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C-Miner: Mining Block Correlations in Storage Systems

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ABSTRACT

Block correlations are common semantic patterns in storage systems. These correlations can be exploited for improving the effectiveness of storage caching, prefetching, data layout and disk scheduling. Unfortunately, information about block correlations is not available at the storage system level. Previous approaches for discovering file correlations in file systems do not scale well enough to be used for discovering block correlations in storage systems.

In this paper, we propose *C-Miner*, an algorithm which uses a data mining technique called *frequent sequence mining* to discover block correlations in storage systems. *C-Miner* runs reasonably fast with feasible space requirement, indicating that it is a practical tool for dynamically inferring correlations in a storage system. Moreover, we have also evaluated the benefits of block correlation-directed prefetching and data layout through experiments. Our results using real system workloads show that correlation-directed prefetching and data layout can reduce average I/O response time by 12-25% compared to the base case, and 7-20% compared to the commonly used sequential prefetching scheme.

1 Introduction

To satisfy the growing demand for storage, modern storage systems are becoming increasingly intelligent. For example, the IBM Storage Tank system [29] consists of a cluster of storage nodes connected using a storage area network. Each storage node includes processors, memory and disk arrays. An EMC Symmetric server contains up to *eighty* 333 MHz microprocessors with up to 4-64 GB of memory as the storage cache [19]. Figure 1 gives an example architecture of modern storage systems. Many storage systems also provide virtualization capabilities to hide disk layout and configurations from storage clients [36, 3].

Unfortunately, it is not an easy task to exploit the increasing intelligence in storage systems. One primary reason is the narrow I/O interface between storage applications and storage systems. In such a simple interface, storage applications perform only block read or write operations without any indication of access patterns or data semantics. As a result, storage systems can only manage data at the block level without knowing any semantic information such as the semantic correlations between blocks. Therefore, much previous work had to rely on simple patterns such as temporal locality, sequentiality, and loop references to improve storage system performance, without fully exploiting its intelligence. This motivates a more powerful analysis tool to discover more complex patterns, especially semantic patterns, in storage systems.

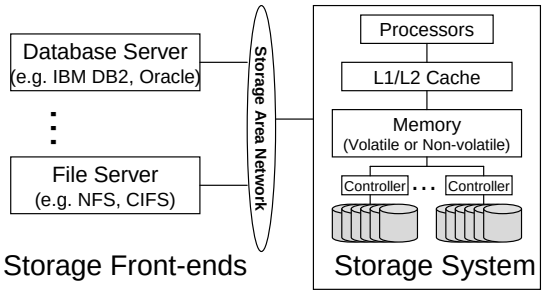


Figure 1: Example of modern storage architecture

Block correlations are common semantic patterns in storage systems. Many blocks are correlated by semantics. For example, in a database that uses index trees such as B-trees to speed up query performance, a tree node is correlated to its parent node and its ancestor nodes. Similarly, in a file server-backend storage system, a file block is correlated to its inode block. Correlated blocks tend to be accessed relatively close to each other in an access stream. Exploring these correlations is very useful for improving the effectiveness of storage caching, prefetching, data layout and disk scheduling. For example, at each access, a storage system can prefetch correlated blocks into its storage cache so that subsequent accesses to these blocks do not need to access disks, which is several orders of magnitude slower than accessing directly from a storage cache. As self-managing systems are becoming ever so important, capturing block correlations would enhance the storage system's knowledge about its workloads, a necessary step toward providing self-tuning capability.

Unfortunately, information about block correlations are unavailable at a storage system because a storage system exports only block interfaces. Since databases or file systems are typically provided by vendors different from those of storage systems, it is quite difficult and complex to extend the block I/O interface to allow upper levels to inform a storage system about block correlations. Recently, Arpaci-Dusseau et al. proposed a very interesting approach called semantically-smart disk systems (SDS) [54] by using a "gray-box" technology to infer data structure and categorize data in storage systems. However, this approach requires probing in the front-end and assumes that

the front-ends conform to the FFS-like file system layout.

An alternative approach is to infer block correlations fully transparently inside a storage system by only observing access sequences. This approach does not require any probing from a front-end and also makes no assumption about the type of the front-ends. Therefore, this approach is more general and can be applied to storage systems with any front-end file systems or database servers. Semantic distances [34, 35] and probability graphs [24, 25] are such "black-box" approaches. They are quite useful in discovering file correlations in file systems (see section 2.3 for more details).

This paper proposes *C-Miner*, a method which applies a data mining technique called *frequent sequence mining* to discover block correlations in storage systems. Specifically, we have modified a recently proposed data mining algorithm called CloSpan [66] to find block correlations in several storage traces collected in real systems. To the best of our knowledge, *C-Miner* is the first approach to infer block correlations involving multiple blocks. Furthermore, *C-Miner* is more scalable and space-efficient than previous approaches. It runs reasonably fast with reasonable space overhead, indicating that it is a practical tool for dynamically inferring correlations in a storage system. Moreover, we have also evaluated the benefits of block correlation-directed prefetching and disk data layout using the real system workloads. Compared to the base case, this scheme reduces the average response time by 12% to 25%. Compared to the sequential prefetching scheme, it also reduces the average response time by 7% to 20%.

The paper is organized as follows. In the next section, we briefly describe block correlations, the benefits of exploiting block correlations, and approaches to discover block correlations. In section 3, we present our data mining method to discover block correlations. Section 4 discusses how to take advantage of block correlations in the storage cache for prefetching and disk layout. Section 5 presents our experimental results. Section 6 discusses the related work and section 7 concludes the paper.

2 Block Correlations

2.1 What are Block Correlations?

Block correlations commonly exist in storage systems. Two or more blocks are correlated if they are "linked" together semantically. For example, Figure 2(a) shows some block correlations in a storage system which manages data for an NFS server. In this example, a directory block "/dir" is directly correlated to the inode block of "/dir/foo.txt", which is also directly correlated to the file block of "/dir/foo.txt". Besides direct correlations, blocks can also be correlated indirectly through another block. For example, the directory block "/dir" is indirectly correlated to the file block of "/dir/foo.txt". Figure 2(b) shows block correlations in a database-backend storage system. Databases commonly use a tree structure such as B-tree or B*-tree to store data. In such a data structure, a node is directly correlated to its parent and children, and also indirectly correlated to its ancestor and descendant nodes.

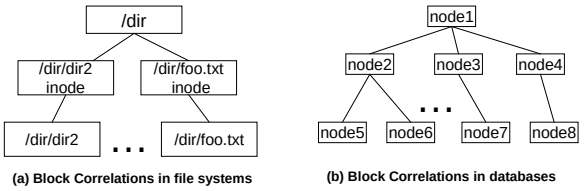


Figure 2: Examples of block correlations

Unlike other access patterns such as temporal locality, block correlations are inherent in the data managed by a storage system. Access patterns such as temporal locality or sequentiality depend on workloads and can therefore change dynamically, whereas block correlations are relatively more stable and do not depend on workloads, but rather on data semantics. When block semantics are changed (for example, a block is reallocated to store other data), some block correlations may be affected. In general, block semantics are more stable than workloads, especially in systems that do not have very bursty deletion and insertion operations that can significantly change block semantics. As we will show in section 5.3, block correlations can remain stable for several days in file systems.

Correlated blocks are usually accessed very close to each other. This is because most storage front-ends (database servers or file servers) usually follow semantic "links" to access blocks. For example, an NFS server needs to access an inode block before accessing a file block. Similarly, a database server first needs to access a parent node before accessing its children. Due to the interleaving of requests and transactions, these I/O requests may not be always consecutive in the access stream received by a storage system. But they should be relatively close within a short distance from each other.

Spatial locality is a simple case of block correlations. An access stream exhibits spatial locality if, after a block is accessed, other blocks that are near it are likely to be accessed in the near future. This is based on the observation that a block is usually semantically correlated to its neighboring blocks. For example, if a file's blocks are allocated in disks consecutively, these blocks are correlated to each other. Therefore, in some workloads, these blocks are likely accessed one after another.

However, many correlations are more complex than spatial locality. For example, in an NFS server, an inode block is usually allocated separately from its file blocks and a directory block is allocated separately from the inode blocks of the files in this directory. Therefore, although accesses to these correlated blocks are close to each other in the access stream, they do not exhibit good spatial locality because these blocks are far away from each other in the disk layout and even on different disks.

In some cases, a block correlation may involve more than two blocks. For example, a three-block correlation might be: if *both* a and b are accessed recently, c is very likely to be accessed in a short period of time. Basically, a and b are correlated to c, but a or b alone may not be correlated to c. To give a real instance of this multi-block correlation, let us consider a B* tree which also links all the leaf nodes together. a, b and c

are all leaf nodes. If a is accessed, the system cannot predict that c is going to be accessed soon. However, if a *and* b are accessed one after another, it is likely that c will be accessed soon because it is likely that the front-end is doing a sequence scan of all the leaf nodes, which is very common in decision-support system (DSS) workloads [7, 68].

2.2 Exploiting Block Correlations

Block correlations can be exploited to improve storage system performance. First, correlations can be used to direct prefetching. For example, if a strong correlation exists between blocks a and b, these two blocks can be fetched together from disks whenever one of them is accessed. The disk read-ahead optimization is an example of exploiting the simple sequential block correlations by prefetching subsequent disk blocks ahead of time. Several studies [55, 14, 31] have shown that using even these simple sequential correlations can significantly improve the storage system performance. Our results in section 5.5 demonstrate that prefetching based on block correlations can improve the performance much better than such simple sequential prefetching in most cases.

A storage system can also lay out data in disks according to block correlations. For example, a block can be collocated with its correlated blocks so that they can be fetched together using just one disk access. This optimization can reduce the number of disk seeks and rotations, which dominate the average disk access latency. With correlation-directed disk layouts, the system only needs to pay a one-time seek and rotational delay to get multiple blocks that are likely to be accessed soon. Previous studies [52, 54] have shown promising results in allocating correlated file blocks on the same track to avoid track-switching costs.

Correlations can also be used to direct storage caching. For example, a storage cache can "promote" or "demote" a block after its correlated block is accessed or evicted. After an access to block A, blocks that are correlated to A are likely to be accessed very soon. Therefore, a cache replacement algorithm can specially "mark" these blocks to avoid being evicted. Similarly, after a block A is evicted, blocks that are correlated to A are not very likely to be accessed soon so it might be OK to also evict these blocks in subsequent replacement decisions. The storage cache can also give higher priority to those blocks that are correlated to many other blocks. Therefore, for databases that use tree structures, it would achieve a similar effect as the DBMIN cache replacement algorithm that is specially designed for database workloads [15]. This algorithm gives higher priority to root blocks or high-level index blocks to stay in a database buffer cache.

Besides performance, block correlations can also be used to improve storage system security, reliability and energy-efficiency. For example, malicious clients accesses the storage system in a very different pattern from the normal clients. By catching abnormal block correlations in an access stream, the storage system can detect such kind of malicious users. When a file block is archived to a tertiary storage, its correlated blocks may also need to be backed up in order to provide consistency. In addition, storage power management schemes can also take advantage of block correlations by clustering correlated blocks in the same disk so it is possible for other disks to transition into standby mode [11].

The experiments in this study focus on demonstrating the benefits of exploiting block correlations in improving storage system performance. The usages for security, reliability and energy-efficiency remain as our future work.

2.3 Obtaining Block Correlations

There can be three possible approaches to obtain block correlations in storage systems. These approaches trade transparency and generality for accuracy at different degrees. The "black box" approach is most transparent and general because it infers block correlations without any assumption or modification to storage front-ends. The "gray box" approach does not need modifications to front-end software but makes certain assumptions about front-ends and also requires probing from front-ends. The "white box" approach completely relies on front-ends to provide information and therefore has the most accurate information but is least transparent.

"Black Box" approaches infer block correlations completely inside a storage system, without any assumption on the storage front-ends. One commonly used method of this approach is to infer block correlations based on accesses. The observation is that correlated blocks are usually accessed relatively close to each other. Therefore, if two blocks are almost always accessed together within a short access distance, it is very likely that these two blocks are correlated to each other. In other words, it is possible to automatically infer block correlations in a storage system by dynamically analyzing the access stream.

In the field of networked or mobile file systems, researchers have proposed semantic distance (SD) [34, 35] or probability graphs [24, 25] to capture file correlations in file systems. The main idea is to use a graph to record the number of times two items are accessed within a specified access distance. In an SD graph, a node represents an accessed item B_1 with edges linking to other items. The weight of each edge (B_1, B_2) is the number of times that B_2 is accessed within the specified lookahead window of B_1's access. So if the weight for an edge is large, the corresponding items are probably correlated.

The algorithm to build the SD graph from an access stream works like this: Suppose the specified lookahead window size is 100, i.e., accesses that are less than 100 accesses apart are considered to be "close" accesses. Initially the probability graph is empty. The algorithm processes each access one after another. The algorithm always keeps track of the items of most recent 100 accesses in the current sliding window. When an item B is accessed, it adds node B into the graph if it is not in the graph yet. It also increments the weight of the edge (B_i, B) for any B_i accessed during the current window. If such an edge is not in the graph, it adds this edge and sets the initial weight to be 1. After the entire access stream is processed, the

algorithm rescans the SD graph and only records those correlations with weights larger than a given threshold.

Even though probability graphs or SD graphs work well for inferring file correlations in a file system, they, unfortunately, are not practical for inferring block correlations in storage systems because of two reasons. (1) *Scalability problem*: a semantic distance graph requires one node to represent each accessed item and also one edge to capture each non-zero-weight correlation. When the system has a huge number of items as in a storage system, an SD graph is too big to be practical. For instance, if we assume the specified window size is 100, it may require more than 100 edges associated with each node. Therefore, one node would occupy at least $100 \times 8 = 800$ (assuming each edge requires 8 bytes to store the weight and the disk block number of B_2). For a small storage system with only 80 GB and a block size of 8 KB, the probability graph would occupy 8 GB, 10% of the storage capacity. Besides space overheads, building and searching such a large graph would also take a significantly large amount of time. (2) *Multi-block correlation problem*: these graphs cannot represent correlations that involve more than two blocks. For example, the block correlations described at the end of the Section 2.1 cannot be conveniently represented in a semantic distance graph. Therefore, these techniques can lose some important block correlations.

In this paper, we present a practical black box approach that uses a data mining method to automatically infer both dual-block and multi-block correlations in storage systems. In Section 3, we describe our approach in detail.

"Gray Box" approaches are investigated by Arpaci-Dusseau et al in [5]. They developed three gray-box information and control layers between a client and the OS, and combined algorithmic knowledge, observations and inferences to collect information.

The gray-box idea has been explored by Sivathanu et al in storage systems to automatically obtain file-system knowledge [54]. The main idea is to probe from a storage front-end by performing some standard operations and then observing the triggered I/O accesses to the storage system. It works very well for file systems that conform to FFS-like structure (if the front-end security is not a concern). The advantage of this approach is that it does not require any modification to the storage front-end software. The tradeoff is that it requires the front-end to conform to specific disk layouts such as FFS-like structure.

"White Box" approaches rely on storage front-ends to directly pass semantic information to obtain block correlations in a storage system. For example, the storage I/O interface can be modified using a higher-level, object-like interface [23] so that correlations can be easily expressed using the object interface. The advantage with this approach is that it can obtain very accurate information about block correlations from storage front-ends. However, it requires modifying storage front-end software, some of which, such as database servers, are too large to be easily ported to object-based storage interface.

3 Mining for Block Correlations

Data mining, also known as knowledge discovery in databases (KDD), has developed quickly in recent years due to the wide availability of voluminous data and the imminent need for extracting useful information and knowledge from them. Traditional methods of data analysis dependent on human handling cannot scale well to huge sizes of data sets. In this section, we first introduce some fundamental data mining concepts and analysis methods used in our paper and then describe *C-Miner*, our algorithm for inferring block correlations in storage systems.

3.1 Frequent Sequence Mining

Different patterns can be discovered by different data mining techniques, including association analysis, classification and prediction, cluster analysis, outlier analysis, and evolution analysis [27]. Among these techniques, association analysis can help discover correlations between two or more sets of events or attributes. Suppose there exists a strong association between events x and y, it means that if event x happens, event y is also very likely to happen. We use the association rule $x \rightarrow y$ to describe such a correlation between these two events.

Frequent sequence mining is one type of association analysis to discover frequent subsequences in a sequence database [1]. A subsequence is considered *frequent* when it occurs in at least a specified number of sequences (called *min_support*) in the sequence database. A subsequence is not necessarily contiguous in an original sequence. For example, a sequence database D has five sequences:

$$D = \{abced, abcef, agbch, abijc, aklc\}$$

The number of occurrences of subsequence abc is 4. We denote the number of occurrences of a subsequence as its $support$. Obviously, the smaller min_sup is, the more frequent subsequences the database contains. In the above example, if min_sup is specified as 5, only the subsequence ac is frequent; if min_sup is specified as 4, the frequent subsequences are $\{ab{:}\,4, ac{:}\,5, bc{:}\,4, abc{:}\,4\}$, where the numbers are the supports of the subsequences.

Frequent sequence mining is an active research topic in data mining [67, 46, 6] with broad applications, such as mining motifs in DNA sequences, analysis of customer shopping sequences etc. To the best of our knowledge, our study is the first one that uses frequent sequence mining to discover patterns in storage systems.

C-Miner is based on a recently proposed frequent sequence mining algorithm called *CloSpan* (Closed Sequential Pattern mining)[66]. The main idea of CloSpan is to find only closed frequent subsequences. A *closed sequence* is a subsequence whose support is different from that of its super-sequences. In the above example, subsequence ac is closed because its support is 5, and the support of any one of its super-sequences (for example, abc and agc, etc.) is no more than 4; on the other

hand, subsequence ab is not closed because its support is the same as that of one of its super-sequences, abc.

CloSpan only produces the closed frequent subsequences rather than all frequent subsequences since any non-closed subsequences can be indicated by their super-sequences with the same support. In the above example, the frequent subsequences are $\{a{:}\,4, b{:}\,4, c{:}\,5, ab{:}\,4, ac{:}\,5, bc{:}\,4, abc{:}\,4\}$, but we only need to produce the closed subsequences $\{ac{:}\,5, abc{:}\,4\}$. This feature significantly reduces the number of patterns generated, especially for long frequent subsequences. More details can be found in [46, 66].

3.2 *C-Miner*: Our Mining Algorithm

Frequent sequence mining is a good candidate for inferring block correlations in storage systems. One can map a block to an item, and an access sequence to a sequence in the sequence database. Using frequent sequence mining, we can obtain all the frequent subsequences in an access stream. A frequent subsequence indicates that the involved blocks are frequently accessed together. In other words, frequent subsequences are good indications of block correlations in a storage system.

One limitation with the basic mining algorithm is that it does not consider the gap of a frequent subsequence. If a frequent sequence contains two accesses that are very far from each other in terms of access time, such a correlation is not interesting for our application. From the system's point of view, it is much more interesting to consider frequent access subsequences that are not far apart. For example, if a frequent subsequence xy always appears in the original sequence with a distance of more than 1000 accesses, it is not a very interesting pattern because it is hard for storage systems to exploit it. Further, such correlations are generally less accurate.

To address this issue, *C-Miner* restricts access distances. In order to describe how far apart two accesses are in the access stream, the access distance between them is denoted as gap, measured by the number of accesses between these two accesses. We specify a maximum distance threshold, denoted as max_gap. All the uninteresting frequent sequences whose gaps are larger than the threshold are filtered out. This is similar to the lookahead window used in the semantic distance algorithms.

3.2.1 Preprocessing

Existing frequent sequence mining algorithms including CloSpan are designed to discover patterns for a sequence database rather than a single long sequence of time-series information as in storage systems. To overcome this limitation, *C-Miner* preprocesses the access sequence (that is, the history access trace) by breaking it into fixed-size short sequences. The size of each short sequence is called *cutting window size*.

There are two ways to cut the long access stream into short sequences - overlapped cutting and non-overlapped cutting. The overlapped cutting divides an entire access stream into many short sequences and leaves some overlapped regions between any two consecutive sequences. Non-overlapped cutting is straightforward; it simply splits the access stream into access sequences of equal size.

Figure 3 illustrates how these two methods cut the access stream $abcabdabeabf$ into short sequences with length of 4. Overlapped cutting may increase the number of occurrences for some subsequences if it falls in the overlapped region. In the example shown in Figure 3, using overlapped cutting results in 5 short sequences: $\{abca, cabd, bdab, abea, eabf\}$. The subsequences ab in $bdab$ and $abea$ occurs only once in the original access stream, but now is counted twice since the short sequences, $bdab$ and $abea$, overlap with each other. It is quite difficult to determine how many redundant occurrences there are due to overlapping. Another drawback is that the overlapped cutting generates more sequences than non-overlapped cutting. Therefore it takes the mining algorithm a longer time to infer frequent subsequences.

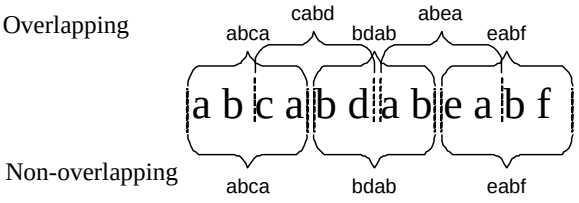


Figure 3: Overlapping and non-overlapping window (Cutting window size is 4)

Using non-overlapped cutting can, however, lead to loss of frequent subsequences that are split into two or more sequences, and therefore can decrease the support values of some frequent subsequences because some of their occurrences are split into two sequences. In the example shown in figure 3, the non-overlapped cutting results in only 3 sequences: $\{abca, bdab, eabf\}$. The support for ab is 3, but the actual support in the original long sequence is 4. The lost support is because the second occurrence is broken across two windows and is therefore not counted.

But we believe that the amount of lost information in the non-overlapped cutting scheme is quite small, especially if the cutting window size is relatively large. Since *C-Miner* restricts the access distance of a frequent subsequence, only a few frequent subsequences may be split across multiple windows. Suppose the instances of a frequent subsequence are distributed uniformly in the access stream, the cutting windows size is w and the maximum access distance for frequent sequences is max_gap ($max\_gap \ll w$). Then, in the worst case, the probability that an instance of a frequent subsequence is split across two sequences is max_gap/w. For example, if the access distance is limited within 50, and the cutting window size is 500 accesses, the support value is lost by at most 10% in the worst case. Therefore, most frequent subsequences would still be considered frequent after non-overlapped cutting. Based on this analysis, we use non-overlapped cutting in our experiments.

3.2.2 Core Algorithm

Once it has a database of short sequences, *C-Miner* mines the database and produces frequent subsequences, which can then be used to derive block correlations. *C-Miner* mainly consists of two stages: (1) generating a candidate set of frequent subsequences that includes all the closed frequent subsequences; and (2) pruning the non-closed subsequences from the candidate set.

In the first stage, *C-Miner* generates a candidate set of frequent sequences using a depth-first search procedure. The following pseudo-code shows the mining algorithm. In the algorithm, D_s is a suffix database which contains all the maximum suffixes of the sequences that contain the frequent subsequence s. For example, in the previous sequence database D, the suffix database of frequent subsequences ab is $D_{ab} = \{ced, cef, ch, ijc\}$.

Algorithm: MINING(s, D_s, min_sup, L)
Input: A frequent subsequence s,
a set of subsequence D_s,
support threshold min_sup.
Output: The frequent sequence set L.
1: insert s to L.
2: scan D_s to find every frequent item α such that $s \diamond \alpha$ is frequent sequence, $D_{s\diamond\alpha} \leftarrow \{$ all maximum suffixes that can be concatenated with $s \diamond \alpha\}$.
3: for each α do
MINING($s \diamond \alpha, D_{s\diamond\alpha}, min\_sup, L$).

(Note: $s \diamond \alpha$ means to concatenate s with α.)

There are two main ideas in *C-Miner* to improve the mining efficiency. The first idea is based on an obvious observation that if a sequence is frequent, then all of its subsequences are frequent. For example, if a sequence abc is frequent, all of its subsequences $\{a, b, c, ab, ac, bc\}$ are frequent. Based on this observation, *C-Miner* recursively produces a longer frequent subsequence by concatenating every frequent item to a shorter frequent subsequence that has already been obtained in the previous iterations.

To better explain this idea, let us consider an example. In order to get the set L_n of frequent subsequences with length n, we can join the set L_{n-1} of frequent subsequences with length $n-1$ and the set L_1 of frequent subsequences with length 1. For example, suppose we have already computed L_1 and L_2 as shown below. In order to compute L_3, we can first compute L'_3 by concatenating a subsequence from L_2 and an item from L_1:

$$\begin{aligned} L_1 &= \{a, b, c\}; \\ L_2 &= \{ab, ac, bc\}; \\ L'_3 &= L_2 \times L_1 \\ &= \{abc, abb, abc, aca, acb, acc, bca, bcb, bcc\} \end{aligned}$$

For greater efficiency, *C-Miner* does not join the sequences in set L_2 with all the items in L_1. Instead, each sequence in L_2 is concatenated with only the frequent items in its suffix database. In our example, for the frequent sequence ab in L_2, its suffix database is $D_{ab} = \{ced, cef, ch, ijc\}$, and only c is the frequent item, so ab is only concatenated with c and then we get a longer sequence abc that belongs to L'_3.

The second idea is used for efficiently evaluating whether a concatenated subsequence is frequent or not. It tries to avoid searching through the whole database. Instead, it only checks with certain suffixes. In the above example, for each sequence s in L'_3, *C-Miner* checks whether it is frequent or not by searching the suffix database D_s. If the number of its occurrences is greater than min_sup, s is added into L_3, which is the set of frequent subsequences of length 3. *C-Miner* continues computing L_4 from L_3, L_5 from L_4, and so on until no more subsequences can be added into the set of frequent subsequences.

In order to mine frequent sequences more efficiently, *C-Miner* uses a technique that can efficiently determine whether there are new closed patterns in search subspaces and stop checking those unpromising subspaces. The basic idea is based on the following observation about a closed sequence property. In the algorithm step 2, among all the sequences in D_s, if an item a always occurs before another item b, *C-Miner* does not need to search any sequences with prefix $s \diamond b$. The reason is that $\forall\gamma$, $s \diamond b \diamond \gamma$ is not closed under this condition. Take the previous sequence database as an example. a always occurs before b, so any subsequence with prefix b is not closed because it is also a subsequence with prefix ab. Therefore, *C-Miner* does not need to search the frequent sequences with prefix b because all these frequent sequences are included in the frequent sequences with prefix ab (e.g., bc is included in abc with support 4). Without searching these unpromising branches, *C-Miner* can generate the candidate frequent sequences much more efficiently.

3.2.3 Generating Association Rules

C-Miner produces frequent sequences that indicate block correlations, but it does not directly generate the association rules in the form of $x_1x_2 \rightarrow y$, which is much easier to use in storage systems.

In order to convert the frequent sequences into association rules, *C-Miner* breaks each sequence into several rules. In order to limit the number of rules, *C-Miner* constrains the length of a rule (the number of items on the left side of a rule). For example, a frequent sequence abc may be broken into the following set of rules with the same support of abc:

$$\{a \rightarrow b, a \rightarrow c, b \rightarrow c, ab \rightarrow c\}$$

Different closed frequent sequences can be broken into the same rules. For example, both abc and abd can be broken into the same rule $a \rightarrow b$, but they may have different support values. The support of a rule is the *maximum* support of all corresponding closed frequent sequences.

3.2.4 Confidence of Rules

For each association rule, we also need to evaluate its accuracy . In order to describe the reliability of a rule, we introduce $confidence$ to measure the accuracy. For example, in the above example, a occurs 5 times, but ab only occurs 4 times; this means that when a is accessed, b is also accessed in the near future (within max_gap distance) with probability 80%. We call this probability the confidence of the rule. When we use an association rule to predict future accesses, its confidence indicates the expected prediction accuracy. Predictions based on low-confidence rules are likely to be wrong and may not be able to improve system performance. Worse still, they may hurt the system performance due to overheads and side-effects. Because of this, we use confidence to restrict rules and filter out those with low probability.

The $support$ metric is different from $confidence$. For example, suppose x and y are accessed only once in the entire access stream and their accesses are within the max_gap distance, the confidence of the association rule $x \rightarrow y$ is 100% whereas its support is only 1. This rule is not very interesting because it happens rarely. On the other hand, if a rule has high support but very low confidence (e.g. 5%), it may not be useful because it is too inaccurate to be used for prediction. Therefore, in practice, we usually specify a minimum support threshold min_sup and a minimum confidence threshold min_conf in order to filter low-quality association rules.

We can estimate the confidence for each rule in a simple way. Suppose we need to compute the confidence for rule $a \rightarrow b$. Assume that the supports for a and b are $sup(a)$ and $sup(b)$, respectively. Then the confidence for this rule is $sup(b)/sup(a)$. Since both sides of each rule are frequent sequences (or frequent items) and the supports for all the frequent sequences are already obtained from post-processing, $sup(a)$ and $sup(b)$ are ready to be used for computing the confidence of the rule.

3.3 Efficiency of *C-Miner*

Compared with other methods such as probability graphs or SD graphs, *C-Miner* can find more correlations, especially those multi-block correlations. From our experiments, we find that these multi-block correlations are very useful for systems.

For dual-block correlations, which can also be inferred using previous approaches, *C-Miner* is more efficient. First, *C-Miner* is much more space efficient than SD graphs because it does not need to maintain the information for non-frequent sequences, whereas SD graphs need to keep the information for every block during the graph building process. Second, in terms of time complexity, *C-Miner* is the same ($O(n)$) as SD. But in practice, since *C-Miner* has much smaller memory footprint size, it is more efficient and can run in a cheap uniprocessor machine with moderate memory size as used in our experiments.

Other frequent sequence mining algorithms such as PrefixSpan[46] can also find long frequent sequences. Compared with these frequent sequence mining algorithms, *C-Miner* is more efficient for discovering long frequent sequences because it not only avoids searching the non-frequent sequences while generating longer sequences, but also prunes all the unpromising searching branches according to the closed sequence property as we have discussed. *C-Miner* can outperform PrefixSpan by an order of magnitude for some datasets.

4 Case Studies

4.1 Correlation-Directed Prefetching (CDP)

The block correlation information inferred by *C-Miner* can be used to prefetch more intelligently. Assume that *C-Miner* has obtained a block correlation rule: if block b_1 is accessed, block b_2 will also be accessed soon within a short distance (of length gap) with a certain confidence (probability). Based on this rule, when there is an access to block b_1, we can prefetch block b_2 into the storage cache since it will probably be accessed soon. Doing such can avoid future accesses to disks to fetch these blocks.

Several design issues should be considered while using block correlations for prefetching. One of the most important issues is how to effectively share the limited size cache for both caching and prefetching. If prefetching is too aggressive, it can pollute the storage cache and may even degrade the cache hit ratio and system performance. This problem has been investigated thoroughly by previous work [9, 10, 45]. We therefore do not investigate it further in our paper. In our simulation experiments, we simply fix the cache size for prefetched data so it does not compete with non-prefetching requests. However, the total cache size is fixed at the same value for the system with and without prefetching in order to have a fair comparison.

Another design issue is the extra disk load imposed by prefetch requests. If the disk load is too heavy, the disk utilization is close to 100%. In this case, prefetching can add significant overheads to demand requests, canceling out the benefits of improved storage cache hit ratio. Two methods can be used to alleviate this problem. The first method is to differentiate between demand requests and prefetch requests by using a priority-based disk scheduling scheme. In particular, the system uses two waiting queues in the disk scheduler: critical and non-critical. All the demand requests are issued to the critical queue, while the prefetch requests are issued to the non-critical queue which has lower priority.

The other method is to throttle the prefetch requests to a disk if the disk is heavily utilized. Since the correlation rules have different confidences, we can set a confidence threshold to limit the number of rules that are used for prefetching. All the rules with confidence lower than the threshold are ignored. Obviously, the higher the confidence threshold is, the fewer the rules are used. Therefore, CDP acts less aggressively. In order to adjust the threshold to make prefetching adapt to the current disk workload, we keep track of the current load on each disk. When the workload is too high, say the disk utilization is more than 80%, we increase the confidence threshold for correlation rules that direct the issuing of prefetch requests to this disk.

Once the disk load drops down to a low level, say the utilization is less than 50%, we decrease the confidence threshold for correlation rules so that more rules can be used for prefetching. By doing this, the overhead on disk bandwidth caused by prefetches is kept within an acceptable range.

4.2 Correlation-directed Disk Layout

Block correlations can help lay out data on disks to improve performance. The dominant latencies in a disk access are the seek time and rotation delay. So if correlated blocks can be allocated together on a disk and can be fetched using one disk access, the total seek time and rotation delay for all these blocks can be reduced. Thereafter, both of the throughput and the response time can be improved. But CDP is more effective than disk layout for improving response time as shown in section 5.5.

We can lay out the blocks on disks based on block correlatoins like that: if we know a correlation $abcd$ from *C-Miner*, we can try to allocate them contiguously in a disk. Whenever any one of these blocks is read, all four blocks are fetched together into the storage cache using one disk access. Since some blocks may appear in several patterns, we allocate the block based on the rules with highest support value.

One of the main design issues is how to maintain the directory information and reorganize data without an impact on the foreground workload. After reorganizing disk layouts, we need to map logical block numbers to new physical block numbers. The mapping table might become very large. Some previous work has studied these issues and shown that disk layout reorganization is feasible to implement [50]. They proposed a two-tiered software architecture to combine multiple disk layout heuristics so that it adapts to different environments. Block correlation-directed disk layout can be one of the heuristics in their framework. Due to space limitation, we do not discuss this issue further.

5 Simulation Results

5.1 Evaluation Methodology

To evaluate the benefits of exploiting block correlations in block prefetching and disk data layout, we use trace-driven simulations with several large disk traces collected in real systems. Our simulator combines the widely used DiskSim simulator [20] with a storage cache simulator, CacheSim, to simulate a complete storage system. CacheSim implements the Least Recently Used (LRU) replacement policy. Accesses to the simulated storage system first go through a storage cache and only read misses or writes access physical disks. The simulated disk specification is similar to that of the 10000 RPM IBM Ultrastar 36Z15. The parameters are taken from the disk's data sheet [28, 11].

Our experiments use the following four real system traces:

- *TPC-C Trace* is an I/O trace collected on a storage system connected to a Microsoft SQL Server via storage area network. The Microsoft Server SQL clients connect to the Microsoft SQL Server via Ethernet and run the TPC-C benchmark [39] for 2 hours. The database consists of 256 warehouses and the footprint is 60GB, and the storage system employs a RAID of 4 disks. A more detailed description of this trace can be found in [69, 13].

- *Cello-92* was collected at Hewlett-Packard Laboratories in 1992 [49, 48]. It captured all low-level disk I/O performed by the system. We used the trace gathered on Cello, which is a timesharing system used by a group of researchers at HP Labs to do simulations, compilation, editing and email. The trace includes the accesses to 8 disks. We have also tried other HP disk trace files, and the results are similar.

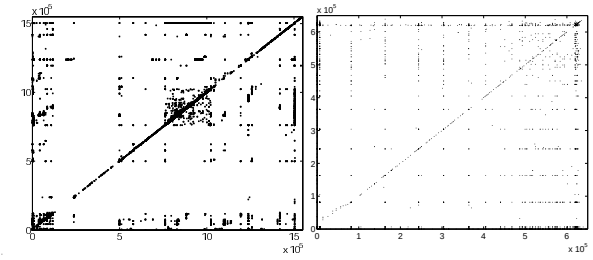
- *Cello-96* is similar to Cello-92. The only difference is that this trace was collected in 1996 and thereby contains more modern workloads. It includes the accesses to 20 disks from multiple users and miscellaneous applications. It contains a lot of sequential access patterns, so the simple sequential prefetching approaches can significantly benefit from them.

- *OLTP* is a trace of an OLTP application running at a large financial institution. It was made available by the Storage Performance Council [58]. The disk subsystem is composed of 19 disks.

All the traces are collected after filtering through a first-level buffer cache such as the database server cache. Fortunately, unlike other access patterns such temporal locality that can be filtered by large first-level buffer caches, most block correlations can still be discovered at the second-level. Only those correlations involving "hot" blocks that always stay at the first-level can be lost at the second-level. However, these correlations are not useful to exploit anyway since "hot" blocks are kept at the first-level and therefore are rarely accessed at the second-level.

In our experiments, we use only the first half part of the trace to mine block correlations using *C-Miner*. Using these correlation rules, we evaluate the performance of correlation-directed prefetching and data layout using the rest of the traces. The correlation rules are kept unchanged during the evaluation phase. For example, in Cello-92, we use the first 3-days' trace to mine block correlations and use the following 4 days to evaluate the correlation-directed prefetching and data layout. The reason for doing this is to show the stable characteristic of block correlations and predictive powers of our method.

To provide a more fair comparison, we also implement the commonly used sequential prefetching scheme. At non-consecutive misses to disks, the system also issues a prefetch request to load 16 consecutive blocks. We have also tried prefetching more or fewer blocks, but the results are similar or worse.



(a) *Cello-96 trace* (b) *TPC-C trace*

Figure 4: Block correlations mined from traces

5.2 Visualization of Block Correlations

5.2.1 Correlations in Real System Traces

Figure 4 plots the block correlations discovered by *C-Miner* from the Cello-96 and TPC-C traces. Since multi-block correlations are difficult to visualize, we plot only dual-block correlations. If there is an association rule $x \rightarrow y$, we plot a corresponding point at (x, y). Therefore, each point (x, y) in the graphs indicates a correlation between blocks x and y. Since the traces contain multiple disks' accesses, we plot the disk block address using a unified continuous address space by plotting one disk address space after another.

Simple patterns such as spatial locality can be demonstrated in such a correlation graph. It is indicated by dark areas around the diagonal line. This is because the spatial locality can be represented by an association rule $x \rightarrow (x \pm k)$ where k is a small number, which means that if block x accessed, its neighbor blocks are likely to be accessed soon. Since k is small, the points $(x, x \pm k)$ are around the diagonal line, as shown on the Cello-96 traces (Figure 4a). The graph for the TPC-C trace does not have such apparent characteristic, indicating TPC-C does not have strong spatial locality.

Some more complex patterns can also be seen from correlation graphs. For example, in figure 4b, there are many horizontal or vertical lines, indicating some blocks are correlated to many other blocks. Because this is a database I/O trace, these hot blocks with many correlations are likely to be the root of trees or subtrees. In the next subsection, we visualize block correlations specifically for tree structures.

5.2.2 Correlations in B-tree

In order to demonstrate the capability of *C-Miner* to discover semantics in a tree structure, we use a synthetic trace that simulates a client that searches data in a B-tree data structure, which is commonly used in databases. The B-tree maintains the indices for 5000 data items, each block has space for four search-key values and five pointers. We perform 1000 searches. To simulate a real-world situation where some "hot" data items are searched more frequently than others, searches are not uniformly distributed. Instead, we use a Zipf distribution and 80% of searches are to 100 "hot" data items.

The block correlations mined from the B-tree trace are visualized in figures 5. Note here constructing this tree does not take any semantic information from the application (the synthetic trace generator). The edges between nodes are reconstructed purely based on block correlations. Due to the space limitation, we only show part of the correlations. Each rule $x \rightarrow y$ is denoted as a directed edge with support as its weight. The figure illustrates that the block correlations implicate a tree-like structure. Also note that our approach to obtain block correlations is fully transparent without any assumption on storage front-ends.

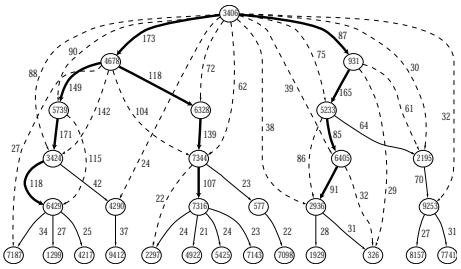


Figure 5: Block correlations in B-tree. The number on an edge is the support value for the corresponding correlation. The dashed lines indicate the correlation between a node and its descendants other than its children. The highlighted lines are the correlations with $support \geq 80$. Note that correlations with $support < 20$ are not produced by *C-Miner* ($min\_sup = 20$) in order to make the tree reasonably small and sparse for plotting.

5.3 Stability of Block Correlations

In order to show that block correlations are relatively stable, we use the correlation rules mined from the *first 3 days* of the Cello-92 trace. Our simulator applies these rules to the next 4 days' trace without updating any rules. Figure 6 shows the miss ratio for the *next 4 days'* trace using correlated-directed prefetching (CDP). The miss ratios in the figure are calculated by aggregating every 10000 read operations. This figure shows that CDP is always better than the base case. This implies that correlations mined from the first 3 days are still effective for the next 4 days. In other words, block correlations are relatively stable for a relative long period of time. Therefore, there is no need to run *C-Miner* continuously in the background to update block correlations. This also shows that, as long as the mining algorithm is reasonably efficient, the mining overhead is not a big issue.

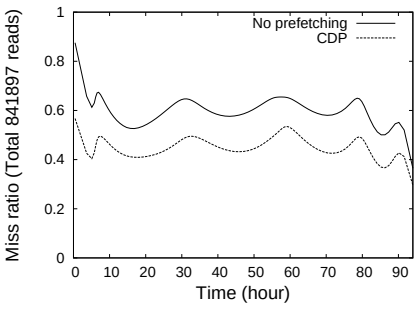


Figure 6: Miss ratio for Cello-92 (64MB; 4MB)

5.4 Data Mining Overhead

Table 1 shows the running time and space overheads for mining different traces. *C-Miner* is running on an Intel Xeon 2.4GHz machine and Windows 2000 Server. The time and space overhead does not depend on the confidence of rules as we discussed in section 3.2 but the number of rules does. The results show that *C-Miner* can effectively and practically discover block correlations for different workloads. For example, it takes less than 1 hour to discover half a million association rules from the Cello-96 trace that contains a full-day's disk requests. For the TPC-C trace, although it takes about 1 hour to mine 1 hour's trace, it is still practical for storage systems. Because block correlations are relatively stable, it is unnecessary to keep mining for correlations in the background. Instead, it might be acceptable to spend one hour every week on running *C-Miner* to update correlation rules. In our experiments, we only use parts of the traces to mine correlations, and use the remaining traces to evaluate correlation-directed prefetching and disk layout. Our experimental results indicate that correlations are relative stable and are useful for accesses made much later after the training period.

Training Trace	# of rules (K)	time (sec)	space (MB)
Cello-92 (3 days)	228	7800	3.1
Cello-96 (1 day)	514	2089	4.6
TPC-C (1 hour)	235	3355	9.2
OLTP (2.5 hours)	186	174	172.6

Table 1: Mining Overhead ($confidence \geq 10\%$)

C-Miner is also efficient in terms of space overhead for most of traces. It takes less than 10 MB to mine the Cello and TPC-C traces. With such a small requirement, the data mining can run on the same machine as the storage system without causing too much memory overhead. A uniprocessor PC with 512MB memory would do the work. In the future, we will investigate using stream mining algorithms to effectively mine continuous information with much less time and space overhead. The stream mining algorithm could be embedded in the storage controllers using their spare CPU power.

5.5 Correlation-directed Prefetching and Disk Layout

The bar graphs in figures 7a-d compare the read miss ratios and response times using the four different schemes: base-line (no-prefetching), sequential prefetching, correlation-directed prefetching (CDP), and correlation-directed prefetching and disk layout (CDP+layout). For the last three schemes with prefetching, the prefetch cache size is set to be the same. All four settings use the same total size of storage cache in order to make a fair comparison. In other words, the $TotalCacheSize$, which equals to the sum of $DemandCacheSize$ and $PrefetchCacheSize$, is the same for all four schemes.

CDP can improve the average I/O response time for the base-line case by up to 25%. For instance, in Cello-92, CDP has 24.4% lower storage cache hit ratios than the base-line case. This translates into 24.75% improvement in the average I/O response time. These improvements are due to the fact that prefetching reduces the number of capacity misses as well as the number of cold misses. When the cache size is small, some blocks are evicted and need to be fetched again for disks upon subsequent accesses. Prefetching can avoid misses at some of these accesses.

The improvement by CDP is much more significant than that by the commonly used sequential prefetching scheme, especially in the case of TPC-C and Cello-92. For example, for the TPC-C trace, sequential prefetching only slightly reduces the cache miss ratio (by only 2%), which is then completely cancelled out by the prefetching overheads. Therefore, sequential prefetching has even worse response time than the base case. For the other two traces (Cello-92 and OLTP trace), the improvement of the sequential prefetching scheme is very small, almost invisible in terms of the average response time. However, in Cello-96, sequential prefetching has a lower miss ratio and slightly better response time than CDP. This is because this trace has a lot of sequential accesses. But these sequential accesses are not frequent enough in the access stream so it is not caught by *C-Miner*. Fortunately, our patterns obtained by *C-Miner* can be complementary and combined with the existing online sequential prefetching algorithms that can detect non-frequent sequential access patterns.

CDP+layout has only small improvement over CDP. Obviously, CDP+layout should not affect cache miss ratio at all. It only matters to average I/O response time when the disk is heavily utilized. Its benefits are only visible in the Cello-96 trace, where CDP+layout has 4% better average response time than CDP. This small improvement indicates that our optimization for hiding prefetching overheads using priority-based disk scheduling is already good enough. Therefore, disk layout does not provide significant benefits. However, when the disk is too heavily utilized for the disk scheduling scheme to hide most of the prefetching overheads, we expect the benefit of correlation-directed disk layout will be larger.

5.6 Impact of Configurations

5.6.1 Effects of the Confidence Threshold

A parameter that might affect the benefits of correlation directed prefetching is the confidence threshold. Figure 8 shows the effects of varying the confidence threshold from 0% to 90% . A lower confidence threshold corresponds to a more aggressive prefetching policy. The figure shows that the miss ratio is minimum when prefetching is most aggressive and all the rules are used. We can see that the line is flat when the confidence is smaller than 30%, which indicates that the rules with small confidence are useless.

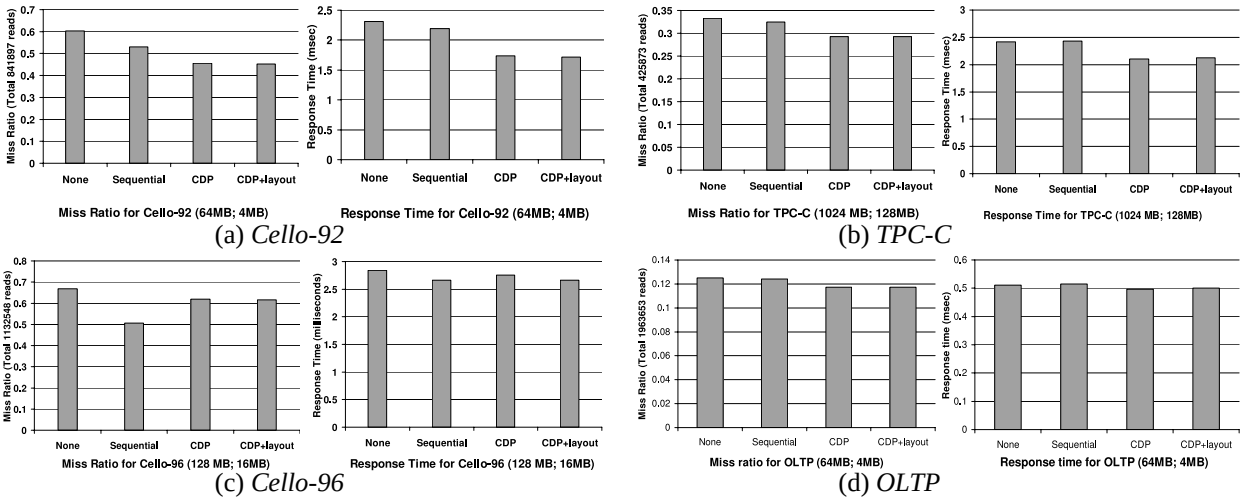


Figure 7: Miss Ratio and Response Time. The first number in the parenthesis is the total cache size, and the second number is the prefetch cache size. In the base-line case "None", the prefetch cache size is 0, so the demand cache size = the total cache size. In the other three schemes, the demand cache size is the total cache size − the prefetch cache size.

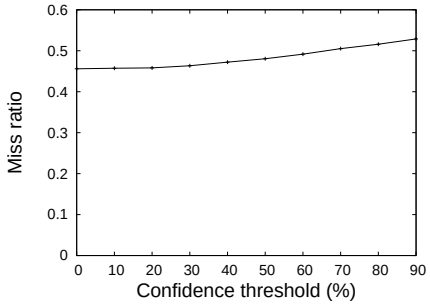


Figure 8: Effect of the confidence threshold (Cello-92)

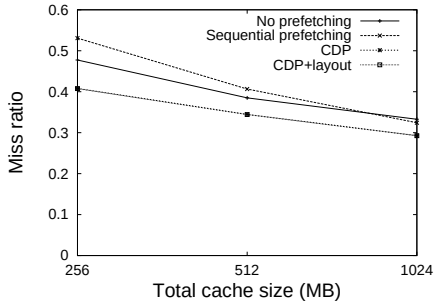


Figure 9: Effect of varying the total cache size for TPC-C

5.6.2 *Effects of the Total Cache Sizes*

If the cache size is comparable to the footprint of a trace, the system simply caches all accesses. Because of this, the read misses in the case of no prefetching are predominantly cold misses since subsequent accesses will be cache hits and will not go to the disk. Therefore, the prefetching schemes do not yield much improvement in performance.

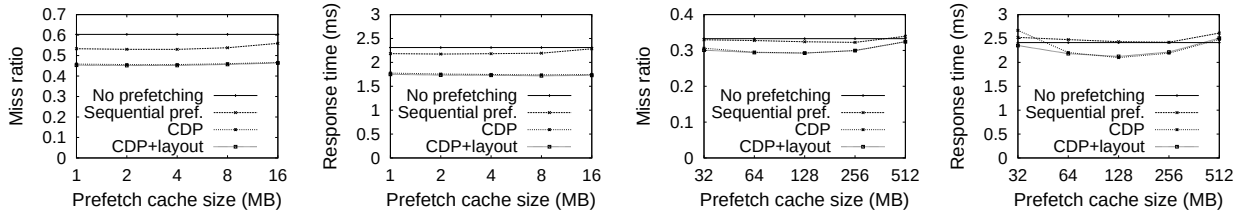
We study the effects of the cache size by varying the cache size for TPC-C exponentially from 256 MB to 1024 MB. In this experiment, we keep the prefetch cache fixed at 128 MB and vary the size of the demand cache. As expected, when the cache size is set at 256 MB, CDP+layout shows an improvement of 14.62% in miss ratio while with 512 MB, the improvement is only 10.58%. It is important to note that our workloads have relatively small working set sizes. In large real systems, it is usually not the case that the entire working set can fit into main memory.

5.6.3 *Effects of the Prefetch Cache Size*

Figures 10a-d show the effects of varying the prefetch cache size while the total cache size is fixed. In TPC-C, for instance, the storage cache miss ratio with CDP initially decreases as the prefetch cache size increases. It reaches the minimum when the prefetch cache size is set to 128 MB. Beyond that point the miss ratio increases again with the prefetch cache size. This phenomenon is also true for the sequential prefetching, even though it performs worse than CDP with almost all prefetch cache sizes.

The above phenomenon can be quite expected. When the prefetch cache size is very small, prefetched blocks may be replaced even before they are used. Even though the demand cache size is increased correspondingly, its benefit is not large enough to offset the loss in unused prefetches. Even worse, the overhead imposed by CDP causes an increase in the response time compared to the base case, as shown on Figure 10d. Fortunately, in this case, the CDP+layout starts to show the benefits of correlation-directed disk layout. It is still able to provide some small improvement over the base line case.

As the prefetch cache size increases, blocks can be retained longer in the prefetch cache and subsequently be used to handle block requests. However, the increase in prefetch cache size corresponds to a reduced demand cache size, but the benefit of prefetching in reducing misses outweighs the loss in the demand cache. Beyond 128 MB, increasing the prefetch cache size no longer has benefits for increasing hit ratio. So the loss due to the reduced demand cache size starts to dominate. Therefore, the overall miss ratio increases.



(a) *Cello-92 - miss ratio* (b) *Cello-92 - response time* (c) *TPC-C - miss ratio* (d) *TPC-C - response time*

Figure 10: Effect of varying the prefetch cache size (Note: the total cache size is fixed. Therefore, the demand cache size is also changing with the prefetch cache size. In the base-line case, there is no prefetch cache)

6 Related Work

In this section, we briefly discuss some representative work that is closely related to our work. Section 2 has discussed various approaches to capture data semantics. Thus, we do not repeat them here.

Data prefetching has also been studied extensively in databases, file systems and parallel applications with intensive I/Os. Most of previous prefetching work either relies on applications to pass hints or is based on simple heuristics such as sequential accesses. Examples of prefetching studies for databases include [56, 63, 44, 22, 21] as well some recent work [53] for mobile data delivery environments. Prefetching for file I/Os include application-controlled prefetching [9, 10] and informed prefetching [60, 32, 45], just to name a few. [57] is an example of prefetching in disk caches. I/O prefetching for out-of-core applications include compiler-assisted prefetching [43, 8] and prefetching through speculative execution [12].

In the spectrum of sophisticated prefetching schemes, research has been conducted for semantic distance-based file prefetching for mobile or networked file servers. Besides the probability graph-based approach described in Section 2, the SEER project from UCLA [34, 35] groups related files into clusters by keeping track of semantic distances between files and downloading as many complete clusters as possible onto the mobile station. The CLUMP project tries to leverage the concept of semantic distance to prefetch file clusters [18]. Kroeger extends the probability graph to a trie with each node representing the sequence of consecutive file accesses from the root to the node [33]. Lei and Duchamp also use a similar structure by building a probability tree [59, 38]. Vellanki and Chervenak combine Patterson's cost-benefit analysis with probabilistic prefetching for high performance parallel file systems [61]. Similar to the probability graph, most of these approaches may be feasible for prefetching at file granularity, but are impractical to track block correlations in a storage system (see Section 2).

Some studies used data compression techniques for prefetching. It was first proposed by Vitter and Krishnan [62]. The basic idea is to encode the data expected with higher probability using fewer bits. The prefetchers based on any optimal character-by-character data compressor were theoretically proven to be optimal in page fault rate. Later, [17] analyzed some practical issues of such a technique, and proposed three practical data compressors for prefetching.

Data mining methods have been mostly used to discover patterns in sales, finance or bio-informatics databases [27, 26]. Only a few studies have applied them in systems. A well-known example is using data mining for intrusion detection [37, 16]. Data mining has recently been used in performance evaluation [40] to model bursty traffic.

Data mining and machine learning have been used in web environments to predict HTTP requests. Schechter et al. introduced path profiling to predict HTTP requests in web environments [51]. Pitkow and Pirolli have used longest repeating subsequences to perform path matching for predicting web accesses from a client [47]. These schemes predict the next HTTP request by matching the surfer's current sequence against the path profile database.

While path-based prediction may work very well for web environments, it is very difficult to capture block correlations in storage systems. This is because web browser/server workloads are different from storage workloads. Each web client usually only browses one page at a time, whereas a storage front-end such as database server can have hundreds of outstanding requests. Since the path-matching schemes do not allow any gaps in the subsequence or path, they cannot be used easily to capture block correlations in a storage system. To support gaps or lookahead distances in these work will suffer the same problem as the probability graph-based approach.

Our work is also related to various adaptive approaches using learning techniques [41, 4], intelligent storage cache management [69, 65, 42, 13], and autonomic storage systems [64, 2, 30]

7 Conclusions and Future Work

This paper proposes *C-Miner*, a novel approach that uses data mining techniques to systematically mine access sequences in a storage system to infer block correlations. More specifically, we have designed a frequent sequence mining algorithm to find correlations among blocks. Using several large real system disk traces, our experiments show that *C-Miner* is reasonably fast with small space requirement and is therefore practical to be used on-line in an autonomic storage system. We have also evaluated correlation-directed prefetching and data layout. Our experimental results with real-system traces have shown that correlation-directed prefetching and data layout can improve I/O average response time by 12-25% compared to no-prefetching, and 7-20% compared to the commonly used sequential prefetching.

Our study has several limitations. First, even though this paper focuses on how to obtain block correlations, our evaluation of the block correlation-directed prefetching and disk layout was conducted using only simulations. We are in the process of implementing correlation-directed prefetching and disk layout in our previously built storage system. Second, we have only evaluated four real-system workloads, it would be interesting to evaluate other workloads such as those with substantially sequential accesses. Third, we do not compare with the semantic-distance graph approach. The main reason is that our preliminary experiment indicates that the SD graphs significantly exceed the memory space, making it extremely slow and almost infeasible to build such graphs.

Currently, *C-Miner* does not consider the recency factor, that is, some recent frequent subsequences may be more important than other "ancient" frequent subsequences. To mine time-series data, our algorithm needs to be modified to change the support or confidence value of a rule dynamically as time progresses. Currently, we are designing efficient stream data mining algorithms specifically for mining access sequences for storage systems and any other similar situations.

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