Characterizing the Spatio-temporal Burstiness of Storage Workloads

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Abstract

Computing technology are undergoing evolutionary changes in platform and environment. Computing becomes more and more data-intensive. The design of the data center storage of cloud-based system determines whether data could be accessed efficiently. Characterizing storage workloads can provide valuable information for storage system design on various aspects, such as system modeling, design decision-making, and simulation-based performance evaluation. I/O behaviors in data center environments typically exhibit temporal burstiness and spatial locality. The strong spatio-temporal correlation of I/O behaviors motivates us to study the spatio-temporal burstiness of storage workloads. In this paper, we analyze several I/O traces collected in enterprise storage systems and characterize the spatio-temporal burstiness by abstracting the spatio-temporal correlation of temporal and spatial behaviors. Then a stochastic model is proposed to emulate and predict I/O arrival rates. We conduct an experimental study based on real-world I/O workloads traces. The results demonstrate that abstracting the spatio-temporal correlation of I/O behaviors contributes to improving the accuracy of the storage workloads prediction.

Categories and Subject Descriptors D.4.2 [*OPERATING SYSTEMS*]: Storage management

Keywords Data center storage, Workload characterization, Spatio-temporal correlation, Burstiness

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1. Introduction

With the evolutionary changes in machine architecture, operating system, network, and application, computing becomes data-intensive and data-centric. DataOS is a research project in Chinese Academy of Sciences to develop a data-centric cloud operating system. Data center storage is one important part of DataOS that aims to provide efficient data access.

Designers of storage systems emulate I/O traces of storage workloads for new algorithm testing and bug fixing. Workloads studies can provide valuable information on various aspects, such as system modeling, design decisions-making, and simulation-based performance evaluation [1–4]. For example, storage systems can proactively warm up the cache with useful data before the I/O intensity increases. Also, according to the I/O patterns, storage systems can dynamically allocate available storage devices to balance workloads. In addition, burstiness patterns can be used to detect anomalous behaviors of I/O workloads.

I/O workloads typically exhibit complicated temporal dependence, known as burstiness, which could be characterized by long-range dependence and self-similarity [5–7]. However, most previous methods analyze I/O workloads only in the time domain. The response time of I/O requests is not only determined by time domain properties, but also by location of the required data. Also, behaviors of I/O workloads exhibit spatial locality [8]. In addition to the temporal and spatial burstiness, I/O requests coming close in time tend to access nearby data, which suggests that I/O requests have strong spatio-temporal correlation. Few studies capture and explain the spatio-temporal correlation, which is the statistical relationship between I/O requests at all time and all blocks. To accurately model and predict storage workloads, the characterization of temporal burstiness, spatial locality, and spatio-temporal correlation are all indispensable.

In this paper, we analyze and model the spatio-temporal burstiness of storage I/O workloads. We describe a stochastic model to capture both the temporal and spatial behaviors of I/O workloads and abstract the spatio-temporal correlation. Our model can be utilized to emulate and predict I/O ar-

	usr2	proj1
WSS (GB)	362	642
Size (GB)	483	870
Number of requests	10,570,046	236,397,42
Read Percentage (%)	81.13	89.44
Avg. read request size (KB)	50.78	37.21
Avg. write request size (KB)	13.91	10.74

Table 1. Characteristics of the two block-level traces

rival rates. We conduct an experimental study based on real-world I/O workloads traces collected from enterprise data center environments. Experimental results demonstrate that abstracting spatio-temporal correlation helps enhance accuracy of modeling and predicting of storage workloads.

The rest of paper is organized as follows. Section 2 demonstrates the burstiness of I/O traces. Section 3 describes the proposed model for spatio-temporal correlation modeling and I/O traffic intensity prediction. Section 4 validates the proposed model with trace simulation. Section 5 reviews related research work. Conclusion and future work are briefed in Section 6.

2. Trace Analysis

We study traces from enterprise data center environments to understand traffic intensity patterns of storage workloads, including the temporal behaviors, spatial behaviors, and spatio-temporal correlation.

2.1 Description of Traces

We randomly select two traces (two servers, two volumes) from the Microsoft Research Cambridge block-level traces set [9] for our study. MSR-Cambridge traces were collected from the core servers in Microsoft's data center using Event Tracing for Windows. In total, Narayanan et al. collected one-week long traces starting from February 22nd, 2007 in 36 volumes containing 179 disks on 13 servers. These traces were collected below the server buffer caches [9], and there were no storage-level caches in the system [3]. Table 1 summarizes the characteristics of the two block-level traces of our study, where *usr* and *proj* indicate the servers used for user home directory and project directory, respectively.

2.2 Burstiness of Traces

2.2.1 Intuitive Feeling of Burstiness

We first have an intuitive feeling about the burstiness of I/O workloads. Figure 1(c) and Figure 1(f) indicate the time-space plot for *usr2* and *proj1* traces, respectively. Other histograms in Figure 1 illustrate arrival rates on the temporal and spatial scale. From Figure 1(a) and Figure 1(d), we observe bursty behavior in time domain. Also, as illustrated in Figure 1(b) and 1(e), some blocks are more popular than others, which is called spatial locality. In addition, we see that I/O requests coming close in time tend to access nearby data from Figure 1(c) and Figure 1(f), which suggests that I/O requests have strong spatio-temporal correlation.

Trace	H (Aggregate Variance, R/S)		
	Read	Write	Total
usr2	0.716, 0.791	0.676, 0.634	0.710, 0.763
proj1	0.821, 0.801	0.743, 0.742	0.821, 0.785

Table 2. Temporal Burstiness (H)

2.2.2 Characterizing Burstiness by Hurst Exponent

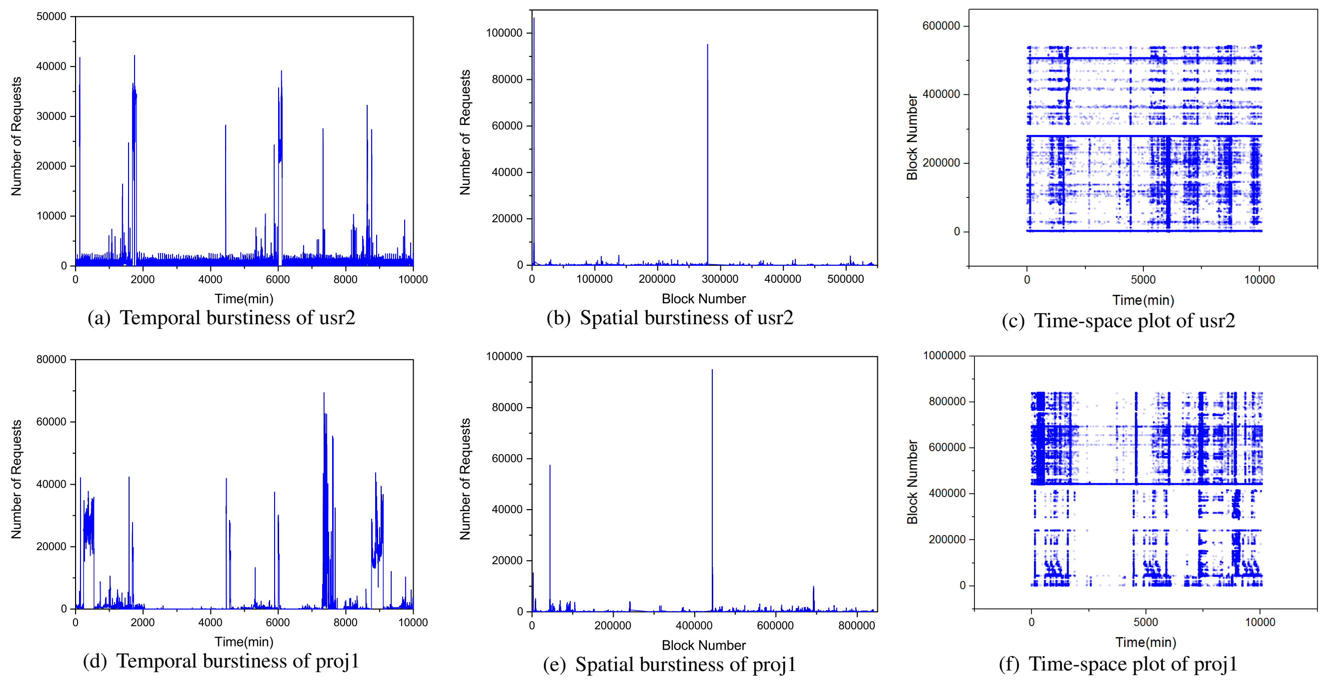
Examination results in section 2.2.1 motivate us to study further on the burstiness of storage I/O workloads. Self-similarity can help describe and model the burstiness of storage workloads [8], which denotes that a certain property of a process is exactly or approximately similar to a part of itself in time and/or space domain.

The autocorrelation function $ACF(k)$, which measures how similar is series with shifted version of itself, of *usr2* and *proj1* traces in time and space domain are plotted in Figure 2(a) and Figure 2(b), respectively. We calculate up to 100 lags to demonstrate the possibly slow decay rate of $ACF(k)$. The decay rate of ACF determines that a process is a short-range dependence or a long-range dependence. A slow decay rate implies a long-range dependence and vice versa. From ACF's decay rate of each process in Figure 2(a) and Figure 2(b), we can infer that I/O workloads in *usr2* and *proj1* traces are long-range dependence processes in time and spatial domain.

Hurst parameter (H) can quantify the degree of the self-similarity. A series exhibits self-similarity when H is between 0.5 and 1. In addition, the closer H is to 1, the stronger the dependence of the process is. Estimation of the value of the Hurst parameter is a well-studied problem. We use aggregate variance approach and R/S analysis [10] to estimate the Hurst parameter of the usr2 and proj1 traces.

We examine the temporal and spatial self-similarity of the arrival processes of I/O requests for the *usr2* and *proj1* traces. Table 2 lists the estimated Hurst exponent values for different arrival processes. In addition to the total arrivals to each system, we also estimate the Hurst parameters of arrival processes for read requests and write requests to each volume. Then we give a similar analysis for the spatial behavior of the disk access locations. Table 3 summarizes the estimated H values for the *usr2* and *proj1* traces. As shown in Table 2 and Table 3, all of the Hurst exponent values are above 0.5. According to this observation, I/O workloads in *usr2* and *proj1* traces have self-similarity in both time and space domain.

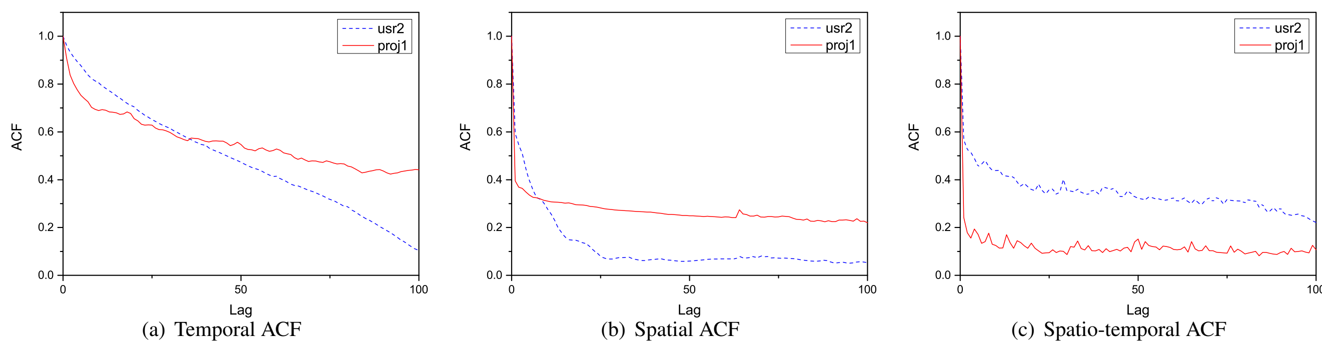
In the following, we measure the spatio-temporal correlation of *usr2* and *proj1* traces. Figure 1(c) and Figure 1(f) shows that I/O requests have strong spatio-temporal correlation. To further study the spatio-temporal correlation, we divide the time-space plot of traces into grids. Then each



(a) Temporal burstiness of usr2 (b) Spatial burstiness of usr2 (c) Time-space plot of usr2

(d) Temporal burstiness of proj1 (e) Spatial burstiness of proj1 (f) Time-space plot of proj1

Figure 1. Intuitive Feeling of Burstiness



(a) Temporal ACF (b) Spatial ACF (c) Spatio-temporal ACF

Figure 2. ACFs of usr2 and proj1 traces

Trace	H (Aggregate Variance, R/S)		
	Read	Write	Total
usr2	0.730, 0.674	0.655, 0.542	0.644, 0.602
proj1	0.727, 0.713	0.741, 0.717	0.708, 0.691

Table 3. Spatial Burstiness (H)

Trace	H (Aggregate Variance, R/S)		
	Read	Write	Total
usr2	0.784, 0.528	0.444, 0.464	0.758, 0.629
proj1	0.808, 0.767	0.435, 0.575	0.825, 0.749

Table 4. Spatio-temporal Burstiness (H)

I/O request falls into corresponding grid. For example, given an I/O request arrives at time t and offers to block number s, then it falls into grid with boundary $t_1 \leq t < t_2$ and $s_1 \leq s < s_2$. The selection of granularity of each grid is a challenging problem in practice. For simplicity, we aggregate time and block into hours and GB, respectively. We first number the grids, then we calculate temporal-spatial ACF and spatio-temporal burstiness (H) according to number of grids. As illustrated in Figure 2(c), traces are long-range dependence processes in spatio-temporal scale. In addition, as shown in Table 4, most of the Hurst exponent values are above 0.5 except the write events in these traces. These results indicate that some grids are more popular than others, and I/O requests exhibit spatio-temporal burstiness (self-similarity).

3. I/O Burstiness Modeling

The motivation of this paper is to develop an OS that can take into account the prediction of storage workloads burstiness. But this paper won't go that far, i.e., we focus only on characterizing I/O burstiness of data center storage workloads.

3.1 Spatio-temporal Correlation Modeling

To enhance accuracy of modeling and prediction of storage workloads, we capture both the temporal and spatial behaviors of I/O workloads and abstract the spatio-temporal correlation.

We first aggregate adjacent blocks into areas. To complete a task, the storage system typically carries a series of I/O requests to flow over a set of areas. We refer a set of areas passed by a series of I/O requests as a region. For simplicity, we assume that the I/O traffic is fluid. Then the amount of I/O requests on area m during the time interval (a, b) is $\int_a^b Y_m(t)dt$, where $Y_m(t)$ is the traffic intensity (requests per unit time) on area m.

Fractional Brownian Motion (FBM)

$$B_H = \{B_H(t)\}_{t\geq 0}$$

is a continuous-time Gaussian process depending on the Hurst parameter $0 < H < 1$, which can be used to model parallel I/O traces [5] and network traffic [11].

The limit FBM has the following covariance function with $t, s \geq 0$:

$$Cov(B_H(t), B_H(s)) = \frac{\sigma^2}{2}(|t|^{2H} + |s|^{2H} - |t-s|^{2H}) \quad (1)$$

Depending on trace analysis in Section 2, spatio-temporal correlation is mainly showed by the fact that I/O requests coming close in time tend to access nearby data. This observation inspires us considering the impact of the nearby areas when we model the I/O requests offer to a certain area.

Stoev et al. [11] proposed a FBM-based space-time probability model to model backbone network traffic. The problem of modeling backbone network traffic is somewhat analogous to the problem we try to solve in this paper. However, compared with the number of links and routes (predetermined sets of links) in the backbone, there are a lot more areas and regions (usually not predetermined) in data center storage. Also, the spatio-temporal correlation of I/O traffic is different from network traffic. The model for backbone network traffic cannot be directly used in the I/O workloads modeling scenario. To solve our problem, we refer the intention of the model proposed by Stoev et al. [11] and modify it more in line with the nature of I/O traffic in data center storage.

Considering the joint behavior of I/O traffic on all areas, we model $Y_m(t)$, which is the distribution of the I/O traffic intensity on area m, as increments of FBM:

$$Y_m(t) = \mu_m + c_m(B_H(t) - B_H(t-1)) \quad (2)$$

where $1 \leq m \leq M$, M is the number of areas, μ_m is the mean I/O requests offered to area m per unit time, and

$$c_m(u) = r(u) * \mathbf{1}_{A_m}(u), u \in \{1, ..., I\} \quad (3)$$

where I is the number of regions, A_m is the set of all regions containing area m, $\mathbf{1}$ is the indicator function,

$$\mathbf{1}_{A_m}(u) = \begin{cases} 1 & u \in A_m \\ 0 & u \notin A_m \end{cases} \quad (4)$$

and the constants $r(u) > 0$ measures the influence of traffic on region u to whole model, i.e., the impact of the nearby areas,

$$r(u) = \frac{\sum(L_k^{-1} * \mu_k)}{N_u}, k \in u \quad (5)$$

where N_u denotes the number of areas in region u, L_k is the distance from area m to area k, and μ_k is the average arrival rate of I/O requests on area k.

3.2 I/O Traffic Intensity Prediction

With the joint distribution of the I/O workloads on the storage servers offered to all areas m and time slots t, we can address the following prediction problem.

Given are the I/O requests workloads

$$\mathcal{D} = \{Y_m(t), 1 \leq t \leq n, m \in \mathcal{O}\} \quad (6)$$

over the set of block areas $m \in \mathcal{O} \subset \{1, ..., M\}$. Predict the traffic load $Y_m(n+h)$ on area m, at some future time $n + h > t$.

For simplicity, let time $t \in \mathbb{N}$ be discrete, and

$$\overrightarrow{Y_t} = (Y_m(t))_{(1\leq m\leq M)} \quad (7)$$

$\widehat{Y}(n+h)$ is the best linear unbiased prediction (BLUP) [13] of covariance stationary time series $Y(n+h)$:

$$\widehat{Y}(n+h) = \mu + \sum_{i=1}^{n} \lambda_i(Y(n-i+1) - \mu) \quad (8)$$

where the vector $\overrightarrow{\lambda}$ of coefficients satisfies the prediction normal equations:

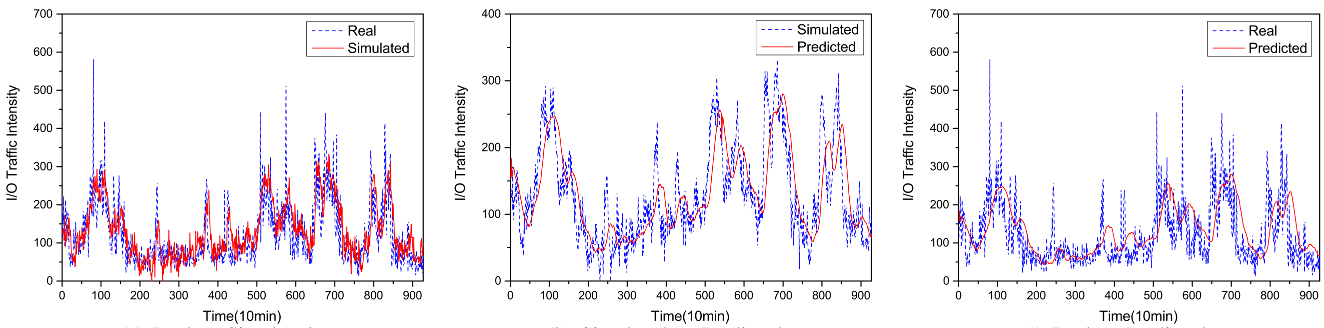
$$\Gamma\overrightarrow{\lambda} = \overrightarrow{r} \quad (9)$$

where Γ is the $(n \times n)$ Toeplitz matrix having $R(|j - k|)$ as its jkth element and the vector $\overrightarrow{r}$ of length n is $(R(h), ..., R(n+h-1))^T$.

According to Equation 2, the autocovariance function $R(i)$ is as follows:

$$R(i) = \frac{\sigma^2}{2}(|i+1|^{2H} + |i-1|^{2H} - 2|i|^{2H}) \quad (10)$$

where the estimation of the Hurst parameter H is a well-studied problem. We use wavelet method [12] to get H in prediction model. Since $R(0) = \sigma^2 > 0$ and $R(i) \to \infty$, as $i \to \infty$, the matrix Γ is invertible, for all $n \in \mathbb{N}$.



(a) Real vs. Simulated (b) Simulated vs. Predicted (c) Real vs. Predicted

Figure 3. Comparisons between actual I/O traffic intensity with predicted results

4. Evaluation

In this section, we use realistic MSR I/O traces collected in data center environments to validate our approach.

In our approach, the partition of block areas and the estimation of the parameters μ_m and $r(u)$ of Equation 2 are challenging problems in practice. For simplicity, we divide blocks into equally sized areas and estimate μ_m and $r(u)$ based on statistical analysis on MSR I/O traces set.

We first get an intuitive feeling about the effectiveness of our approach. Figure 3 compares the actual I/O traffic intensity with predicted results of a random trace segment from *usr2* traces. Figure 3(a) evaluates whether Equation 2 are appropriate for characterizing the trace segment. Figure 3(b) and Figure 3(c) compares the predicted I/O traffic intensity by Equation 8 with simulated workloads and real workloads, respectively. As shown in Figure 3, our approach can roughly capture burstiness in the selected trace segment.

To further validate our approach, we adopt relative mean square error (Relative MSE) to evaluate the prediction accuracy of our approach:

$$RelativeMSE = \frac{\sum_{t=0}^{T}(\hat{Y}_m(t) - Y_m(t))^2}{\sum_{t=0}^{T} Y_m(t)^2} \qquad (11)$$

where m is the given area, T is the time span of the trace segment, $Y_m(t)$ is the actual I/O traffic intensity, and $\hat{Y}_m(t)$ is the predicted result.

We randomly choose 100 trace segments from *usr2* and *proj1*, respectively. We run our approach on each trace segment and obtain the Relative MSE. The blue bars in Figure 4 display the results of average Relative MSE on trace segments selected from *usr2* traces, average Relative MSE on trace segments selected from *proj1* traces, and average Relative MSE on all trace segments. As we expect, the results in Figure 4 indicate the predicted I/O traffic intensity can roughly capture burstiness of real-world traces. As shown in Figure 4, the average Relative MSE on trace segments selected from *proj1* traces is smaller than the average Relative MSE on trace segments selected from *usr2* traces. According to the trace analysis in Section 2, the Hurst parameter of *proj1* traces is higher than *usr2* in time, space, and spatio-temporal domains. This phenomenon might be the reason why the results of trace segments selected from *proj1* traces are better than the results of trace segments selected from *usr2* traces, which suggests that the higher the self-similarity of I/O traffic, the better the accuracy of prediction of our approach.

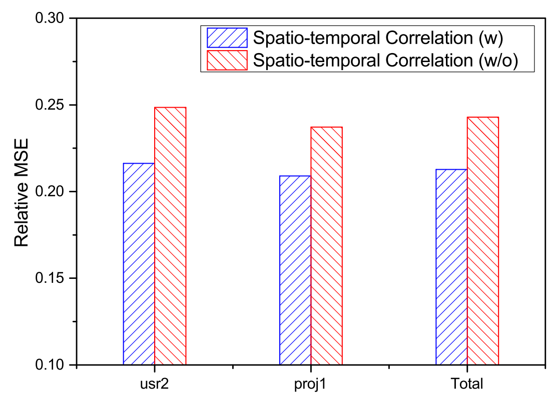


Figure 4. Evaluation results of compared approaches

In the following, we demonstrate the effectiveness of abstracting spatio-temporal correlation of I/O workloads. Figure 4 summarizes the result with spatio-temporal correlation and the result without spatio-temporal correlation on accuracy evaluation metrics. As we can see from Figure 4, spatio-temporal correlation (w) performs better than spatio-temporal correlation (w/o). This result is consistent with our expectations, i.e, abstractubg spatio-temporal correlation helps enhance accuracy of modeling and prediction of storage workloads. The spatio-temporal correlation (w) achieves 12.96% and 11.89% improvements compared with spatio-temporal correlation (w/o) on *usr2* and *proj1* traces, respectively. This result suggests that I/O traffic in *proj1* traces has stronger spatio-temporal correlation than I/O traffic in *usr2* traces.

5. Related Work

In cloud-based systems, one important issue is the design of the data center storage, which aims to provide efficient data access. Many researchers working on modeling storage workloads. Workload studies can provide valuable design implications for storage systems. Harter et al. [1] studied the I/O behaviors of Apple desktop applications. Zhang et al. [3] analyzed server-side workload traces and quantify key workload characteristics that can be utilized to design warm-up mechanisms. Several techniques have been used to characterize storage workloads, such as machine learning [14], feature matrices [15], Markov chains [16], and counter stacks [4].

Burstiness is an important indicator of storage workloads [5, 8] and network traffic [11, 17]. I/O workloads typically exhibit complicated temporal dependence. Zoll et al. [5] and Kavalanekar et al. [8] characterized the temporal burstiness of I/O workloads by self-similarity. Also, behaviors of I/O requests workloads exhibit spatial locality [8]. In addition, I/O requests coming close in time tend to access nearby objects, which suggests that I/O requests have strong spatio-temporal correlation. However, few studies capture and explain the spatio-temporal correlation, and cannot describe storage workloads accurately.

6. Conclusion and Future Work

Workloads studies can provide valuable data for cloud-based systems on various aspects. I/O behaviors in data center environments typically exhibit temporal burstiness and spatial locality. The correlation of temporal and spatial behaviors of I/O requests motivates us to study the spatio-temporal burstiness of data center storage workloads. In this paper, we analyze several I/O traces collected in enterprise storage systems and propose a stochastic model, which can characterize the spatio-temporal burstiness of storage workloads and can be utilized to emulate and predict future I/O traffic intensity.

The motivation of this paper is to develop a data center OS that can take into account the prediction of storage workloads burstiness. But this paper does not go that far, i.e., we focus only on characterizing I/O burstiness of data center storage workloads and the evaluation of our model is based on trace simulation. In the future, we plan to integrate our model into DataOS to know how much performance impact it has when it monitors the system and analyzes the data in real time. In addition, we intend to utilize the temporal, space, and spatio-temporal burstiness to optimize the design of DataOS storage systems.

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