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Managing Capacity in Deduplicated Storage Systems

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Managing Capacity in Deduplicated Storage Systems

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Abstract

Deduplication decreases the physical occupancy of files in a storage volume by removing duplicate copies of data chunks, but creates data-sharing dependencies that complicate standard storage management tasks. Specifically, data migration plans, which consist the information of which files are remapped and which are not, must consider the dependencies between files that are remapped to new volumes and files that are not. Thus far, only greedy approaches have been suggested for constructing such plans, and it is unclear how they compare to one another and how much they can be improved theoretically and practically.

We set to bridge this gap for seeding—migration in which the target volume is initially empty. We prove that even this basic instance of data migration is NP-hard in the presence of deduplication. We then present GoSeed, a formulation of seeding as an integer linear programming (ILP) problem, and three acceleration methods for applying it to real-sized storage volumes. Our experimental evaluation shows that, while the greedy approaches perform well on "easy" problem instances, instances with relatively low deduplication ratio, the cost of their solution can be significantly higher than that of GoSeed's solution, which is our approach, on "hard" instances, for which they are sometimes unable to find a solution at all.

Abbreviations and Notations

V	:	Storage volume
B_V	:	Set of unique blocks stored on V
F_V	:	Set of files mapped to V
I_V	:	Inclusion relation, where $(b, f) \in I_V$ means that block b is included in file f
s	:	Size function, assigns a size for each block
M	:	Desired physical size for migration
ϵ	:	Tolerance value of migration size
k	:	Sampling degree used in fingerprint sampling acceleration method

Chapter 1

Introduction

Data deduplication is one of the most effective ways to reduce the size of data stored in large scale systems. Deduplication consists of identifying duplicate data chunks in different files, storing a single copy of each unique chunk, and replacing the duplicate chunks with pointers to this copy. Deduplication reduces the total physical occupancy, but increases the complexity of management aspects of large-scale systems such as capacity planning, quality of service, and chargeback [SCJ16].

Another example, which is the focus of this study, is data migration—the task of moving a portion of a physical volume's data to another volume—typically performed for load balancing and resizing. Deduplication complicates the task of determining which files to migrate: the physical capacity freed on the source volume, as well as the physical capacity occupied on the target volume, both depend on the amount of deduplication within the set of migrated files, as well as between them and files outside the set (i.e., files that remain on the source volume and files that initially reside on the target volume). An efficient migration plan will free the required space on the source volume while minimizing the space occupied on the target. However, as it turns out, even seeding, in which the target volume is initially empty, is a computationally hard problem.

Data migration in deduplicated systems and seeding in particular are the subject of several recent studies, each focusing on a different aspect of the problem. Harnik et al. [HHS+19] address capacity estimation for general migration between volumes, while Duggal et al. [DJS+19] describe seeding a cloud-tier for an existing system. Rangoli [NK13] is designed for space reclamation—an equivalent problem to seeding. These studies propose greedy algorithms for determining the set of migrated files, but the efficiency of their resulting migration plans has never been systematically compared. Furthermore, in the absence of theoretical studies of this problem, it is unclear whether and to what extent they can be improved. Our objective in this study is threefold: a theoretical framework for the seeding optimization problem, a practical framework for finding concrete solutions, and a rigorous evaluation of our practical framework with respect to the state-of-the-art

We present GoSeed, a new approach that bridges this gap for the seeding and, consequently, space reclamation problems. GoSeed consists of a formulation of seeding as an integer linear programming (ILP) problem, providing a theoretical framework for generating an optimal plan by minimizing its cost—the amount of data replicated. Although ILP is known to be NP-Hard, commercial optimizers can solve it efficiently for instances with hundreds of thousands of variables [SYM, lps, GNU, CPL, Gur]. At the same time, ILP instances representing real-world storage systems may consist of hundreds of millions of variables and constraints—too large even for the most efficient optimizers, that may require prohibitively long time to process these instances. Thus, GoSeed also includes three practical acceleration methods, each presenting a different tradeoff between runtime and optimality.

The first method, solver timeout, utilizes the optimizer's ability to return a feasible suboptimal solution when its runtime exceeds a predetermined threshold. A larger timeout value allows the optimizer to continue its search for the optimal solution, but increasing the timeout may yield diminishing returns. The second method, fingerprint sampling, is similar to the sketches used in [HHS+19], and generates an ILP instance from a probabilistically sampled subset of the system's chunks. An optimal seeding plan generated on a sample will not necessarily be optimal for the original system. Thus, increasing the sample size may reduce the plan's cost, but will necessarily increase the required processing time of the solver.

Our third method, container aggregation, generates an ILP instance in terms of containers—the basic unit of storage and I/O in many deduplication systems. Containers typically store several hundreds of chunks, where chunks in the same container likely belong to the same files. When they do, containers represent the same data sharing constraints as their chunks. In addition to reducing the problem size, migrating entire containers can be done without decompressing them, and without increasing the system's fragmentation. At the same time, a container-based ILP instance may introduce "false" sharing between files, resulting in a suboptimal plan.

We implement GoSeed with the Gurobi [Gur] commercial optimizer, and with the three acceleration methods. We generate seeding plans for volumes based on deduplication snapshots from two public repositories [MB11, FSL]. Our evaluation reveals the limitations of the greedy algorithms proposed for seeding thus far—while they successfully generate good plans for "easy" problems (with modest deduplication), GoSeed generates better solutions for the harder problems, for which the greedy approaches sometimes return no solution.

We performed a detailed analysis of the distribution of blocks into containers, and the number of files containing each block or pointing to each container. Our results explain what makes some problem instances harder than others. Our analysis further demonstrates the efficiency of the acceleration methods in GoSeed. It shows that (1) the suboptimal solution returned by GoSeed after a timeout is often better than the greedy solutions, (2) fingerprint sampling "hides" some of the data sharing in volumes

with modest deduplication, but provides an accurate representation of systems with substantial deduplication, and (3) GoSeed's container-based solutions are optimal if entire containers are migrated. Our results suggest several rules of thumb for applying and combining these three methods in practical settings.

The rest of this paper is organized as follows. Chapter 2 provides background on deduplication and ILP, as well as related previous work. We present the ILP formulation of GoSeed in Chapter 3, its acceleration methods in Chapter 4, and our implementation Chapter 5. Our experimental setup and evaluation are described in Chapter 6, with a discussion in Chapter 7. Chapter 8 concludes this work.

Chapter 2

Background and Related Work

2.1 Deduplication

The smallest unit of data in a deduplication system is a chunk, which typically consists of 8-64KB. The incoming data is split into chunks of fixed or variable size, and the fingerprint of each chunk is used to identify duplicates and to replace them with pointers to existing copies. Each Fingerprint is computed by a predefined hash function. The fingerprint is used as a lookup key in the fingerprint index, which stores the fingerprints of all the chunks currently in the system. If the fingerprint is large enough compared to the size of the chunk, the probability of a collision, where different chunks have the same fingerprint, is lower than the probability of an error in the underlying storage media [ZLP08]. Thus, chunks with the same fingerprint are considered identical, or duplicate.

In many systems, new chunks are written to durable storage in containers, which are the system's I/O unit, and typically consist of hundreds of chunks [ZLP08, LEB+09, LSD+14, DSL10, GE11]. New chunks are added to containers in a log structure. Thus, chunks belonging to the same file will likely reside in adjacent containers. Designs that do not employ containers typically also persist the chunks in a log structure, and thus adjacent chunks will likely belong to the same files [SBGV12, CLZ11, DGH+09, CAVL09].

To recover a file, all the containers pointed to by the file recipe are fetched into memory, after which the file's chunks are collected. The efficiency of this process, in terms of I/O and memory usage, strongly depends on the file's fragmentation: the physical location of the different containers and the portion of the container's chunks that belong to the requested file [NLP+11]. Some systems reduce the amount of fragmentation by limiting the number of containers a file may point to, or their age [LEB13, FFH+14].

Over the last decade, numerous studies addressed the various aspects of deduplication system design, such as characterizing and estimating the system's deduplication potential [WDQ+12, FS13, MKB+12, MB11, SKM+16, HKS16], efficient chunking and fingerprinting [Man94, XJF+14, XZJ+16, MCM01, AAA+10], indexing

and lookups [ZLP08, SBGV12, ADK+18], restore performance [FFH+14, zCWWD18, LEB13, KBKD12], compression[YJTL16, LLD+14], and security [HPSP10, BCQ+13, SGLM08, LCL+14]. Their success (among others) has made it possible to use deduplication for primary storage and not just for archives. Additional studies explored ways to adapt the concept of deduplication to related domains such as page caching [IG06, LSD+14], minimizing network bandwidth [MCM01, AAA+10], management of memory resident VM pages [GLV+08, CWC+14, XTL+18], and minimizing flash writes [CLZ11, EMC15, GPUS11, LSD+14, Wal02, SK12].

Recently, Shilane et al. [SCJ16] described the "next" challenge in the design of deduplication systems: providing these systems with a set of management functions that are available in traditional enterprise storage systems, Their examples include quality of service guarantees, fault tolerance, end-to-end security, and analysis functions such as capacity estimation and free space reclamation. Traditional techniques for implementing these functions are not directly applicable to deduplicated systems. In this research, we address the challenge of capacity management in deduplicated systems, and specifically, fast and effective data migration.

2.2 Data migration

Data migration is typically performed in the background, according to a migration plan specifying which data is moved to which new location. Typical objectives when generating a migration plan include minimizing the amount of data transferred, optimizing load balancing, or minimizing its effect on ongoing jobs.

The effectiveness of data migration and the resources it consumes may greatly affect the system's performance. Thus, efforts have been made to optimize its various aspects including service down-time, geolocation, provisioning, memory consumption, and system-specific performance requirements and constraints [MHS18, TAB11, LAW02, STFG08]. Hippodrome [AHK+02] and Ergastulum [AKS+02] formulated the storage allocation problem as an instance of bin-packing, while Anderson et al. [AHH+01] experimentally evaluated several theoretical algorithms, concluding that their theoretical bounds are overly pessimistic.

The distinction between logical and physical capacity in deduplicated systems introduces additional complexity to the data migration problem. For optimal read and restore performance, the physical copies of a file's chunks must reside on the same storage volume. Thus, when migrating a file from one volume to another, this file's chunks that also belong to another file must be copied (duplicated), rather than moved. As a result, migrating data from a full volume to an empty one is likely to increase the total physical capacity of the system. Migrating data between two non-empty volumes can either increase or decrease the total physical capacity, depending on the degree of duplication between the migrated data and the data on the target volume. Intuitively, to optimize the system's overall storage utilization, a migration plan should minimize

the amount of data that is duplicated as a result.

Deduplication complicates other related tasks in a similar manner. Garbage collection must consider the logical as well as the physical relationships between chunks, files, and containers. Unfortunately, specific approaches for optimizing garbage collection are not directly applicable to data migration [DDS+17, LEB13, FFH+14]. As another example, online assignment of streams to servers in distributed systems must consider both content similarity and load balancing. Current solutions distribute data to servers in the granularity of individual chunks [DGH+09], super-chunks [DDL+11], files [BELL09], or users [DBQS11], considering server load as a secondary objective. These online solutions are based on partial knowledge of the data in the system, and may result in suboptimal plans if applied directly to data migration.

2.3 Existing data migration approaches

A recent paper describes the Data Domain Cloud Tier, in which customers maintain two tightly connected deduplication domains, in an on-premises system and in a remote object store [DJS+19]. They dedicate special attention to the process of seeding the cloud-tier—migrating a portion of the on-premises system into an initially empty object store. While the choice of the exact files to migrate is deferred to the client, the general use-case is to keep older backups in the cloud-tier and newer ones on-premises. The authors refer to "many days or weeks possibly required to transfer a large dataset to the cloud", strongly motivating our goal to minimize the amount of data replicated during migration.

Rangoli is a greedy algorithm for space reclamation in a deduplicated system [NK13]. Although it predates [DJS+19] by several years, its problem formulation is equivalent: choose a set of files for migration from an existing volume to a new empty volume. Rangoli constructs a migration plan by greedily grouping files into roughly equal-sized bins according to the blocks they share, and then chooses for migration the bin whose files have the least amount of data shared with other bins. The migration objective is specified as the number of bins.

In another recent paper, Harnik et al. address migration in the broader context of load balancing [HHS+19]. Their system consists of several non-empty volumes, each operating as an independent deduplication domain. The goal is to estimate the amount of deduplication between files on different volumes, to determine the potential occupancy reduction achieved by migrating files between volumes.[1] The focus of the study is a sketching technique that facilitates this estimation. In their evaluation, the authors propose a greedy algorithm that iteratively migrates files from one volume to another, with the goal of minimizing the overall physical occupancy in the system.

[1] In the original paper, migration is described in terms of moving logical volumes between physical servers. Thus, their volumes are equivalent to what we refer to as files, for simplicity.

Capacity planning and space reclamation in deduplicated systems are relatively new challenges. Current solutions are either naïve—migrating backups according to their age—or greedy. At the same time, migration carries significant costs in terms of physical capacity and bandwidth consumption, and it is unclear whether and how much the greedy solutions can be improved upon. This gap is the main motivation of our study.

2.4 Integer linear programming (ILP)

Integer linear programming (ILP) is a well-known optimization problem. The input to ILP is a set Ax of linear constraints, each of the form $a_0x_0 + a_1x_1 \cdots + a_{n-1}x_{n-1} \leq c$, where $a_1, \ldots, a_n, c \in \mathbb{Z}$, and an objective function of the form $Tx = t_0x_0 + t_1x_1 + \cdots + t_{n-1}x_{n-1}$. The problem is finding, given Ax and Tx, an integer assignment to $x_0, x_1, \ldots, x_n$ that satisfies A_x and maximizes Tx. There is no known efficient algorithm for solving ILP. In particular, when the variables are restricted to Boolean assignments (0 or 1), then merely deciding whether Ax has a solution has been long known to be NP-Complete[Kar72].

Nevertheless, ILP is used in various fields for modeling a wide range of problems [RH02, Aba89, ZWM12, ZSW16]. This wide use has been made possible by efficient ILP solvers—designated heuristic-based tools that can handle and solve very large instances. Thus, despite its theoretical hardness, ILP can in many cases be solved in practice for instances that contain hundreds of thousands and even millions of variables and constraints.

Most ILP solvers are based on the Simplex algorithm [Dan63], which efficiently solves linear programming where the variables are not necessarily integers. They then search for an optimal integer solution, starting the search at the vicinity of the non-integer one. The wide variety of ILP solvers includes open-source solvers such as SYMPHONY [SYM], lp_solve [lps], and GNU LP Kit [GNU]. Industrial tools include IBM CPLEX [CPL] and the Gurobi optimizer [Gur]. In this research, we take advantage of these highly-optimized solvers for finding the optimal migration plan in a deduplicated storage system.

Chapter 3

GoSeed ILP optimization

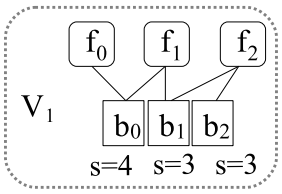
We formulate the goal of generating a migration plan as follows. Move physical data of size M from one volume to another, while minimizing R, the total size of the physical data that must be copied (replicated) as a result. In a seeding plan, the target volume is initially empty. We refer to R as the cost of the migration. Note that in a seeding plan, minimizing R minimizes the total capacity of the system, as well as the amount of data transferred between volumes during the migration.

3.1 Problem definition and hardness

For a storage volume V, let $B_V = \{b_0, b_1, \ldots, b_{m-1}\}$ be the set of unique blocks stored on V, and let $s(b)$ be the size of block b. The storage cost of the volume is the total size of the blocks stored on it, i.e., $s(V) = \Sigma_{b_i \in B_V} s(b_i)$. Let $F_V = \{f_0, f_1, \ldots, f_{n-1}\}$ be the set of files mapped to V, and let $I_V \subseteq B_V \times F_V$ be an inclusion relation, where $(b, f) \in I_V$ means that block b is included in file f. We intentionally disregard the order of blocks in a file, or blocks that appear several times in one file. While this information is required for restoring the original file, it is irrelevant for the allocation of blocks to volumes.

We require that all the blocks included in a file are stored on the volume this file is mapped to. Thus, if a file f is remapped from V_1 to V_2, then every block that is included in f must be either migrated to V_2 or replicated. Similarly, if we migrate a block b from volume V_1 to volume V_2, then every file f such that $(b, f) \in I_{V_1}$ must be remapped from V_1 to V_2.

The seeding problem is to decide, given a source volume V_1 with $B_{V_1}, F_{V_1}, I_{V_1}$, an empty destination volume V_2, a target size M and a threshold size R, whether there exists a set $B' \subseteq B_{V_1}$ of blocks whose total size is M, that can be migrated from V_1 to V_2, such that the total size of blocks that are replicated is at most R. In practice, we are interested in the respective optimization problem. Namely, the seeding optimization problem is to find such a set B' while minimizing R. A solution to the seeding optimization problem is a migration plan: the list of files that are remapped,



1. $0 \leq x_0, x_1, x_2, m_0, m_1, m_2, r_0, r_1, r_2 \leq 1$
2. $m_0 \leq x_0, \quad m_0 \leq x_1, \quad m_1 \leq x_1, \quad m_1 \leq x_2, \quad m_2 \leq x_2$
3. $x_0 \leq m_0 + r_0, \quad x_1 \leq m_0 + r_0, \quad x_1 \leq m_1 + r_1, \quad x_2 \leq m_1 + r_1, \quad x_2 \leq m_2 + r_2$
4. $4 \cdot m_0 + 3 \cdot m_1 + 3 \cdot m_2 = 3$

Goal: minimize $4 \cdot r_0 + 3 \cdot r_1 + 3 \cdot r_2$

Figure 3.1: Example system and its formulation as an ILP problem, where the goal is to migrate 30% of the physical space ($M = 3$).

the list of blocks that are replicated, and B'—the list of blocks that are migrated from V_1 to V_2.

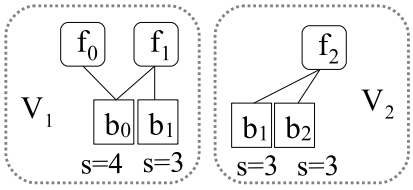
We prove that the seeding problem is NP-hard using two polynomial reductions from a known NP-hard problem. Intuitively, the relationship between files and blocks influences the quality of the solution, because the decision whether to migrate a specific block depends on the decision regarding other blocks. In this aspect, seeding is similar to many other set-selection problems such as Set Cover, Vertex Cover, and Hitting Set, that are known to be NP-hard [Kar72].

The first polynomial reduction is from the k-clique problem, which is known to be NP-hard, to the (k, m)-full cover problem. The k-clique problem is to determine in a given graph, $G = (V, E)$, if there exists a clique of size k. A set of vertices is considered a clique if there exists an edge, in the original graph, between each two vertices in the set. The second polynomial reduction is from the (k, m)-full cover problem to the seeding problem. The (k, m)-full cover problem is to determine if there exists a set of vertices of size at most k s.t it covers at least m edges. An edge is considered covered if both of its vertices are in the chosen set. A concatenation of the reductions will prove that the seeding problem is NP-hard. The full proof is demonstrated in Appendix A.

The hardness of the seeding problem, which is the most basic form of data migration, implies that all other related problems are hard as well. This includes data migration in more complex instances: systems with more than one source and one destination volumes, non-empty destination volumes, and optimizations that must also consider additional objectives, such as I/O load or migration traffic. The hardness of the problem also implies that there is an inevitable gap between the greedy solution and the optimal one. This gap is the focus of this study.

3.2 ILP formulation

We model the seeding optimization problem as an ILP problem as follows. For every file $f_i \in F_{V_1}$ we allocate a Boolean variable x_i. Assigning 1 to x_i means that f_i is



- Block b_2 is migrated: $m_2 = 1$
- File f_2 is remapped: $x_2 = 1$
- Block b_1 is replicated: $r_1 = 1$
- The remaining files and blocks are untouched: $x_0 = x_1 = m_0 = m_1 = r_0 = r_2 = 0$
- The total cost is $R = 3 \cdot r_1 = 3$

Figure 3.2: The system from Figure 3.1 after applying the optimal migration plan with $M = 3$.

remapped from V_1 to V_2. For every block $b_i \in B_{V_1}$ we allocate two Boolean variables, m_i, r_i. Assigning 1 to m_i means that b_i is migrated from V_1 to V_2, and assigning 1 to r_i means that b_i is replicated and will be stored in both V_1 and V_2.

We model the problem constraints as a set of linear inequalities, as follows.

1. All variables are Boolean: $0 \leq x_j \leq 1$, $0 \leq m_i \leq 1$, and $0 \leq r_i \leq 1$ for every $f_j \in F_{V_1}$ and $b_i \in B_{V_1}$.
2. If a block b is migrated, then every file that b is included in is remapped: $m_i \leq x_j$ for every i, j such that $(b_i, f_j) \in I_{V_1}$.
3. If a file f is rempapped, then every block that is included in f is either migrated or replicated: $x_j \leq m_i + r_i$ for every i, j such that $(b_i, f_j) \in I_{V_1}$.
4. The total size of migrated blocks is M: $\Sigma_{b_i \in B_{V_1}} s(b_i) \cdot m_i = M$.

The objective function minimizes the total size of blocks that are replicated: minimize $\Sigma_{b_i \in B_{V_1}} s(b_i) \cdot r_i$.

Another intuitive constraint is that a block cannot be migrated and replicated at the same time: $m_i + r_i \leq 1$ for every $b_i \in B_{V_1}$. This constraint will be satisfied implicitly in any optimal solution—if a block is migrated ($m_i = 1$) then replicating it will only increase the value of the objective function, and thus r_i will remain 0. This is also true for all the solutions in the space defined by the Simplex algorithm, and consequently for suboptimal solutions returned when the solver times out.

A solution to the ILP instance is an assignment of values to the Boolean variables. We note, however, that such an assignment does not necessarily exist. If a solution does not exist, Simplex-based solvers will return quickly—we observed a few minutes in our evaluation. If a solution to the ILP instance exists, we find B' by returning every block b_i such that $m_i = 1$, and the list of replicated blocks by returning every block b_i such that $r_i = 1$. The list of files to remap is given by every file f_i such that $x_i = 1$.

Figure 3.1 shows an example of a simple deduplicated system, and the formulation as an ILP instance of the respective seeding optimization problem with $M = 3$. The optimal solution, depicted in Figure 3.2, is to migrate b_2, replicate b_1, and remap f_2,

which yields $R = 3$. Another feasible solution is to migrate b_1, whose size is also 3. However, migrating b_1 results in replicating both b_0 and b_2, which yields $R = 7$.

3.3 Refinements

The requirement to migrate blocks whose total size is exactly M may severely limit the possibility of finding a solution. Fortunately, in real settings, there is some range of acceptable migrated capacities. For example, for the file system in Figure 3.1, a solution exists for $M = 3$ but not for $M = 2$. In realistic systems, feasible solutions may be easier to find but their cost, R, might be unnecessarily high. Thus, we redefine our problem by adding a slack value, ϵ, as follows.

For a given $B_{V_1}, F_{V_1}, I_{V_1}$, target size M, and slack value ϵ, the seeding optimization problem with slack is to find $B' \subseteq B_{V_1}$ of blocks whose total size is M', $M - \epsilon \leq M' \leq M + \epsilon$, that can be migrated from V_1 to V_2. In the formulation as an ILP problem, we require that the total size of migrated blocks is $M \pm \epsilon$: $M - \epsilon \leq \Sigma_{b_i \in B_{V_1}} s(b_i) \cdot m_i \leq M + \epsilon$. For example, for the system in Figure 3.1, the optimal solution for $M = 2$ and $\epsilon = 1$, is the solution given above for $M = 3$.

Another refinement in the problem formulation is required to prevent "leftovers" on the source volume V_1. An orphan block is copied because a file it is included in is remapped, but no other file that includes it remains in V_1. For example, consider the system in Figure 3.3(a), with a migration objective of $M = 3$. For simplicity, assume that $\epsilon = 0$. The only feasible solution is depicted in Figure 3.3(b), where b_1 is migrated, f_1 and f_2 are remapped, and b_2 is replicated. b_2 cannot be migrated because this would exceed the target migration size, $M = 3$. Replicating b_2 leaves an extra copy of this block in V_1, where it is not contained in any file.

Although a migration plan with orphan blocks represents a feasible solution to the ILP problem, it is an inefficient one. For example, b_2 in Figure 3.3(b) consists of 20% of the system's original capacity. Orphans can be eliminated by garbage collection, or even as part of the migration process [DJS+19]. This is essentially equivalent to migrating the orphan blocks, rather than replicating them, resulting in a migrated capacity which exceeds the original objective. For example, removing b_2 from volume V_2 in Figure 3.3(b) is equivalent to a migration plan with $M = 5$, rather than the intended $M = 3$.

We eliminate such solutions by adding the following constraint: if a block b is copied, then at least one file it is included in is not remapped: $r_i \leq \Sigma_{\{j|(b_i,f_j)\in I_{V_1}\}}(1 - x_j)$ for every $b_i \in B_{V_1}$. This additional constraint may result in the solver returning without a solution. Such cases should be addressed by increasing ϵ or modifying M. Nevertheless, the decision whether to prevent orphan blocks in the migration plan or to eliminate them during its execution is a design choice that can easily be realized by adding or removing the above constraint.

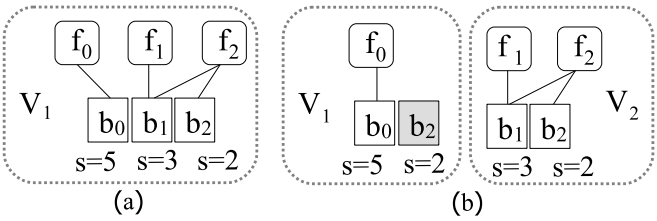


Figure 3.3: A migration plan with an orphan block. The goal is to migrate 30% ($M = 3$) of the system in (a). b_2 is the orphan—it was duplicated when f_2 was remapped (b).

3.4 Complexity

The number of constraints in the ILP formulation is linear in the size of I_V—the number of pointers from files to blocks in the system. Although the size of I_V can be at most $|B_V| \cdot |F_V|$, it is likely considerably smaller in practice: the majority of the files are small, and the majority of the blocks are included in a small number of files [MB11].

In general, the time required for an ILP solver to find an optimal solution depends on many factors, including the number of variables, the connections between them (represented by the constraints), and the number of feasible solutions. In our context, the size of the problem is determined by the number of files and blocks, and its complexity depends on the deduplication ratio and on the pattern of data sharing between the files. It is difficult to predict how each of these factors will affect the solving time in practice. Furthermore, small changes in the target migration size and in the slack value may significantly affect the solver's performance. We evaluate the sensitivity of GoSeed to these parameters in Chapter 6.

Chapter 4

GoSeed Acceleration Methods

The challenge in applying ILP solvers to realistic migration problems is their size. In a system with an average chunk size of 8KB, there will be approximately 130M chunks in each TB of physical capacity. Thus, the runtime for generating a migration plan for a source volume with several TBs of data would be unacceptably long. In this chapter, we present three methods for reducing this generation time. We describe their advantages and limitations and the ways in which they may be combined, and evaluate their effectiveness in Chapter 6.

4.1 Solver timeout

The runtime of an ILP solver can be limited by specifying a timeout value. When a timeout is reached before the optimal solution is found, the solver will halt and return the best feasible solution found thus far. This approach has the advantage of letting the solver process the unmodified problem. It does not require any preprocessing, and, theoretically, the solver may succeed in finding the optimal solution. The downside is that when the solver is timed out, we cannot necessarily tell how far the suboptimal solution is from the optimal one.

4.2 Fingerprint sampling

Sampling is a standard technique for handling large problems, and has been used in deduplication systems to increase the efficiency of the deduplication process [LEB+09, BELL09, CLZ11], to route streams to servers [DDL+11], for estimating deduplication ratios [HKS16], and for managing volume capacities [HHS+19]. We use sampling in the same way it is used in [HHS+19]. Given a sampling degree k, we include in our sample all the chunks whose fingerprint contains k leading zeroes, and all the files containing those chunks. When the fingerprint values are uniformly distributed, the sample will include $\frac{1}{2^k}$ chunks. Harnik et al. show in [HHS+19] that $k = 13$ guarantees small enough errors for estimating the capacity of deduplicated volumes larger than 100GB.

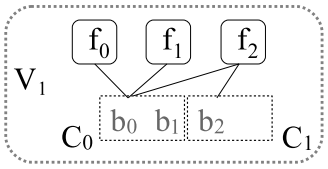


Figure 4.1: The system from Figure 3.1 with container aggregation.

Sampling reduces the size of the ILP instance by a predictable factor: incrementing the sampling degree k by one reduces the number of blocks by half. Combining sampling and timeouts presents an interesting tradeoff: a smaller sampling factor results in a larger ILP instance that more accurately represents the sampled system. However, solving a larger instance is more likely to time out and return a suboptimal solution. It is not clear which combination will result in a better migration plan—a suboptimal solution on a large instance, or an optimal solution on a small instance. Our analysis in Chapter 6 shows how the answer depends on the original (unsampled) instance and on the length of the timeout.

4.3 Container-based aggregation

Aggregation is often employed as a first step in analysing large datasets. In deduplication systems, containers are a natural basis for aggregation. Containers are often compressed before being written to durable storage, and are decompressed when they are fetched into memory for retrieving individual chunks. Thus, generating and executing a migration plan in the granularity of containers holds the advantage of avoiding decompression as well as an increase in the fragmentation in the system by migrating individual chunks from containers.

To formulate the migration problem with containers we coalesce chunks that are stored in the same container into a single block, and remove parallel edges, i.e., pointers from the same file to different chunks in the same container. Figure 4.1 shows the container view of the volume from Figure 3.1. In a real system, formulating the migration problem with containers is more efficient than with chunks: when processing file recipes, we can ignore the chunk fingerprints and use only the container IDs for generating the variables and constraints.

In a system that stores chunks in containers, the container-based migration problem accurately represents the system's original constraints. At the same time, we can further leverage container-based aggregation as an acceleration method by artificially increasing the container size beyond the size used by the system. With aggregation degree K, we coalesce every K adjacent containers into one, like we do for chunks. Thus, a system with 4MB containers can be represented as one with $4K$-MB containers by coalescing every K original containers. Containers typically store hundreds of chunks, which means that the size of the resulting ILP problem will be smaller by several orders of

magnitude. Furthermore, containers are allocated as fixed-size extents, which further reduces the ILP problem complexity: the optimization goal of minimizing the total size of migrated blocks becomes a simpler goal of minimizing their number.

A container-based seeding plan can be obtained more quickly than a chunk-based one. Thus, if aggregation is combined with solver timeouts, a container-based suboptimal solution will likely be closer to the optimal (container-based) solution than in an execution solving the chunk-based instance. At the same time, container-based aggregation (like any aggregation method) reduces the granularity of the solution, which affects its efficiency as an acceleration method for the original chunk-based problem. Namely, an optimal container-based migration plan is not necessarily optimal if the migration is executed in the granularity of chunks.

Consider a migration plan generated with containers, and let F_{V_2} be the set of files that are remapped to V_2 as a result of that plan. F_{V_1} is the set of files that remain on V_1. If a container is not part of the migration plan, this means that all of its chunks are contained only in files from F_{V_1}. When a container is marked for migration, this means that all of its chunks are contained only in files from F_{V_2}. When a container includes at least one chunk that is contained in a file from F_{V_1} as well as in a file from F_{V_2}, the entire container is marked for replication. However, this container may also contain some "false positives"—chunks that are contained only in files from F_{V_1} (and should not be part of the migration), or only in files from F_{V_2} (and should be migrated rather than replicated).

These false positives increase the cost of the container-based solution, and can be eliminated by performing the actual migration in the granularity of chunks, as done in [DJS+19]. However, this would eliminate the advantages of migrating entire containers, and may cause the solver to "miss" the migration plan that would have been optimal for the chunk-based ILP instance. We observe this effect in Chapter 6

Chapter 5

Implementation

We use the commercial Gurobi optimizer [Gur] as our ILP solver, and use its C++ interface to define our problem instances. The problem variables (x_i, m_i, r_i) are declared as Binary and represented by the GRBVar data type. The constraints and objective are declared as GRBLinExpr data type. M and ϵ are given in units of percents of the physical capacity. Our program for converting the input files into an ILP instance and retrieving the solution from Gurobi consists of approximately 400 lines of code. Our implementation, as well as a description of the input format, are available at https://github.com/avivnachman1/GoSeed.

We specify three parameters for each execution: a timeout value, the parallelism degree (number of threads), and a random seed. These parameters do not affect the optimality of the solution, but they do affect the solver's runtime. Specifically, the starting point for the search for an integer solution is chosen at random, which may lead some executions to complete earlier than others. If the solver times out, different executions might return solutions with slightly different costs. In our evaluation, we solve each ILP instance in three separate executions, each with a different random seed, and present the average of their execution times and costs.

We initiate an empty model with the GRBEnv and GRBModel constructors, and allocate $2|B_{V_1}| + |F_{V_1}|$ binary variables by calling addVars(). The linear constraints, described in Chapter 3, are added to the model while reading the input, as a vector of GRBLinExpr. We assign the constraints and objective by calling addConstrs() and setObjective(), respectively. At this point, the instance is complete and we initiate the solving process by calling optimize(). When the optimization stage is complete, or when the time limit is reached, the method returns and we can retrieve the assignment for our binary variables (x_i, m_i, r_i) by calling the model's method, get().

Chapter 6

Evaluation

The goal of our experimental evaluation is to answer the following questions:

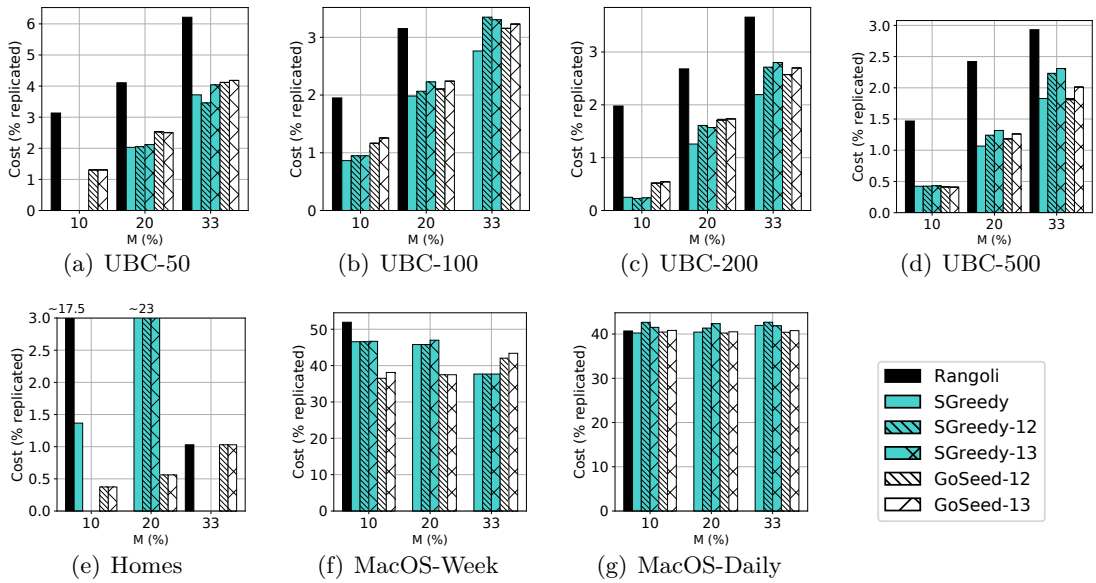
- What is the difference, in terms of cost, between the ILP-based migration plan and the greedy ones?
- How do the ILP instance parameters (its size, M, and ϵ) affect it's complexity, indicated by the solver's runtime?
- How does timing out the solver affect the quality (cost) of the returned solution?
- How do the sampling and aggregation degrees affect the solver's runtime and the cost of the migration plan?
- Can we improve the container-based solutions by modifying the assignment of blocks to containers during the deduplication process?

6.1 Experimental setup

6.1.1 Deduplication snapshots

We use static file system snapshots from two publicly available repositories. The UBC dataset [MB11] includes file systems of 857 Microsoft employees available via SNIA IOTTA [SNI]. The FSL dataset [FSL] includes daily snapshots of a Mac OS X Snow Leopard server and of student home directories at the File System and Storage Lab (FSL) at Stony Brook University [SKM+16, TMB+12]. The snapshots include, for each file, the fingerprints calculated for each of its chunks, as well as the chunk size in bytes. Each snapshot file represents one entire file system, which is the migration unit in our model, and is represented as one file in our ILP instance.

To obtain a mapping between files and unique chunks, we emulate the ingestion of each snapshot into a simplified deduplication system. We assume that all duplicates are detected and eliminated. We emulate the assignment of chunks to containers by assuming that unique chunks are added to containers in the order of their appearance in the original snapshot file. We create snapshots of entire volumes by ingesting several file-system snapshots one after the other, thus eliminating duplicates across individual



(a) UBC-50 (b) UBC-100 (c) UBC-200 (d) UBC-500

(e) Homes (f) MacOS-Week (g) MacOS-Daily

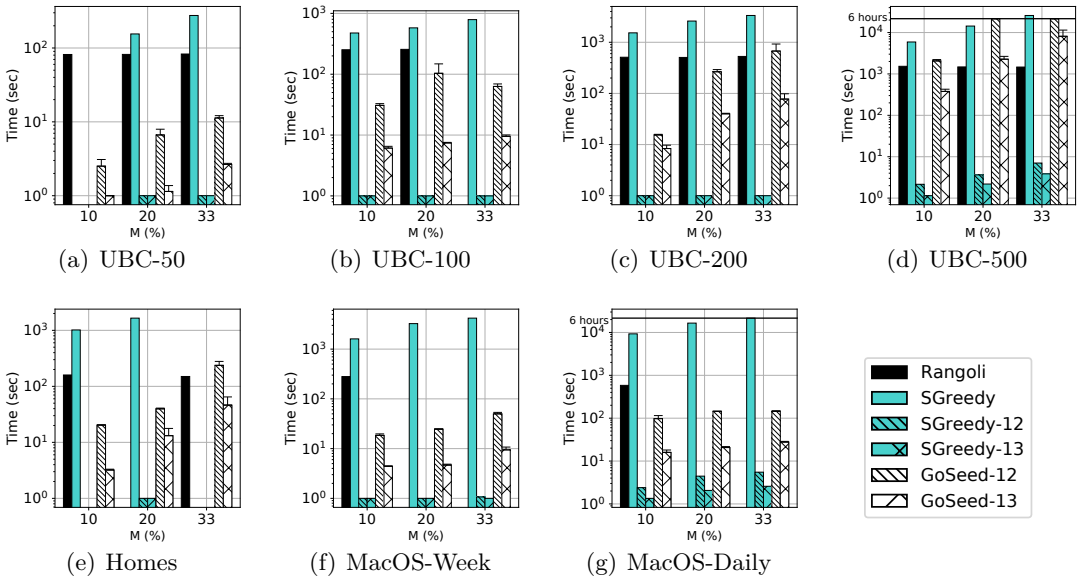
Figure 6.1: Replication cost of seeding plans. Missing bars indicate a solution was not found.

Table 6.1: Volume snapshots in our evaluation. The container size is 4MB. Dedupe is the deduplication ratio—the ratio between the physical and logical size of each volume. Logical is the logical size.

Volume	Files	Chunks	Dedupe	Containers	Logical
UBC-50	50	27M	0.59	122K	807 GB
UBC-100	100	73M	0.34	317K	3.5 TB
UBC-200	200	138M	0.32	570K	6.7 TB
UBC-500	500	382M	0.31	1.6M	19.5 TB
Homes	81	19M	0.13	325K	9.4 TB
MacOS-Week	102	6M	0.02	74K	11.8 TB
MacOS-Daily	200	6.3M	0.01	85K	26.3 TB

snapshots. The resulting volume snapshot represents an independent deduplication domain.

The volume snapshots used in our experiments are detailed in Table 6.1. The UBC-X volumes contain the first X file systems in the UBC dataset. These snapshots were created with variable-sized chunks with Rabin fingerprints, whose specified average chunk size is 64KB. In practice, however, many chunks are 4KB or less. The FSL snapshots were also generated with Rabin fingerprints and average chunk size of 64KB. The MacOS-Daily volume contains all available daily snapshots of the server between May 14, 2015 and May 8, 2016, while the MacOS-Week volume contains weekly snapshots, which we emulate by ingesting the snapshots from all the Fridays in repository. The Homes volume contains weekly snapshots of nine users between August 28 and October 23, 2014 (nine weeks in total).



(a) UBC-50 (b) UBC-100 (c) UBC-200 (d) UBC-500

(e) Homes (f) MacOS-Week (g) MacOS-Daily

Figure 6.2: Runtime of seeding algorithms. For GoSeed, we present the average of three runs, with error bars indicating the maximum runtime.

6.1.2 Evaluation platform

We ran our experiments on a server running Ubuntu 18.04.3, equipped with 64GB DDR4 RAM (with 2666 MHz bus speed), Intel® Xeon® Silver 4114 CPU (with hyper-threading functionality) running at 2.20GHz, one Dell® T1WH8 240GB TLC SATA SSD, and one Micron 5200 Series 960GB 3D TLC NAND Flash SSD. We let Gurobi use 38 CPUs, and specify a timeout of six hours, to allow for experiments with a wide range of setup and problem parameters.

6.1.3 Comparison to existing approaches

We use our volume snapshots to evaluate the quality of the migration plans generated by the existing approaches described in Chapter 2.3. We implement Rangoli according to the original paper [NK13]. Rangoli's greedy grouping into bins is performed as follows. First, it divides the blocks into disjoint sets, such that all the blocks in a set are contained in the same files. Each set of blocks is represented by a block-node whose weight is the sum of its blocks' sizes. Each block-node is connected by an edge to each of the files containing its blocks. The algorithm then iteratively groups files into bins: it initializes each file as a bin, and traverses the block-nodes in descending order of their weights. For each block-node, it creates a list of bins connected to it and merges them in order of their logical size. The merge continues as long as the resulting bin is no larger than the logical volume size divided by B.

We convert our migration objective M into a number of bins B, such that $B = \frac{1}{M}$. We modified Rangoli to comply with the restriction that the migrated capacity is between $M - \epsilon$ and $M + \epsilon$: when choosing one of B bins for migration, our version of

Rangoli chooses only from those bins whose capacity is within the specified bounds.

For evaluation purposes, we implemented a seeding version of the greedy load balancer that was used for evaluating the capacity sketches in [HHS+19]. We refer to this algorithm as SGreedy. In each iteration, SGreedy chooses one file from V_1 to remap to V_2. The remapped file is the one which yields the best space-saving ratio, i.e., the ratio between the space freed from V_1 and that added to V_2. The iterations continue until the migrated capacity is at least $M - \epsilon$, and if, at this point, it does not exceed $M + \epsilon$, a solution is returned. SGreedy returns a seeding plan in the form of a list of files that are remapped from V_1 to V_2. We then use a dedicated "cost calculator" to derive the cost of the migration plan on the original (unsampled) system.

Our calculator creates an array of the volume's chunks and their sizes, and two bit indicators, V_1 and V_2, that are initialized to false for each chunk. It then traverses the files in the volume snapshot and updates the indicators of their blocks as follows. If a file is remapped, then the V_2 indicators of all its chunks are set to true. If a file is not remapped, then the V_1 indicators of all its chunks are set to true. A final pass over the chunk array calculates the replication cost by summing the sizes of all the chunks whose V_1 and V_2 indicators are both true. The migrated capacity is the sum of the sizes of all the chunks whose V_2 indicator is true and V_1 indicator is false.

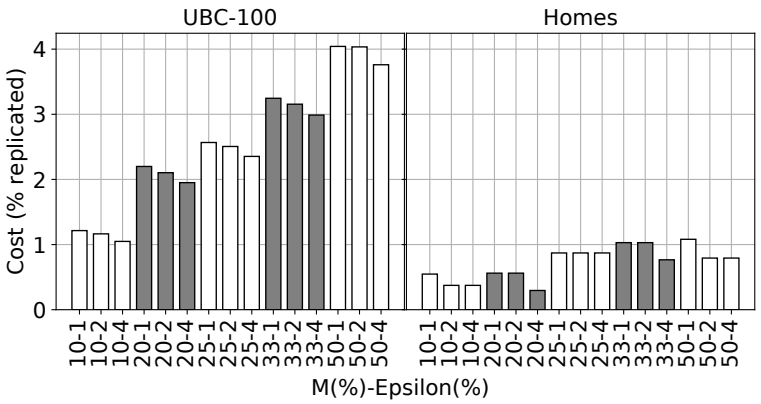


Figure 6.3: GoSeed plans generated with sampling degree K=12.

6.2 Results

6.2.1 Comparison of different algorithms

We first analyze the migration cost incurred by the different algorithms on the various volume snapshots. Figure 6.1 shows our results with three values of M (10,20,33) and $\epsilon = 2$. A missing bar of an algorithm indicates that it did not find a solution for that instance. GoSeed-K and SGreedy-K depict the results obtained by these algorithms running on a snapshot created with sampling degree K (the cost was calculated on the original snapshot).

Rangoli does not perform well on most of the volume snapshots. It incurs the highest replication cost on the UBC snapshots, except UBC-100 with $M = 33$, for which it does not find a solution. On the FSL snapshots, it finds a good solution only for the Homes volume with $M = 33$ and MacOS-Daily with $M = 10$, but not for the remaining instances. The backups on the MacOS volumes share most of their data, with a very low deduplication ratio. In these circumstances, Rangoli mostly fails because it is unable to partition the files into separate bins of the required size.

SGreedy returns a solution in all but two instances (UBC-50 with $M = 10$ and Homes with $M = 33$). For the UBC snapshots, the cost of its solution is 37%-87% lower than the cost of Rangoli's solution. When SGreedy is applied to a sampled snapshot, as it was originally intended, this cost increases by as much as 28% and 27%, for sample degrees 12 and 13, respectively. This increase is expected, as the sampled snapshot "hides" some of the data sharing in the real system. However, the increase is smaller in most instances. It is also interesting to note a few cases where SGreedy returns a better solution (with a lower replication cost) on the sampled snapshot than on the original one, such as for UBC-50 with $M = 33$. These situations can happen when "hiding" some of the sharing helps the greedy process find a solution that it wouldn't find otherwise.

We can now classify our volumes into three rough categories. We refer to the

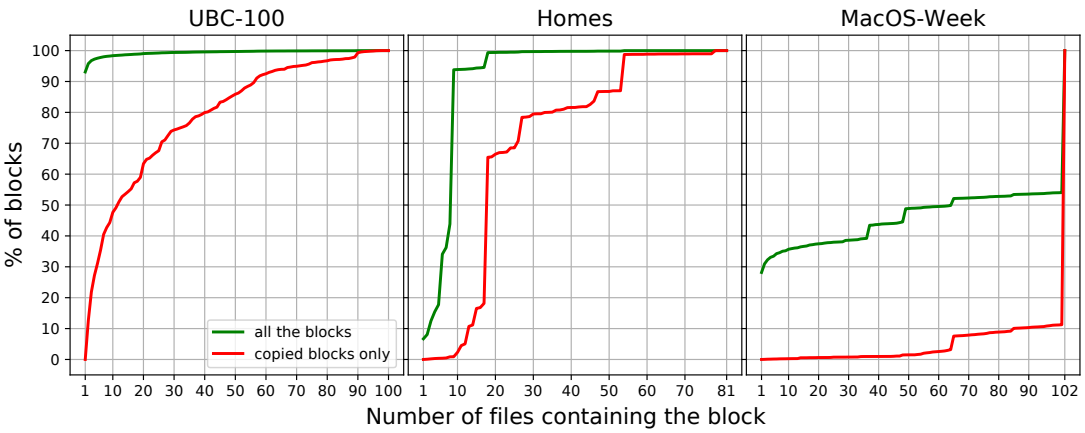


Figure 6.4: Cumulative distribution of blocks, ranked by the number of files they are contained in.

UBC volumes as easy—their data sharing is modest and the greedy algorithms find good solutions for them. We refer to the Homes volume as hard—its data sharing is substantial and the greedy algorithms mostly return solutions with high costs (up to 29%), or don't find a solution at all. We consider the MacOS volumes to be very hard because of their exceptionally high degree of sharing between files. This sharing prevents Rangoli from finding any solution with $M = 20, 33$, and incurs very high costs (up to 60%) in the plan generated by SGreedy.

To explain these differences between the volumes, we ranked the blocks in each volume according to the number of files they belong to. We then repeated this process considering only the blocks that are copied in GoSeed's solution with M=20%. Figure 6.4 shows the CDF for three representative volumes. In UBC-100 (Figure 6.4a), only 7% of the blocks are contained in more than one file. This makes it relatively easy to find a solution that minimizes the amount of data copied by the seeding plan.

In Homes (Figure 6.4b), only 7% of the blocks are contained in exactly one file, which makes it harder to find a solution. At the same time, only 6% of the blocks are contained in more than nine files. This corresponds to the backups of each user included in this volume. In other words, only 6% of the blocks are contained in files belonging to more than one user. Indeed, almost all the blocks copied in the solution (98%) are contained in ten or more files, i.e., files belonging to at least two users. The steps in the CDF of copied blocks, occurring at 9, 18, and 27 files, correspond to files belonging to one, two, and three users, respectively.

Figure 6.4c shows what makes the MacOS volumes very hard. 72% of the blocks in the MacOS-Week volume are shared by more than one file, and 46% of its blocks are contained in all 102 files. The blocks shared by all files make up 89% of all the copied blocks. This explains the high cost of the solutions in this volume.

GoSeed cannot find a solution for the full snapshots, which translate to ILP instances with hundreds of millions of constraints. We thus use fingerprint sampling to

apply GoSeed to the volume snapshots, with two sampling degrees, 12 and 13. Our results show that GoSeed finds a solution for all the volumes and all values of M. It generates slightly better plans with a smaller sampling degree, when more of the system's constraints are manifested in the ILP instance.

In the easy (UBC) volumes, the cost of GoSeed's migration plan is similar to that of SGreedy's plan on the sampled snapshots. It is higher for four instances (UBC-50 with $M = 20, 33$, and for UBC-100 and UBC-200 with $M = 10$) and equal or lower for the rest. This shows that greedy solutions may suffice for volumes with modest data sharing between files.

The picture is different for the hard volumes. For Homes, GoSeed consistently finds a better migration plan, besides M=33 where Rangoli also output a good solution. Each of the greedy algorithms finds a solution for some values of M but fails to find one for others. The biggest gap between the greedy and optimal solutions occurs for $M = 20$: SGreedy (with and without sampling) replicates approximately 23% of the volume's capacity, while the replication cost of the plan generated by GoSeed is only slightly higher than 0.5%. This demonstrates a known property of greedy algorithms—their solutions are good enough most of the time, but very bad in the worst case.

Finally, for the very hard (MacOS) volumes, GoSeed finds similar solutions and most of the time better than the greedy algorithms. Although more than 35% of the volume is replicated in all of the migration plans, the replication cost of GoSeed for MacOS-Weekly with $M = 10$ and $M = 20$ is at least 8% lower than that of the greedy algorithms. The exceptionally high degree of sharing in this volume indicates that better solutions likely do not exist. This conclusion was supported in our attempt to apply the "user's" migration plan from [DJS+19], remapping the oldest backups (files, in our case) to a new tier. In MacOS-Weekly and MacOS-Daily, remapping the single oldest backup to a new volume resulted in migrating 0.2% and 0.3% of the volume's capacity, and replicating 49% and 55% of it, respectively.

Figure 6.2 shows the runtime of the different algorithms. The runtime of GoSeed is longer than that of SGreedy on the sampled snapshot, but shorter than that of SGreedy and Rangoli on the original snapshots. GoSeed timed out at six hours only in one execution (UBC-500 and $K = 12$). The rest of the instances were solved by GoSeed in less than one hour (UBC) or five minutes (FSL). We note, though, that GoSeed utilizes 38 threads, while the greedy algorithms use only one. For a migration plan transferring several TBs of data across a wide area network or a busy interconnect, these runtimes and resources are acceptable.

6.2.2 Effect of ILP parameters

We first investigate how M and ϵ affect the solver's ability to find a good solution. We compare the cost of the plan generated by GoSeed with five values of M (used in [NK13]) and three values of ϵ on an easy (UBC-100) volume and on a hard one

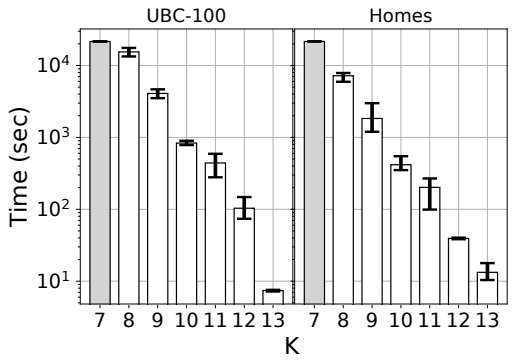


Figure 6.5: Solving time increases exponentially with instance size (gray bars indicate that the solver timed out).

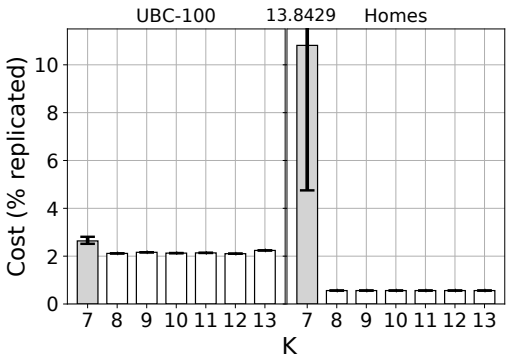


Figure 6.6: Cost is hardly affected by the sampling degree, unless the instance becomes too large.

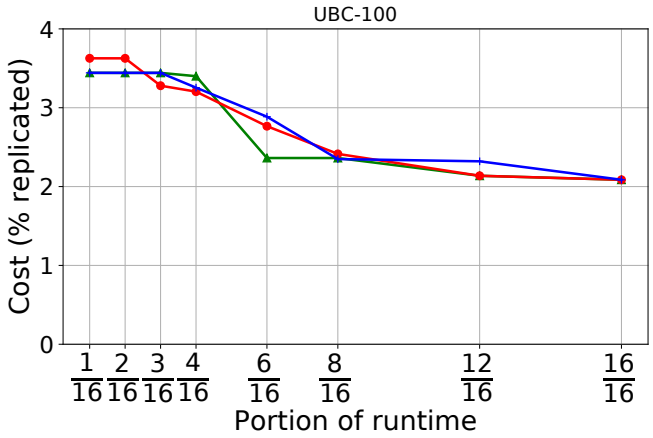


Figure 6.7: Migration cost decreases when timeout increases (costs are shown for three random seeds).

(Homes). The results in Figure 6.3 show that in the easy volume, higher values of M result in a higher cost, and that this cost can be somewhat reduced by increasing ϵ, which increases the number of feasible solutions. We observe a similar effect in Homes, but to a much smaller extent. We note that this effect is also shared by the greedy algorithms (not shown for lack of space), for which differences in ϵ often make a difference between finding a feasible solution or returning without one. Increasing M also exponentially increases the runtime of the solver—migrating more blocks results in more feasible solutions in the search space. We omit the runtimes of this experiment, but the effect can be observed in Figure 6.2.

We next investigate how the size of the snapshot affects the time required to solve the ILP instance. We compare problems with similar constraints and different sizes by generating sampled snapshots with K between 7 and 13 of the above two volumes. Figure 6.5 shows the average runtime of GoSeed on these snapshots with $M = 20$ and $\epsilon = 2$. Error bars mark the minimum and maximum runtimes. Note that both axes are

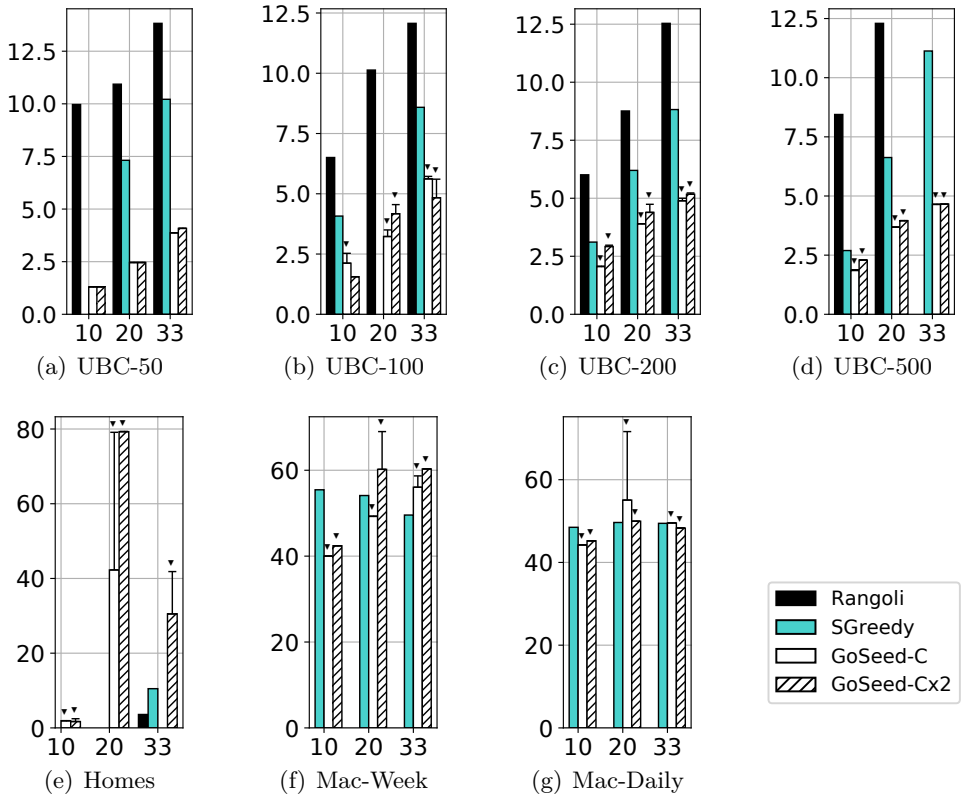


Figure 6.8: Replication cost of container-based migration plans. For GoSeed, we present the average of three runs (error bars indicate the maximum cost). Triangles indicate experiments in which the solver timed out. GoSeed outperforms the greedy solutions by as much as 87%.

log-scaled—incrementing K by one doubles the number of blocks in the ILP instance. As we expected, the time increases exponentially with the number of blocks. The figure also shows that the runtime of the same instance with one random seed can be as much as 1.45× longer than with another seed. We discuss the implications of this difference below.

6.2.3 Effect of solver timeout

To evaluate the effect of timeouts on the cost of the generated plan, we generate a volume snapshot by sampling UBC-100 with $K = 8$, for which the solver's execution time is approximately four hours. We repeatedly solve this instance (with the same random seed) with increasing timeout values. We set the timeouts to fixed portions of the full runtime, after having measured the complete execution. We repeat this process for three different seeds. To eliminate the effect of sampling, we present the cost of migration assuming the sample represents the entire system.

The results in Figure 6.7 show that the most substantial cost reduction occurs in the first half of the execution, after which the quality of the solution does not improve considerably. The three processes converge to the same optimal solution at different speeds, corresponding to the different runtimes in Figure 6.5. At the same time, we

note that the largest differences in cost occur between suboptimal solutions returned in the first half of the execution, when the solver makes most of its progress. The cost difference is relatively small and does not exceed 22% (at $\frac{6}{16}$)—a much smaller difference than the difference in time required to find the optimal solution.

Gurobi provides an interface for querying the solver for intermediate results without halting its execution. We did not use this interface because it might compromise the accuracy of our time measurements. However, it can be used to periodically check the rate at which the intermediate solution improves. When the rate decreases and begins to converge, continuing the execution yields diminishing returns, and it can be halted.

6.2.4 Effect of fingerprint sampling

We evaluate the effect of the sampling degree on the cost of the solution by calculating the costs of the plans generated for UBC-100 and Homes with $M = 20$, $\epsilon = 2$, and K between 7 and 13. Figure 6.6 shows that the difference between the cost of optimal solutions is very small. However, when the solver times out, the cost of the suboptimal solution can be as much as 3× higher.

Our results for varying the ILP instance parameters and sampling degrees suggest the following straightforward heuristic for obtaining the best seeding plan within a predetermined time frame. Generate a sample of the system with degree between 10 and 13—smaller degrees are better for smaller systems. If the solver times out, increase the sampling degree by one. If the solver completes and there is still time, solve instances with increasing values of ϵ until the end of the time frame is reached. This process results in a set of solutions that form a Pareto frontier—their cost decreases as their migrated capacity is farther from the original objective M. The final solution should be chosen according to the design objectives of the system.

6.2.5 Efficiency of container-based plans

The container-based aggregation generates a reduced ILP instance which is an accurate representation of the connections between files and containers. This representation can also be used to generate container-based migration plans with Rangoli and SGreedy. Thus, our next experiment compares the costs of GoSeed and the greedy algorithms on the same instances. Our results in Figure 6.8 show that in these circumstances, GoSeed can reduce the migration cost obtained by Rangoli and SGreedy by as much as 87% and 66%, respectively. These results are not surprising given the size of the ILP instances—they consist of several hundred thousand variables, well within Gurobi's capabilities. As a result, even in experiments in which Gurobi times out (indicated by the small triangles in the figure), its suboptimal solutions are considerably better than the greedy ones. The costs with aggregated containers (GoSeed-C×2) are higher because of the false dependencies described in Chapter 4.3.

We used our cost calculator to compare the chunk-level cost of the container-based

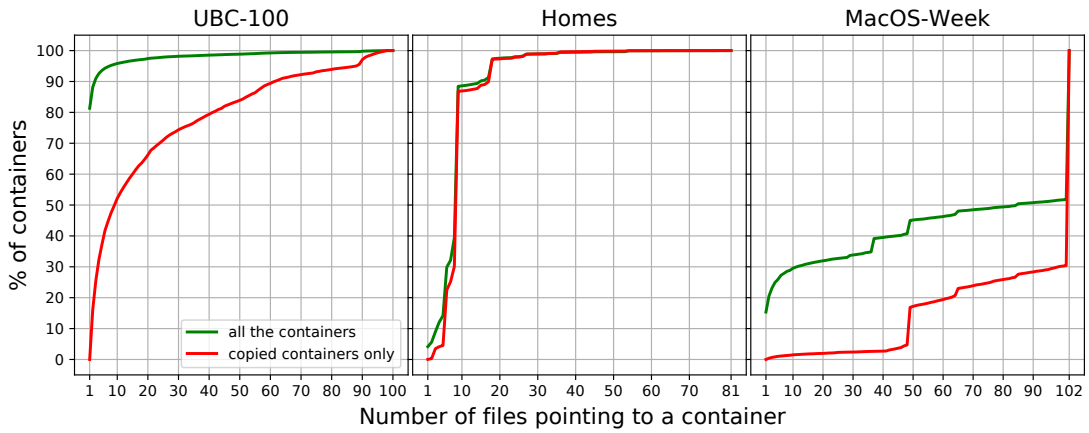


Figure 6.9: Cumulative distribution of containers, ranked by the number of files pointing to them.

migration plan to the greedy plans generated for the original system. For the MacOS volumes and for UBC-50, GoSeed's container-based plan outperforms Rangoli and is comparable to SGreedy. However, for the larger UBC volumes and for Homes, SGreedy and Rangoli find solutions with as much as 7.6× and 13.6× lower cost, respectively. On these instances, Gurobi returned a suboptimal solution which was close to the container-based optimum, but far from the chunk-based optimum. The reason are the false dependencies, described in Chapter 4.3 and analyzed in detail in the following section. We therefore recommend using GoSeed with container-based aggregation if the migration is to be performed with entire containers, and with fingerprint sampling otherwise. We summarize the main findings from our experimental results as follows.

- GoSeed combined with fingerprint sampling always finds a solution to the migration problem. In most cases, it is the best solution in terms of cost, when compared to the greedy algorithms.

- The solutions generated by the greedy algorithms are comparable to those of GoSeed in volumes with modest data sharing between files.

- In general, the deduplication ratio is the major factor determining the difficulty of the seeding problem for a given workload.

- Most of the solver's progress towards an optimal solution occurs early in its optimization stages. This supports the effectiveness of the timeout heuristic.

- When migration is performed in granularity of containers, GoSeed with container-based aggregation is superior to the greedy algorithms. When blocks care migrated individually, fingerprint sampling is the preferable acceleration method.

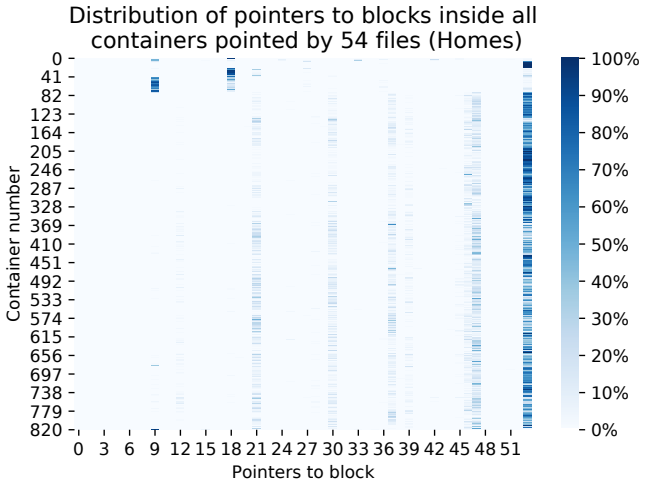


Figure 6.10: Distribution of pointers to each block within all containers with 54 files pointing to themt.

6.3 Containers analysis

For a better understanding of the effect of sharing and false sharing in the container-based seeding instances, we repeated the analysis in Figure 6.4 with containers instead of blocks. Figure 6.9 shows a CDF of the number of files pointing to each container in three representative volumes, as well as the CDF for containers copied in GoSeed's solution with M=20%. The UBC and MacOS containers exhibit a high degree of false sharing. In UBC-100 (Figure 6.9a), 19% of the containers contain blocks from more than one file, while only 7% of the blocks are contained in more than one file (Figure 6.4a). Similarly, in MacOS-Week (Figure 6.9c), only 15% of the containers contain blocks from one file, as opposed to 28% of the blocks that are contained in one file (Figure 6.4c).

Homes exhibits a different behavior: the distributions of pointers to all containers, as well as to containers copied in the solution (Figure 6.9b) are similar to the distribution of files containing each block (Figure 6.4b)—more than 88% of copied containers include blocks from at most nine files, i.e., belonging to a single user. This is counter-intuitive: the optimal seeding plan divides the users between the source and destination volumes—it does not split a user's file between the volumes. Thus, blocks contained in at most one user's files should not be copied as part of an optimal solution. However, the container-based solution is not optimal. In this instance, the solver timed out and returned a sub-optimal solution, which explains this copying as well as its high cost.

Collocating blocks from different files in the same container does not only interfere with optimal seeding plans. Previous studies addressed this false sharing in the context of efficient I/O during the restore process. One approach to reduce the number of files pointing to each container is to enforce an explicit limitation. When the number of files with blocks in the container exceed this limit, new files containing blocks in this

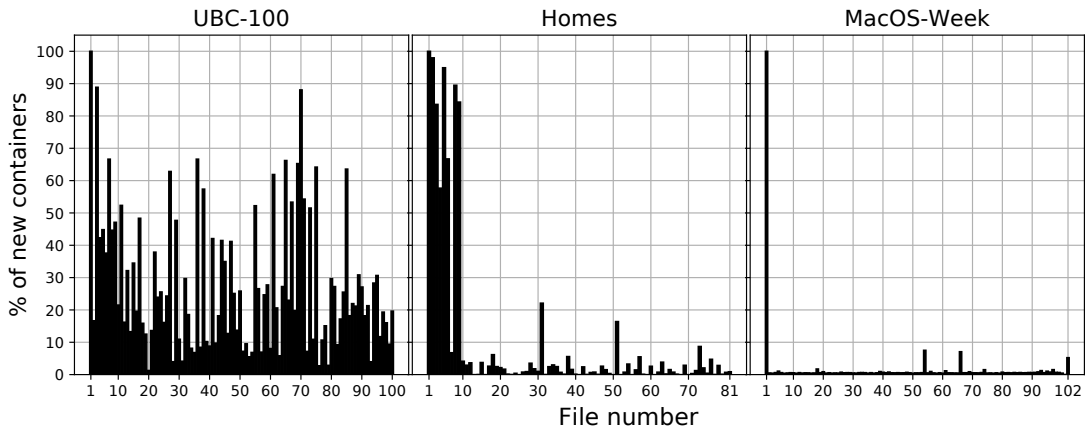


Figure 6.11: Percent of new containers within the containers pointed by each file.

container will result in additional physical copies of these blocks [LEB13]. Another approach is to limit the "distance" (difference in creation times) between files pointing to each container. In other words, new files cannot point to blocks in containers that were created too long ago [FFH+14].

We first examined the effect of the number of pointers to a container on its degree of false sharing. For a container with p pointers, we calculated the percentage of its blocks pointed to by i files, for $1 \leq i \leq p$. We repeated this analysis for all the containers in each volume, and aggregated the results by p. Figure 6.10 shows the results of all the containers with 54 pointers in Homes. The results are presented as a heat map, with the number of pointers in the X axis, the container ID in the Y axis, and the color representing the percentage of the container's blocks. On average, only 50% of the blocks in each container belong to all the files pointing to this container, and only 68% of the blocks are contained in 47 files or more. A large portion of the blocks are contained in much fewer files, creating the effects of false sharing described above.

This analysis yielded similar results on containers from other volumes and with a different number of pointers. They imply that even when the number of files pointing to each container is limited, we can still expect a high rate of false sharing within individual containers. Thus, such a limitation is not likely to eliminate the effect of false-sharing.

Figure 6.11 shows the percentage of each file's containers that are new, i.e., containers created while ingesting this file. Each file in UBC-100 (Figure 6.11a) is a snapshot of a different user's home directory. The percentage of new containers in each snapshot is between 1% to 89%. The snapshots in Homes (Figure 6.11b) were processed chronologically. The first day contained snapshots of nine different home directories, resulting in a considerable percentage of new containers. The following eight days contained weekly backups of these directories, which contained a low percentage of new data, and respectively few containers. In MacOS-Week (Figure 6.11c), which contains 102 weekly backups of the same server, almost all of the data in each file is a duplicate

of data already in the system.

In all these volumes, limiting the distance between containers pointed to by a single file would clearly reduce the dependencies between files. However, as noted in [FFH+14], this will also increase the physical size of the volume. This increase is a valid tradeoff when it comes to improving restore performance. However, for the purposes of data migration, there is no reason to increase the physical size before migration only for the purpose of minimizing the effect of migration.

In summary, false sharing is inevitable when aggregating blocks into containers. The analyses presented in this chapter were performed on volumes that have not experienced any file deletions. When files are deleted, garbage collection is triggered to reclaim physical space in old containers. This process aggregates otherwise unrelated blocks into containers, and is likely to further increase the degree of false sharing, beyond what is shown in our analysis. Thus, container-based solutions in such systems should be used only when the migration itself is performed in the granularity of containers, for reasons such as I/O efficiency or reduced computation.

Chapter 7

Discussion

Data migration within a large-scale deduplicated system can reallocate tens of terabytes of data. This data is possibly transferred over a wide area network or a busy interconnect, and some of it may be replicated as a result. The premise of our research is that the potentially high costs of data migration justify solving a complex optimization problem with the goal of minimizing these costs.

Thus, in contrast to existing greedy heuristics to this hard problem, GoSeed attempts to solve it. By formulating data migration as an ILP instance, GoSeed can "hide" its complexity by leveraging off-the-shelf highly optimized solvers. This approach is independent of specific design and implementation details of the deduplication system or the ILP solver. However, it introduces an inherent tradeoff between the time spent generating a seeding plan, and the cost of executing it. As this cost depends on the system's characteristics, such as network speed, cost of storage, and read and restore workload, the potential for cost saving by GoSeed is system dependent as well.

Our evaluation showed that the benefit of GoSeed is high in two scenarios. The first is when the problem's size allows the solver to find the optimal (or near optimal) solution within the allocated time. Container-based migration is an example of this case, where GoSeed significantly reduced the migration cost of the greedy algorithms. The second case is when a high degree of data sharing in the system makes it hard for the greedy solutions to find a good migration plan, causing them to produce a costly solution or no solution at all. At the same time, for systems with low or exceptionally high degrees of data sharing, the greedy solutions and that of GoSeed are comparable.

Accurately identifying the large instances for which GoSeed would significantly improve on the greedy solution is not straightforward, and requires further research. Fortunately, a simple hybrid approach can provide 'the best of both worlds': one can run the greedy algorithm, followed by GoSeed, and execute the migration plan whose cost is lower.

7.1 Generalizations

Seeding is the simplest form of data migration in large systems. A natural next step to this work is to generalize our ILP-based approach to more complex migration scenarios, such as migration into a non-empty volume, and migration where both source and target volumes are chosen as part of the plan. Each generalization introduces additional aspects, and might require reformulating not only the ILP constraints, but also its objective function.

For example, when the destination volume is not empty, the optimal migration plan can be the one that minimizes the total storage capacity on the source and destination volumes combined. An alternative formulation might minimize the total amount of data that must be transferred from the source volume to the destination. In the most general case, generating the migration plan also entails determining either the source or the destination volume, or both, such that the migration goal is achieved and the objective is optimized. Data migration in general introduces additional objectives, such load balancing between volumes, or optimizing the migration process under certain network conditions and limitations. The problem can be further extended by allowing some files to be split between volumes, introducing a new tradeoff between the cost of migration and that of file access.

The ILP formulation of these problems will result in considerably more complex instances than those of the seeding problem. As a result, we might need to apply our acceleration methods more aggressively, e.g., by increasing the fingerprint sampling degree, or construct new methods. Thus, each generalization of the seeding problem introduces non-trivial challenges as well as additional tradeoffs between the solving time and the cost of migration.

Chapter 8

Conclusions

We presented GoSeed, an algorithm for generating theoretically optimal seeding plans in deduplicated systems, and three acceleration methods for applying it to realistic storage volumes. Our evaluation demonstrated the effectiveness of the acceleration methods: GoSeed can produce an optimal seeding plan on a sample of the system in less than an hour, even in cases where the greedy solutions do not find a feasible solution to the problem. When executed on the original system, GoSeed's solution is not theoretically optimal, but it can substantially reduce the cost of the greedy solutions.

Finally, our formulation of data migration as an ILP problem, combined with the availability of numerous ILP solvers, opens up new opportunities for additional contributions in this domain, and for making data migration more efficient.

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Appendix A

Hardness proof

We now explain why the seeding problem is most likely intractable. First, we define the (m, ϵ, r)-block move problem which is the decision problem corresponding to our seeding optimization problem. We also define the (k, m)-full cover problem. Second, we show a polynomial-time reduction from the k-clique problem to the (k, m)-full cover problem. Since the k-clique problem is NP-complete the conclusion here is that the (k, m)-full cover problem is also NP-complete. Third, we show a polynomial-time reduction from the (k, m)-full cover problem to the (m, ϵ, r)-block move problem. Since the (k, m)-full cover problem is NP-complete the final conclusion is that the (m, ϵ, r)-block move problem is NP-complete.

Definition. Let $G = \langle V, E \rangle$ be an undirected graph. We say that a set $V' \subseteq V$ is a full cover of $E' \subseteq E$ if for every $(u, v) \in E'$, it holds that $u, v \in V'$. We then also say that E' is fully covered by V'.

The (k, m)-full cover problem is to decide, given G and $k, m \in \mathbb{N}$ whether there exists a subset of vertices V' of size at most k that fully covers at least m edges.

Definition. Let B be a set of blocks, let $s : B \to \mathbb{N}$ be a size function which assigns every block b a size $s(b)$, let F be a set of files, and let $C \subseteq F \times B$ be a set of inclusions, where $\langle f, b \rangle \in C$ means that block b is in file f. A block b is moved only if every file that contains b is remapped. A block b is replicated only if at least one file that contains b is remapped and at least one file that contains b is not remapped.

The (m, ϵ, r)-block move problem is to decide whether there exists a set of files whose remap will move blocks whose total size is at least $m - \epsilon$ and at most $m + \epsilon$, such that the total size of block replication will not exceed r.

Theorem 1. The (k, m)-full cover problem is NP-complete.

Proof of Theorem 1: It is easy to see that the problem is in NP. Indeed, given a set of k vertices its easy to verify whether they cover at least m edges. To show that the problem is NP-hard, we show a reduction from the k-clique problem. Given G and k, the reduction returns G,k and $m = \binom{k}{2}$. Obviously, the reduction is polynomial. To prove correctness, given an undirected graph $G = \langle V, E \rangle$, there exists a clique of size (at least) k iff there exist V' of size at most k and E' of size (at least) $\binom{k}{2}$ such that V'

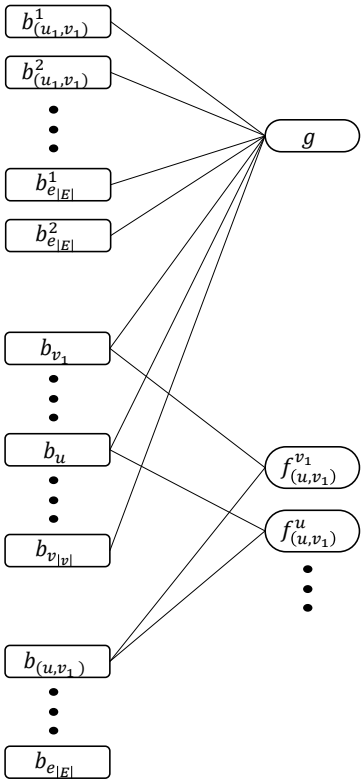

Figure A.1: An illustration of the (k, m)-full cover $\rightarrow$ (m, ϵ, r)-block move reduction.

is a full cover of E' in G.

- For the first direction, if V' is a clique of size k, then it spans $\binom{k}{2}$ edges, and obviously covers them all from both sides.
- For the second direction, suppose that V' of size at most k covers E' of size at least $\binom{k}{2}$. The maximal number of edges for which both sides are in V' is $\binom{k}{2}$, since between two vertices there is at most one edge. If $\binom{k}{2}$ is the minimal number of edges that V' covers then $|E'| = \binom{k}{2}$ and there exists an edge between every two vertices in V'. The conclusion is that V' is a clique of size k.

Note that with the same reduction we can prove that a variant of this problem, where m is a strict requirement (rather than a lower bound), is also NP-complete.

Theorem 2. the (m, ϵ, r)-block move problem is NP-complete.

Proof of Theorem 2: It is easy to see that the problem is in NP. Indeed, given a set of files, it is easy to verify that remapping them will move blocks with accumulated size in the range of $m - \epsilon$ to $m + \epsilon$, and that the block replication is at most r. To show that the problem is NP-hard, we show a reduction from the (k, m)-full cover problem, illustrated in figure A.1. Given a graph $G = \langle V, E \rangle$ with n vertices and t edges and numbers k, m', we construct a file system as follows. The set of blocks (B) comprises:

- A block b_v for every $v \in V$

- A block b_e for every $e \in E$
- Blocks b_e^1, b_e^2 for every $e \in E$

We set $s(b) = 1$ for every $b \in B$ (all blocks are of size 1). The set of files (F) comprises:

- A file labeled g
- Two files $f^u_{(u,v)}, f^v_{(u,v)}$ for every edge $(u, v) \in E$

The set of inclusions (C) comprises:

- (b_v, g) for every $v \in V$
- $(b_e^1, g), (b_e^2, g)$ for every $e \in E$, i.e., g contains $2|E| + |V|$ blocks.
- $(b_e, f^u_{(u,v)}), (b_e, f^v_{(u,v)})$ for every $e = (u, v) \in E$
- $(b_v, f^v_{(u,v)})$ for every $v \in V$ and $u \in V$ s.t $(u, v) \in E$, i.e., overall the file $f^v_{(u,v)}$ contains 2 blocks.

Given an undirected graph $G = \langle V, E\rangle$, there exist V' of size k and E' of size m' such that V' is a full cover of E' in G iff in the file system we described above there exists a set of files whose remapping will move blocks with accumulated size of m' and block replication is at most k. That is, for the (m, ϵ, r)-block move problem, we set $\epsilon = 0, m = m', r = k$.

- For the first direction, suppose that there exists a set V' s.t $|V'| = k$ that covers E' where $|E'| = m'$. We remap the set of files $F' = \{f^u_{(u,v)}, f^v_{(u,v)} | (u, v) \in E'\}$. Accordingly the set of blocks that is moved is $B_m = \{(b_e | e = (u, v), f^u_{(u,v)} \in F'\}$ and $|B_m| = |E'| = m'$. Additionally, $B_r = \{b_v | f^v_{(u,v)} \in F'\}$ is the set of blocks that is replicated due to the remapping of F' and $|B_r| = |V'| = k$. Therefore, F' is a solution to the $m', 0, k$-block move problem.
- For the second direction, suppose there exists a set $F' \subseteq F$ such that remapping F' moves exactly m' blocks and replicates exactly k blocks. According to Lemma 1 below we know that B_m contains only blocks of the type b_e. We claim that $F' = \{f^u_{(u,v)}, f^v_{(u,v)} | (u, v) = e, b_e \in B_m\}$. Since B_r contains blocks that are contained in at least one file that is being remapped and at least one file that is not remapped, we have that $B_r = \{b_v | f^v_{(u,v)} \in F'\}$. Let $V' = \{v | f^v_{(u,v)} \in F'\}$ and $E' = \{(u, v) | f^v_{(u,v)} \in F'\}$. It holds that V' covers E' since for every $(u, v) \in E'$ there exists $f^v_{(u,v)}, f^u_{(u,v)} \in F'$ and thus $u, v \in V'$. Additionally, $|V'| = |B_r| = k$ and $|E'| = |B_m| = m'$. Therefore, V', E' is a solution to the (k, m')-full cover problem.

Lemma 1: Only blocks of the form b_e can be moved under the restrictions of $m = m'$ and $r = k$. Proof of Lemma 1: Suppose, by way of contradiction that a block of the

form b_v or b_e^1 or b_e^2 is moved. Any of these three cases will cause file g to be remapped. Indeed, remapping g leads to either moving or replicating each of its $2|E| + |V|$ blocks, thus exceeding $m + r$. Therefore, only blocks of the type b_e can be moved

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אופטימיזציית בעיית הזריעה בתור בעיית תכנון לינארי בשלמים (ILP-integer linear programming), כאשר הפונקציה שנרצה למזער תייצג את ההעתקה של פיסות המידע. למרות שבעיית התכנון הלינארי בשלמים ידועה גם כן כקשה לחישוב פולינומי, קיים מגוון רחב של כלים, חלקם מבוססי קוד פתוח וחלקם מסחריים, שיודעים לתת פתרון מבוסס היוריסטיקות יחסית ביעילות. לאור גודלן של מערכות האחסון בעולם האמיתי, בעיית התכנון לינארי בשלמים שתיגזר מתוך בעיית הזריעה תכיל מאות מיליונים של משתנים ואילוצים - הרבה מעבר לסדר הגודל של בעיות עבורן אותם כלים יתנו פתרון בזמן סביר.

על מנת לצמצם את אותם פערים בין הרצוי למצוי אנחנו מציעים קבוצה של שיטות האצה: מצד אחד נצליח לצמצם את זמן הריצה הדרוש לאותם כלים, אבל מצד שני נאבד את האופטימליות התאורטית שלנו ונצטרך להסתפק בפתרון "מספיק טוב". בהמשך העבודה מתוארות שלוש שיטות האצה שהגדרנו, וניתחנו את ביצועיהן. השיטה הראשונה מבוססת על האפשרות לעצור את הכלי לפני מציאת הפתרון האופטימלי – הפתרון המתקבל הוא פתרון זריעה קביל, אך ייתכן שעלותו גבוהה מזו של הפתרון שהיה מתקבל בסוף הריצה. שתי השיטות האחרות מבוססות על הקטנת הבעיה באמצעות דגימה ואיחוד, בהתאמה. אנו ממירים את הבעיה המוקטנת לבעיית התכנון לינארי בשלמים מזינים אותה אל הכלי ומהתוצאה של הכלי אנחנו מסיקים פתרון עבור בעיית הזריעה המקורית. בשיטות אלה מתקבל פתרון אופטימלי לקירוב של הבעיה המקורית, אך לא מובטח שהפתרון המתאים לבעיה המקורית הוא אכן האופטימלי עבורה. מימשנו את GoSeed בעזרת Gurobi [Gur] שהוא כלי תעשייתי לפתרון בעיות תכנון לינארי בשלמים. בנוסף, מימשנו את שיטות האצה שלנו וגם מצאנו פתרון לבעיות זריעה עבור מערכות אמתיות מבוססות דדופליקציה [MB11, FSL] . הניתוח המעמיק שלנו בין היתר מציג את מגבלות הפתרונות החמדניים שהוצגו לבעיית הזריעה. עבור בעיות הנחשבות קלות יחסית, עם יחס דדופליקציה נמוך, השיטות החמדניות מוצאות פתרונות טובים, אך עבור בעיות מסובכות יותר עם יחס הדדופליקציה גבוה יותר, הפתרונות של GoSeed ברוב המקרים הופכות לעדיפות יותר.

תקציר

דדופליקציה (deduplication) היא אחת הדרכים היעילות ביותר לצמצום נפח המידע המאוחסן במערכות אחסון גדולות. דדופליקציה היא שיטה שבה מזהים פיסות מידע זהות בקבצים שונים, ומאחסנים בשרת האחסון רק עותק פיזי אחד של כל פיסת מידע. כל עותק נוסף של אותה פיסת מידע יוחלף במצביע אל פיסת המידע הפיזית בדיסק. דדופליקציה אכן מצמצמת את נפח האחסון הדרוש לשמירה על המידע שלנו, אך היא גם מסבכת את תהליך הניהול של המידע, במיוחד במערכות גדולות- פעולות ניהול כמו שערוך גודל המידע, שירות לקוחות בצורה יעילה והוגנת, גביית כסף בצורה מדויקת מהלקוחות עבור המידע שלהם וכו'.

דוגמה נוספת לפעולת ניהול שהופכת מסובכת יותר בעקבות דדופליקציה היא "הגירת נתונים" data migration- בחירת חלק מן המידע הפיזי בשרת מסוים והעברתו לשרת אחר. בדרך כלל פעולה זאת נדרשת כחלק מתהליך איזון עומסים או משינוי נפח האחסון שמוקצה למערכת או לשרת מסוים. דדופליקציה מסבכת את תהליך בחירת הקבצים המתאימים להעברה, שכן שיתוף המידע בין קבוצת הקבצים המיועדת להעברה, והקבוצה המשלימה לה (כל שאר הקבצים במערכת), קובעים באופן חד משמעי את גודל המקום שהמידע יתפוס בשרתי היעד והמקור, בהתאמה. תכנון יעיל של העברת מידע מצד אחד יוריד תפוסת שרת המקור על פי הכמות הנדרשת, ומצד שני ימזער ככל הניתן את המקום שידרוש המידע המועבר בשרת היעד. בעיית ה"זריעה" (seeding), שהיא תת בעיה של בעיית העברת המידע בה שרת היעד ריק מתוכן לפני העברה, קשה לחישוב יעיל. במילים אחרות, בעיה זאת במערכות עם דדופליקציה נמצאת במחלקה NP-Hard.

בעיית הגירת הנתונים ובעיית הזריעה במערכות עם דדופליקציה נחקרו לא מעט בעולם האקדמי בשנים האחרונות הודות להשפעה הישירה שלהן על ארכיטקטורה של מערכות אחסון מידע בתעשייה. Harnik ושות' [HHS+19] מטפלים בבעית שערוך נפח הנתונים עבור הגירת נתונים באופן כללי, בעוד Duggal ושות' [DJS+19] מתארים זריעה של יחידת אחסון בענן עבור מערכת קיימת. Rangoli [NK13] היא שיטה לפינוי נתונים ממערכת עם דדופליקציה – בעיה שקולה לבעיית הזריעה. כל המחקרים האמורים מציעים שיטות חמדניות לבחירת הקבצים שיועברו לשרת היעד, כך היעילות של הפתרונות המתקבלים לא הושוותה בצורה שיטתית מעולם.

בנוסף, לאור העובדה שיש חסך גדול במחקרים מתחום התאוריה על אותן בעיות, לא ברור עד כמה ניתן לשפר את התוצאות הקיימות, אם בכלל. מטרת המחקר היא: להקנות בסיס תאורטי לבעיית הזריעה ושיטת הפתרון, לבנות בסיס מימושי למציאת פתרונות עבור מערכות אמיתיות ולספק ניתוח מעמיק של השפעת השיטה לצד השיטות הכי טובות שהעולם האקדמי והתעשייתי מכיר.

אנחנו מציגים את GoSeed, גישה חדשה לפתרון בעיית הזריעה. בגישה החדשה אנחנו מפרמלים את

המחקר בוצע בהנחייתה של דר׳ גלה ידגר, בפקולטה למדעי המחשב ע״ש הנרי ומרילין טאוב.

חלק מן התוצאות בחיבור זה פורסמו כמאמרים מאת המחבר ושותפיו למחקר בכנסים ובכתבי-עת במהלך תקופת מחקר המאסטר של המחבר, אשר גרסאותיהם העדכניות ביותר הינן:

Aviv Nachman, Gala Yadgar, and Sarai Sheinvald. GoSeed: Generating an optimal seeding plan for deduplicated storage. In 18th USENIX Conference on File and Storage Technologies (FAST 20), pages 193–207, Santa Clara, CA, February 2020. USENIX Association.

תודות

ברצוני להודות למנחה שלי דר׳ גלה ידגר, על ההנחיה, העידוד והתמיכה לאורך כל עבודת המגיסטר. בנוסף ארצה להודות לשרי שינולד ואריאל קוליקנט על עזרתם החשובה בפרוייקט זה. לסיום ארצה להודות למשפחתי ולחברי על תמיכתם ואהבתם המתמשכת ובמיוחד להורי האהובים ירון וסיגלית שהיו שם בשבילי לכל אורך הדרך.

אני מודה לטכניון על התמיכה הכספית הנדיבה בהשתלמותי.

ניהול מידע במערכות אחסון מבוססות דדופליקציה

חיבור על מחקר

לשם מילוי חלקי של הדרישות לקבלת התואר
מגיסטר למדעים במדעי המחשב

אביב נחמן

הוגש לסנט הטכניון — מכון טכנולוגי לישראל
חשוון התשפ"א חיפה אוקטובר 2020

ניהול מידע במערכות אחסון מבוססות דדופליקציה

אביב נחמן