next 10 minutes for specific pieces.

gateway: starts downloading pieces using bandwidth allocation protocol (promises to pay). storage node keeps track of promises to pay and sends them to appropriate heavy client. gateway reed solomon decodes, decrypts, returns data.

TODO discuss long tail elimination via overencoding

4.6.3 Detailed walkthrough: delete

TODO similar to puts TODO needs guarantees for garbage collection that deletes were issued TODO heavy client forces gateway to help heavy client keep reputation with farmers

4.6.4 Detailed walkthrough: list

TODO just talks to heavy client directly

4.6.5 Detailed walkthrough: repair

The repair and maintenance component (also known as data repair) is essential to ensure data integrity is maintained. It confirms that nodes responsible for pieces continue to store the data that the light client sent. To do this, it first makes a request to the network state to receive pointers. From there, the repair and maintenance component extracts the node IDs from the response and makes a request with that information to the DHT cache. The DHT cache sends a response containing only the online nodes from the original node ID list. The data repair component takes the response from the DHT cache and the repair threshold value from the pointer, then calculates which pieces need to get repaired. The light client directly downloads pieces that need to get repaired from farmers and re-uploads them to new reputable farmers. To ensure the network state has up-to-date information about the data, the light client then sends a put request of new pointers with the updated node IDs.

Diagram Technical Detail ¡WIP¿

TODO Deep dive into example repair steps

4.6.6 Detailed walkthrough: payment

TODO Deep dive into example payment steps

TODO

4.6.7 Detailed walkthrough: export/import

TODO Deep dive into how porting your account to a new heavy client works

5 Future Areas of Research

TODO Storj is a work in progress, and many features are planned for future versions. There are relatively few examples of functional distributed systems at scale, and many areas of research are still open.

5.1 Improving user experience around metadata

TODO automatic exports, backups, distributed consensus

5.2 Fast Byzantine Consensus

Over time, we plan to program the heavy client out of the platform. The heavy client's role on the network means that the network could be prone to some centralization if others outside of the Storj Labs team do not run their own heavy clients. The biggest challenge is achieving fast byzantine consensus, where farmer nodes can interact with one another, share encoded pieces of files and still operate within the performance levels users will expect from a platform that is competing with traditional cloud storage providers.

Our team will be researching ways to store lots of small pieces of metadata in a distributed manner, even when those pieces are constantly changing. There currently is not a way to achieve this without significant investment in time, compute and bandwidth. A practical byzantine fault tolerance algorithm could work. They are generally faster and use less disk space than blockchain protocols, however there is significant trade off around network usage and coordination contention, as there could be problematic overlap with two farmer nodes trying to communicate with one another at the same time.

5.3 Distributed Repair

The system can detect when a files' Reed Solomon erasure encoding pieces fall below a certain threshold. At that time, the file would need to be repaired and the missing pieces would need to be stored on new farmer nodes. Currently, this repair process takes place on the heavy client. The heavy client downloads all the file fragments needed to repair the file, the file is rebuilt and the previously missing shards are sent to farmers selected by the heavy client.

Long term, it would be better to create a technique where file repair takes place in a distributed manner on farmer nodes, putting their excess CPU cycles to work. This will be a first step to eliminating the heavy client. This approach would also be more decentralized than file repair on heavy clients. It is also more efficient to execute this operation at the edge of the network.

The system would need more checks and balances to ensure the farmer is correctly executing a repair and that the data inside the encrypted file is accurate. Merkle tree roots will greatly help with distributed repair. The farmer node executing the repair would get approval from the heavy client to repair a file, the heavy client would share its merkle tree root with the farmer and notify which farmers should store the restored file pieces. The farmer would then download the file pieces needed for the repair from the farmers where they reside. The farmer repair node would execute the repair and run the shards through the merkle tree root to prove the data was correct and properly repaired. We are currently taking the steps needed to ensure the network and our data format will support merkle tree repair in the future.

TODO

A Attacks

As with any distributed system, a variety of attack vectors exist. Many of these are common to all distributed systems. Some are storage-specific, and will apply to any distributed storage system.

A.1 Spartacus

TODO Spartacus attacks, or identity hijacking, are possible on Kademlia. Any node may assume the identity of another node and receive some fraction of messages intended for that node by simply copying its Node ID. This allows for targeted attacks against specific nodes and data. This is addressed by implementing Node IDs as ECDSA public key hashes and requiring messages be signed. A Spartacus attacker in this system would be unable to generate the corresponding private key, and thus unable to sign messages and participate in the network.

A.2 Sybil

Sybil attacks involve the creation of large amounts of nodes in an attempt to disrupt network operation by hijacking or dropping messages. Kademlia, because it relies on message redundancy and a concrete distance metric, is reasonably resistant to Sybil attacks. A node's neighbors in the network are selected by Node ID from an evenly distributed pool, and most messages are sent to at least three neighbors. If a Sybil attacker controls 50% of the network, it successfully isolates only 12.5% of honest nodes. While reliability and performance will degrade, the network will still be functional until a large portion of the network consists of colluding Sybil nodes.

A.2.1 Google

The Google attack, or nation-state attack, is a hypothetical variant of the Sybil attack carried out by an entity with extreme resources. Google attacks are hard to address, as it is difficult to predict the actions of an organization with orders of magnitude more resources than the sum of the resources of network participants. The only reliable defence against a Google attack is to create a network whose resources are on the same order of magnitude as the attacker's. At that scale, any attack against the network would represent an unsustainable commitment of resources for such an organization.

A.2.2 Honest Geppetto

The Honest Geppetto attack is a storage-specific variant of the Google attack. The attacker operates a large number of 'puppet' nodes on the network, accumulating trust and contracts over time. Once he reaches a certain threshold he pulls the strings on each puppet to execute a hostage attack with the data involved, or simply drops each node from the network. Again, the best defence against this attack is to create a network of sufficient scale that this attack is ineffective. In the meantime, this can be partially addressed by relatedness analysis of nodes. Bayesian inference across downtime, latency and other attributes can be used to assess the likelihood that two nodes are operated by the same organization, and data owners can and should attempt to distribute shards across as many unrelated nodes as possible.

A.3 Eclipse

TODO mention S/Kademlia

An eclipse attack attempts to isolate a node or set of node in the network graph, by ensuring that all outbound connections reach malicious nodes. Eclipse attacks can be hard to identify, as malicious nodes can be made to function normally in most cases, only eclipsing certain important messages or information. Storj addresses eclipse attacks by using public key hashes as Node IDs. In order to eclipse any node in the network, the attacker must repeatedly generate key pairs until it finds three keys whose hashes are closer to the targeted node than its nearest non-malicious neighbor, and must defend that position against any new nodes with closer IDs. This is, in essence, a proof-of-work problem whose difficulty is proportional to the number of nodes in the network.

It follows that the best way to defend against eclipse attacks is to increase the number of nodes in the network. For large networks it becomes prohibitively expensive to perform an eclipse attack (see Section 6.2). Furthermore, any node that suspects it has been eclipsed may trivially generate a new keypair and node ID, thus restarting the proof-of-work challenge.

A.3.1 Tunnel Eclipse

TODO Because tunneled connections rely on the tunnel provider, it is trivial for a tunnel provider to eclipse nodes for which it provides tunneled connections. This attack cannot affect publicly addressable nodes, so it can be trivially defeated with proper configuration. This attack can be mitigated by encrypting messages intended for tunneled nodes, thus removing the malicious tunnel provider's ability to inspect and censor incoming messages. Like a typical eclipse attack, any node that suspects it is the victim of a tunnel eclipse can easily generate a new Node ID, and find a new tunnel.

A.4 Hostage Bytes

The hostage byte attack is a storage-specific attack where malicious farmers refuse to transfer shards, or portions of shards, in order to extort additional payments from data owners. Data owners should protect themselves against hostage byte attacks by storing shards redundantly across several nodes (see Section 2.7). As long as the client keeps the bounds of its erasure encoding a secret, the malicious farmer cannot know what the last byte is. Redundant storage is not a complete solution for this attack, but addresses the vast majority of practical applications of this attack. Defeating redundancy requires collusion across multiple malicious nodes, which is difficult to execute in practice.

A.5 Cheating Owner

TODO A data owner may attempt to avoid paying a farmer for data storage by refusing to verify a correct audit. In response the farmer may drop the data-owner's shard. This attack primarily poses a problem for any future distributed reputation system, as it is difficult for outside observers to verify the claims of either party. There is no known practical publicly verifiable proof of storage, and no known scheme for independently verifying that a privately verifiable audit was issued or answered as claimed. This indicates that a cheating client attack is a large unsolved problem for any reputation system.

A.6 Faithless Farmer

TODO While the farming software is built to require authentication via signature and token before serving download requests, it is reasonable to imagine a modification of the farming software that will provide shards to any paying requestor. In a network dominated by faithless farmers, any third-party can aggregate and inspect arbitrary shards present on the network.

However, even should faithless farmers dominate the network, data privacy is not significantly compromised. Because the location of the shards that comprise a given file is held solely by the data owner, it is prohibitively difficult to locate a target file without compromising the owner (see Section 6.3). Storj is not designed to protect against compromised data owners. In addition, should a third-party gather all shards, strong client-side encryption protects the contents of the file from inspection. The pointers and the encryption key may be secured separately. In the current implementation of Bridge, the pointers and the keys are held by the Bridge and the client, respectively.

A.7 Defeated Audit Attacks

TODO A typical Merkle proof verification does not require the verifier to know the depth of the tree. Instead the verifier is expected to have the data being validated. In the Storj audit tree, if the depth is unknown to the verifier the farmer may attack the verification process by sending a Merkle proof for any hash in the tree. This proof still generates the Merkle root, and is thus a valid proof of some node. But, because the verifier does not hold the data used to generate the tree, it has no way to verify that the proof is for the specific leaf that corresponds to the challenge. The verifier must store some information about the bottom of the tree, such as the depth of the tree, the set of leaves nodes, or the set of pre-leaves. Of these, the depth is most compact, and thus preferable.

Using the pre-leaf as an intermediary defeats another attack, where the farmer simply guesses which leaf corresponds to the current challenge. While this attack is unlikely to succeed, it's trivially defeated by forcing the farmer to provide the pre-leaf. The farmer cannot know the pre-leaf before the challenge is issued. Requiring transmission of the pre-leaf also allows the data owner to proceed through the challenge set linearly instead of being forced to select randomly. This is desireable because it allows the data owner to maintain less state information per tree.

B Selected Calculations

The following are several interesting calculations related to the operation of the network.

B.1 Difficulty of Eclipsing a Target Node

The probability of eclipsing a targeted node in the a network with k nodes in h hashes is modeled by a similar binomial distribution:

$$\Pr_{success}(h,k) = \sum_{i=3}^{h-1} k^{-i}(1-\frac{1}{k})^{h-i}\binom{h}{i}$$

h	i	$\Pr_{success}\, h, i$
100	100	7.937e-02
100	500	1.120e-03
100	900	2.046e-04
500	100	8.766e-01
500	500	8.012e-02
500	900	1.888e-02
900	100	9.939e-01
900	500	2.693e-01
900	900	8.020e-02

Code:

```
choose(h,k): return fac(h) / fac(k) / fac(h-k) def bin(i,h,k): return
choose(h,i) * k ** -i * (1-(1.0/k)) ** (h-i) def prob_succ(h,k): return
sum([bin(i,h,k) for i in range(3,h)])
```

B.2 Beach Size

As the number of shards on the network grows, it becomes progressively more difficult to locate a given file without prior knowledge of the locations of its shards. This implies that even should all farmers become faithless, file privacy is largely preserved.

The probability of locating a targeted file consisting of k shards by n random draws from a network containing N shards is modeled as a hypergeometric distribution with $K = k$:

$$Pr_{Success}(N,k,n) = \frac{\binom{N-k}{n-k}}{\binom{N}{n}}$$

Code:

```
choose(h,k): return fac(h) / fac(k) / fac(h-k) def hyp(N,k,n): return
```

N	k	n	$\Pr_{success} N, k, n$
100	10	10	5.777e-14
100	10	50	5.934e-04
100	10	90	3.305e-01
100	50	50	9.912e-30
100	50	90	5.493e-04
500	50	200	1.961e-22
500	50	400	7.361e-06
900	10	200	2.457e-07
900	10	400	2.823e-04
900	10	800	3.060e-01
900	50	200	1.072e-35
900	50	400	4.023e-19
900	50	800	2.320e-03

```
choose(N-k,n-k) / float(choose(N,n)) def prob_success(N,k,n):
    return hyp(N,k,n)
```

B.3 Partial Audit Confidence Levels

Farmers attempting to game the system may rely on data owners to issue partial audits. Partial audits allow false positives, where the data appears intact, but in fact has been modified. Data owners may account for this by ascribing confidence values to each partial audit, based on the likelihood of a false positive. Partial audit results then update prior confidence of availability. Data owners may adjust audit parameters to provide desired confidence levels.

The probability of a false positive on a parital audit of n bytes of an N byte shard, with K bytes modified adversarially by the farmer is a hypergeometric distribution with $k = 0$:

$$Pr_{falsepositive}(N, K, n) = \frac{\binom{N-K}{n}}{\binom{N}{n}}$$

Code:

```
choose(h,k): return fac(h) / fac(k) / fac(h-k) def hyp(N,K,n):
    return
float(choose(N-K, n) / choose(N,n) def prob_false_pos(N,K,n):
    return hyp(N,K,n)
```

As demonstrated, the chance of false positives on even small partial audits

N	K	n	$\Pr_{falsepositive} N, K, n$
8192	512	512	1.466e-15
8192	1024	512	1.867e-31
8192	2048	512	3.989e-67
8192	3072	512	1.228e-109
8192	4096	512	2.952e-162

becomes vanishingly small. Farmers failing audits risk losing payouts from current contracts, as well as potential future contracts as a result of failed audits. Dropping 10% of a shard virtually guarantees a loss greater than 10% of the contract value. Thus it stands to reason that partially deleting shards to increase perceived storage capcity is not a viable economic strategy.

C File piece loss model

In the context of storing an erasure-coded file on a decentralized network, we consider file piece loss from two different perspectives.

C.1 Direct file piece loss: the simple case first

With direct file piece loss, we assume that for a specific file, its erasure pieces are lost according to a certain rate. We point out that modeling this is straightforward: if file pieces are lost at a rate $0 < p < 1$ and we start with n pieces, then file piece decay follows an exponential decay pattern of the form $n(1-p)^t$, with t being the time elapsed according to the units used for the rate[2]. To account for multiple checks m per month, we may extend this to $n(1-p/m)^{mt}$. If r is the rebuild threshold which controls when a file is rebuilt, we may solve $n(1-p/m)^{mt} = r$ for t (taking the ceiling when necessary) to determine how long it will take for the n pieces of a file to decay to less than r pieces. This works out to the smallest t for which $t > \frac{\ln(r/n)}{m\ln(1-p/m)}$. Thus it becomes clear, given parameters n, r, m and p, how long we expect a file to last between repairs.

[2]So if we assume a proportion of $p = .1$ pieces are lost per month, t is given in months.

C.2 Indirect file piece loss: it's not that much harder

When modeling indirect file piece loss, we suppose that a fixed rate of nodes drop out of the network each month[3] whether or not they are holding pieces of the file under consideration. To describe the probability that d of the dropped nodes were delegates for a specific file coded into n pieces, we turn to the Hypergeometric probability distribution. Suppose c nodes are replaced per month out of C total nodes on the network. Then the probability that d nodes were delegates for the file is given by

$$P(X = d) = \frac{\binom{n}{d}\binom{C-n}{c-d}}{\binom{C}{c}} \tag{3}$$

which has mean nc/C. We then determine how long it will take for the number of pieces to fall below the desired threshold r by iterating, holding the overall churn c fixed but reducing the number of existing pieces by the distribution's mean in each iteration and counting the number of iterations required. For example, after one iteration, the number of existing piececs is reduced by nc/C, so instead of n pieces on the network (as the parameter in (3)), there are $n-nc/C$ pieces, changing both the parameter and the mean for (3) in iteration 2.

We may extend this model by considering multiple checks per month (as in the direct file piece loss case), assuming that c/m nodes are lost every $1/m$-th of a month instead of assuming that c nodes are lost per month, where m is the number of checks per month. This yields an initial Hypergeometric probability distribution with mean nc/mC.

In either of these two cases (single or multiple file integrity checks per month), we track the number of iterations until the number of available pieces fall below the repair threshold. This number may then be used to determine the expected number of rebuilds per month for any given file.

C.3 Numerical simulations for indirect file piece loss

C.3.1 Introduction

We produce decision tables showcasing worst-case mean file rebuild outcomes based on simulating file piece loss for files encoded with varying Reed-Solomon parameters. We assume an $(n : k)$ RS encoding scheme, where n pieces are

[3] Though the rate may be taken over any desired time interval.

generated, with k pieces needed for reconstruction, using three different values for n. We assume that a file undergoes the process of repair when less than r pieces remain on the network, using three different values of r for each n. For the initial table, we use a simplifying assumption that pieces on the network are lost at a constant rate per month[4], which may be due to node churn, data corruption, or an alien megarace extracting a farmer's hard-drive to a higher dimension (amongst other possibilities).

To arrive at the value for mean rebuilds per month, we consider a single file that is encoded with n pieces which are distributed uniformly randomly to nodes on the network. To simulate conditions leading to a rebuild, we uniformly randomly select a subset of nodes from the total population and designate them as failed. We do this multiple times per (simulated) month, scaling the piece loss rate linearly according to the number of file integrity checks ("checks") per month[5]. Once enough nodes have failed to bring the number of file pieces under the repair threshold, the file is rebuilt, and we track the number of rebuilds over the course of 24 months. We repeat this simulation for 1000 iterations, simulating 1000 2-year periods for a single file. We then take the number of rebuilds at the 99-th percentile (or higher) of the number of rebuilds occuring over these 1000 iterations. In other words, we choose the value for which the value of the observed CDF (describing the number of rebuilds over this 2 year period) is at least 0.99. This value is then divided by the number of months to arrive at the mean rebuilds/month value. An example of the approach is shown in Figure 1. We perform the experiment on a network of 10,000 nodes, observing that the network size will not directly impact the mean rebuilds/month value for a single file under our working assumption of a constant rate of loss per month[6].

[4]This constant rate may be viewed as the mean of the Poisson distribution modeling piece loss per month.

[5] For example, if the monthly network piece loss rate is assumed to be 0.1 of the network size (or 10%), and if 10 file integrity checks are performed per month, we assume that, on average, 1% of pieces are lost between checks.

[6]We represent piece loss as a proportion of nodes selected uniformly randomly from the total network. The proportion scales directly with network size, so the overall number of pieces lost stays the same for networks of different sizes.

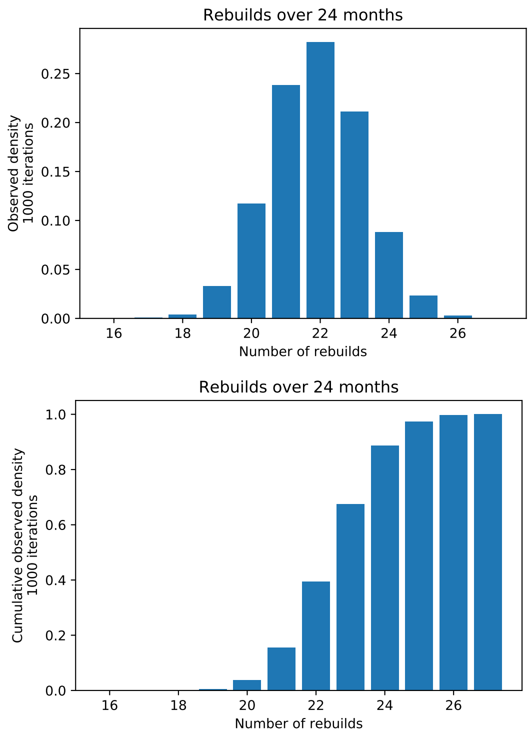


Figure 1: Top: Density for the number of rebuilds over a 24 month period, repeated for 1000 iterations. Bottom: CDF of the number of rebuilds. In this case, the mean rebuilds/month value would be taken as $26/24 \approx 1.083$*, with there being a 99.7% chance that a file is rebuilt at most 26 times over the course of 24 months.*

C.3.2 The decision tables

Churn rate	n	r	Mean rebuilds/month
0.1	40	35	0.833
0.1	40	30	0.416
0.1	40	25	0.292
0.2	40	35	1.500
0.2	40	30	0.792
0.2	40	25	0.500
0.3	40	35	2.042
0.3	40	30	1.083
0.3	40	25	0.708
0.5	40	30	1.750

Table 2: Table for $n = 40$.

Churn rate	n	r	Mean rebuilds/month
0.1	80	70	0.833
0.1	80	60	0.416
0.1	80	50	0.292
0.2	80	70	1.583
0.2	80	60	0.792
0.2	80	50	0.500
0.3	80	70	2.125
0.3	80	60	1.083
0.3	80	50	0.708
0.5	80	60	1.750

Table 3: Table for $n = 80$.

Churn rate	n	r	Mean rebuilds/month
0.1	200	160	0.500
0.1	200	140	0.333
0.1	200	120	0.250
0.2	200	160	1.000
0.2	200	140	0.625
0.2	200	120	0.458
0.3	200	160	1.375
0.3	200	140	0.875
0.3	200	120	0.625
0.5	200	140	1.458

Table 4: Table for $n = 200$.

C.4 Making a decision

We conclude by observing that these models may be tuned to target specific network scenarios and requirements. One network may require one set of Reed-Solomon parameters, while a different network may require another. In general, the closer r/n is to 1, the more rebuilds per month one should expect under a fixed churn rate. While having a larger ratio for r/n increases file durability for any given churn rate, it comes at the expense of more bandwidth used since repairs are triggered more often. To maintain a low mean rebuilds/month value while also maintaining a higher file durability, one may aim to increase the value of n as much as feasible given other network conditions (latency, download speed, etc.), which allows for a lower relative value of r while still not jeopardizing file durability.

Informally, it takes longer to lose more pieces under a given fixed network size and churn rate, so to maximize durability while minimizing repair bandwidth usage, n should be as large as existing network conditions allow for. This allows for a value of r that is relatively closer to k, reducing the mean rebuilds/month value, which in turn lowers the amount of repair bandwidth used.

For example, assume we have a fixed network size of $10,000$ nodes and a fixed churn rate of 0.1, so that a fixed number of $1,000$ pieces are lost on the network each month[7]. Suppose we consider the same file encoded with two different RS parameters: once under a $(40 : 20)$ schema and the other as an $(80 : 40)$ schema. If we want to set r so that $r = k + 10$ for both cases, we observe from Tables 2 and 3 that the expected mean rebuilds is 0.416 in the $(40 : 20)$ case and is 0.292 in the $(80 : 40)$ case. Both encoding schemes have similar durabilities, as a repair in both cases is triggered when there are $k + 10$ pieces left, though the mean rebuilds per month is empirically and theoretically lower for the $(80 : 40)$ case using $r = k + 10$.

Finally, we remark that this work has focused on analyzing the bandwidth used by different RS encoding schemes under differing network conditions. As a prospect for future research, we propose considering how the choice of r relative to k affects file durability under differing network conditions. We expect that the choice of r relative to k depends on the ratio of k/C, where C is the total number of nodes on the network, and on the churn rate c. If the number of required pieces k is large relative to C and c, the expected number of shards lost per interval is increased, which must be taken into account when selecting r to ensure that the file is not lost.

[7] Technically, we assume this figure represents "churn", so while we assume $1,000$ nodes are lost each month, we also assume $1,000$ new nodes have come online.

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