The TRaCaR Ratio: Selecting the Right Storage Technology for Active Dataset-Serving Databases

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Abstract

Main memory database systems aim to provide users with low latency and high throughput access to data. Most data resides in secondary storage, which is limited by the access speed of the technology. For hot content, data resides in DRAM, which has become increasingly expensive as datasets grow in size and access demand. With the emergence of low-latency storage solutions such as Flash and Intel’s 3D XPoint (3DXP), there is an opportunity for these systems to give users high Quality-of-Service while reducing the cost for providers.

To achieve high performance, providers must provision the server hosts for these datasets with the proper amount of DRAM and secondary storage, as well as selecting a storage technology. The growth of capacity and transaction load over time makes it expensive to flip back-and-forth between different storage technologies and memory-storage combinations. Servers set up for one storage technology must now be reconfigured, repartitioned, and potentially replaced altogether. As more low-latency storage solutions become available, how does one decide on the right memory-storage combination, as well as selecting a storage technology, given a predicted trend in dataset growth and offered load?

In this paper, we describe and make the case for using the TRaCaR ratio — the transaction rate divided by the storage capacity needed for a workload — for allowing providers to choose the most cost-effective memory-storage combination and storage technology given their predicted dataset trend and load requirement. We explore how the TRaCaR ratio can be used with 3DXP and Flash with a highly-zipfian b-tree database, and discuss potential research directions that can leverage the ratio.

1 Introduction

Datasets actively used by applications today are growing in size and access demand, making it difficult for providers such as Amazon and Google to keep transaction latencies low and throughput high. A provider is tasked with finding the right balance between the amount of DRAM needed to service hot content actively being operated on, and secondary storage for keeping the majority of the dataset. However, over the last few years, tight supplies from DRAM vendors has led to increases in DRAM cost. For example, from 2016-2017, DDR4 increased in cost by $2.3 \times [2,3]$. Hence, keeping all content in DRAM, or over-provisioning the amount of DRAM needed to service the active content of one’s dataset can lead to a high total cost of ownership (TCO). Furthermore, when transactions cannot be serviced from main memory, performance degrades [16, 19].

The increasing size and access demand of datasets has led to newly proposed storage technology solutions called Storage Class Memories. These are characterized by being non-volatile, having short access times, and having lower cost-per-bit compared to DRAM. Figure 1 shows that Storage Class Memories lie between SSD (Flash) and DRAM in terms of both cost and access time, making such technologies viable for servicing page faults on the order of microseconds. For example, in-production today is Intel’s 3D XPoint (3DXP). With access latencies of about $10 \mu s$, 3DXP has an order of magnitude higher performance and durability than NAND.
Flash [9]. Thus, the technology offers a promising solution for databases that require low-latency access to secondary storage. However, this performance comes at a cost: 3DXP is currently about 6× more expensive than Flash [13,14]. Therefore, in addition to configuring the proper amount of DRAM and secondary storage, a provider would need to decide on whether a more expensive, low-latency storage technology is necessary to meet their access demands.

Choosing the right storage backend for a provider’s dataset has performance and cost implications. For example, previous work has shown that an SQL equijoin query on two tables of over 100GB in size can have a performance variation of over 30× and a cost difference of 8× when selecting between storage technologies [10]. Providers will typically over-provision the amount of main memory and storage needed, or select the most expensive secondary storage technology (e.g., choosing 3DXP over Flash). Under-provisioning the datacenter is unacceptable, as strict Quality-of-Service can be violated.

The growth in capacity and offered load makes it expensive, both in cost and time, to constantly have to revisit these decisions and flip back-and-forth between different storage technologies, as well as main memory-secondary storage setups. Providers would need to migrate data, optimize transactions for the underlying storage technology, and potentially switch out the servers themselves if the CPU, DRAM, or slots (e.g., PCIe) are insufficient. Given a predicted performance and capacity growth trend, providers need a way to make these decisions to save cost and avoid constant reprovisioning. However, existing studies [11, 12, 17] that attempt to define which storage technology is most suitable for a given workload (1) consider technology such as DRAM, Flash, and Hard Disk separately (i.e., it all resides in only one), (2) do not consider Storage Class Memory technologies such as 3DXP, and (3) do not consider the expected trend of one’s dataset growth.

In this paper, we introduce the Transaction Rate - Capacity Requirement — TRaCaR — ratio (pronounced “tracker” ratio). The TRaCaR ratio gives providers a way to both select a storage technology and configure main memory-storage capacity based on the expected trend between offered transaction load and dataset capacity growth. We make that case for the TRaCaR ratio’s efficacy by considering whether to provision between 3DXP and Flash for a database with a highly-zipfian access pattern with different read/write ratios. In doing so, we show how a provider would use the computed TRaCaR given their growth trend.

2 Using the TRaCaR Ratio

To understand how providers would use the TRaCaR ratio to provision their servers, we present a motivating example for a highly-zipfian database with 50% random reads and writes.

In our example scenario, the provider starts with a 50% random read/write dataset that is 1TB in size and has an access demand of 20,000 transactions per second. The provider

Figure 2: The TRaCaR ratio for when 3DXP (shaded region) is more cost-effective versus Flash for 50% random reads and writes. 5YE denotes the 5-year expected requirements from Section 2.2.

| Random Read/Write Mix   | TRaCaR |
|-------------------------|--------|
| 100% Reads              | 1.25KHz/TB |
| 50% Reads/Writes        | 1.24KHz/TB |
| 100% Writes             | 1.17KHz/TB |

Table 1: The TRaCaR ratio for selecting between 3DXP and Flash for different random read/write mixes. 3DXP is cost-optimal if a provider’s predicted trend TRaCaR is greater than the TRaCaR listed in a given row.
to determine which storage technology is most cost-effective given their performance trend. If the provider’s TRaCaR is greater than the value in Table 1 for a given random read/write mix, 3DXP is cost-optimal. For our motivating example, 3DXP would still be cost-optimal for different read/write mixes.

### 2.2 Configuring the Servers

After a provider uses their computed TRaCaR ratio to select the most cost-effective storage technology, they must provision the datacenter with the right number of servers, as well as amount of DRAM and secondary storage in each server. To do this, the provider finds the point along their TRaCaR ratio that represents their predicted capacity and access demand at a future time (e.g., 5-10 years out), and computes the lowest cost-setup for the corresponding secondary storage technology. In our motivating example, if we are looking 5 years into the future (denoted as 5YE, or 5-year expected in Figure 2), this would correspond to a dataset size of 60TB and 120,000 transactions per second.

Table 2 shows the optimal cost setup using 3DXP to meet this requirement, and for reference, also shows the Flash setup. For our motivating example, the predicted trend’s setup is almost 25% cheaper by using 3DXP over Flash, since 3DXP requires fewer servers and less DRAM. A provider’s TRaCaR ratio can also be used to determine how many new servers to provision per year to meet the performance demands. Further details about the cost model used are described in Section 4.1.1.

Determining the lowest cost setup for a given storage technology and discussing how the TRaCaR ratio of Figure 2 was computed is detailed in Section 4.

### 2.3 Variations in Predicted Trend

Determining how one’s dataset will grow 5-10 years into the future can be difficult. In addition, secondary storage and memory prices can vary over time. To account for this, providers are often willing to accept a maximum cost difference if it means not having to switch between different storage technologies. For example, one may be willing to pay up to 10% more for an 3DXP setup if it decreases the TRaCaR ratio in 3DXP’s favor. This corresponds to computing the TRaCaR ratio in Figure 2 for setups in which 3DXP is at most $E\%$ more expensive, where $E$ is the extra cost that providers are willing to pay. Providers can then select a storage technology and server setup as described in Sections 2.1 and 2.2. A cost sensitivity analysis for TRaCaR is discussed in Section 5.

### 3 Why TRaCaR

The TRaCaR ratio is motivated by the need to configure host servers for high throughput, low latency database systems as the capacity and access demands change over time. The following observations guided us in our development and analysis of the TRaCaR ratio:

- **O1**: Devices such as 3DXP have latencies that are low enough such that one can focus on the throughput needs for a particular dataset.
- **O2**: Selecting between storage technologies need not be mutually exclusive (e.g., not all the data needs to reside in DRAM). A combination of DRAM and secondary storage can be significantly cheaper than only using DRAM. Furthermore, one can still benefit from storing the hot content being operated on in DRAM.
- **O3**: Content that would normally be completely stored in DRAM tends to have a zipfian access pattern, where a small percentage of the data accounts for the majority of accesses.

To the best of our knowledge, there is no existing work in evaluating storage cost-performance that captures all three of these observations in their analysis.

### 3.1 Target Dataset

Based on O3, we envision using TRaCaR for datasets that could be split across DRAM and low-latency secondary storage backends. To clarify what these datasets look like, we first describe the two extreme dataset types before introducing Active Datasets.

**Extreme Latency Sensitivity.** Workloads with sub-10μs latency requirements cannot tolerate the latency of going to secondary storage — even with a low-latency technology such as 3DXP.
as 3DXP. Thus, they must reside in DRAM, and the decision of what storage backend to use becomes irrelevant.

Archival Data. Rarely-accessed data with low throughput requirements is normally stored in low-cost storage facilities. For example, Facebook has built cold-storage facilities that can hold up to 1,000PB (one exabyte) of “less popular” data and replicas [4]. These large and infrequently accessed datasets are best served using inexpensive disks, and are not discussed in this paper [1].

Active Datasets. The focus for TRaCaR is on Active Datasets, which have the following characteristics. First, they are on the order of hundreds of GBs to several tens of TBs. Second, their data is frequently accessed and exhibits a zipfian access pattern. Third, they have high throughput and low latency requirements. Examples of such datasets include popular stocks in high-frequency trading or popular songs on music streaming platforms. Today’s Active Datasets are almost entirely stored in DRAM to meet their stringent performance requirements. While DRAM offers low latency and high throughput benefits, it has drawbacks:

- Storing hundreds of GBs to several tens of TBs in memory is expensive, both in terms of the DRAM itself and the servers needed to service the dataset.
- DRAM has reliability limitations: if there is a sudden loss of power or system malfunction, recovering lost content from DRAM can take hours, especially if the amount of data lost is on the order of TBs.

3.2 Summary

From these observations, the challenge lies in finding the most cost-effective combination of DRAM-secondary storage server setup for a predicted performance trend. The TRaCaR ratio encompasses these observations and allows a service provider to characterize their dataset in terms of size and offered load to decide what secondary storage technology and server setup is cost-optimal over the next 5-10 years.

4 Computing TRaCaR

In this section, we describe how we compute the TRaCaR ratio used in our motivating example throughout Section 2. We focus on 3DXP and Flash for one particular database, but this methodology generalizes to any Active Dataset-serving database, set of storage backend technologies, and storage hierarchies (e.g., an 3DXP tier backed by Flash).

4.1 Methodology

Our methodology for computing TRaCaR for low-latency storage technologies is based on observations O1 and O2 in Section 3. The objective is to find the cost break point (i.e., the TRaCaR ratio) between the secondary storage technologies under comparison given a range of throughput and dataset size requirements. For each (dataset size, throughput) tuple, we want to find the lowest cost setup.

Algorithm 1 describes how we compute the TRaCaR ratio. db is the user’s database, workld is the workload (e.g., 50% random reads/writes), and stor1, stor2 are the storage technologies under consideration (e.g., 3DXP and Flash). Given the workload, getThroughputMem computes the throughput for the database as the amount of DRAM is reduced. This allows us to create a throughput versus memory reduction percentage relationship for a particular storage technology. After computing this for both technologies, we get all the valid server setups for each of the storage technologies with getSetups. A valid server setup entails figuring out whether a given amount of DRAM, storage devices, and nodes can meet the throughput requirement for an inputted dataset size.

We use the output of getThroughputMem to determine how much DRAM is necessary for meeting a given throughput and dataset size requirement. Finally, getTRaCaR finds (1) the cheapest storage technology and (2) the cheapest server setup for all (dataset size, throughput) pairs. The TRaCaR ratio is then determined by finding the breakpoint line separating one storage technology from being more cost-effective over the other. As done in Section 2, providers can then compare their predicted performance trend against the TRaCaR ratio computed for the storage technologies under consideration.

In getSetups, to increase the throughput of our system, we add more nodes, and spread the dataset across the nodes [5]. Thus, as the number of nodes increases, the amount of storage per node decreases, but the total amount of storage stays the same. For instance, to double the throughput of a single node system, we would add a second node, and put half of the dataset in each node. We assume storage device costs are linear in their capacity when computing the cost of a complete system setup.

Depending on the database and workload being profiled, computing the TRaCaR ratio can take tens of minutes (i.e., the time taken in getThroughputMem). getSetups and getTRaCaR are both currently greedy configuration searches implemented using techniques from [21]. However, we envision providers only needing to do this once when initially provisioning their servers.

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**Algorithm 1 Computing TRaCaR**

1: function COMPUTE_TRaCaR(db, workld, stor1, stor2)
2:   tpMem1 = getThroughputMem(db, workld, stor1)
3:   tpMem2 = getThroughputMem(db, workld, stor2)
4:   validSetup1 = getSetups(stor1, tpMem1)
5:   validSetup2 = getSetups(stor2, tpMem2)
6:   tracar = getTRaCaR(validSetup1, validSetup2)
7:   return tracar
8: end function
4.1 Cost Model

To compute the cost of a setup, we use traditional server nodes that use $400 processors and server equipment and maintenance costs of $1,000 [1, 6]. At the time of writing, Flash is about $0.20/GB [13], 3DXP is about $1.20/GB [14], and DRAM is about $5.50/GB [15].

4.2 Abstracting the Database

We abstract a database servicing Active Datasets with a highly-zipfian b-tree benchmark. The b-tree benchmark has the following attributes:

- We performed 1 million random transactions on a key-value dataset. We evaluated three different read/write mixes: 100% reads, 50% read/writes, and 100% writes.
- B-tree nodes are multiples of the page size, and are page-aligned. This also means that accesses to secondary storage are page size multiples.
- Transactions have a zipfian distribution such that about 80% of the accesses go to 20% of the b-tree’s values. Thus, 20% of the b-tree’s values are the hot-content.

4.3 Configuring the Storage Backends

All b-tree memory accesses are memory-mapped to Flash and 3DXP partitions. For Flash, we use Intel’s SSD DC 3600 [8] and for 3DXP we use Intel’s Optane SSD DC P4800X [7]. Both devices are connected over PCIe NVMe 3.0x4 and have an HHHL Form Factor. To vary the amount of memory available to the b-tree application as a function of the data size, we used Linux CGroups [18]. In all of our experiments, we use a sufficient number of threads to maintain a high throughput and amortize the cost of a page fault (i.e., a sufficient queue depth). For 3DXP, we found that 4 threads was sufficient, while for Flash, we used 16 threads. We ran all experiments on a dual-socket Intel Xeon E5-2630 @ 2.30GHz (12 virtual cores per socket) and 64GB of memory. We used Ubuntu 16.04 and Linux kernel 4.4.0-116.

5 TRaCaR Sensitivity

TRaCaR’s breakpoints are sensitive to the parameter costs described in Section 4.1. For example, a reduction in cost per byte of Flash would increase the TRaCaR ratio, while a reduction in cost per byte of 3DXP would have the opposite effect. We note that if DRAM were to increase in price, it would likely benefit 3DXP. To meet the throughput requirement, systems configured with a Flash backend require more servers than those with an 3DXP backend. In addition, we found that less than 5% of the dataset needs to be in memory regardless of the backend, thus making the additional servers less cost-effective for Flash. It should also be noted that, in the particular case of 3DXP, Intel’s multi-billion dollar investment in the technology makes it unlikely that there will be significant variations in the cost/GB of the storage technology, or in the TRaCaR breakpoint presented in Section 2. However, depending on the storage technology, “cost-volatility” may be more significant, thus motivating the use of the extra cost TRaCaR ratio described in Section 2.3.

6 Related Work

Throughput versus dataset tradeoffs have been previously studied for Flash, DRAM, and Hard Disk technologies. The work most similar to ours is Narayanan et al. that analyzed when and how Flash devices should be used over Hard Disk [12]. For their workloads, they conclude that Flash would have to be 3-3,000 times higher in terms of capacity/$ to be more cost-effective than Hard Disks. Our work differs in several aspects: First, we consider Active Datasets with highly-zipfian distributions. Second, we consider the use of DRAM with the secondary storage technology, whereas they only use the secondary storage (or use Flash as a caching layer). Third, our results show that low-latency technology, such as 3DXP can potentially be more cost-effective than Flash given a dataset and throughput trend. RAMCloud also studied the throughput-versus-dataset tradeoff to justify using DRAM over Flash [17]. Lomet studied the cost versus performance for Deuteronomy and MassTree, and focused on particular techniques to improve the cost and performance of data caching systems [11]. FAWN [1] highlighted the need for multiple nodes in a cluster for both storage space and query rates, and demonstrated how different storage technologies combined with Fawn can affect a service provider’s TCO. TRaCaR is based on computing the most cost-effective number of servers and amount of DRAM for each secondary storage technology under consideration. In addition, the TRaCaR ratio can be applied to any secondary storage technology.

7 Conclusion

In this paper, we introduced and made the case for the TRaCaR ratio: a promising technique to select a storage technology and provision host database servers based on the capacity and throughput trends for Active Datasets. We showed how providers would use TRaCaR to select between 3DXP and Flash for workloads with different read and write mixes. Our findings show that Active Datasets, which are typically serviced from DRAM, can leverage low-latency devices such as 3DXP to save on cost while still meeting performance objectives. As database datasets continue to grow, we hope this study will change how service providers provision their servers with their dataset trends in mind, and how researchers approach and quantify future database systems with low-latency backends.
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