ISBN

9781665457194

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Publication Date

2023-02-22

DOI

10.1109/icnc57223.2023.10074058

Effectiveness and predictability of in-network storage cache for Scientific Workflows

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Abstract*—Large scientific collaborations often have multiple scientists accessing the same set of files while doing different analyses, which create repeated accesses to the large amounts of shared data located far away. These data accesses have long latency due to distance and occupy the limited bandwidth available over the wide-area network. To reduce the wide-area network traffic and the data access latency, regional data storage caches have been installed as a new networking service. To study the effectiveness of such a cache system in a scientific application, we examine the Southern California Petabyte Scale Cache for a high-energy physics experiment. By examining about 3TB of operational logs, we show that this cache removed 67.6% of file requests from the wide-area network and reduced the traffic volume on wide-area network by 12.3TB (or 35.4%) a day on average. The reduction in the traffic volume (35.4%) is less than the reduction in file counts (67.6%) because the larger files are less likely to be reused. Due to this difference in data access patterns in this application, the cache system has to implement special policy to avoid eviction of the smaller files by requests to larger files. We also build a machine learning model to study the predictability of the cache behavior. Tests show that this model is able to predict the cache accesses, cache misses, and network throughput with good accuracy, making the model useful for further studying the resource provisioning and planning.

***Index Terms*—in-network caching, data throughput, transfer performance, data access trends**

I. Introduction

Large scientific projects often involve thousands of scientists sharing a massive data collection [1]. These projects, such as the Large Hadron Collider (LHC), have collaborators around the world, each with their own analysis tasks, accessing a different portion of the data collection, transferring data files over long distances, and causing high demand over the limited wide-area network. While efficient tools for data movement over wide-area network are available, there is a new networking service, in-network storage caches, that could remove a significant portion of the traffic on wide-area network. These caches take advantage of the geographical sharing of data accesses as there are overlapping in data accesses among the colleagues in the same institution who often work on related scientific objectives. In particular, the High Energy Physics (HEP) community has been exploring such a caching system under the term of regional "data lakes" [2] as a part of their federated data storage infrastructure [3]. There are evidences that a regional data cache could improve data accesses [4]–[6]. However, real-world deployment sometimes bring up unexpected challenges. This work studies the effectiveness of one such in-network deployment to see how to address the challenges encountered.

This work studies the operational logs of a large-scale deployment of storage cache nodes. These logs are from the Southern California Petabyte Scale Cache (SoCal Repo) [7] developed for High-Energy Physics (HEP) analysis jobs, where the wide-area network traffic is primarily carried by the Energy Sciences Network (ESnet) [8]. There have been some reports about the performance characteristics including number of file requests, cache misses, and data volumes [9], [10]. The first objective of this work is to understand the networking characteristics such as network traffic reduction, data throughput performance, and so on. We expect this part of the study to confirm that SoCal Repo significantly reduce the traffic over the wide-area network. Nevertheless, there are surprises due to a special user access patterns.

The second objective of our work is to understand the predictability of the network utilization patterns in order to plan for additional deployment of in-network caches in the science network infrastructure. For this purpose, we developed a machine learning model to predict the network utilization metrics for the regional storage cache. Despite the high variability in the cache usage, as shown in Figure 1, it is still possible to model the cache requests with accuracy. Our model takes the SoCal Repo performance characteristics as the input time series and learns the performance patterns through a recurrent neural network architecture known as the Long Short-Term Memory (LSTM) [11], [12]. The errors of the predictions are significantly less than the standard deviation of the original values. With accurate predictions, we could plan for days with unusually high network demands and maximize the overall system performance.

II. Background and XCache Log Files

SoCal Repo is a storage cache supporting computing jobs in Southern California for US Compact Muon Solenoid (CMS) experiment, a HEP collaboration with participants around the world [3], [13]. The analysis jobs involve files of different types, for example, analysis object data (AOD), MiniAOD, or NanoAOD files, where the information content per proton collision differs by more than O(10) each going from AOD to MiniAOD to NanoAOD. NanoAOD is thus O(10,000) smaller than AOD. More than 90% of analyses work with either MiniAOD or NanoAOD [14], [15]. The analysis work mostly starts with exploration of MiniAOD files. In a number of cases, after scientists have determined the most useful algorithms and found the most promising collision events for their analysis work, they might apply the algorithms on the larger data file formats (which has more detailed information about the selected events) to produce the final results. This data usage pattern effectively creates two types of accesses, one type touches small file formats frequently and the other retrieves large infrequently. The analysis jobs requiring large file formats might take a considerable amount of time because the file transfers, including potentially retrieval from tape archives, and computation both are time consuming.

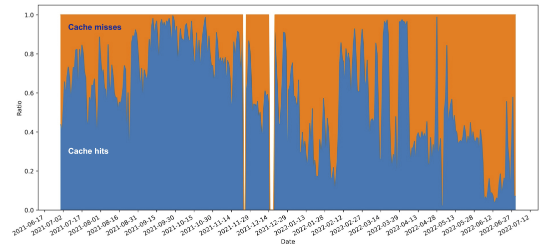
The SoCal Repo has approximately 2.5PB of total storage with 24 federated caching nodes. There are 11 nodes at Caltech with storage sizes ranging from 96TB to 388TB, 12 nodes at UCSD with 24TB each node, and one node at ESnet Sunnyvale endpoint with 44TB of storage. Furthest distance to the cache node from the computing resources is about 500 miles from UCSD to ESnet Sunnyvale endpoint, with an RTT of about 10ms. The measurement data has been collected from July 2021 through June 2022, consisting of 8.7 million data accesses where 67.6% are satisfied with files in cache, see Table I for additional summary statistics. Among the 12.7 PB requested, 4.5 PB (35.4%) could be served from the cache, while 8.2 PB needs to be transferred over wide-area network. The difference between 67.6% and 35.4% is one of the issues we seek to resolve.

TABLE I
SUMMARY OF DATA ACCESS FROM JULY 2021 TO JUNE 2022. ABOUT 67.6% OF FILE REQUESTS ARE SATISFIED BY THIS CACHE, WHILE 35.4% REQUESTED BYTES ARE IN THE CACHE.

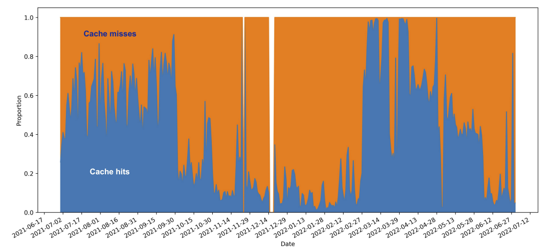
	# of accesses	cache miss size (TB)	cache hit size (TB)	number of cache misses	number of cache hits
Total	8,713,894	8,210.78	4,499.44	2,822,014	5,891,880
Daily	23,808	22.43	12.29	7,710	16,098

Cache misses occur when the client's requested data file is not in any of the cache nodes and needs to be transferred from a remote storage over the wide-area network. When the client's requested data is in one of the cache nodes, it is a cache hit, and the data is served from the cache without a wide-area data transfer. The network traffic reduction comes from these cache hits.

The cache nodes run on XCache software [7], [16], [17]. The information used in this study is extracted from XCache log files. We've processed 8,433 log files amounting to about 3 TB, and extracted information about the request sizes, how the request is satisfied, etc. From such information, we derived

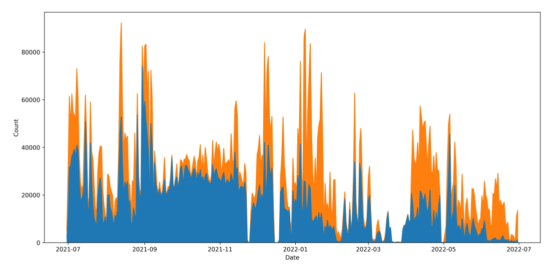


(a) Fraction of daily file requests: cache misses (in orange) and cache hits (in blue)

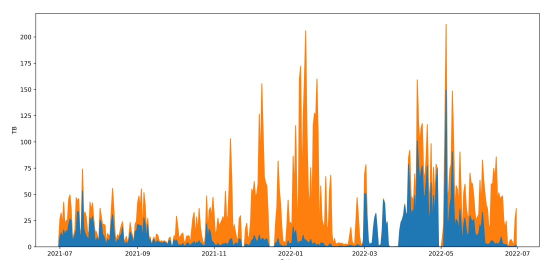


(b) Fraction of daily requested bytes: cache misses (in orange) and cache hits (in blue)

Fig. 1. Cache miss rates versus cache hit rates based on (a) files requested and (b) bytes requested.



(a) Daily file requests (count): cache misses (in orange) and cache hits (in blue)



(b) Daily traffic volume: cache misses (in orange) and cache hits (in blue)

Fig. 2. Daily network traffic statistics: (a) files requested and (b) bytes requested. Note that only file requests that miss the cache trigger remote network file transfers.

cache hits, cache misses, along with network performance information such as remote transfer throughput that are are used in later sections.

III. NETWORK TRAFFIC REDUCTION

In this section, we show how much wide-area network traffic is actually saved by SoCal Repo. Figure 1 shows the daily cache hit rate and cache miss rate, where Figure 1a shows these rates based on the file request counts and Figure 1b based on bytes requested.[1] Cache misses trigger wide-area network traffic. We show the cache miss rates with bright orange in Figure 1 and Figure 2

Overall, the cache miss rates based on files requested (in Figure 1a) are more stable than those based on bytes requested in Figure 1b. In particular, there is a 5-month long period between Oct. 2021 and Feb. 2022, where the majority of bytes requested are cache misses. An examination of the number of files requested and number of bytes requested in Figure 2 provides more information.

Figure 2a shows the number of files requested, separated into those could be satisfied with files in the cache (hits, in blue) and those require wide-area network transfers (misses, in orange). Across all 24 cache nodes in the SoCal Repo, an average day sees about 16,000 file requests as hits along with 8,000 misses. In terms of bytes requested, Figure 2b shows that about 12.3 TB per day are served out of the cache during the whole year. In the early part of the year, between Jul. 2021 and Sep. 2021, the wide-area network traffic is reduced by about 13 TB per day, and between March 2022 and May 2022, the wide-area network traffic is reduced by about 29TB per day.

In the middle of our observation period, for example January 13, 2022, there are about 60,000 cache misses amounting to about 200TB of wide-area traffic. On average each of these files is over 3.3GB, which means they are large among CMS data files. This observation from the cache statistics conforms to the usage patterns involving large files described in Section II. We also received additional confirmation from the site operators that these are indeed a small number of data analyses involving large files.

This particular usage pattern involving large files has the potential of evicting the smaller files (that are used more frequently)[2] and reducing the overall effectiveness of the cache system. The operators of SoCal Repo recognized this usage pattern and have separated and limited the accesses to the cache nodes based on file types, which effectively prevents cache pollution. In cases where one couldn't differentiate the cache usages based on simple known characteristics, an alternative strategy could be to have these requests bypass the cache system [18].

IV. Modeling Transfer Throughput

Now that we know the storage cache is effective in reducing the traffic on wide-area network, and there are strategies to mitigate the impact of special access patterns that pollute the cache, we'd like to see how to provision additional storage cache nodes in the future. For this purpose, we start to model the current cache usage and network performance. More specifically, we build machine learning models for the hourly and daily average data throughput performance as well as statistics about cache misses. The data throughput is defined as the data transfer size over the transfer time. This information is useful for anticipating the time needed for file transfers.

[1]There are two narrow gaps in Figure 1 due to brief periods of down time.

[2]This is colloquially known as cache pollution.

TABLE II

Hyper-parameters of the LSTM models

# of LSTM unit	activation function	dropout rate	# of epochs
128	tanh	0.04	50

TABLE III

RMSE of daily/hourly LSTM model results for network storage cache performance. The relative prediction errors (inside parentheses) are measured against the standard deviations. Note that all six rows are about cache misses.

	Training RMSE	Testing RMSE	standard deviation
Daily cache misses	4306.01	3637.39 (.32)	11317.08
Hourly cache misses	175.11	99.31 (.17)	595.81
Daily volume	9.75	14.54 (.49)	29.46
Hourly volume	0.19	0.49 (.35)	1.42
Daily average throughput	33.20	23.49 (.21)	110.43
Hourly average throughput	27.08	22.79 (.19)	121.36

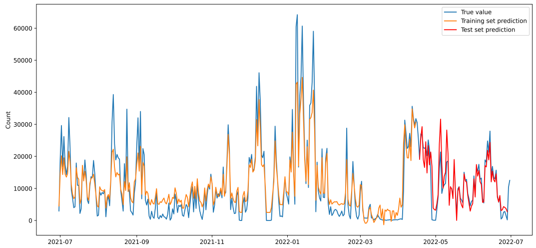
We have decided to use a neural network architecture called LSTM [11], [12] because it is effective in capturing time series patterns. Our model includes the following features: cache miss count, cache miss size, cache hit count, cache hit size, aggregate throughput for cache misses on all nodes, aggregate throughput on cache hits for all nodes, average throughput for each cache miss, and average throughput for each cache hit. In the remaining of this section, we discuss the information relates to cache misses, which are more relevant to the wide-area network performance. The training data comes from the first 80% of the whole monitoring period, and the testing data comes from the last 20%. Table II shows hyper-parameters chosen after exploring about 1400 different parameter combinations.

As an overall performance measure, Table III shows the root-mean-square error (RMSE) of both the daily and hourly models for the data volume and average (wide-area) network transfer performance. The column labeled "standard deviation" is the standard deviation of the input data values. It provides a reference for us to judge how large are the errors of predictions. The ratios of testing RMSE and standard deviation are shown inside parentheses. In all cases shown, this relative error is less than 0.5, indicating the predictions are pretty accurate.

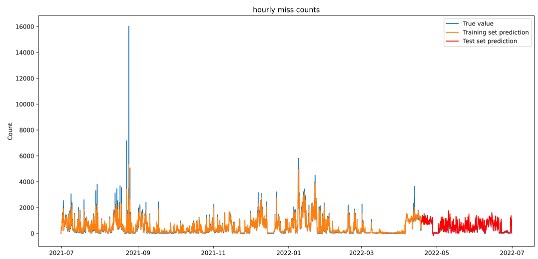
In all three sets of measures shown in Table III, the LSTM models are more accurate with the hourly time series than with the daily time series as both absolute and relative error are smaller. The most likely reason might be there are more training data records for the hourly time series. Next, we look into more details of these prediction models.

Figure 3 and Figure 4 show LSTM model output for the number of cache misses and their associated data volumes. In these cases, we see the predictions on the hourly time series are indeed closer to the actual values in the last period of time than the predictions with daily time series, even thought the hourly time series often shows stronger spikes.

Figure 5 shows the LSTM model performance with daily

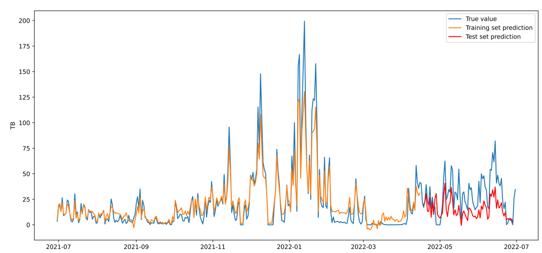


(a) Daily number of cache misses

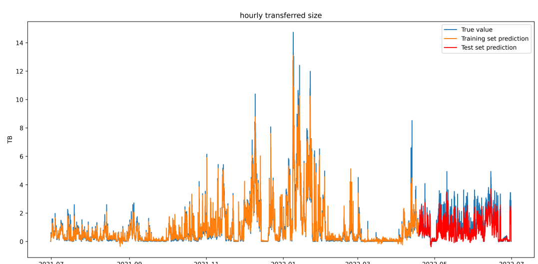


(b) Hourly number of cache misses

Fig. 3. Number of cache misses

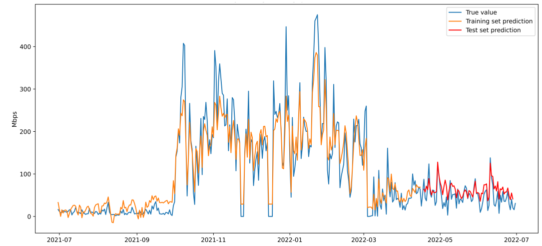


(a) Daily volume of cache misses

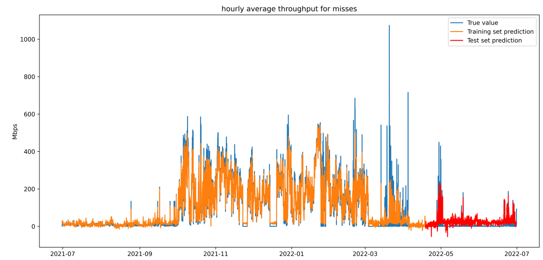


(b) Hourly volume of cache misses

Fig. 4. Bytes in cache misses

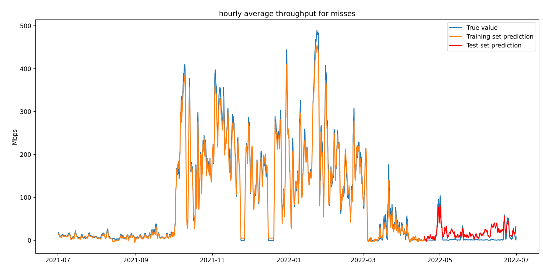


(a) Daily throughput of wide-area transfers

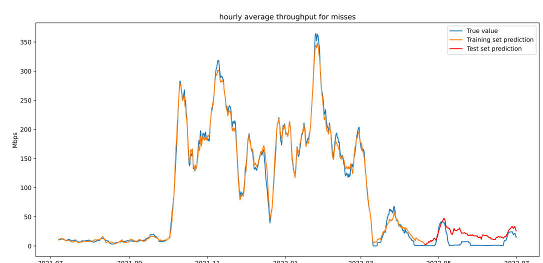


(b) Hourly throughput of wide-area transfers

Fig. 5. Average throughput of wide-area file transfers



(a) Network throughput with 24-hour moving average



(b) Network throughput with 168-hour moving average

Fig. 6. Modeling hourly average wide-area throughput on smoothed time series.

and hourly average throughput values. From figure 5a, we see that during the middle of the observation period (10/21 – 2/22), the wide-area network traffic throughput are quite high because the network transfers are dominated by relatively large files that are typically better able to utilize the network capacity. In the other time periods, the average throughput is relatively low due to small files being transferred.

In the hourly model from Figure 5b, there are significant number of spikes during late March and early May. Examining Figures 3b and 4b, we see that these spikes occur during time periods with very few cache misses, i.e., very few wide-area file transfers. We are interested in exploring these spikes further in the future. For modeling network performance, it is not necessary for us to capture such spikes precisely. We could use the moving average method to smooth out the spike to obtain a performance model for the general trends.

Figure 6 shows two different versions of Figure 5b with two different moving-averaged hourly throughput measured by the cache misses. We clearly see that LSTM results match the moving-averages much better than the original time series shown in Figure 5b. The testing error (RMSE) of the LSTM predictions on the 24-hour moving-averages is 15.05 (i.e., model in Figure 6a) and corresponding error on the 168-

hour moving average is 14.56. Both of these errors are less than 22.79 on the original hourly throughput time series. Even though the 24-hour moving averages look like the daily throughput time series shown in Figure 5a, the LSTM predictions matches the 24-hour moving averages much better based on visual inspection. The RMSE of 15.05 (Figure 6a) is noticeably smaller than 23.49 (Figure 5a). For anticipating future network performance, the LSTM model based on the moving averages is likely to work better.

V. Conclusion

In this study, we set out to understand the effectiveness of in-network storage cache used by a distributed scientific collaboration. The source information is from about 3TB of operational logs from the XCache servers on SoCal Repo. The data analysis operations of the collaboration commonly involve two types of files, the smaller sized ones are used frequently with more reuse, while the larger sized ones are invoked infrequently with less reuse. We observed that SoCal Repo could on average serve about 67.6% of files from its disk cache, while on average only 35.4% of bytes requested could be served from the cache, because the large files are less often reused. To avoid cache pollution from this usage pattern of large files, the system operators have adopted the separate policies with different storage nodes. During the period where fewer large files are requested (3/2022 – 5/2022), the wide-area network traffic is reduced by about 29TB per day. Over the whole period of observation, there is a five-month period where the large file requests are noticeably high. The average reduction of wide-area network traffic by this cache over the whole observation period is still about 12.3TB per day, which is quite significant.

This work also explores an option to model the network performances with a neural network architecture known as LSTM. Tests show that the prediction error (measured as RMSE) are quite small. In a case where the original time series has large variations, we also show that the LSTM model could work quite well on moving-averaged versions of the time series. With this model, we plan to consider how to provision future deployments of in-network caches. We are also planning to study other storage caches currently under deployment to gain better understanding of in-network caches.

Acknowledgment

This work was supported by the Office of Advanced Scientific Computing Research, Office of Science, of the US Department of Energy under Contract No. DE-AC02-05CH11231, and also used resources of the National Energy Research Scientific Computing Center (NERSC). This work was also supported by the National Science Foundation through the grants OAC-2030508, OAC-1836650, MPS-1148698, PHY-2121686 and OAC-1541349. This work was also supported in part by the US Department of Energy, Office of Science, Office of Workforce Development for Teachers and Scientists (WDTS) under the Science Undergraduate Laboratory Internship (SULI) program.

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