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Towards Optimizing Storage Costs on the Cloud

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Abstract—We study the problem of optimizing data storage and access costs on the cloud while ensuring that the desired performance or latency is unaffected. We first propose an optimizer that optimizes the data placement tier (on the cloud) and the choice of compression schemes to apply, for given data partitions with temporal access predictions. Secondly, we propose a model to learn the compression performance of multiple algorithms across data partitions in different formats to generate compression performance predictions on the fly, as inputs to the optimizer. Thirdly, we propose to approach the data partitioning problem fundamentally differently than the current default in most data lakes where partitioning is in the form of ingestion batches. We propose access pattern aware data partitioning and formulate an optimization problem that optimizes the size and reading costs of partitions subject to access patterns.

We study the various optimization problems theoretically as well as empirically, and provide theoretical bounds as well as hardness results. We propose a unified pipeline of cost minimization, called SCOPe that combines the different modules. We extensively compare the performance of our methods with related baselines from the literature on TPC-H data as well as enterprise datasets (ranging from GB to PB in volume) and show that SCOPe substantially improves over the baselines. We show significant cost savings compared to platform baselines, of the order of 50% to 83% on enterprise Data Lake datasets that range from terabytes to petabytes in volume.

Index Terms—storage costs, multi-tiering, compression, data partitioning, optimization

I. INTRODUCTION

Customer activities on the internet generate a huge amount of data daily. This is usually stored in cloud platforms such as Azure, AWS, Google Cloud etc. and is used for various purposes like analytics, insight generation and model training. With the massive growth in data volumes and usages, the costs of storing and accessing data have spiraled to new heights, significantly increasing the COGS (cost of goods sold) for enterprises, thus making big data potentially less profitable.

Cloud storage providers offer a tiered form of storage that has different costs and different throughput and latency limits across tiers. Table I shows the storage costs, read costs and latency (measured as the time to first byte) for the different tiers of storage offered by Azure, a popular cloud storage provider. There is a clear trade-off between storage cost, read cost and latency across the tiers.

TABLE I: Cost and latency numbers for Azure [8].

	Premium	Hot	Cool	Archive
Storage cost cents/GB (first 50 TB)	15	2.08	1.52	0.099
Read cost (cents, every 4 MB per 10k operations)	0.182	0.52	1.3	650
Time to first byte	Single digit ms	ms	ms	Hours

To further complicate things, enterprise workloads often exhibit non-trivial and differing patterns of access. Data access patterns are often highly skewed; only a few datasets are heavily accessed and most datasets see very few or 0 accesses. Another common trend is recency, i.e., access frequency falls with age of dataset or file (Fig 1). There are other interesting patterns too as shown in Fig 2. While some data see a constant number of read or write accesses, others may see periodic peaks, or read accesses decreasing over time. For marketing use cases, data is ingested for activation, leading to one-time read and write spikes followed by long inactive periods. Rule

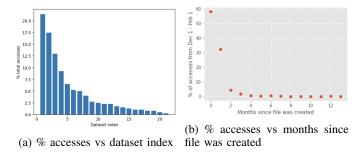


Fig. 1: Enterprise Data access patterns

based methods such as pushing data to cooler tiers after x days of inactivity fail due to seasonality and periodicity in access patterns, such as year-on-year analysis. Other intuitive rules such as caching the most recently accessed data in hot tiers are also ineffective, because even with a consistent number of accesses, it is non-trivial to determine the right tier for the data¹. Caching rules generally consider access related

¹Some cloud storage providers have recently started providing tiering and lifecycle management options based on last access [6], [7]. However, such methods are oblivious to varied and long term data usage patterns such as seasonal trends, year on year analysis, as well as required SLAs on certain types of data even if they are accessed less frequently.

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information (recency of access or frequency of accesses) for goals different from storage cost optimization. The optimal storage tier would depend on a trade-off between the storage costs (as determined by the size of the dataset and storage cost per unit size in each tier), access costs (determined by the amount of data being accessed, the access frequency, cloud provider's costs for different access types per unit size of data), the tier change costs, as well as the SLAs (i.e., latency and availability agreements with the clients).

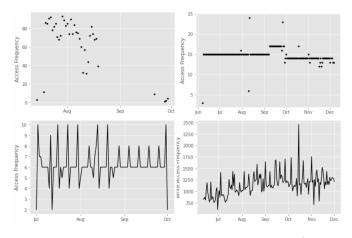


Fig. 2: Enterprise workloads on our data lake. **Top-left:** Read accesses decreasing over time for a particular dataset. **Top-right:** Read accesses remaining relatively constant over time for a particular dataset. **Bottom-left:** Periodic trend of read accesses for a certain class of datasets. **Bottom-right:** Write access trend across all datasets

Datasets in enterprise setting are often large, of the order of terabytes. Often, certain parts (files) of the data are more "important" or heavily accessed than the others, hence applying lifecycle management on entire datasets as a whole might be inefficient or sub-optimal. Recently, workload aware and adaptive data partitioning schemes have been explored in the literature [9], [17], [30], [33], [36], [37]. However, these approaches often suffer from scalability issues as dataset sizes increase or query workloads becomes richer, and can have difficulty in dynamically adapting to changing workloads.

Another approach used to reduce the storage and read costs is data compression [14], [15], but this can potentially add the overhead of decompression, which might increase the latency and compute cost. There have been efforts that enable efficient queries and analytics directly on compressed and/or sampled data, discussed further in Section II. A solution is thus needed which reduces the total storage, read, write and compute costs (which includes the necessary decompression costs, where unavoidable) from the cloud while meeting any service level agreements (SLAs).

Our contributions:

1) We analyze the cost optimization problem theoretically and show it is strongly NP-HARD (proof sketch). For special cases, we give optimal, polynomial algorithms including an efficient greedy algorithm.

- 2) Our greedy algorithm is both scalable and effective. We apply it on enterprise Data Lake datasets of the order of **petabytes** in volume using real (historical) enterprise workloads that have substantial skew and other patterns. We show significant cost benefits, ranging from **50% to 83%** compared to platform baselines. The prediction model is near optimal with F1 > 0.96 and does significantly better than intuitive baselines.
- 3) We propose a Compression Predictor that predicts the compression ratio and decompression times for popular compression schemes on data partitions in different storage formats (csv, parquet) with good accuracy. We empirically study different features, models, data layouts, and data distributions across multiple schemes.
- 4) We study the access-pattern-aware data partitioning problem and show that it is strongly NP-HARD (proof sketch). We propose a heuristic that achieves a good trade-off of space and cost empirically. For time series data, we give polynomial time approximation schemes.
- 5) We propose a unified pipeline of the above optimizers, predictor, and partitioner called SCOPe: Storage Cost Optimizer with Performance Guarantees, that allows tunable, access pattern aware storage and access cost optimization on the cloud while maintaining SLAs. We provide substantial empirical validation and ablation studies on enterprise and TPC-H data. SCOPe outperforms related baselines by a significant margin. We also show that applying our partitioning heuristic can directly improve the baselines.

The rest of the paper is organized as follows. We discuss the related work in Section II. We discuss the problem setting and datasets in Section III. We study the cost optimization in Section IV. We explain the compression predictor in Section V. We study the query aware data partitioning problem in details in Section VI. We discuss the entire pipeline SCOPe (in comparison with baselines) in Section VII. Finally, we conclude in Section VIII.

II. RELATED WORK

Different aspects of the cloud storage problem have been studied in the literature.

Multi-tiering Recently, there has been some work that exploits multi-tiering to optimize performance, e.g., [11], [14], [16], [21] and/or costs, e.g., [11], [18], [20], [28], [29], [34]. Storage and data placement in a workload aware manner, e.g., [4], [5], [11] and in a device aware manner, e.g., [24], [25], [38] have also been explored. [14] combine compression and multi-tiering for optimizing latency, but do not consider the storage, read and compute costs. Many of the existing works towards optimizing storage and read costs in a multi-tiered setting, e.g., [11], [18], [20], [28], [29], [31], [32], [34] propose policies for data transfer between tiers in online or offline settings, however there is no focus on data partitioning or data compression. In general, we did not find a direct baseline for

SCOPe that tries to optimize storage costs while maintaining latency guarantees, estimating compression performance and considering query aware data partitioning. However, we have modified some of the existing works on tiering as baselines for SCOPe, and we have extensively evaluated SCOPe against such baselines.

Data Compression: Data compression has been heavily studied in the literature. While some of the works have studied compression that enables efficient querying, others have studied the memory footprint and cost aspects. Bit map compression schemes that enable efficient querying, such as WAH, EWAH, PLWAH, CONCISE, Roaring, VAL-WAH etc. [10], [12], [13], [19], [26], [27], [40], [41] have been extensively studied, however these are more efficient and popular for read-only datasets. Several researchers have studied enabling efficient queries and analytics directly on compressed and/or sampled data, e.g., [1]-[3], [45]. Others have considered the cost aspect, e.g., [14], [15]. Yet others have looked at the dynamic estimation of compression performance, e.g., [14], [22] based on data type, size, similarity and distribution. In our setting, features suggested in literature did not work well, hence we proposed new, effective features. We have comprehensively evaluated multiple compression schemes, data layouts (parquet, csv, sorted data etc.), different sources of data (TPC-H and enterprise) and different query workload distributions (uniform, skewed), and evaluated the effect of prediction errors on the overall optimization.

The benefits of caching and computation pushdown in a disaggregated storage setting have been explored [43], [44]. However not all cloud service providers support computation pushdown for commonly used data formats such as parquet, and even if they do, it generally comes at a higher price. Moreover, not all types of queries can be accelerated by directly performing on compressed data or pushing down to the storage layer. Nevertheless, our optimization module can support query accesses that directly run on compressed data (i.e. no decompression) as well.

Data Partitioning: Data partitioning has been studied in the database literature as a means of efficient query execution. Attribute based partitioning have been heavily studied [17], [30], [33], [35]-[37], [46]. Workload and workflow aware partitioning [9], [23], [39] has also been explored for different types of workflows. In particular, partitioning with respect to query workload has been explored by [17], [36], [37]. However, [36], [37] require row level labeling and hence the required compute is not scalable to enterprise data lake scale with 10^{12} rows in datasets of the order of terabytes. [37] requires modification of data (by appending tuple ids to rows) which is difficult on client data due to access restrictions. [37] proposed tuple reconstruction which becomes non-trivial to apply in our setting in tandem with tiering and compression (for both cost and latency estimation to maintain performance guarantees), due to variability of parameters across tiers and compression schemes. [17], [36], [37] do not easily adapt to dynamically changing data and workloads. We give a novel graph based modeling at file and query level which is

scalable, and easily adaptable to dynamically changing query workloads. Existing work considers disjoint partitions that often do not benefit the median query in a rich query set, whereas we allow overlapping partitions.

III. PROBLEM SETTING

Our problem is motivated by the cloud storage cost and performance considerations in the Adobe Experience Platform Data Lake, that is home to huge volumes of customer datasets, often being time series or event logs. The data resides in the cloud (e.g., Azure) and we get a break-up of costs at the end of a billing period, e.g., a month. The cost is incurred for storage over a period of time and per every access. We consider optimizing the total $costs^2$ at the end of a billing period, say, 'k' months for optimizing the COGS of the organization. Our model is run at the beginning of every billing period, to generate storage recommendations for all the datasets in the data lake for that billing period. The reader might be curious as to whether it adversely affects the cost to change storage tiers in such a periodic (batch processing) manner, instead of doing this much more frequently, in an ad-hoc way, especially if the data has an extremely fast changing access pattern. Note that changing storage tiers too frequently has the following disadvantages: i) early deletion charges per tier: data once moved to a tier, needs to reside there for a minimum period before we move it, otherwise we incur a penalty; ii) tier change costs: for every tier change there are read and write costs incurred, iii) tier change scheduler: this would need to run with increased frequency, hence incurring high compute costs, offsetting the tier change benefits. Moreover, if data compression and data partitioning are also involved, frequent changes would result in a huge amounts of additional compute cost of data processing, thus increasing the COGS.

We study the following problems.

- OPTASSIGN: Given predicted volume of accesses for datasets for a projected period, determine the optimal (in expectation) assignment of tier and compression scheme, while maintaining latency and capacity requirements.
- COMPREDICT: Accurately estimate the compression ratios and decompression speeds for different compression schemes on various datasets.
- DATAPART: Access pattern aware optimal and efficient partitioning of data.

Finally, we present the results for the unified pipeline, SCOPe: Storage Cost Optimizer with Performance Guarantees.

Datasets and Workloads (Access logs):

 Enterprise Data: (a) Enterprise Data I: enterprise Data Lake data (ADLS Gen 2), with hundreds of datasets ranging from TB to PB in size for several customers. Here we only have access to meta data and historical access logs at dataset level. (b) Enterprise data II: 3 tables for which queries as well as timestamp information are available. These are about 1.5 GB in total size.

²We use the cost parameters of ADLS Gen2. Similar analysis and modeling can be done with AWS, GoogleCloud and other cloud providers' parameters.

Here we have full access to data, but not the access logs, hence we have generated queries based on a skewed power-law (Zipf-like) distribution.

2) We use four variants of TPC-H data. It consists of 8 different tables of varying sizes with 22 different types of complex queries. We generated 20 queries from each query template and used them for experiments on our unified pipeline as well as for the compression predictor module in each case. (a) TPC-H 1GB with uniformly generated data, (b) TPC-H Skew generated with Zipfian skew (high skew factor of 3), (c) TPC-H-100GB with uniformly generated data, and (d) TPC-H 1TB with uniformly generated data.

We used PostgreSQL for TPCH data, and Apache Spark for enterprise data. Our enterprise data is partitioned and stored on ADLS Gen2 in parquet format.

IV. OPTASSIGN: OPTIMIZING OVERALL COSTS

OPTASSIGN determines optimal (in expectation) assignment of tier and compression schemes, given data partitions with predicted number of accesses for the projected period. It assumes that compression performance prediction is available as a look up for the given data partitions, or, in absence of that, only optimizes the tier assignments. OPTASSIGN maintains latency requirements, and also handles capacity constraints, in case there are storage reservations on tiers.

A. Mathematical Formulation

Let the number of storage tiers or layers be L. The storage cost of layer $\ell \in [L]$ is C_{ℓ}^s , read cost is C_{ℓ}^r , write cost is C_{ℓ}^w and the read latency is B_{ℓ} seconds per unit data. Let the reserved capacity (space) for storage be S_{ℓ} and the compute cost per second be C^c . Layer 0 denotes the lowest latency layer and L - 1 denotes the archival layer with the highest latency. Typically, S_{L-1} is ∞ . The tier change cost from tier u to tier v is $\Delta_{u,v}$, and this includes reading from layer u, writing to layer v and any other charges.

Let there be N data partitions \mathcal{P} and for each partition P_i , the span (or, size) is $Sp(P_i)$, and the projected number of accesses is $\rho(P_i)$. There is also a latency threshold $T(P_i)$ associated with each partition. Among these, \mathcal{I} (let $I = |\mathcal{I}|$) denotes existing ones, and the remaining are newly ingested in the current billing period. The current tier assignment for P_i is $L(P_i)$, and for newly ingested ones, we denote $L(P_i) = -1$. Now, the write costs for new partitions to tier ℓ can be written as $\Delta_{-1,\ell}$. In other words, $C_{\ell}^w = \Delta_{-1,\ell}$. All existing partitions have a predicted number of accesses based on past behaviour and dataset characteristics. In the case of newly ingested data, this is approximately estimated based on data quality considerations, query patterns on similar historical data, or client specific/domain knowledge. There are K compression algorithms, where one option is 'no compression', and R_i^k denotes the predicted compression ratio of algorithm k on P_i , and similarly D_i^k denotes the predicted decompression time (for 'no compression', R_i^k is 1 and D_i^k is 0 for all *i*). The compression scheme applied to a partition P_i is $K(P_i)$.

We give an ILP for the problem OPTASSIGN. $x_{n,\ell,k}$ is an indicator variable that is 1 when partition P_n is assigned to tier ℓ with compression scheme k, and 0 otherwise. α , β , γ are hyper-parameters to decide the weight for corresponding cost terms. The first term in the objective function represents the cost of writing data (either new data or existing data from another tier) and then storing it in a tier after applying a particular compression algorithm. The second term represents the expected decompression cost (compute cost) and read cost of the merged partitions. The first equality is for feasibility purposes: every partition must go to one tier and at most one compression algorithm can be applied to it. The second inequality constraint ensures that the data stored does not exceed the capacity for that layer, where the capacity is determined by capacity reservations on the cloud. (Note that in case there are no reservations, hence no upper bound, the capacity would be ∞ .) The third inequality is to ensure that decompression and read don't cause overhead in latency, and are less than the maximum latency threshold for any partition. Finally, the last equality forces that for existing partitions, the compression scheme does not change once applied; this is imposed to prevent additional latency and operational costs of frequently changing the compression of data partitions. Note that the above ILP can become infeasible due to capacity restrictions and latency constraints. In that case, the latency requirements need to relaxed iteratively till a feasible solution is found. However, in this case, there can be no solution satisfying all constraints, and it is a limitation of the system constraints, and not the solution.

$$\min \sum_{n=1}^{N} \sum_{k=1}^{K} \sum_{\ell=1}^{L} \left[\left(\alpha \ C_{\ell}^{s} + \gamma \Delta_{L(P_{n}),\ell} \right) \ \frac{Sp(P_{n})}{R_{n}^{k}} + \beta \rho(P_{n}) \left(C^{c} \ D_{n}^{k} + \ C_{\ell}^{r} \frac{Sp(P_{n})}{R_{n}^{k}} \right) \right] x_{n,\ell,k}$$

$$s.t. \ \sum_{\ell=1}^{L} \sum_{k=1}^{K} x_{n,\ell,k} = 1 , \forall \ n \in [N]$$

$$\sum_{n=1}^{N} \sum_{k=1}^{K} \frac{Sp(P_{n})}{R_{n}^{k}} x_{n,\ell,k} \leq S_{\ell} , \forall \ \ell \in [L]$$

$$\sum_{\ell=1}^{L} \sum_{k=1}^{K} \left(D_{n}^{k} + B_{\ell} \right) x_{n,\ell,k} \leq T(P_{n}) , \ n \in [N]$$

$$x_{n,\ell,k} \in \{0,1\} \ \forall n \in [N], \ \ell \in [L], \ k \in [K]$$

$$x_{n,\ell,k} = 0 \ \forall n \in [I], \ \ell \in [L], \ \forall k \neq K(P_{n})$$

$$(1)$$

The ILP can be extended to handle the scenario of computation pushdown or compression schemes allowing certain operations directly on the compressed data. Let f fraction of queries be amenable to such a pushdown and the remaining (1 - f)fraction would require decompression. Then only $(1-f)\rho(P_i)$ would contribute to the read and decompression-compute costs in the objective function for partition P_i , and similarly to the latency constraint, while the remaining fraction, $f\rho(P_i)$ would have 0 contribution to either. In this way OPTASSIGN can handle a partial storage disaggregation. Also note that OPTASSIGN is a general framework and can easily handle following scenarios: a total storage capacity provisioned per tier by the enterprise³, a customer specific capacity per tier ⁴, an unlimited (infinite) capacity per tier where there is no pre-determined storage entitlement but billing is per usage⁵ These variations would be determined from customer licensing agreements, pricing by the cloud storage operator, and internal cost considerations and demand projections. Moreover, by tuning the weights in the objective, one can give more weight to one type of cost over others as required by the application. (We show this in Section VII).

Theorem 1. OPTASSIGN is strongly NP-HARD.

Proof. This follows by a reduction from 3-PARTITION. Here we provide a proof sketch due to limited space. Consider an instance $\mathcal{I} = \{a_i\}$ of 3-PARTITION with n = 3v integers such that $\sum_{i \in [n]} a_i = Bv$. The decision question is whether there exists a partition of \mathcal{I} in to v groups, such that each group sums to exactly B. Now, construct a relaxed instance of OPTASSIGN, where cost parameters are 0, K = 0 (no compression algorithms) and latency thresholds are met by all tiers. We create a data partition of span $= a_i$ for each $a_i \in \mathcal{I}$. Let there be v tiers of storage, with a capacity limit of B per tier. It can be seen that a YES instance in the 3-PARTITION instance, and vice versa.

B. Polynomial Algorithms for Special Cases

1) Equal sized Partitions, No compression: Consider the case where the data partitions are of equal spans (i.e., $Sp(P_i) = S \ \forall i \in [N]$ for some S), and there are no compression schemes $(K = 0)^6$. Let all partitions be ingested at the same time, and no prior assignments exist. This is a possible scenario in practice when for a given storage account existing data are purged periodically, and new set of data are ingested. Since the span of each of the N data partitions is S, the capacity of each storage tier can be expressed as a multiple of S, without loss of any generality. Also, as earlier, archive tier has capacity ∞ . Since the data partitions are of equal sizes, we can consider the partitions to be of unit size. Now the capacity of each layer ℓ can be expressed as an integer Z_{ℓ} , where $Z_{\ell} = \min\{N, \lfloor \frac{S_{\ell}}{S} \rfloor\}$, because there are at most N partitions that need to be assigned.

Now, let us construct a bipartite graph $\mathcal{G} = (\mathcal{U}, \mathcal{V}, \mathcal{E}, \mathcal{W})$. There would be N nodes corresponding to the N data partitions in \mathcal{U} . For each of the L tiers (including archive), create Z_{ℓ} number of nodes in \mathcal{V} . Denote these as Z_{ℓ} copies of tier ℓ . The edge e = (u, v) between a data segment and every copy of a tier would exist only if the latency threshold of the data segment would not be violated by assigning the segment to the tier. The weight of each such edge would be determined by the storage cost of the tier and the expected read cost from that tier, as determined by the projected number of accesses of that data segment. Now, we solve a minimum weighted bipartite matching problem in this bipartite graph. Note that the size of the bipartite graph is polynomial since, there are at most N + N L nodes. The minimum weighted matching would select the edges of minimum total weight, such that every node is assigned to at most one copy of at most one tier. There would be at most Z_{ℓ} assignments to any tier, since there are only Z_{ℓ} nodes corresponding to each tier that can be selected by the matching. The selected edges would not violate the latency thresholds, as the edges exist only if the threshold would be satisfied by the assignment. Therefore, the assignment found by minimum weight bipartite matching is not only feasible, in terms of latency requirement for assignments to regular tiers, but also optimal in terms of overall costs for the projected period. The edge weights can also be tuned based on the chosen hyperparameters and weightage of the various cost factors. The run time is polynomial in the input size: $O(N^2L^2E)$. Fig.6(b) shows the above construction.

Theorem 2. There exists a polynomial time optimal algorithm for the case of equal sized data partitions and no compression.

Proof. The proof follows from the above discussion. Specifically, the assignment found by the matching is feasible by construction, and the overall weight of the edges chosen is minimum by the optimality of the minimum weight bipartite matching algorithm. The time complexity follows from the that of Hungarian method.

2) Unbounded Capacity: Consider the general version of OPTASSIGN (unequal sized partitions, multiple compression schemes) with the relaxation of the capacity constraints. Specifically, there are no capacity bounds on the tiers. This is a commonly occurring scenario in practice, including in our private enterprise Data Lake setting. In this case, a simple greedy algorithm gives the optimal solution. For every partition P_i , compute the set of feasible tuples (ℓ, k) of tier and compression algorithm, and the choosing the lowest cost option per partition. This is feasible since there are no capacity restrictions and gives the optimal solution overall. The run time is $O(N \ L \ K)$, and for constant L and K, this becomes linear in the number of partitions.

Theorem 3. There exists an optimal polynomial time algorithm for OPTASSIGN when there are no capacity constraints.

Proof. Since the greedy algorithm evaluates the lowest cost option for every merge, the overall cost is the lowest. If the

³In this case, the *L* constraints on per layer storage capacity S_{ℓ} would be replaced by a single constraint, on the total sum of the storage used across all layers being bound by a capacity *S*.

⁴Here, the per layer storage constraint would be replaced by Q constraints, one per customer for a total of Q customers.

⁵Here, $S_{\ell} = \infty \forall L$, hence the L constraints on capacity can be removed. ⁶We **do not require partitions to be equal sized** and can handle different compression algorithms. The **datasets are of varying sizes in our experiments**. However, it is a possible scenario that can be enforced from the system administrator end, as a part of the data ingestion workflow, if the client requires this functionality or for facilitating data management. For example, one can configure file sizes to a certain set value by the command ' write.targetfile-size-bytes' as per https://iceberg.apache.org/docs/latest/configuration/), or specify the default parquet compression level to be null.

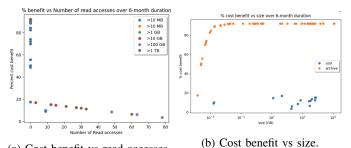
overall cost is not the lowest, there has to be at least one feasible assignment of lower cost, but the greedy algorithm would have considered at one of the options, and would have therefore selected it. $\hfill \Box$

C. Empirical Validation on Enterprise Data

We applied OPTASSIGN with K = 0 on Enterprise Data I using datasets as the data partitions, and projected access patterns for 6 months using historical access logs. These datasets are large, ranging from TB to PB. We observed significant cost reduction benefits over the platform baseline. Figure 3 shows the % cost benefit vs size and number of accesses for files for 6 month projections for one customer account. We show in Table II the projected cost benefits for 4 different customer accounts. Our methods are scalable and computationally efficient (e.g., the optimization took 2.53s on 463 datasets of customer B from Table II).

TABLE II: % cost benefits for data across 4 customers.

	Total Size (PB)	% Cost	Benefit
	Iotal Size (PD)	2 mos	6 mos
Customer A	0.56	10.59	61.6
Customer B	0.45	8	53.72
Customer C	0.053	11.58	83.69
Customer D	0.085	9.93	49.6

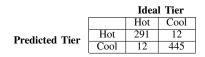


(a) Cost benefit vs read accesses.

Fig. 3: Projected percent cost benefit for next 6 months (considering transfer from hot tier to cool+archive tiers)

Predicting Access Patterns and Quantifying Errors Predicting access patterns is a non-trivial problem. We have proposed a Random Forest model that is near optimal, with high precision and recall (F-1 score > 0.96). Table III shows the confusion matrix for one storage account. Random Forest showed the best overall performance compared to others like Gradient Boosted Trees and LSTMs. We used OPTASSIGN

TABLE III: Confusion matrices for predicted vs ideal tiering for one storage account (Around 700TBs of data in 760 datasets) over a 2 month prediction horizon.



to assign the ground truth label encoding (i.e. the optimal tier) for each dataset while training the model. For prediction

experiments, we ensured out-of-time validation and testing, and ran experiments on Apache Spark. The features used were (i) dataset size, (ii) months since dataset creation, and aggregated monthly (iii) read and (iv) write accesses for the last few months. The model needs to be retrained periodically for the next cycle (whose duration is adjustable) to account for changes in access pattern distributions. The cost for this batch job and the compute cost of applying the tiering operation is negligible compared to the tier change costs of the public cloud storage provider. The % benefit shown is computed after deducting this cost, which shows that our model is practically feasible. Table IV shows how our results are consistent over multiple prediction horizons as well as how we compare to other tiering baselines, including caching based ones. Note that even after making errors, the % benefit is close to the ideal case where all access information is known beforehand. Moreover, making significant mistakes is unlikely given the typical skewed or seasonal enterprise query workloads which are predictable enough by ML models to determine the optimal tier. Also note that the benefit is higher when we look at longer prediction horizons since lesser number of tier changes are required, as expected. Bringing in the archive layer helps increase the % as well. Regarding performance considerations - while expected latencies are bounded as required by SLAs, there can be occasional unexpected accesses, causing tail latencies to be longer. A comparison with additional nontrivial baselines that also consider partitioning, latency, and compression along with multi-tiering is given at the end of the paper. Caching inspired baselines in rows 2 and 3 perform poorly because of two main reasons. i) Firstly, recency of access does not guarantee access in the next projected period, and one would need to train an ML model for that. ii) Secondly, even if access prediction is 100% correct and a dataset is certainly going to be accessed in the next billing period, the optimal tier (from cost perspective, subject to performance considerations) might still not be hot, given the dataset size, the number and type of accesses, the amount of data to be accessed, tier change costs (if applicable), cloud cost parameters, as well as SLA and availability agreements with clients, which vanilla caching rules do not consider.

TABLE IV: Comparison of OptAssign (with predicted or known access information) with intuitive baselines for the same storage account in Table III.

Model	Access Information	Duration (months)	Benefit
All hot	N/A	2	0%
"Hot" if data accessed in last 2 mos	N/A	4	2.67%
"Hot" if data accessed in last 1 mo	N/A	4	3.25%
Use optimal tier of prev. month	N/A	2	5.07%
OptAssign (Hot, Cool)	Predicted	2	9.570%
OptAssign (Hot, Cool)	Predicted	4	13.58%
OptAssign (Hot, Cool)	Known	2	9.574%
OptAssign (Hot, Cool)	Known	4	13.62%
OptAssign (Hot, Cool)	Known	6	15.39%
OptAssign (Hot, Cool, Archive)	Known	6	43.8%

V. COMPREDICT: COMPRESSION PREDICTOR

We present COMPREDICT, which estimates compression ratios and decompression speeds for data partitions on the fly. This involves training a model that is a one-time task, assuming the distribution of data types and other features remain largely unchanged⁷. The model is trained to predict for a few popular compression schemes: gzip, snappy, and lz4 and two different data storage layouts (row-store and columnstore). We found that our method also works well on other compression schemes like bz2, zlib, lzma, lzo, and quicklz, however we have omitted those results due to lack of space.

Data Sources and Features: Intuitively, compression performance can depend on various factors, such as, choice of compression scheme, data storage layout (row ordering vs column ordering), size of datasets, and characteristics of the data, e.g. data types, repetition in the data, entropy in the data, organization of data contents (sorted vs unsorted) among others. Existing approaches for predicting comrpession performance often use random samples from the dataset and simple features based on size or datatype. From Fig. 4 we can see that a sample formed from randomly sampled rows is typically not a good representation of the data that is usually queried from tabular datasets. We propose that this is because queried data typically has more repetition, which results in higher compression ratios compared to random samples. Note that if samples are generated in query aware pattern, skew in query workload can also have an effect. Considering only features like dataset size, datatype, or assuming a fixed data distribution like in prior art [14] is not enough to capture such notions. We created 'weighted entropy' features for each partition P, with one feature for each data type present in P: $H(P,d) = -\sum_{s \in P[:,d]} len(s) \times pr(s) \times \log(pr(s)), d \in D$ Here D denotes the set of datatypes of columns present

in the partition P (e.g. int, float, object, etc). For all strings s that occur within the columns of a particular datatype d, we compute the probability of occurrence pr(s) and length len(s) of each string. H(P,d) gives us an approximate representation of the amount of repetition in the table with datatype d. Computing these features requires a one-time full scan of each partition. The samples used to train the model

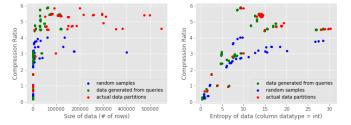


Fig. 4: Compression Ratio vs Size (left) and Compression Ratio vs Entropy (right) on TPC-H dataset using gzip.

are derived from results of queries run on partitions. The

number of samples required depends on the nature of the query workload. Computing the samples and features took around 2-3 hours. Training the model takes a few seconds, and inference is almost instantaneous. Table V shows a comparison of data samples (random vs query based) and features (size vs weighted entropy) for prediction on gzip, using Random Forest model. From Fig. 4 and Table V we can conclude that query based sampling using weighted entropy features are more effective for prediction.

TABLE V: Compression Ratio & Decompression Speed Prediction by Random Forest model for Various Training Data and Features (GZIP Compression on TPC-H 1GB)

	Training Data	Features	MAE	MAPE	R2
	Random Samples	Weighted Entropy	1.022	72.188	-0.656
Compression Ratio	Queries	Size	0.049	3.013	0.995
	Queries	Weighted Entropy	0.021	0.527	0.988
	Random Samples	Weighted Entropy	18.713	268.627	0.069
Decompression Speed	Queries	Size	2.398	5.555	0.792
	Queries	Weighted Entropy	0.254	1.215	0.989

Row vs Column Oriented Storage: Data can be stored in a row oriented fashion, with consecutive row entries stored adjacently, or in a column oriented fashion, with consecutive column entries stored adjacently. It is important to consider how this nuance effects the dynamics for compression ratio predictions. In our experiments, we used CSV files as an example of row storage and Parquet files (common in enterprise data lakes) for columnar storage. Overall, the prediction performance was good in both cases, though the results are slightly better for row storage.

Models and Datasets: We trained several statistical models (XGBoost, Random Forest, SVR) and a Neural Network (MLP) with the features as input to predict compression ratios and decompression speeds. Apart from the naive model of simply averaging, these models performed well and are comparable, while Random Forest performs the best. Tables VI, VII and VIII, show the results on TPC-H 1GB, TPC-H 100GB and TPC-H 1GB with Zipfian skew.

Sorting Data: We briefly investigated how the prediction varies if the data is sorted by different columns. The difference in compression ratios between data sorted by different columns is generally small (of the order of our prediction error). We proposed 'bucketed weighted entropy' features for capturing the effect of sorting on the entropy of columns. Specifically, the bucketed entropy would be computed for each successive 20% of rows. Our hypothesis was that for column-store data, there would be a greater change in the compression ratios because entries of a column are stored together, and thus the model should work better for parquet compared to csv files. Empirically, however we observed that prediction performance using the new entropy features was similar to using the older features. We leave further exploration on this as future work.

Effect of COMPREDICT on OPTASSIGN: We compare the effect of the predictions of compression ratios and decompression times on OPTASSIGN. We compute the storage cost, read + compute cost, and latency time of this placement using ground truth compression values as the baseline. The optimization is computed for a range of many different values of α and

⁷This has to be repeated at periodic intervals to handle slow changing data type distributions

TABLE VI: Compression Ratio Prediction for Various Models, Compression Schemes, & Data Layouts (TPC-H 1GB)

Model	gzip				snappy			parquet + gzip			parquet + snappy			parquet + lz4		
Niodei	MAE	MAPE	R2	MAE	MAPE	R2	MAE	MAPE	R2	MAE	MAPE	R2	MAE	MAPE	R2	
Averaging	0.215	5.353	-	0.074	3.315	-	0.781	23.154	-	0.531	20.101	-	0.483	19.494	-	
XGBoost	0.033	0.851	0.991	0.017	0.733	0.991	0.057	1.482	0.989	0.040	1.305	0.988	0.036	1.206	0.992	
Neural Network	0.030	0.793	0.993	0.02	0.930	0.985	0.062	1.549	0.991	0.049	1.730	0.992	0.047	1.747	0.990	
SVR	0.071	1.920	0.977	0.069	3.049	0.885	0.089	2.633	0.991	0.089	3.477	0.984	0.091	3.632	0.983	
Random Forest	0.021	0.527	0.988	0.011	0.453	0.989	0.043	0.996	0.983	0.029	0.948	0.985	0.026	0.901	0.989	

TABLE VII: Compression Ratio Prediction for Various Models, Compression Schemes, and Data Layouts

Model		gzip		pa	rquet + gz	zip
Would	MAE	MAPE	R2	MAE	MAPE	R2
		TPC-H	100GB			
Averaging	0.083	2.378	-	0.324	8.795	-
XGBoost	0.105	2.838	0.936	0.151	3.751	0.943
Neural Network	0.081	2.232	0.968	0.147	3.535	0.962
SVR	0.105	3.077	0.948	0.19	4.765	0.914
Random Forest	0.078	2.151	0.969	0.134	3.369	0.966
		ТРС-Н	Skew			
Averaging	0.120	4.915	-	0.601	32.491	-
Neural Network	0.125	3.868	0.975	0.336	15.953	0.847
SVR	0.101	4.280	0.992	0.163	8.526	0.969
Random Forest	0.093	3.005	0.988	0.251	12.127	0.894
XGBoost	0.066	2.467	0.992	2.009	6.145	0.897

 β for comparing the cost-vs-latency tradeoffs for the predictors (Fig. 5). Here we show OPTASSIGN using prediction from SVR on queried samples using weighted entropy features performs very close to ground truth compression for the TPC-H 1GB dataset, not leaving much room for improvement. The magnitude of errors made by our compression predictor is low as seen from the tables shown. In fact, the impact of these errors on the final cost is also minimal since the purple (ground truth compression) and green (our predictor) curves in Fig. 5 are almost the same. This means both would result in similar latency and storage cost across different tier assignments, unlike other baselines (shown in red and blue).

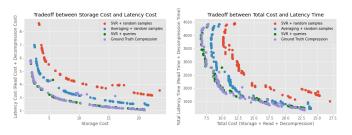


Fig. 5: Left: Latency Cost vs Storage Cost, Right: Total Cost vs Latency Time. Different tradeoff curves correspond to different compression predictors used.

VI. DATAPART: ACCESS AWARE DATA PARTITIONING

Data partitioning in an access pattern aware manner is important for skewed workloads where different parts of a dataset are accessed with widely different frequencies.

DATAPART considers the (minimal) set of records that need to be scanned by a query in an attribute agnostic manner. It then merges these sets of records to generate the data partitions, such that the total scans (read cost) incurred by

TABLE VIII: Decompression (sec/GB) Prediction for Models,
Compression Schemes, Data Layouts

Model		gzip		pa	rquet + gz	ip
woder	MAE	MAPE	R2	MAE	MAPE	R2
		ТРС-Н	100GB			
Averaging	0.679	3.732	-	5.672	43.472	-
XGBoost	0.322	1.773	0.972	1.606	10.168	0.75
Neural Network	0.147	3.535	0.962	1.86	10.875	0.522
SVR	0.399	2.153	0.961	1.147	10.152	0.949
Random Forest	0.292	1.601	0.98	1.165	9.698	0.799
		ТРС-Н	Skew			
Averaging	7.037	29.979	-	30.134	125.23	-
MLP	1.862	5.860	0.917	9.380	21.526	0.880
SVR	3.431	15.568	0.847	7.020	19.508	0.955
XGBoost	2.009	6.145	0.897	6.330	12.284	0.948
Random Forest	1.141	4.910	0.922	5.194	7.983	0.915

queries is **within a limit**, while the overall space required by such partitions is **minimized** (by reducing overlapping content across partitions). We want to generate balanced size partitions and not fragment the data too much. The decision to make the partitioning attribute agnostic was driven by enterprise data privacy regulations. Fragmenting users' data across multiple partitions is also undesirable, since that would require that many additional scans of files, hence increasing compute costs (COGS). Informally, our goal is to partition the datasets such that all the files that are generally accessed together belong to the same partition. The files or the contiguous blocks of records need not be adjacent in general (Fig. 6(a)).

A. Problem Definition

Define a query family to comprise of all queries that map to the same files in the data tables. Consider a query family Qaccessing the following files from $D: \{R_1, R_2, \ldots, R_u\}$. This set constitutes an initial (naive) partition of the dataset $P_Q =$ $\{R_1, R_2, \ldots, R_u\}$. Let there be N such initial partitions: \mathcal{P} , generated from historical access logs. DATAPART would generate the final partitions by merging (some of) these initial partitions in order to optimize certain metrics. We define the span of a partition $P_i \in \mathcal{P}$ as: $Sp(P_i) := \sum_{R_k \in P_i} |R_k|$, where $|R_k|$ denotes the number of rows or records in the file R_k . The overlap between two partitions P_i and P_j is the length of files (or, number of records) in common to both partitions, and is computed as $Ov(P_i, P_j) = Sp(P_i) + Sp(P_j) - Sp(P_i \cup P_j).$ Span of a merge of partitions P_i and P_j , $Sp(P_i \cup P_j) \leq$ $Sp(P_i) + Sp(P_i)$ due to potential overlap between P_i and P_i . Formally, a merge \mathcal{M} refers to the union of a set of partitions $\{P_i, P_j, \ldots, P_k\}$ with a span $Sp(\mathcal{M}) = Sp(\bigcup_{P_\ell \in \mathcal{M}} P_\ell).$

Each partition P_i has an associated access frequency $\rho(P_i)$. The access frequency of a merge is simply the sum of the accesses of the constituent partitions. We require the access frequencies of partitions merged should be comparable. Hence we define a feasible merge \mathcal{M}_k as: any pair of partitions $(P_i, P_j) \in \mathcal{M}_k$ satisfy at least one of following conditions: (i) $\frac{1}{\rho_c} \leq \frac{\rho(P_i)}{\rho(P_j)} \leq \rho_c$, or, (ii) $|\rho(P_i) - \rho(P_j)| \leq \rho'_c$, for constants ρ_c and ρ'_c .

Let the 'cost' of a merge, measured as the expected read cost, depending on the size and expected number of accesses be defined as: $C(\mathcal{M}_k) = Sp(\mathcal{M}_k)\rho(\mathcal{M}_k)$.

The goal is to choose a set of merges Z such that each (initial) partition is part of at least one merge, the total cost of Z is bounded, and the total space required by Z is minimized.

We formulate this MERGE PARTITIONS mathematically as an ILP as follows. Let \mathcal{M} denote the set of feasible merges (as defined earlier). In order to ensure that there is always a feasible solution, we allow individual partitions also as feasible choices for merges. Let y_k be an indicator variable that is 1 if merge \mathcal{M}_k is chosen in the solution, and 0 otherwise. The first inequality ensures that the (expected) total read cost of all the merges is at most C_{thresh} . Let $x_{\ell,k}$ be another indicator variable that is 1 if initial partition (or, vertex) P_ℓ is covered by merge \mathcal{M}_k in the solution, and 0 otherwise. In other words, this is 1 when $P_\ell \in \mathcal{M}_k$ and \mathcal{M}_k is chosen in the solution, and 0 otherwise (if a merge \mathcal{M}_k is not part of the solution, $x_{\ell,k}$ must be 0, and this is ensured by the second inequality). Every partition P_ℓ must be covered by at least one merge chosen in the solution, and this is ensured by the third inequality.

$$\min \sum_{k \in [1,...,|\mathcal{M}|]} Sp(\mathcal{M}_k) \ y_k$$

s.t.
$$\sum_{k \in [1,...,|\mathcal{M}|]} Sp(\mathcal{M}_k)\rho(\mathcal{M}_k) \ y_k \le C_{thresh}$$
$$x_{\ell,k} \le y_k \ \forall P_\ell \in \mathcal{M}_k, \ \forall \mathcal{M}_k \in \mathcal{M}$$
$$\sum_{\mathcal{M}_j \in \mathcal{M}|P_\ell \in \mathcal{M}_j} x_{\ell,j} \ge 1 \ \forall P_\ell \in \mathcal{P}$$
$$y_k \in 0, 1 \ \forall M_k \in \mathcal{M},$$
$$x_{\ell,k} \in 0, 1 \ \forall P_\ell \in \mathcal{P}$$
(2)

The ILP finds the set of merges to minimize the overall space, while covering all segments, keeping cost of merges bounded by C_{thresh} .

Theorem 4. MERGE PARTITIONS is NP-HARD.

Proof. This follows by a reduction from a partitioning problem studied by Huang et al. [42], where records are shared across versions of datasets, leading to overlap. Their goal is to divide the set of all versions into different groups, and simply store the groups (or, merges), reducing overall storage space and the overall average checkout cost, assuming equal frequency of checkout of each version. They show the problem of minimizing the checkout cost while keeping the storage cost less than a threshold is NP-HARD. We construct an instance of MERGEPARTITIONS, where corresponding to each version, we create a query family (initial partition), and corresponding to each record we create a file, that can be shared across partitions. We want to merge them into groups, reducing overall

storage cost, keeping read costs under a threshold. Assuming equal access frequency, it can be seen that the decision version of MERGEPARTITIONS reduces to the decision version of MINIMIZE CHECKOUT COST (that is, storage cost $\leq \gamma$ and read cost $\leq C_{thresh}$), shown to be NP-HARD by Huang et al. Details omitted due to lack of space.

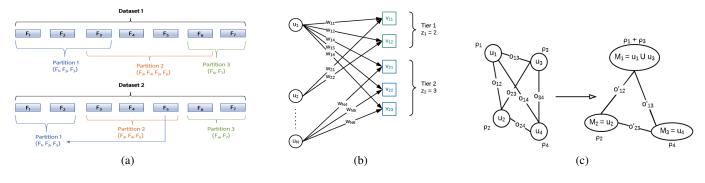
1) Algorithm for the General Case: G-PART: In order to understand the merging problem better, let us consider a graph representation $\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathcal{W})$ where each initial partition P_i is a node $\in \mathcal{V}$ in graph \mathcal{G} . An edge e = (v, u, w) between two vertices v and u in \mathcal{V} with weight $w = \frac{Ov(v,u)}{Sp(v\cup u)} > 0$ denotes the fractional overlap between the partitions v and u. (w = 0corresponds to no overlap between two partitions, hence, there is no edge between them). Now, merging can be thought of as merging of nodes to create meta-vertices, collapsing the internal edges, and re-defining edges incident on the metavertices from neighbors. (Fig.6(c)).

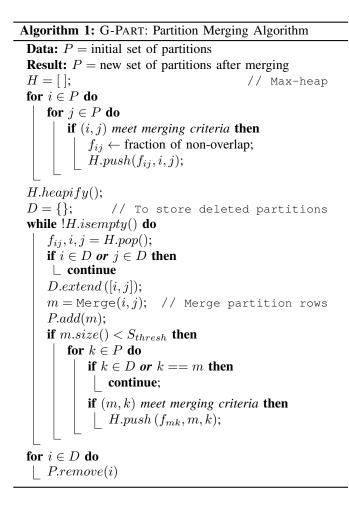
We give a greedy algorithm G-PART for the general graph case that does very well in practice, especially as a key ingredient in the unified pipeline SCOPe and also helps baselines improve significantly. In this algorithm, along with the hard feasibility (based on accesses, as defined earlier) constraints, we address a soft constraint S_{thresh} on the span of merges. Specifically, once a merge is $\geq S_{thresh}$, we don't merge other partitions to it. The intuition is to prevent the merging of too many vertices together, to avoid undue increase in read costs.

We next describe G-PART informally. (The pseudocode is given in Algorithm 1.) We first filter the edges to determine the set of feasible edges. We store the edges in a max-heap, where the heapification is on the weights (denoting the fractional overlaps) of the edges. We pick the top most heap element edge (this has the highest fractional overlap between the pair of segments) and merge the corresponding pair of partitions. Let u and v be the corresponding nodes. We create a new (merge) node u', while removing u and v from \mathcal{V} . \mathcal{V} is updated as $u' \cup \{\mathcal{V} \setminus \{u, v\}\}$. Similarly, the edge $e_{v,u}$ is deleted from \mathcal{E} . If the span of the merged node $Sp(u') \geq S_{thresh}$, for some constant S_{thresh} , then we don't consider the merged node any further. Specifically, we remove every edge e' = (w, x), where $x \in \{u, v\}$), for any $w \in \mathcal{V}$ from \mathcal{E} , and delete these edges from the heap. However, if $Sp(u') < S_{thresh}$, then it goes back as a candidate for further merging. In this case, for every edge e' = (w, x) for any $x \in \{u, v\}$ and $w \in \mathcal{V}$, we replace it with e'' = (w, u') in \mathcal{E} (and delete e' from the heap, if it was present in the heap). If e'' satisfies the feasibility constraints, we add it to the heap with a weight corresponding to the fractional overlap of u' with w. Now, we repeat the process with the next top heap element, till the heap is empty. Note that at the end we might be left with singleton partitions that do not meet the feasibility constraints for merging. These are (individually) added to the set of final merges or partitions.

Space and Cost trade-off achieved by G-PART: We evaluate G-PART on TPC-H 1GB and TPC-H 100GB to compare the duplication of data with the cost of merging

Fig. 6: (a) Data partitioning examples. (b) Bipartite matching for equal sized partitions with no compression. (c) Merging of nodes by G-PART in a graph setting.





in Fig. 7^8 . G-PART provides a good trade-off between the unmerged case and merging all partitions.

Complexity of G-PART: Consider there are m query families. Let the number of files across all datasets in a client org be n. Initial processing to generate initial partitions would require a space of at most O(mn) (In general it would be

much less, say, O(mk) where k is the average number of files accessed by each query family). There would be m initial partitions, and $O(m^2)$ edges. For estimating the cost of each edge, one would need to find the intersection of the sets (of files in each partitions) and the total length of each partition (sum of the size of the files, maintained as file meta data). The heap construction followed by G-PART merging and heapifying would take $O(m^2 \log m)$. This can adapt dynamically to changing query workloads. For each new query family observed in the workload, we create an initial partition, by labeling the query family with the accessed files. This results in a new node in the graph. If the current number of merged partitions is $m' \ll m$, at most O(m') new edges get added. This can result in $O(m' \log m')$ operations for heapifying followed by merging operations.

B. Special Case: Ordered Partitions

Consider an inherent ordering between the files, such as that arising for time series data. Let us assume that the data is time stamped. Each query, and hence partition P_i has a fixed start time $s(P_i)$ and a fixed end time $e(P_i)$. Let us order the partitions by their end times. We only consider distinct queries. Let this ordered set be \mathcal{P} , where $|\mathcal{P}| = N$. Partition $P_i \in \mathcal{P}$, has the i^{th} latest end time and P_1 has the first end time.

Since the main motivation in merging is exploiting the overlap between partitions or segments, we only consider combinations of adjacent segments in the order in which they occur in the ordered list. More specifically, consider partitions $\{P_i, P_{i+1}, P_{i+2}\} \in \mathcal{P}$. The possible set of (merged) segments corresponding to these are: (i) $\{P_i\}, \{P_{i+1}\}, \{P_{i+2}\}$, or, (ii) $\{P_i, P_{i+1}\}, \{P_{i+2}\},$ or, (iii) $\{P_i, P_{i+1}\}, \{P_{i+2}\},$ or, (iv) $\{P_i, P_{i+1}, P_{i+2}\},$ but not $[\{P_i, p_{i+2}\}, \{p_{i+1}\}].$

The number of possible merges, that is, $|\mathcal{M}|$ is $O(N^2)$. Without loss of generality, we assume that for every P_i , with end time $e(P_i)$, the start time of P_{i+1} , $s(P_{i+1}) < e(P_i)$. (For any pair of *i* and *i*+1 where this does not hold, we can consider the set of partitions $\{P_1, \ldots, P_i\}$ and $\{P_{i+1}, \ldots, P_N\}$ to be disjoint and solve the merging separately for each set.)

We define a dynamic program here. Consider the subproblem of covering partitions $[P_1, \ldots, P_i]$. Define the set of feasible merges containing partition P_i as \mathcal{F}_i . As defined

⁸Duplication is computed as $1 - \frac{|\{P_i\}|}{|P_i|}$, where $\{P_i\}$ denotes the set of distinct elements (records) in P_i . The cost of merging is computed as the increase in expected read cost due to merging.

earlier, $\mathcal{F}_i = \{[P_1, P_2, \dots, P_i], [P_2, \dots, P_i], \dots, [P_i]\}$. Any feasible solution on partitions $[P_1, \dots, P_i]$ must include a merge in \mathcal{F}_i . For ease of analysis, WLOG, we add a dummy partition P_0 of $Sp(P_0) = 0$ and $\rho(P_0) = 0$.

Let us denote the merge $[P_{i-k}, \ldots, P_i]$ as \mathcal{M}_i^k for $k \in \{0, 1, \ldots, i-1\}$. We define the parent of \mathcal{M}_i^k as $P(\mathcal{M}_i^k) := P_{i-k-1}$ for $k \leq i-1$ (P_0 for k = i-1). The notion of parent simply implies that if a feasible solution chooses \mathcal{M}_i^k , then (i) it must include additional merges to cover $[P_0, \ldots, P(\mathcal{M}_i^k)]$, and such a solution must fit within the remaining cost budget after the choice of \mathcal{M}_i^k . The recurrence relations are:

For i = 0, $ALG[P_0, C] = 0 \ \forall C \ge 0$.

For i > 0 and $0 \le C \le C_{thresh}$,

 $ALG[P_i, C] = \min_{k \in [0, \dots, i-1] | C(\mathcal{M}_i^k) \le C} ALG[(P(\mathcal{M}_i^k)), C - C(\mathcal{M}_i^k)] + Sp(\mathcal{M}_i^k) \ \forall \ i \in [N], \ \forall \ 0 < c \le C.$

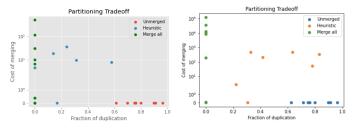
Theorem 5. $ALG(P_N, C_{thresh})$ minimizes the overall space given a budget C_{thresh} on the total (expected) read cost.

Proof omitted due to lack of space, however it follows by induction, based on induction hypothesis, after proving the optimality of base cases. The time complexity of ALG is $O(N^2C_{thresh})$, which makes it pseudo-polynomial solution because of the dependence on C_{thresh} . To get a polynomial approximation scheme, we bucket the range of C_{thresh} .

Theorem 6. Let the optimal solution for N partitions with a cost threshold C_{OPT} require space $OPT[N, C_{OPT}] = S_{OPT}$. Then there exists a polynomial algorithm that finds a solution of space $\leq S_{OPT}$, within a cost at most $(1 + N\epsilon)C_{OPT}$ in $O(N^2(N + \frac{1}{\epsilon}))$ time for any fixed $\epsilon > 0$. For $\epsilon = \frac{1}{N}$, we get a (1, 2) bi-criteria approximation of (S_{OPT}, C_{OPT}) in $O(N^3)$.

Proof is omitted due to lack of space. The main idea is to discretize the range of cost values by rounding up by ϵ , extending the cost threshold by $N\epsilon$, and solving ALG on this setting. It can be argued that extending the cost threshold by $N\epsilon$ would ensure a feasible solution exists. By optimality of ALG, the space required by ALG would be minimum, hence $\leq S_{OPT}$, and by feasibility of ALG, the total cost would be bounded by $\leq (1 + N\epsilon)C_{OPT}$. For $\epsilon \leq 1/N$, the cost is $\leq 2C_{OPT}$, giving the (1, 2) bi-criteria solution.

Fig. 7: Space cost tradeoffs in partitioning. Each dot in the scatterplot represents a table. We consider 3 cases - (i) no merging, (ii) G-PART heuristic, and (iii) merging all partitions. Left: TPC-H 1GB, Right: TPC-H 100GB.



VII. UNIFIED PIPELINE SCOPE

Here we present the unified pipeline SCOPe that combines all the modules OPTASSIGN, COMPREDICT and G-PART to optimize the overall costs, while maintaining performance guarantees. We use TPC-H 100GB, TPC-H 1TB datasets and Enterprise datasets I for these experiments. The pipeline is as follows. First we generate initial partitions using query logs. These are merged using G-PART to generate final partitions. After this, COMPREDICT predicts the compression ratio and decompression speeds for each partition. Finally, OPTASSIGN finds optimal tier and compression scheme assignment for the partitions, minimizing the overall costs, including storage and read costs, subject to capacity constraints and latency SLAs.

Comparison with Baselines: To the best of our knowledge, SCOPe as a pipeline is unique, and there are no direct baselines we could compare with. However, by tuning the parameters of OPTASSIGN, we can choose to optimize either only tiering and no compression (K = 0), or, only compression and no tiering (L = 0), or, minimize the latency due to read costs and decompression costs ($\alpha = 0$). These variants would map to an adaption of existing storage optimization approaches like HCompress [14] (focused on reducing latency), Hermes [21] (focused on multi-tiering), and Ares [15] (focused on compression), which were originally designed for different settings with I/O workloads. Hence, these can be thought of as our baselines, adapted to our setting. We can see that overall, SCOPe performs very well and minimizes the costs while maintaining good trade-offs on the different costs and latency. Moreover, we show that applying G-PART to generate data partitions before applying the baseline methods, significantly improves the performance of baselines⁹. The optimization takes about 47.4 ms on average (min 35 ms, max 470 ms) for optimization given one set of hyperparameters. Tuning the hyperparameters for optimization takes ≈ 18.9 s.

All costs of Tables IX, X and XI are calculated over a 5.5 month duration using Azure cost parameters. We considered the cost savings opportunity by only considering Premium, Hot and Cool Layers (and not Archive, since that has an early deletion period of 6 months. We have examined Archive benefits in our Enterprise Data I experiments described earlier). Next we explain the structure of the tables and the results. The rows refer to policies. The column ('Other methods ...') refers to the closest baseline in the literature. The last column 'Tiering Scheme' refers to the to the number of partitions (or, datasets) assigned to tiers [Premium, Hot, Cool] respectively. The other columns are self-explanatory.

The first 4 rows of the table focus on standard approaches that are generally followed and these typically have higher total costs. Row 1 and 2 store everything on premium, generally incurs low read costs and high storage costs. Row 3 'Multi-Tiering' refers to optimal multi-tiering and incurs much lower storage costs, but read costs and read latencies are higher. Since there is no compression, there is no decompression cost

⁹All results are generated using ground truth compression data ensuring a fair comparison.

TABLE IX: Results for Enterprise Data II.

Variants we can support	Other methods we can adapt	Р	Т	С	Storage Cost	Decomp. Cost	Read Cost	Total Cost	Read Latency (TTFB, s)	Expected Decomp. Latency (ms)	Tiering Scheme
Default (store on premium)	-	-	-	-	150.1	0.0	18.74	168.9	0.024	0.0	[3, 0, 0]
Compress & store on premium	Ares	-	-	Y	138.8	0.1	18.5	157.4	0.024	0.016	[3, 0, 0]
Multi-Tiering	Hermes	-	Y	-	20	0.0	62	82	0.281	0.0	[0, 2, 1]
Latency time focused	HCompress	-	Y	Y	49.6	0.0	49.4	98.9	0.165	0.0	[2, 1, 0]
Partition & store on premium	-	Y	-	-	102.7	0.0	1.2	103.9	0.024	0.0	[23, 0, 0]
Partitioning + Tiering	Hermes + G-PART	Y	Y	-	36.3	0.0	26.7	62.9	0.281	0.0	[0, 4, 19]
Partitioning + Compression	Ares + G-PART	Y	-	Y	130.1	0.8	2.3	133.1	0.024	0.170	[23, 0, 0]
SCOPe (Latency time focused)	HCompress + G-PART	Y	Y	Y	94.9	0.0	26.4	121.2	0.164	0.0001	[16, 3, 4]
SCOPe (No capacity constraint)	-	Y	Y	Y	22.7	0.6	7.0	30.3	0.216	0.131	[2, 11, 10]
SCOPe (Read+Decomp. cost focused)	-	Y	Y	Y	75.5	0.5	5.2	81.2	0.084	0.110	[6, 15, 2]
SCOPe (Total cost focused)	-	Y	Y	Y	22.7	0.6	7.0	30.3	0.216	0.131	[2, 11, 10]

TABLE X: Results for the TPC-H dataset (100GB).

Variants we can support	Other methods we can adapt	Р	Т	C	Storage Cost	Decomp. Cost	Read Cost	Total Cost	Read Latency (TTFB, s)	Expected Decomp. Latency (ms)	Tiering Scheme
Default (store on premium)	-	-	-	-	8741.9	0.0	3828.5	12570.4	0.18	0.0	[8, 0, 0]
Compress & store on premium	Ares	-	-	Y	7138.2	121.1	3387.5	10646.8	0.18	3.61	[8, 0, 0]
Multi-Tiering	Hermes	-	Y	-	8741.8	0.0	3828.5	12570.4	0.18	0.0	[5, 3, 0]
Latency time focused	HCompress	-	Y	Y	3288.4	0.0	22805.0	26093.4	0.68	0.0	[7, 0, 1]
Partition & store on premium	-	Y	-	-	8702.6	0.0	117.3	8819.9	0.18	0.0	[137, 0, 0]
Partitioning + Tiering	Hermes + G-PART	Y	Y	-	1397.0	0.0	415.3	1812.4	2.06	0.0	[0, 94, 43]
Partitioning + Compression	Ares + G-PART	Y	-	Y	5480.4	32.1	60.9	5573.4	0.18	0.96	[137, 0, 0]
SCOPe (Latency time focused)	HCompress + G-PART	Y	Y	Y	5178.1	0.0	544.5	5722.6	0.48	0.0	[108, 0, 29]
SCOPe (No capacity constraint)	-	Y	Y	Y	691.4	29.9	219.3	940.6	2.06	0.89	[0, 94,43]
SCOPe (Read+Decomp cost focused)	-	Y	Y	Y	4733.9	17.4	80.9	4832.1	0.35	0.52	[103, 34, 0]
SCOPe (Total cost focused)	-	Y	Y	Y	679.2	31.1	242.4	952.7	2.06	0.93	[0, 82, 55]

TABLE XI: Results for TPC-H dataset (1TB), (K refers to a multiplicative factor of 10³.)

Variants we can support	Other methods we can adapt	Р	Т	С	Storage Cost	Decomp. Cost	Read Cost	Total Cost	Read Latency (TTFB, s)	Expected Decomp. Latency (ms)	Tiering Scheme
Default (store on premium)	-	-	-	-	89.23K	0.0	39.13K	128.36K	0.18	0.0	[8, 0, 0]
Compress & store on premium	Ares	-	-	Y	73.79K	3.36K	34.85K	112.01K	0.18	100.31	[8, 0, 0]
Multi-Tiering	Hermes	-	Y	-	89.11K	0.0	38.94K	128.05K	0.18	0.0	[5, 3, 0]
Latency time focused	HCompress	-	Y	Y	41.58K	0.0	242.47K	284.05K	1.07	0.0	[6, 2, 0]
Partition& store on premium	-	Y	-	-	81.37K	0.0	3.16K	84.53K	0.18	0.0	[212, 0, 0]
Partitioning + Tiering	Hermes + G-PART	Y	Y	-	26.77K	0.0	7.51K	34.28K	2.91	0.0	[0, 148, 64]
Partitioning + Compression	Ares + G-PART	Y	-	Y	47.05K	2.20K	1.13K	50.38K	0.18	65.68	[212, 0, 0]
SCOPe (Latency time focused)	HCompress + G-PART	Y	Y	Y	64.68K	0.0	4.76K	69.44K	1.44	0.0	[101, 77, 34]
SCOPe (No capacity constraint)	-	Y	Y	Y	17.93K	1.03K	6.46K	25.42K	2.91	30.89	[0, 176, 36]
SCOPe (Read+Decomp cost focused)	-	Y	Y	Y	61.30K	0.78K	1.66K	63.74K	1.15	23.32	[89, 123, 0]
SCOPe (Total cost focused)	-	Y	Y	Y	15.14K	0.12K	4.53K	19.79K	3.20	36.63	[0, 155, 57]

or latency. Row 4 'Latency time focused' aims at minimizing the storage costs with a focus on keeping total latency low. Rows 5-7 employ G-PART on top of Rows 1, 3 and 2. We can see that the total costs are significantly lower now, while the latencies remain comparable. Also note that the total number of partitions has increased from the original number of datasets (as observed from the last column). The last 4 rows illustrate

TABLE XII: Parameters for ILP Optimization on TPC-H.

Parameters	Premium	Hot	Cool	Archive	
Storage cost C_{ℓ}^{s} (cents/GB)	15	2.08	1.52	0.099	
Read cost C_{ℓ}^{T} (cents/GB)	0.004659	0.01331	0.0333	16.64	
Layer capacity S_{ℓ} (GB)	0.163	0.326	0.4891	inf	
Read latency or TTFB (Time to first byte) B_{ℓ} (sec)	0.0053	0.0614	0.0614	3600	
compute cost C^c (cents/sec)	0.001				

the different variants of the entire pipeline SCOPe (with partitioning, multi-tiering and compression). These highlight how SCOPe can be tuned based on user requirements. We can see SCOPe optimizes the respective objectives while maintaining a very good trade-off on other metrics. SCOPe consistently performs well across all datasets at different scales, namely, enterprise, TPC-H 1GB (not shown here), 100GB and 1TB. 'SCOPe (Total cost focused)' is consistently within 8 - 18% of the 'Default' (platform baseline), and incurs the lowest cost among all the other baselines and variants. Read latency (Time to First Byte) does not change significantly since it is independent of size (Table XII). The expected decompression latency (average across accesses) and other costs grow with the size of partitions.

VIII. CONCLUSION AND FUTURE WORK

We present SCOPe: a tunable framework that optimizes storage and access costs on the cloud while maintaining latency guarantees. It is substantially better than baselines and works extremely well across different types and scales of data, giving cost benefits of the order of 50% or greater. Going forward, we want to extend SCOPe to optimize compute costs, including recommending optimal configurations.

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