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Research Article

Efficient Reduction of Access Latency through Object Correlations in Virtual Environments

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Object correlations are common semantic patterns in virtual environments. They can be exploited to improve the effectiveness of storage caching, prefetching, data layout, and disk scheduling. However, we have little approaches for discovering object correlations in VE to improve the performance of storage systems. Being an interactive feedback-driven paradigm, it is critical that the user receives responses to his navigation requests with little or no time lag. Therefore, we propose a class of view-based projection-generation method for mining various frequent sequential traversal patterns in the virtual environments. The frequent sequential traversal patterns are used to predict the user navigation behavior and, through clustering scheme, help to reduce disk access time with proper patterns placement into disk blocks. Finally, the effectiveness of these schemes is shown through simulation to demonstrate how these proposed techniques not only significantly cut down disk access time, but also enhance the accuracy of data prefetching.

1. INTRODUCTION

With ever-increasing demands for storing very large volumes of data for applications such as telemedicine, online computer entertainment systems, and other large multimedia repositories, large amounts of live data are being stored on the storage systems. Random accesses to data stored on storage system can suffer unacceptable delays as media are swapped on drives. The need for swapping media is dictated by the placement of data. Judicious placement of data on the storage media is therefore critical, and can significantly affect the overall performance of the storage system. One primary factor is the placement of data for storage system [1, 2]. The placement of data for specific domains such as multidimensional arrays [1], relational databases [3], and satellite images [4] has been addressed earlier. Research on the storage placement in a more general setting has been addressed under the assumption that data objects are accessed independently [1]. This assumption is rarely valid in practice-data objects typically *related* (*correlated*) and this is reflected in the access of the data [5].

On the other side, with the advent of advanced computer hardware and software technologies, virtual environments (VE) are becoming larger and more complicated. To satisfy the growing demand for fidelity, there is a need for interactive and intelligent schemes that assist and enable effective and efficient storage management. Unfortunately, it is not an easy task to exploit the intelligence in storage systems. File access patterns are not random, they are driven by applications and user behaviors [6]. This fact, coupled with the growing performance bottleneck of computer storage systems, has resulted in a significant amount of research improving file systems behavior through *predicting* future access objects. *Latency* is an ever-increasing component of data access cost, which in turn is usually the bottleneck for modern high performance systems [7]. For this reason, accurate access prediction mechanism is very desirable for data storage system. In such a case, VEs do not consider the problem of access times of objects in the storage systems. They are always simply concerned about how to display the object in the next frame. As a result, the VE can only manage data at the rendering and other related levels without knowing any semantic information such as semantic correlations between data. Therefore, much previous work had to rely on simple patterns such as level-of-detail (LOD) [8], view-dependent simplification [9], out-of-core simplification [8], bounding volume hierarchies (BVHs) [10–12], and occlusion culling to improve system performance, without fully exploiting its

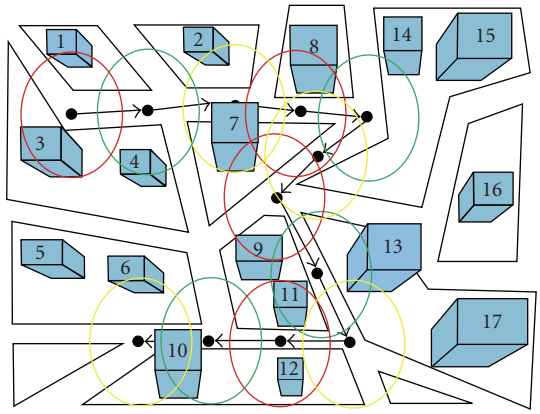


FIGURE 1: The circle shows how many objects the view contains, and arrow line represents view sequence when user traverses the path.

intelligence. This motivates a more powerful analysis tool to discover more complex patterns, especially *semantic patterns*, in storage systems. Therefore, the aim of our work is to decrease this latency through intelligent organization of the accessed objects and enabling the clients to perform predictive prefetching.

In this paper, we consider the problem and solve this using data mining techniques [13, 14]. Clearly, when users traverse in a virtual environment, some potential semantic characteristics will emerge on their traversal paths. If we collect the users' traversal paths, mine and extract some kind of information of them, such meaningful semantic information can help to improve the performance of the interactive VE. For example, we can reconstruct the placement order of the objects of 3D model in disk according to the common section of users' path. Exploring these correlations is very useful for improving the effectiveness of storage caching, prefetching, data layout, and disk scheduling. Consider the scenario in Figure 1, the rectangle represents an object, and the circle represents a view associated with a certain position. Due to spatial locality, we may take objects 1 and 3 into the same disk block. However, if the circular view does exist in the path, the mining algorithm will give us different information for such situation. The mining algorithm may suggest to collect object 1, 4, and 7 into the same disk block, instead of object 1 and 3, because of the semantic correlation.

This paper proposes *VSPM* (*viewed-based sequential pattern mining*), a method which applies a data mining technique called *frequent sequential pattern mining* to discover object correlations in VE. Specially, we have modified several recently proposed data mining algorithms called *FreeSpan* [15] and *PrefixSpan* [16] to find object correlations in several traversal traces collected in real systems. To the best of our knowledge, *VSPM* is the first approach to infer object correlations in a VE. Furthermore, *VSPM* 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 VE. Besides, we have also proposed a clustering method to cluster similar patterns for reducing the access time. According to some similarity functions, or other measurements, clustering aims to partition a set of objects into several groups such that "similar" objects are in the same group. It will make similar objects much closer to be accessed in one time. This results in less access times and much better performance. In order to evaluate the validity of clustering, the two criteria, *cluster cohesion* and *inter-cluster similarity*, were presented. Moreover, we also have evaluated the benefits of object correlation-directed prefetching and disk data layout using the synthetic datasets [17] and the real system workloads. Compared to the base case, under the number of files accessed condition, this scheme reduces the *average number of accessed files* by 33.3% ($(4-3)/3 = 0.333$ is shown in Figure 12) to 2.625 ($(27-8)/8 = 2.625$ is shown in Figure 12). Compared to the sequential prefetching scheme, it also reduces the *average response time* by 35.6% ($(624-460)/460 = 0.356$ is shown in Figure 13) to 1.249 ($(4983-2215)/2215 = 1.249$ is shown in Figure 13).

The rest of this paper is organized as follows. Related works are given in Section 2. In Section 3, we describe our problem formulation. The system architecture is suggested in Section 4. The suggested mining and clustering mechanisms are explained with illustrative examples shown in Section 5. Section 6 presents our experiment results. Finally, we summarize our current results with suggestions for future research in Section 7.

2. RELATED WORKS

In this section, we summarize related work in the area of virtual environments, sequential pattern mining, and pattern clustering.

2.1. Virtual environments methods

Despite the use of advanced graphics hardware, real-time navigation in high complex virtual environments is still a challenging problem because the demands on image quality and details increase exceptionally fast. The navigation in virtual environments consists of many different detailed objects, for example, of CAD data that cannot all be stored in main memory but only on hard disk. In other words, providing efficient access to huge VR datasets has attracted a lot of attention. A great deal of work has been done in related visualization algorithms. These algorithms can be classified into several categories according to their used data structures, data management systems, storage ordering, or optimizing file systems using techniques like prefetching and caching.

2.1.1. Chunking

Sarawagi and Stonebraker [18] describe chunking, which groups spatially adjacent data elements into n-dimensional chunks which are then used as basic I/O unit, making access to multidimensional data and order of magnitude faster. They also arrange the storage order of these chunks to minimize sought distance during access. Related chunking algorithms [19] reorganize their data according to the expected

query type, and the likelihood that data values will be accessed together. However, for extremely large datasets, it is impractical to make a copy of the dataset for each expected access pattern [20].

2.1.2. Prefetching and caching

Prefetching has been used by many researchers to hide or minimize the cost of I/O stalling. Current researches focus on visibility-based prefetching algorithm for retrieving out-of-core 3D models and rendering them at interactive rates [21]. The goal of prefetching through the multithreading mechanism is to have the geometry already in memory by the time it is needed. But the threads will occupy some of the main memory and this strategy need well-planned switching mechanism to handle threads. Especially, for large datasets in virtual environments, this scheme cannot be scalable. Rhodes et al. [22] propose *iterators* and *threaded prefecthing* scheme based on the concept of *spatial prefteching* for improvement on I/O performance. Yoon and Manocha [10] discuss the cache-efficient layout of bounding volume hierarchies (BVHs) of polygonal models. They also introduce a new probabilistic model to predict the running access patterns of a BVH. Since such large BVH-based *kd*-trees will be stored in the storage system for access, this will result in large I/O times. Chisnall et al. [23] present knowledge-based out-of-core prefetching algorithms without using hard-coded rendering-related logic by utilizing the access history and patterns dynamically, and adapting their prefetching strategies accordingly. However, it seems to be weak for the basis for such knowledge-based out-of-core algorithm of LRU-related schemes. Semantic correlations seem to lack in this scheme.

2.1.3. Level-of-detail models

An LOD model essentially permits to obtain different representations of an object at different levels of detail, where the level can also vary over the object. Performance requirements impose several challenges in the design of system based on LOD models, where geometric data structures play a central role. There is a necessary tradeoff between time efficiency and storage costs. And also there is a tradeoff between generality and flexibility of models on one hand, and optimization of performance (both in time and storage) on the other hand. We classify LOD data structures according to the dimensionality of the basic structural element they represent into point- [24], triangle- [25], and tetrahedron-based [26, 27] data structures. Current researches [28, 29] exploit the feature of on-board video memory to store geometry information. This strategy significantly reduces the data transfer overhead from sending geometry data over the (AGP) bus interface from the main memory to the graphics card.

2.1.4. Occlusion culling

Known occlusion culling algorithms [30–32] manage the polygons in volume-separating data structures, as, for example, *quad-trees*, *oct*-tree [33–35], and *R*-trees [36] were presented. All polygons in a certain 3D-volume bounded by a box are attached with it. If such a bounding box is not visible, all attached polygons are also not visible. There are two different types of occlusion culling algorithms. One is image-space occlusion culling algorithms: these algorithms test the visibility of a box with its projection onto the viewing plane. However, in practice, reading the values appears to be quite expensive, especially on PC architectures. The other is object-based occlusion culling algorithms: these algorithms need no expensive accesses to any buffer, but they often have the disadvantage that they depend on occluders that are large or well chosen in the preprocessing. Furthermore, they obtain only poor results in virtual environments which consist of many single noncoherent polygons. Of course there exist some algorithms, for example, see [37], which allow a real-time navigation in complex scenes, but they often have the disadvantages that they only fit for office rooms or other similar architectural scenes that have a volume-separating structure. A more precise overview on occlusion culling algorithms can be found in [38].

In addition, massive model rendering (MMR) system [39] was the first published system to handle models with tens of millions of polygons at interactive frame rates. On the other side, it is desirable to store only the polygons and not to produce additional data, for example, textures or prefiltered points. However, polygons of such highly complex scenes require a lot of hard disk space so that the additional data could exceed the available capacities [40, 41]. To meet these requirements, an appropriate data structure and an efficient technique should be developed with the constraints of memory consumptions.

2.2. Sequential pattern mining methods

Sequential pattern mining was first introduced in [42], which is described as follows. A sequence database is formed by a set of data sequences. Each data sequence includes a series of transactions, ordered by transaction times. This research aims to find all the subsequences whose ratios of appearance exceed the minimum support threshold. In other words, *sequential patterns* are the most frequently occurring subsequences in sequences of sets of items. A number of algorithms and techniques have been proposed to deal with the problem of sequential pattern mining. Many studies have contributed to the efficient mining of sequential patterns [15, 16]. Almost all of the previously proposed methods for mining sequential patterns are *a priori*-like, that is, based on the *a priori* property proposed in association rule mining [15], which states the facts that *any super pattern of a nonfrequent pattern cannot be frequent*. The studies [15, 16] show that the *a priori*-like sequential pattern mining methods bear three nontrivial, inherent costs which are independent of detailed implementation techniques. First is that the *a priori*-like method may generate potentially huge set of candidate sequences during the permutations of elements and repetition of items in a sequence. Second is that multiple scans of databases are needed for deciding the support of these candidates. As the length of candidates increases, the times of scans of databases become worse. Third is that there

are many difficulties in mining long sequential patterns. Sequential pattern mining algorithms, in general, can be categorized into three classes: (1) *a priori-based*, *horizontal partition* methods, and *GSP* [43] is one known representative; (2) *a priori-based*, *vertical partition* methods, and *SPADE* [44] is one example; (3) *projection-based pattern growth* method, such as the famous *FreeSpan* [16] and *PrefixSpan* algorithms [15].

In this study, we develop a new sequential pattern mining method, called *view-based sequential pattern mining*. Since our input data are different from those of traditional data mining algorithms [45], we make several major modifications about the idea of pattern-growth method. Its general idea is to use frequent objects to recursively project sequence databases into a set of smaller projects database and grow subsequence fragments in each projected database. This process partitions both the database and the set of frequent objects to be tested, and confines each test being conducted to the corresponding smaller projected database.

2.3. Pattern clustering methods

Clustering is one of the main tasks in the data mining process for discovering groups, and identifying interesting distributions and patterns in the underlying data. The fundamental clustering problem is to partition a given dataset into groups (clusters), such that data points in a cluster are more similar to each other (i.e., intrasimilar property) than points in different clusters (intersimilar property) [46].

There is a multitude of clustering methods available in literature, which can be distinguished with respect to its algorithmic properties [47]. First, *partition algorithms* strive for a successive improvement of an existing clustering and can be further classified into examplar-based and commutation-based approaches. These approaches need information with regard to expected cluster number k. Representatives are k-means [47] and k-medoid [48]. Second, *hierarchical algorithms* create a tree of node subsets by successively merging (*agglomerative* approach) or subdividing (*divisive* approach) the objects. In order to obtain a unique clustering, a second step is necessary that prunes this tree at adequate places. Representatives are k-nearest-neighbor and linkage [49]. Finally, density-based algorithms try to separate a similarity graph into subgraphs of high connectivity values. In the ideal case, they can determine the cluster number k automatically and detect clusters of arbitrary shape and size. Representatives are: DBSCAN and Chameleon [50].

Although there are many clustering algorithms presented above, they cannot be applied to our dataset directly. The reasons are as follows [51]. First is that our database is composed of many *transactions*. There is a finite set of elements, called *items* from a common item universe, contained in a transaction. Every transaction can be presented in a point-by-attribute format, by enumerating all items j, and by associating with a transaction the binary attributes that indicate whether j items belong to a transaction or not. Such representation is sparse that two random transactions have very few items in common. Common to this and other examples of point-by-attribute format for transaction data is high dimensionality, significant amount to zero values, and small number of common values between two objects. Conventional clustering methods, based on similarity measures, do not work well. Since transactional data is important in clustering profiling, web analysis, DNA analysis, and other applications, different clustering methods founded on the idea of *cooccurrence* of transaction data have been developed. They are usually measured by *Jaccard* coefficient $\mathrm{SIM}(T_1, T_2) = |T_1 \cap T_2|/|T_1 \cup T_2|$ [52, 53].

However, there are some drawbacks of the existing methods. First, they always consider the single item accessed in the storage systems. They only care about how many I/O times the item is accessed. On the other side, we pay more attention to whether we can fetch objects together involved in the same view as many as possible, this scheme will help to respond to users' requests more efficiently. Second, existing algorithms for efficient accessing patterns often rely on different data structures or heuristic principles (e.g., prefetching mechanism based on LRU and the like [11, 22, 23, 54]) to support the prediction on future desired patterns. Whatever the data structures or schemes were applied, one problem always happens. If object a and object b are frequently accessed together, but the locations between them may be far away, it is possible for us to access them in more than two or more times. In this case, not only which objects are accessed frequently, but also how to layout these objects in the storage system for reducing the access times. Finally, many existing algorithms used in visualization are closely coupled with application-specific logic. Since the intelligence or semantic correlations were embedded in the previous processing, they neglect exploiting the valuable information to help to arrange the *data layout* in the storage systems. One possible solution is to propose a framework of data management based on *knowledge* to discover the possible *promising* objects for future access. Then, we can minimize disk I/O overhead by clustering those promising objects into the proper data layout in the storage systems [55, 56].

3. MOTIVATIONS

3.1. Motivations on theoretical foundations

Data mining research deals with finding relationships among data items and grouping the related items together. The two basic relationships that are of particular concern to us are

(i) *association*, where the only knowledge we have is that the idea items are frequently occurring together, and when one occurs, it is highly probable that the other will also occur;
(ii) *sequence*, where the data items are associated, and in addition to that, we know the order of occurrence as well.

Our ideas can be divided into several concerns. First, object correlations can be exploited to improve storage system performance. Correlations can be used to direct prefetching [46]. For example, if a strong correlation exists between objects, these two objects 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 [46, 57, 58] have shown that using even these simple sequential correlations can significantly improve the storage system performance. Second, a storage system can also lay out data in disks according to object correlations. For example, an object 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 correlated-directed disk layouts, the system only needs to pay one-time seek and rotational delay to get multiple blocks that are likely to be accessed soon. Previous studies [55, 56] have shown promising results in allocating correlated file blocks on the same track to avoid track-switching costs.

As the concept of sequence is based on associations, we first briefly introduce the issue of finding associations. The formal definition of the problem of finding association rules among items is provided by [59] as follows. Let $I = i_1, i_2, \ldots, i_n$ be a set of literals, called items, and let D be a set of transactions such that for all $T \in D$, $T \subseteq I$. A transaction T contains a set of items X if $X \subseteq T$. An *association rule* is denoted by an implication of the form $X \Rightarrow Y$, where $X \subseteq I$, $Y \subseteq I$, and $X \cap Y = \emptyset$. As a rule, $X \Rightarrow Y$ is said to hold in the transaction set D with *support* s in the transaction set D if s % of transactions in D contain $X \cup Y$. The rule $X \Rightarrow Y$ has *confidence* c if c % of the transactions in D that contain X also contain Y. The thresholds for support and confidence are called *minsup* and *minconf*, respectively.

One of the challenges of mining client access histories is that such histories are continuous while mining algorithms assume transactional data. This causes a mismatch between the data required by current algorithms and the access history we are considering. Therefore, we need to convert continuous requests into transactional form, where client requests in transactions correspond to a session. A session consists of a set of virtual objects accessed by a user in a certain amount of time. Similar researches can be found in [60]. They presented methods for efficiently organizing the sequential web log into transactional form suitable for mining. Besides, they used the temporal dimension of user access behavior and divided the sequence of web logs into chunks where each chunk can be thought of as a session encapsulating a user's interest span.

3.2. Motivations on practical demands

From the practical view of point, we will demonstrate several practical examples to explain our observation. Suppose that we have a set of data items $\{a, b, c, d, e, f, g\}$. A sample access history over these items consisting of five sessions is shown in Table 1. The request sequences extracted from this history with minimum support 40% are (a, f) and (c, d). The rules obtained out of these sequences with 100% minimum confidence are $a \Rightarrow f$ and $c \Rightarrow d$, as shown in Table 2. Two accessed data organizations are depicted in Figure 2. An accessed schedule without any intelligent pre-

Table 1: Sample database of user requests.

Session no.	Accessed request
1	e, a, f
2	b, d
3	c, d, a, f, g
4	b, a, f, g
5	c, d, a, f

Table 2: Sample association rules.

Rule	Support	Confidence
$a \Longrightarrow f$	80%	100%
$c \Longrightarrow d$	40%	100%

processing is shown in Figure 2(a). A schedule where related items are grouped together and sorted with respect to the order of reference is shown in Figure 2(b). Assume that the disk is spinning counterclockwisely and consider the following client request sequence $a, f, b, c, d, a, f, g, e, c, d$, shown in Figure 2. Note that dashed lines mean that the first element in the request sequence (counted from left to right) would like to fetch the first item supplied by disk, and directed graph denotes the rotation of disk layout in a counterclockwise way. For this request, if we have the access schedule (a, b, c, d, e, f, g), which dose not take into account the rules, the total I/O access times for the client will be $a : 5$, $f : 5$, $b : 3$, $c : 2$, $d : 6$, $a : 5$, $f : 5$, $g : 1$, $e : 5$, $c : 6$, $d : 6$. The total access times is 49 and the average latency will be $49/11 = 4.454$. However, if we partition the items to be accessed into two groups with respect to the sequential patterns obtained after mining, then we will have $\{a, b, f\}$ and $\{c, d, e, g\}$. Note that data items that appear in the same sequential pattern are placed in the same group. When we sort the data items in the same group with respect to the rules $a \Rightarrow f$ and $c \Rightarrow d$, we will have the sequences (a, f, b) and (c, d, g, e). If we organize the data items to be accessed with respect to these sorted groups of items, we will have the access schedule presented in Figure 2(b). In this case, the total access times for the client for the same request pattern will be $a : 1$, $f : 1$, $b : 1$, $c : 1$, $d : 1$, $a : 3$, $f : 1$, $g : 4$, $e : 1$, $c : 4$, $d : 1$. The total access times is 19 and the average latency will be $19/11 = 1.727$, which is much lower than 4.454.

Another example that demonstrates the benefits of rule-based prefetching is shown in Figure 3. We demonstrate three different requests of a client as a snapshot. With the help of the rules obtained from the history of previous requests, the prediction can be achieved. The current request is c and there is a rule stating that if data item c is requested, then data item d will be also be requested (i.e., association rule $c \Rightarrow d$). In Figure 3(a), data item d is absent in the cache and the client must spend more waiting time for item d. In Figure 3(b), although the item d is also absent in the cache, the client still spends one disk latency time for item d. In Figure 3(c), the cache can supply the item d and no disk latency time is needed.

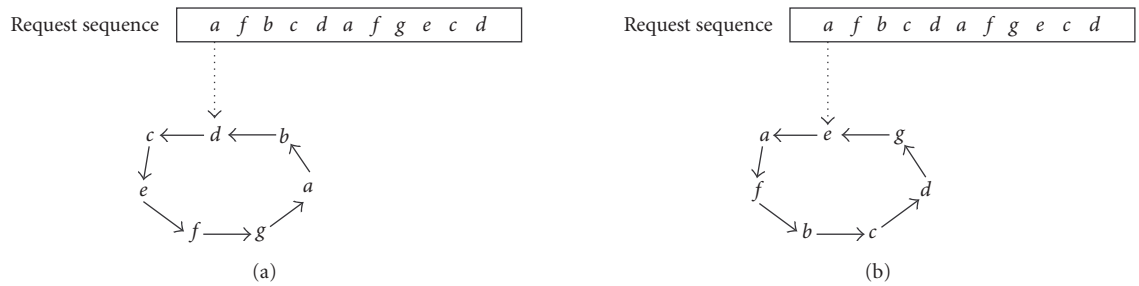


Figure 2: Effects on accessed objects organization in disk: (a) without association rules; (b) with association rules.

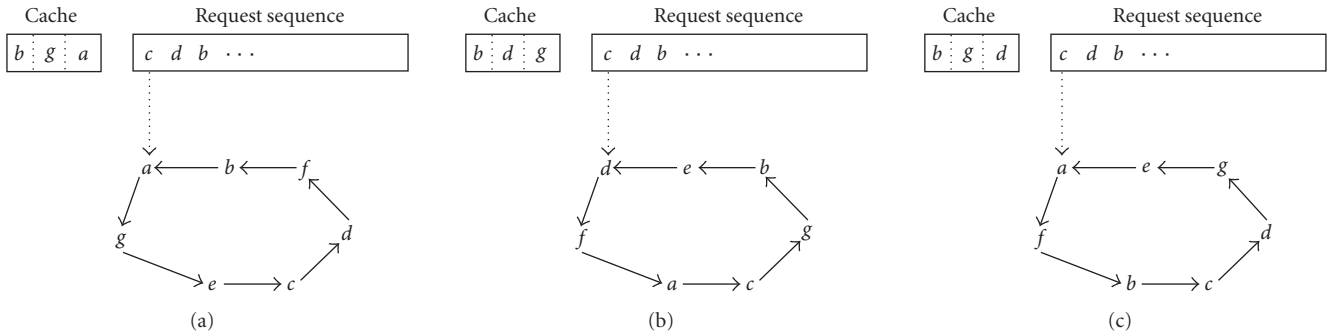


Figure 3: Effects of prefetching.

These simple examples show that with some intelligent grouping, reorganization of data items with predictive prefetching, average latency for clients can be considerably improved. In the following sections, we describe how we can extract sequential patterns out of client requests. We also explain how we group data items with respect to sequential patterns.

4. TRAVERSAL HISTORIES MINING AND PROBLEM FORMULATION

In this section, we describe the idea and the detailed steps of mining algorithm and give a demonstration example for this. In order to mine sequential patterns, we assume that the continuous client requests are organized into discrete sessions. *Sessions* specify user interest periods and a *session* consists of *a sequence of client requests* for data items ordered with respect to the time of reference. The client request consists of the objects which a client browses and traverses at will in the VEs. We denote this type of clients request as a *view*. A session consists of one or more views. In correspondence with terminologies used in data mining, a session can be considered as a *sequence*. The whole *database* is considered as a set of sequences. Formally, let $\sum = \{l_1, l_2, \ldots, l_m\}$ be a set of m literals, called *objects* (also called *items*) [61, 62]. The *view* v is defined as snapshot of sets of objects which a user observes during the period. A *view* (also called *itemset*) is an *unordered* nonempty set of objects. A sequence is an *ordered* list of views. We denote a sequence s (also called *transaction*) by $\{v_1, v_2, \ldots, v_n\}$, where v_j is a view and ordered property is obeyed. We also call v_j an *element* of the sequence. An item can occur only once in an element of a sequence, but can occur multiple times in different elements. We assume, without loss of generality, that items in an element of a sequence are in lexicographical order.

A sequence $\langle a_1 a_2 \cdots a_n \rangle$ is *contained in* another sequence $\langle b_1 b_2 \cdots b_m \rangle$ if there exist integers $i_1 < i_2 < \cdots < i_n$ such that $a_1 \subseteq b_{i_1}, a_2 \subseteq b_{i_2}, \ldots, a_n \subseteq b_{i_n}$. For example, $\langle (a)(b,c)(a,d,e) \rangle$ is contained in $\langle (a,b)(b,c)(a,b,d,e,f) \rangle$, since $(a) \subseteq (a,b)$, $(b,c) \subseteq (b,c)$, and $(a,d,e) \subseteq (a,b,d,e,f)$. However, the sequence $\langle (c)(d) \rangle$ is not contained in $\langle (c,d) \rangle$ and vice versa. The former represents objects c and d being observed one after the other, while the latter represents objects c and d being observed together. In a set of sequences, a sequence s is *maximal* if s is not contained in any other sequence. Let the database D be a set of sequences ordered by increasing recording time. Each sequence records each user's traversal path in the VEs. The *support* for a sequence is defined as the fraction of D that "contains" this sequence. A *sequential pattern* p is a sequence whose *support* is equal to or more than the user-defined threshold. *Sequential patter mining* is the process of extracting certain sequential patterns whose support exceeds a predefined minimal support threshold.

Given a database D of client transactions, the problem of mining sequential patterns is to find the maximal sequences

among all sequences that have a certain user-specified minimum support. Each maximal sequence represents a *sequential pattern*.

Sequential rules are obtained from sequential patterns. For a sequential pattern $p = \langle p_1, p_2, \ldots, p_k \rangle$. The possible sequential rules are

$$\begin{aligned} \langle p_1 \rangle &\Longrightarrow \langle p_2, p_3, \ldots, p_k \rangle, \\ \langle p_1, p_2 \rangle &\Longrightarrow \langle p_3, p_4, \ldots, p_k \rangle, \\ &\vdots \\ \langle p_1, p_2, p_3, \ldots, p_{k-1} \rangle &\Longrightarrow \langle p_k \rangle. \end{aligned} \tag{1}$$

A sequential rule such as

$$P_n = \langle p_1, p_2 \ldots, p_n \rangle \Longrightarrow \langle p_{n+1}, p_{n+2}, \ldots, p_k \rangle, \tag{2}$$

where $0 < n < k$, has confidence c if c % of the sequences that support $\langle p_1, p_2, \ldots, p_n \rangle$ also support $\langle p_1, p_2, \ldots, p_k \rangle$, that is,

$$\text{confidence } (p_n) = \frac{\text{support } (\langle p_1, p_2, \ldots, p_k \rangle)}{\text{support } (\langle p_1, p_2, \ldots, p_n \rangle)} \times 100\%. \tag{3}$$

For a sequential pattern $p = \langle p_1, p_2, \ldots, p_k \rangle$, among the possible rules that can be derived from p, we are interested in the rules with the smallest possible antecedent (i.e., the first part of the rule). This is due to the fact that the rules used for inferring should start as early as possible. The rest of the rules trivially meet the confidence requirement [59].

Finally, we will define our problem in two phases. Phase I: given a sequence database $D = \{s_1, s_2, \ldots, s_n\}$, we design efficient mining algorithms to obtain our sequential patterns P; Phase II: in order to reduce the disk access time, we distribute P into a set of clusters, so as to minimize intercluster similarity and maximize intracluster similarity.

5. PATTERN-ORIENTED MINING AND CLUSTERING ALGORITHMS

In many applications, it is not unusual that one may encounter a large number of sequential patterns. Similarly, our virtual environments consist of many complex objects. These relationships are always behind the scenes. Therefore, it is important to explore a new efficient and scalable method. With this motivation, we developed a sequential pattern mining method, called *view-based sequence pattern mining (VSPM)*. Its general idea is to use frequent items to recursively project sequence databases into a set of smaller projected databases and grow subsequence fragments in each projected database. This process partitions both the data and set of frequent sequential patterns to be tested, and confines each test being conducted to the corresponding smaller projected database.

Before we describe our algorithm, some definitions and conventions are presented. Since items within an element of a sequence can be listed in any order, without loss of generality, we assume they are listed in alphabetical order. For example, the sequence is listed as $\langle (a)(a,b,c,d)(a,d)(e)(c,f) \rangle$ instead of $\langle (a)(b,c,a,d)(d,a)(e)(f,c) \rangle$. With such a convention, the expression of a sequence is unique.

Definition 1 (prefix). Suppose all items in an element are listed alphabetically. Given a sequence $\alpha = \langle \alpha_1 \alpha_2 \cdots \alpha_n \rangle$, and a sequence $\beta = \langle \beta_1 \beta_2 \cdots \beta_m \rangle$, $(m \leq n)$ is called a *prefix* of α if and only if (1) $\beta_i = \alpha_i$ for $(i \leq m-1)$; (2) $\beta_m \subseteq \alpha_m$; (3) all the items in $(\alpha_m - \beta_m)$ are alphabetically after those in β_m.

Definition 2 (projection). Given sequences α and β such that β is a subsequence of α, denote $\beta \ll \alpha$. A subsequence α' of sequence α (i.e., $\alpha' \ll \alpha$) is called a *projection* of α with respect to prefix β if and only if (1) α' has prefix β; (2) there exists no proper supersequence α'' of α' (i.e., $\alpha' \ll \alpha''$ but $\alpha' \neq \alpha''$) such that α'' is a subsequence of α and also has prefix β.

For example, $\langle a \rangle$, $\langle a,a \rangle$, $\langle a(a,b) \rangle$, $\langle a(a,b,c) \rangle$, and $\langle (a)(a,b,c)a \rangle$ are all prefixes of sequence $\langle (a)(a,b,c)(a,c,d)(d)(c,ef) \rangle$, but the sequences $\langle a,b \rangle$, $\langle a,c \rangle$, $\langle a(b,c) \rangle$, and $\langle (a)(a,c) \rangle$ are all not considered as prefixes.

5.1. View-based sequential pattern mining algorithm

Now, we will explain our mining algorithms. The main ideas come from both *bounded-projection* and *pattern appending* mechanisms. The *bounded-projection* mechanism has one special characteristic, that is, it always projects the remaining sequence recursively after a new sequential pattern is found. They will not mine the objects across different prefix views though. As a result, we would mine the trimmed database recursively. The *pattern appending* mechanism uses the concept of *prefix property*. When we want to find a new sequential pattern in our database, we use the sequential pattern found in previous round as prefix, and append a new object as the new candidate pattern for verification. If the candidate pattern satisfies the minimum support, we regard it as a new sequential pattern and create a bounded projection of it recursively. In order to explore the interesting relationships among these objects, we propose two different kinds of appending methods called *intraview-appending* method and *interview-appending* method. The *intraview-appending* method is used to *append a new object in the same view*, and the *interview-appending* method is used to *append a new object in the next view*. Demonstration example will be given later. The following is the pseudocode of view sequence mining algorithm (Algorithm 1).

Example 3 (VSPM). Given the traversal database S and min_support = 3, we demonstrate the complete steps as follows:

Path1: $\langle (1,2)(3,4)(5,6) \rangle$;
Path2: $\langle (1,2)(3,4)(5) \rangle$;
Path3: $\langle (1,2)(3)(4,5) \rangle$.

Step 1 (*find frequent patterns* with length-1. //in the form of "*item: support*"). First, we will have the following data: 1 : 3, 2 : 3, 3 : 3, 4 : 3, 5 : 3, 6 : 1. Therefore, we have *length-1* frequent sequential patterns: $\langle 1 \rangle$, $\langle 2 \rangle$, $\langle 3 \rangle$, $\langle 4 \rangle$, and

```
//D is the database. P is the set of frequent patterns, and is set
to empty initially.
Input: D and P.
Output: P.
Begin
(1) Find length-1 frequent sequential patterns.
(2) While (any projected subdatabase exits) do
(3) Begin
(4)     Project corresponding subsequences into
        sub-databases under the intraview appending and
        interview appending.
(5)     Mine each subdatabase corresponding to each
        projected subsequence.
(6)     Find all frequent sequential patterns by applying
        Steps 4 and 5 on the subdatabases recursively.
(7) End; // while
(8) return P;
(9) End; // procedure
```

Algorithm 1: View-based sequential pattern mining (VSPM) algorithm.

$\langle 5 \rangle$. Finally, we will have 5 projection-based subdatabases $\langle 1 \rangle$_DB, $\langle 2 \rangle$_DB, $\langle 3 \rangle$_DB, $\langle 4 \rangle$_DB, and $\langle 5 \rangle$_DB, respectively.

Step 2. Take the projection-based subdatabase $\langle 1 \rangle$_DB for example. First, since item 2 and item 1 are *in same view*, the *intraview appending* works. After the projection, we will get the sub-database $\langle (1,2) \rangle$_DB. And the original database is shrunk to the following database:

P1: $\langle (3,4)(5,6) \rangle$; P2: $\langle (3,4)(5) \rangle$; P3: $\langle (3)(4,5) \rangle$.

In this step, pattern $\langle (1,2) \rangle$ becomes a frequent sequent pattern since its support satisfies the minimum support. Next, item 3 is projected for the candidate.

Step 3 (continued from Step 2). Since item 3 and (1,2) are *in different views*, the *interview appending* works. We will have the projection-based subdatabase $\langle (1,2)(3) \rangle$_DB and the shrunk database is as follows:

P1: $\langle (4)(5,6) \rangle$; P2: $\langle (4)(5) \rangle$; P3: $\langle (4,5) \rangle$.

In this step, pattern $\langle (1,2)(3) \rangle$ becomes a frequent sequential pattern since its support satisfies the minimum support. Next, item 4 is projected for the candidate.

Step 4 (continued from Step 3). Since item 4 and item 3 are in the same view, the intraview appending works. We will have the projection-based subdatabase $\langle (1,2)(3,4) \rangle$_DB and the shrunk database is as follows:

P1: $\langle (5,6) \rangle$; P2: $\langle (5) \rangle$; P3: $\langle (5) \rangle$.

In this step, pattern $\langle (1,2)(3,4) \rangle$ becomes an *infrequent* sequent pattern since its support does not satisfy the minimum support. The *VSPM* stops further mining and returns to the previous subdatabase $\langle (1,2)(3) \rangle$_DB recursively. Next, item 5 is projected for the candidate.

Step 5 (continued from Step 4). Since item 5 and item 3 are in different views, the interview appending works. We will have the projection-based subdatabase $\langle (1,2)(3)(5) \rangle$_DB and the result is as follows:

P1: $\langle (6) \rangle$; P2: $\varnothing$; P3: $\varnothing$.

In this step, pattern $\langle (1,2)(3)(5) \rangle$ becomes an *infrequent* sequent pattern since its support does not satisfy the minimum support. The *VSPM* stops further mining and goes to the previous subdatabase $\langle (1,2) \rangle$_DB recursively. Note that item 6 will be discarded since item 6 is not a length-1 frequent sequential pattern. We observe that subdatabase $\langle (1,2) \rangle$_DB could not have any projected subdatabase through the intraview mining. Apparently, only item 2 and item 1 are in the same view, other items are not. Therefore, we return to the previous subdatabase $\langle (1) \rangle$_DB recursively.

Step 6 (continued from Step 5). Since item 3 and item 1 are in different views, the interview appending works. We will have the projection-based subdatabase $\langle (1)(3) \rangle$_DB and the result is as follows:

P1: $\langle (4)(5,6) \rangle$; P2: $\langle (4)(5) \rangle$; P3: $\langle (4,5) \rangle$.

In this step, pattern $\langle (1)(3) \rangle$ becomes a frequent sequential pattern since its support satisfies the minimum support.

Step 7. the remaining steps are the same as the above. The final mining result is depicted in Figure 4. In Figure 4, the patterns which contain item 6 are circled. They show that the differences between projected-based mining and nonprojected-based mining. In other words, without projecting mechanism, we have to expand *eight* subdatabases for candidates (i.e., *two* "stop" without circled plus *six* "stop" with circled). Compared to this case, with projecting mechanism, we only expand *two* subdatabases for candidates (i.e., "stop" without circled).

5.2. Disk organization by clustering sequential patterns

Clustering is a good candidate for inferring object correlations in storage systems. As the previous sections mentioned, object 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 objects *a* and *b*, these two objects can be fetched together from disks whenever one of them is accessed. The disk read-ahead optimization is an example of exploiting the simple data correlations by prefetching subsequent disk blocks ahead of time. Several studies [46, 55–57] have shown that using these correlations can significantly improve the storage system performance. Our results in Section 6.2.2 demonstrate that prefetching based on object correlations can improve the performance much better than that of non-correlation layout in all cases.

A storage system can also organize data is disks according to object correlations. For example, an object can be placed next to its correlated objects so that they can be

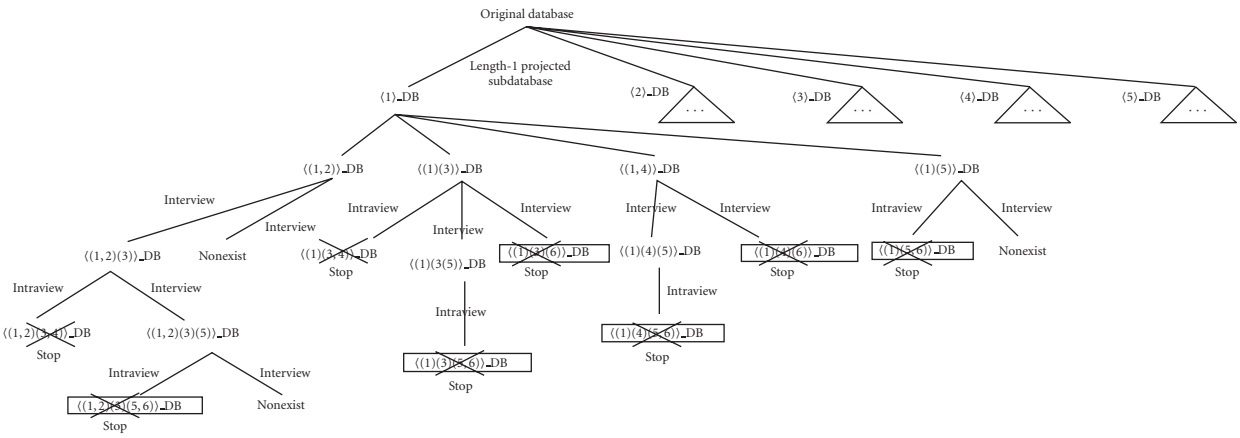


Figure 4: Demonstration of our *VSPM* for generating projected-based subdatabases and sequential patterns.

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 cost of one-time seek and a rotational delay to get multiple objects that are likely to be accessed soon. Previous studies [55, 56] have shown promising results in allocating correlated file blocks on the same track to avoid track-switching costs.

The main idea of our clustering approach is to define a new notion of cluster *centroid*, which represents the common properties of cluster elements. Similarity inside a cluster is hence measured by using the cluster representative. The cluster representative becomes a natural tool for finding an explanation of the cluster population. Our definition of cluster centroid is based on a data representation model which simplifies the ones used in pattern clustering. In fact, we use compact representation of Boolean vector v that states only presence or absence of items, while traditional pattern clustering methods require to store the frequencies of items. In this paper, we show that using our concept of cluster centroid associated with *Jaccard distance* [53], we obtain results that have a quality comparable with other approaches used in this kind of task, but we have better performances in terms of execution time. Moreover, cluster representatives provide an immediate explanation of cluster features.

5.3. Distance measure

In the simplified hypothesis that frequent patterns do not contain frequencies, but behave simple as Boolean vectors (like value 1 corresponds to the presence and value 0 corresponds to the absence), a more intuitive but equivalent way of defining the *Jaccard distance function* can be provided. This measure captures our idea of similarity between items that is directly proportional to the number of common values, and inversely proportional to the number of different values for the same item.

Definition 4 (intradistance measure (cooccurrence)). Let P_1 and P_2 be two sequential patterns. $D(P_1, P_2)$ can be represented as the normalized difference between the cardinality of their union and the cardinality of their intersection:

$$D(P_1, P_2) = 1 - \frac{|P_1 \cap P_2|}{|P_1 \cup P_2|}. \tag{4}$$

Example 5 (intradistance measure). Let P_1 and P_2 be two sequential patterns: $P_1 = \langle (a,b,c),(b,c,d),(e,f)\rangle$ and $P_2 = \langle (a,b,c,d),(e,f,g)\rangle$. The distance between P_1 and P_2 is

$$\begin{aligned} D(P_1, P_2) &= 1 - \frac{|P_1 \cap P_2|}{|P_1 \cup P_2|} = 1 - \frac{|\{a,b,c,e,f\}|}{|\{a,b,c,d,e,f,g\}|} \\ &= 1 - \frac{5}{7} = \frac{2}{7}. \end{aligned} \tag{5}$$

5.4. Cluster representative and pattern clustering algorithm

Intuitively, a cluster representative for virtual environment data should model the content of a cluster, in terms of the objects that are most likely to appear in a pattern belonging to the cluster. A problem with the traditional distance measures is that the computation of a cluster representative is computationally expensive. As a consequence, most approaches [38] approximate the cluster representative with the Euclidean representative. However, those approaches may suffer the following drawbacks.

(i) Huge cluster representatives cause poor performances, mainly because as soon as the clusters are populated, the cluster representatives are likely to become extremely huge.
(ii) For different kinds of patterns, it seems to be difficult to find the proper cluster representatives.

In order to overcome such problems, we can compute an approximation that resembles the cluster representatives associated to Euclidean and mismatch-count distances. Union and intersection seem good candidates to start with. Since our clustering operations are based on set operations, we ignore the order of frequent patterns.

To avoid these undesired situations, we supply three tables. The first table is *FreqTable*. It records the frequency of

// P is the set of frequent patterns. T is the set of clusters, and is set to empty initially.
Input: P and T.
Output: T.
Begin
(1) $FreqTable = \{ft_{ij} \mid$ the frequency of $pattern_i$ and $pattern_j$ coexisting in the database $D\}$;
(2) $DistTable = \{dt_{ij} \mid$ the distance between $pattern_i$ and $pattern_j$ in the database $D\}$;
(3) $C_1 = \{C_i \mid$ at the beginning each pattern to be a single cluster$\}$
(4) // Set up the extra-similarity table for evaluation
(5) $M_1 =$ Intrasimilar $(C_1, \varnothing)$;
(6) $k = 1$;
(7) *while* $|C_k| \rangle n$ do *Begin*
(8) $C_{k+1} =$ PatternCluster $(C_k, M_k, FreqTable, DistTable)$;
(9) $M_{k+1} =$ Intrasimilar (C_{k+1}, M_k);
(10) $k = k + 1$;
(11) *End;*
(12) return C_k;
(13) *End;*

Algorithm 2: Pattern clustering algorithm.

any two patterns coexisting in the database D. The second table is *DistTable*. It records the distance between any two patterns. The last table is *Cluster*. It records how many clusters are generated. Algorithm 2 is our clustering algorithm.

Consider a database of learner transactions shown in Table 3. For each transaction, we keep the transaction's time, objects accessed in the VR system, and a unique learner identifier. Table 4 shows an alternative representation of the database, where an ordered set of purchased items is given for each learner.

Let us assume that the system wants to cluster these users according to the similar frequent objects into three clusters. Table 5 shows frequent sequential patterns discovered in the database shown in Table 4 (with minimum support >25%).

The intermediate results of clustering starting at the third iteration to the eighth iteration are presented in Tables 8 to 13, respectively. The following relations between patterns hold: $P_2 \subset P_1$, $P_3 \subset P_1$, $P_4 \subset P_1$, $P_5 \subset P_1$, $P_6 \subset P_1$, $P_7 \subset P_1$, $P_5 \subset P_2$, $P_6 \subset P_2$, $P_5 \subset P_3$, $P_7 \subset P_3$, $P_6 \subset P_4$, $P_7 \subset P_4$, $P_9 \subset P_8$, and $P_{10} \subset P_8$. This leads to removing P_8 from the description of cluster C_{ahij}, and P_2, P_3, and P_4 from the description of cluster C_{bcdefg} because each of them includes some other patterns from the same description, for example $P_9 \subset P_8$, and they are both in the description of cluster C_{ahij}. After completion of the description pruning step, we get the final result of clustering shown in Table 14.

6. SYSTEM ARCHITECTURE AND PERFORMANCE EVALUATION

We implemented the data mining algorithms and prefetching mechanisms to show the effectiveness of the proposed methods. A traversal path database recorded each user's traversal path and was used for mining interesting patterns. The simulation model we used and the experimental results are provided in Sections 6.1 and 6.2, respectively.

Table 3: Database sorted by user ID and transaction time.

User ID	Transaction time	Objects accessed
1	17:30 PM Sep 9. 2005	10 60
1	17:37 PM Sep 9. 2005	20 30
1	17:45 PM Sep 9. 2005	40
1	17:55 PM Sep 9. 2005	50 55
2	16:30 PM Sep 10. 2005	40
2	16:37 PM Sep 10. 2005	50
2	17:00 PM Sep 10. 2005	10
2	17:30 PM Sep 10. 2005	20 30 70
3	12:33 PM Sep 11. 2005	40
3	12:38 PM Sep 11. 2005	50
3	13:00 PM Sep 11. 2005	10
3	13:36 PM Sep 11. 2005	80
3	13:45 PM Sep 11. 2005	20 30
4	16:35 PM Sep 12. 2005	10
4	17:30 PM Sep 12. 2005	20 55
5	17:34 PM Sep 13. 2005	80
6	15:23 PM Sep 12. 2005	10
6	15:30 PM Sep 12. 2005	30 90
7	17:30 PM Sep 10. 2005	20 30
8	16:13 PM Sep 13. 2005	60
8	16:32 PM Sep 13. 2005	100
9	16:36 PM Sep 13. 2005	100
10	16:45 PM Sep 14. 2005	90 100

Table 4: User-sequence representation of the database.

User ID	Traversal sequence
1	$\langle$(10 60) (20 30) (40) (50 55)$\rangle$
2	$\langle$(40) (50) (10) (20 30 70)$\rangle$
3	$\langle$(40) (50) (10) (80) (20 30)$\rangle$
4	$\langle$(10) (20 55)$\rangle$
5	$\langle$(80)$\rangle$
6	$\langle$(10) (30 90)$\rangle$
7	$\langle$(20) (30)$\rangle$
8	$\langle$(60) (100)$\rangle$
9	$\langle$(100)$\rangle$
10	$\langle$(90 100)$\rangle$

6.1. Test data and simulation model

We use the virtual power plant model from http://www.cs.unc.edu/~walk/ created by Walkthrough Laboratory of Department of Computer Science of University of North Carolina at Chapel Hill. The power plant model is a complete model of an actual coal fired power plant. The model consists of 12, 748, 510 triangles. Its size is 334 megabytes. Our traversal database keeps track of the traversal of the power plant by many anonymous random users. For each user, the data records list all the areas of the power plant that user visited in

Table 5: Pattern set used for clustering.

Patterens with support > 25%	
P_1	$\langle(10)\ (20\ 30)\rangle$
P_2	$\langle(10)\ (20)\rangle$
P_3	$\langle(10)\ (30)\rangle$
P_4	$\langle(20\ 30)\rangle$
P_5	$\langle(10)\rangle$
P_6	$\langle(20)\rangle$
P_7	$\langle(30)\rangle$
P_8	$\langle(40)\ (50)\rangle$
P_9	$\langle(40)\rangle$
P_{10}	$\langle(50)\rangle$
P_{11}	$\langle(100)\rangle$

Table 6: Pattern-oriented representation of the database.

Cluster	Description	Sequences
C_a	P_1	1, 2, 3
C_b	P_2	1, 2, 3, 4
C_c	P_3	1, 2, 3, 6
C_d	P_4	1, 2, 3, 7
C_e	P_5	1, 2, 3, 4, 6
C_f	P_6	1, 2, 3, 4, 7
C_g	P_7	1, 2, 3, 6, 7
C_h	P_8	1, 2, 3
C_i	P_9	1, 2, 3
C_j	P_{10}	1, 2, 3
C_k	P_{11}	8, 9, 10

Table 7: Initial similarity matrix.

	C_a	C_b	C_c	C_d	C_e	C_f	C_g	C_h	C_i	C_j	C_k
C_a	x	0.75	0.75	0.75	0.6	0.6	0.6	1	1	1	0
C_b	0.75	x	0.6	0.6	0.8	0.8	0.5	0.75	0.75	0.75	0
C_c	0.75	0.6	x	0.6	0.8	0.5	0.8	0.75	0.75	0.75	0
C_d	0.75	0.6	0.6	x	0.5	0.8	0.8	0.75	0.75	0.75	0
C_e	0.6	0.8	0.8	0.5	x	0.66	0.66	0.6	0.6	0.6	0
C_f	0.6	0.8	0.5	0.8	0.66	x	0.66	0.6	0.6	0.6	0
C_g	0.6	0.5	0.9	0.8	0.66	0.6	x	0.6	0.6	0.6	0
C_h	1	0.75	0.75	0.75	0.6	0.6	0.6	x	1	1	0
C_i	1	0.75	0.75	0.75	0.6	0.6	0.6	1	x	1	0
C_j	1	0.75	0.75	0.75	0.6	0.6	0.6	1	1	x	0
C_k	0	0	0	0	0	0	0	0	0	0	x

a one-week timeframe. Each path consists of $30 \sim 40$ views. Each view consists of $20 \sim 30$ objects on average. The number of objects is 11, 949, where each object is a meaningful combination of triangles of power plant and it is considered as a data item. On the other side, the whole system consists of four parts: (1) log-data manager; (2) mining unit; (3) clustering unit; (4) storage manager.

The log-data manager performs the interaction between the user and power plant, and records the states which the user visited. The mining unit performs the task of extracting sequential patterns and rules from the traversal database. Rules set with different minimum support requirements can be constructed by the mining unit. The resulting sequential patterns are written to a file in a specific format to be read later by the clustering unit and storage manager. The clustering unit performs clustering of data items using our clustering algorithm based on the sequential patterns. After clustering, the clusters are placed into the disk block for prefetching.

The architecture of our system is depicted in Figure 5. In this architecture, we use the traversal database to simulate the access history. The sequence of traversal paths that are organized into views is fed into the data mining programs to be used for extracting sequential patterns. The resulting pattern set is fed into the clustering unit, which is then used for disk organization and prefecthing.

As we present in Figure 5, we summarize the main steps as follows. First, each user enters into the VEs using the user interface. The interface will send one request handle to acquire the service from the system. The system not only records the views along the traversal path for each user, but also processes these views into appropriate data format for later mining. Second, the mining unit performs the mining tasks according to our mining algorithms. After the completion of mining phase, the clustering unit will take over the remaining work—clustering the patterns. Finally, when the clustering phase ends, the final clusters will enable predicting the next view request of users.

6.2. Experimental results and performance study

In this section, the effectiveness of the proposed clustering algorithm is investigated. All algorithms were implemented in Java. The experiments were run on a PC with an AMD Athlon 1800+ and 512 megabytes main memory, running Microsoft Windows 2000 server. Our main performance metric is the *average latency*. We also measured the *client cache hit ratio*. A decrease in the average latency is an indication of how useful the proposed methods are. The average latency can decrease as a result of both increase cache hit ratio via prefetching methods and better data organization in the disk. An increase in the cache hit ratio will also decrease the number of requests sent to server, and thus lead to both saving of the scare memory resource of the server and reduction in the server load.

We have two major tasks—mining algorithm and clustering algorithm. We report our experimental results on the performance of mining and clustering, respectively.

6.2.1. Experimental results on mining unit

In this section, we report our experimental results on the *VSPM* algorithm. Since *GSP* and *SPADE* are the two most important sequential pattern mining algorithms, we conduct an extensive performance study to compare *VSPM* with them. To evaluate the effectiveness and efficiency of the VSPM algorithm, we performed an extensive performance study of *GSP*, *SPADE*, *FreeSpan*, and *PrefixSpan*, on both real and synthetic datasets, with various kinds of sizes and data

Table 8: Similarity matrix and database after 3rd iteration.

	C_{ahij}	C_b	C_c	C_d	C_e	C_f	C_g	C_k
C_{ahij}	x	0.75	0.75	0.75	0.6	0.6	0.6	0
C_b	0.75	x	0.6	0.6	0.8	0.8	0.5	0
C_c	0.75	0.6	x	0.6	0.8	0.5	0.8	0
C_d	0.75	0.6	0.6	x	0.5	0.8	0.8	0
C_e	0.6	0.8	0.8	0.5	x	0.66	0.66	0
C_f	0.6	0.8	0.5	0.8	0.66	x	0.66	0
C_g	0.6	0.5	0.8	0.8	0.66	0.66	x	0
C_k	0	0	0	0	0	0	0	x

Cluster	Description	Sequences
C_{ahij}	P_1, P_8, P_9, P_{10}	1, 2, 3
C_b	P_2	1, 2, 3, 4
C_c	P_3	1, 2, 3, 6
C_d	P_4	1, 2, 3, 7
C_e	P_5	1, 2, 3, 4, 6
C_f	P_6	1, 2, 3, 4, 7
C_g	P_7	1, 2, 3, 6, 7
C_k	P_{11}	8, 9, 10

Table 9: Similarity matrix and database after 4th iteration.

	C_{ahij}	C_{be}	C_c	C_d	C_f	C_g	C_k
C_{ahij}	x	0.6	0.75	0.75	0.6	0.6	0
C_{be}	0.6	x	0.8	0.5	0.66	0.66	0
C_c	0.75	0.8	x	0.6	0.5	0.8	0
C_d	0.75	0.5	0.6	x	0.8	0.8	0
C_f	0.6	0.66	0.5	0.8	x	0.66	0
C_g	0.6	0.66	0.8	0.8	0.66	x	0
C_k	0	0	0	0	0	0	x

Cluster	Description	Sequences
C_{ahij}	P_1, P_8, P_9, P_{10}	1, 2, 3
C_{be}	P_2, P_5	1, 2, 3, 4, 6
C_c	P_3	1, 2, 3, 6
C_d	P_4	1, 2, 3, 7
C_f	P_6	1, 2, 3, 4, 7
C_g	P_7	1, 2, 3, 6, 7
C_k	P_{11}	8, 9, 10

Table 10: Similarity matrix and database after 5th iteration.

	C_{ahij}	C_{bce}	C_d	C_f	C_g	C_k
C_{ahij}	x	0.6	0.75	0.6	0.6	0
C_{bce}	0.6	x	0.5	0.66	0.66	0
C_d	0.75	0.5	x	0.8	0.8	0
C_f	0.6	0.66	0.8	x	0.66	0
C_g	0.6	0.66	0.8	0.66	x	0
C_k	0	0	0	0	0	x

Cluster	Description	Sequences
C_{ahij}	P_1, P_8, P_9, P_{10}	1, 2, 3
C_{bce}	P_2, P_3, P_5	1, 2, 3, 4, 6
C_d	P_4	1, 2, 3, 7
C_f	P_6	1, 2, 3, 4, 7
C_g	P_7	1, 2, 3, 6, 7
C_k	P_{11}	8, 9, 10

Table 11: Similarity matrix and database after 6th iteration.

	C_{ahij}	C_{bce}	C_{df}	C_g	C_k
C_{ahij}	x	0.6	0.6	0.6	0
C_{bce}	0.6	x	0.66	0.66	0
C_{df}	0.6	0.66	x	0.66	0
C_g	0.6	0.66	0.66	x	0
C_k	0	0	0	0	x

Cluster	Description	Sequences
C_{ahij}	P_1, P_8, P_9, P_{10}	1, 2, 3
C_{bce}	P_2, P_3, P_5	1, 2, 3, 4, 6
C_{df}	P_4, P_6	1, 2, 3, 4, 7
C_g	P_7	1, 2, 3, 6, 7
C_k	P_{11}	8, 9, 10

Table 12: Similarity matrix and database after 7th iteration.

	C_{ahij}	C_{bcdef}	C_g	C_k
C_{ahij}	x	0.5	0.6	0
C_{bcdef}	0.5	x	0.83	0
C_g	0.6	0.83	x	0
C_k	0	0	0	x

Cluster	Description	Sequences
C_{ahij}	P_1, P_8, P_9, P_{10}	1, 2, 3
C_{bcdef}	P_2, P_3, P_4, P_5, P_6	1, 2, 3, 4, 6, 7
C_g	P_7	1, 2, 3, 6, 7
C_k	P_{11}	8, 9, 10

Table 13: Similarity and database after 8th iteration.

	C_{ahij}	C_{bcdef}	C_g	C_k
C_{ahij}	x	0.5	0.6	0
C_{bcdef}	0.5	x	0.83	0
C_g	0.6	0.83	x	0
C_k	0	0	0	x

Cluster	Description	Sequences
C_{ahij}	P_1, P_8, P_9, P_{10}	1, 2, 3
C_{bcdefg}	P_2, P_3,P_4, P_6, P_5, P_7	1, 2, 3, 4, 6, 7
C_k	P_{11}	8, 9, 10

Table 14: Discovered clusters.

Cluster	Description	Sequences
C_{ahij}	$P_1 = \langle(10)\ (20\ 30)\rangle$, $P_9 = \langle(40)\rangle$, $P_{10} = \langle(50)\rangle$	1, 2, 3
C_{bcdefg}	$P_5 = \langle(10)\rangle$, $P_6 = \langle(20)\rangle$ $P_7 = \langle(30)\rangle$	1, 2, 3, 4, 6, 7
C_k	$P_{11} = \langle(100)\rangle$	8, 9, 10

distributions. Four algorithms, *GSP*, *SPADE*, *FreeSpan*, and *PrefixSpan* were implemented in Java. Detailed algorithm implementation is described as follows: (1) *GSP*, the *GSP* algorithm is implemented according to the description in [59]; (2) *SPADE*, the *SPADE* algorithm is implemented according to the description in [44]; (3) *FreeSpan*, the *FreeSpan* algorithm is implemented according to the description in [16]; (4) *PrefixSpan*, the *PrefixSpan* algorithm with level-by-level projection is implemented according to the description in [15].

For the datasets used in our performance study, we use two kinds of datasets: one *real dataset* and a group of *synthetic datasets*. The synthetic datasets used in our experiments were generated using the standard procedure described in [42]. The same data generator has been used in most studies on sequential pattern mining, such as [15, 16, 59]. For real dataset, we have obtained our traversal database.

For synthetic datasets, we have also used a large set of synthetic sequence data generated by the IBM data generator [42] designed for testing sequential patterns mining algorithm. Since the format of such datasets has its specific meanings, we explain the convention for the datasets as follows. For example, *C200T2.5S10I1.25* means that the dataset contains 200 k sequences (denoted as *C*200) and the number of items is 10 000. The average number of items in a transaction is 2.5 (denoted as *T*2.5), and the average number of transactions in a sequence is 10 (denoted as *S*10). On average, each transaction is composed of 1.25 items (denoted as *I*1.25).

Synthetic dataset experiments

The first test is performed on the dataset *C200T2.5S10I1.25*. It contains 200 k transactions and the number of items is 10 000. Figure 6 shows the processing time of the five algorithms at different support thresholds. The processing times are sorted in time ascending order as "*PrefixSpan* < *VSPM* < *SPADE* < *FreeSpan* < *GSP*." When the support threshold is set to 0.4%, the running time of *PrefixSpan* is 12.374 seconds. Under the same condition, the running time of our algorithm (*VSPM)* is 19.736 seconds. Compared to other algorithms, the running times of *SPADE*, *FreeSpan*, and *GSP* are 26.478, 35.949, 91.595 seconds, respectively. When the support threshold drops to 0.3%, the running time of *PrefixSpan* is 19.948 seconds. Similarly, our running time is 27.857 seconds. Compared to other algorithms, the running times of *SPADE*, *FreeSpan*, and *GSP* are 37.475, 89.459, 188.895 seconds, respectively.

The second test is performed on the data set *C10T8S8I8*. It contains 10 K transactions and the number of items is still 10 000. Figure 7 shows the processing time of the five algorithms at different support thresholds. The processing times are sorted in time ascending order as "*PrefixSpan* < *VSPM* < *SPADE* < *FreeSpan* < *GSP*." When the support threshold is set to 1%, the running time of *PrefixSpan* is 8.785 seconds. Under the same condition, the running time of our algorithm (*VSPM*) is 11.783 seconds. Compared to other algorithms, the running times of *SPADE*, *FreeSpan*, and *GSP* are 12.785, 79.378, 845.658 seconds, respectively. As Figure 7 shows, the support threshold is 1%, the running time of *GSP* is empty. Since the difference between any other algorithms is so sharp, we decide that value not to be plotted in Figure 7. Similarly, when the support threshold drops to 0.5%, the running time of *PrefixSpan* is 49.369 seconds. Under the same condition, the running time of our algorithm (*VSPM)* is 89.764 seconds. Compared to other algorithms, the running times of *SPADE*, *FreeSpan*, and *GSP* are 109.234, 120.874, 6,685.213 seconds, respectively. Compared with the second dataset, the first set is larger than the second dataset since it contains more transactions. However, it is sparser than the second data set since the average number of items in a transaction is 2.5 (i.e., 2.5 < 8) and the average number of transactions in a sequence is 10 (i.e., 10 > 8). In other words, the second data set is much denser than the first dataset. This results in one fact that the running time of the second dataset is more than that of the first dataset.

Scale-up experiments

In order to verify the scalability of *VSPM*, we set up the following experimental environments. First, all five algorithms run the test dataset T2.5S10I1.25, with the database size growing from 200 K to 900 K transactions, and with different

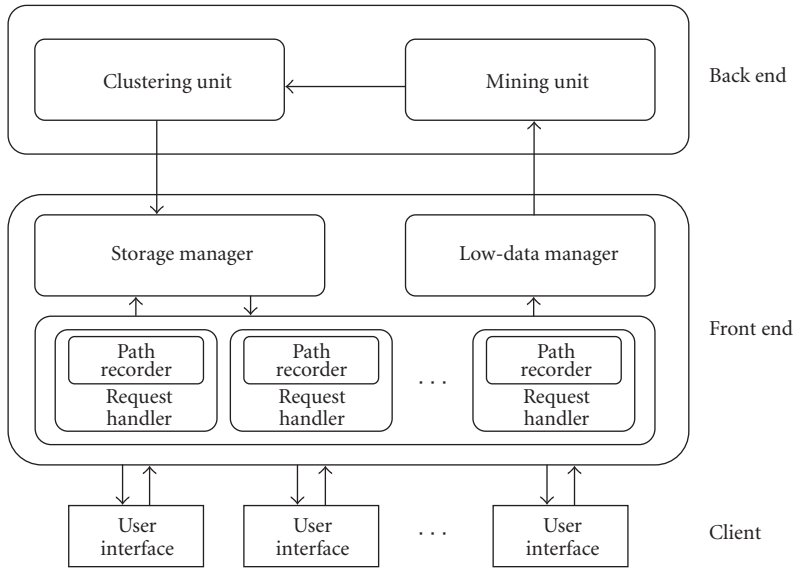


Figure 5: System architecture diagram.

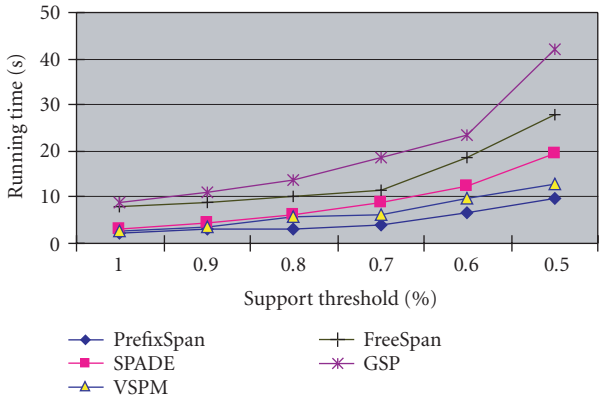


Figure 6: Performance of the five algorithms on dataset C200T2.5 S10I1.25.

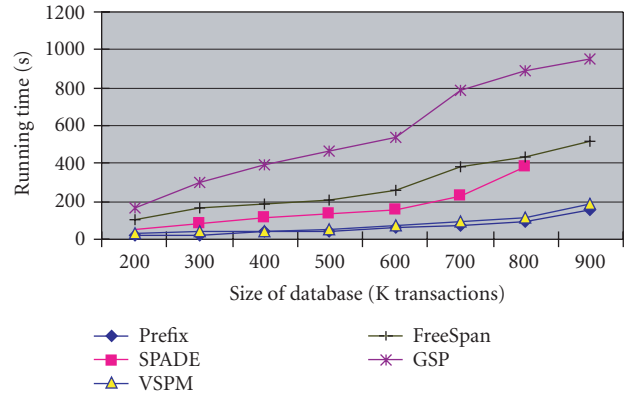


Figure 8: Scalability measure of the five algorithms on dataset T2.5S10 I1.25 with support threshold = 0.25%.

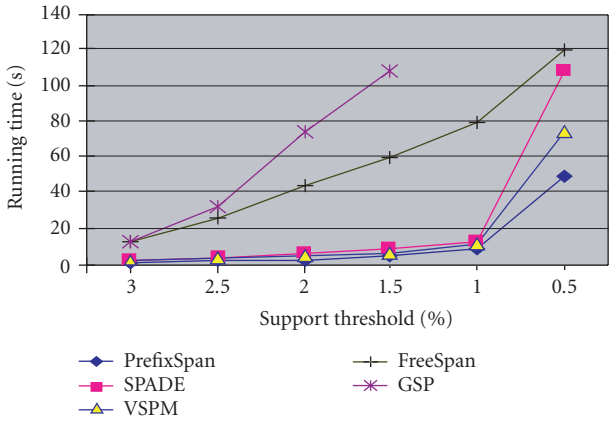


Figure 7: Performance of the five algorithms on dataset C10T8S8I8.

support threshold settings. Since the algorithm *SPADE* runs more than 1200 seconds at 900 K transactions, shown in Figure 8, we cannot include this data into the figure. However, the running time of *SPADE* is shown in Figure 9. It obeys the property that as the support threshold decreases, the more candidates are generated and tested. As a result, the system performance becomes worse. Moreover, the performance of *VSPM* was very stable, even when support threshold was very low for large databases.

Virtual environment traces

The performance of our traversal database is reported as follows. First, we follow the procedure described in [59] to set up dataset parameters. Meanings of all parameters are listed in Table 15. Figures 10 and 11 show the performance comparison among the five algorithms for our virtual environment dataset. From Figures 10 and 11, we can see that *VSPM* is as efficient as *PrefixSpan* does, but it is much more efficient than *SPADE*, *FreeSpan*, and *GSP*.

Table 15: Parameters for our traversal dataset.

Symbol	Meaning
$\|D\|$	Number of data sequences (i.e., size of database)
$\|C\|$	Average number of transactions per data sequence
$\|T\|$	Average number of item per transaction
$\|S\|$	Average length of maximal possible frequent sequences
$\|I\|$	Average size of itemsets in maximal possible frequent sequences
$\|N_s\|$	Number of maximal potentially frequent sequences
$\|N_I\|$	Number of maximal potentially frequent itemsets
$\|N\|$	Number of items

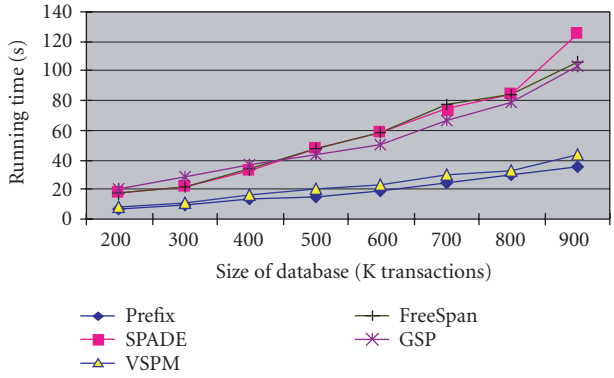


Figure 9: Scalability measure of the five algorithms on dataset T2.5S10 I1.25 with support threshold = 0.5%.

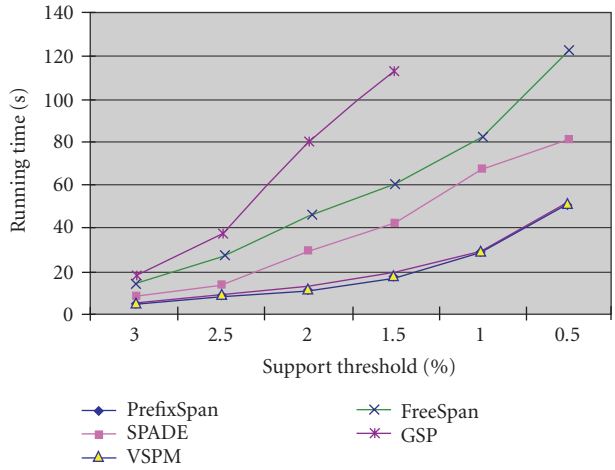


Figure 10: Execution time with respect to various support thresholds using our real dataset-1 (daraset D1000-C40-T10-S3-T5).

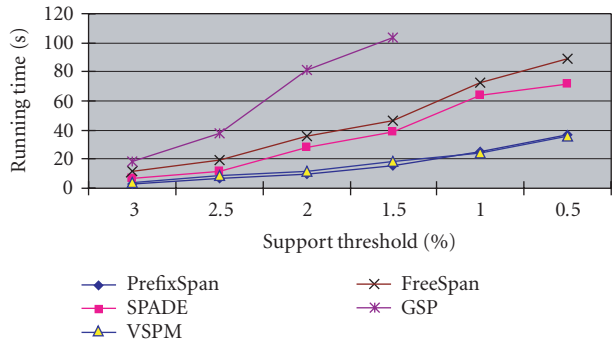


Figure 11: Execution time with respect to various support thresholds using our real dataset-2 (dataset D750-C30-T10-S2.5-T5).

6.2.2. *Experimental results on clustering unit*

For quality measure of clustering result, we adopted the cluster cohesion and the interclustering similarity. All are defined as follows.

Definition 6 (large item). Given a *pattern*$_i$ and a user-defined threshold θ, if it satisfies the criterion

$0 <$ minimum support threshold $< \theta \leq$ support(pattern$_i$) ≤ 1, the pattern$_i$ is called as a large item.

Definition 7 (cluster cohesion (Cluster-Coh (C_i))). It is the ratio of the large items to the whole items $T(C_i)$ in the cluster C_i. This is calculated using the following formula, and if it is near 1, it is a good quality cluster; otherwise, it is not:

$$\text{Cluster-Coh}\ (C_i) = \frac{C_i(L)}{T(C_i)}, \tag{6}$$

where $C_i(L)$ is the number of large items in cluster C_i, and $T(C_i)$ is the number of all items in cluster C_i.

Definition 8 (inter-cluster similarity (inter-sim (C_i, C_j))). It is based on the large items is the rate of the common large items of the cluster C_i and C_j. The intercluster similarity is calculated by the following formula, and if it is near 0, it is the good clustering; otherwise it is not:

$$\text{Sim}\ (C_i, C_j) = \frac{\text{LarCom}\ (C_i \cap C_j)}{C_i(L) + C_j(L)} \times \frac{|\text{LarCom}(C_i \cap C_j)|}{|\text{LarCom}(C_i + C_j)|}, \tag{7}$$

where *LarCom* $(C_i \cap C_j)$ is the number of *common large items* in the clusters C_i and C_j, $|LarCom(C_i \cap C_j)|$ is the

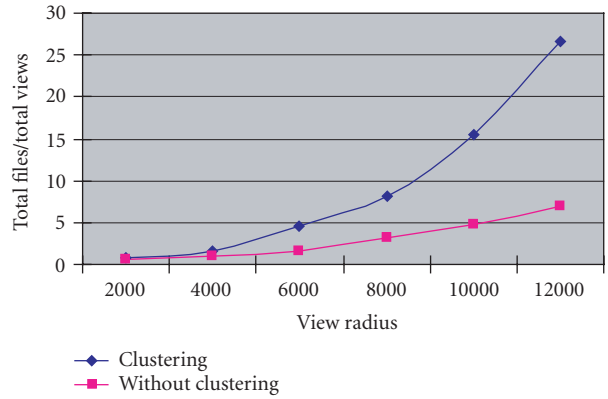


Figure 12: Comparison of different algorithms on the number of files retrieved under the same view.

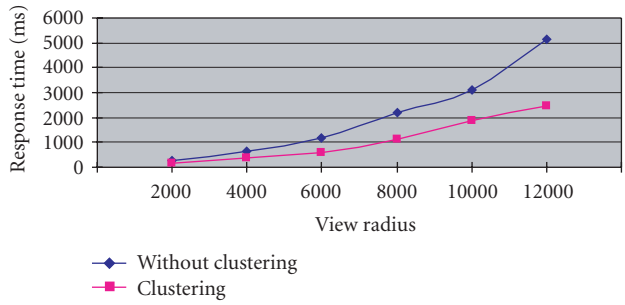


Figure 13: Comparison of different algorithms on system response time under the same view radius.

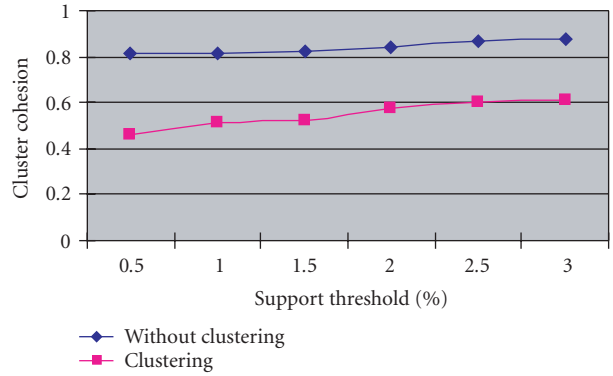


Figure 14: Comparison of different support thresholds on cluster cohesion under the same view radius and database.

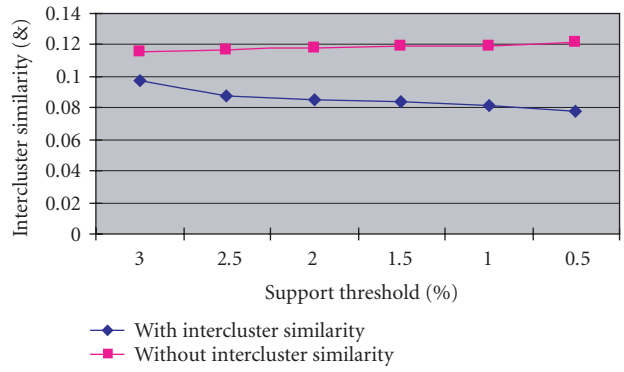


Figure 15: Comparison of different support thresholds on intercluster similarity under the same view radius and database.

total occurrence number of the common large items, and $|LarCom(C_i \cap C_j)|$ is the total occurrence number of the large items in the clusters C_i and C_j.

Definition 9 (view radius). The *view radius* is defined as the radius of the visible circle in the virtual environments. As the radius increases, more objects are observed. In other words, it controls how many objects are visible at the same time in one view.

Meanwhile, we select the different views radius for comparison. Figures 12 and 13 show the results. Algorithm with clustering outperforms other algorithms without clustering. The clustering mechanism can accurately support prefetching objects for future usage. Not only is the access time cut down, but also the I/O efficiency is improved.

Observing both Figures 14 and 15, we can easily realize, there exist relations between the number of clusters and intercluster similarity, and also between the number of clusters and cluster cohesion. The less the number of clusters is, the smaller intercluster similarity we can get. On the contrary, if the less the number of clusters is, the larger cluster cohesion we can get. In summary, we can determinate that our clustering algorithm is overall better at cluster cohesion and intercluster similarity. This means that our clustering algorithm groups similar patterns together and improves the efficiency of storage systems.

7. CONCLUSIONS AND FUTURE WORK

This paper proposes a *VSPM*, a novel approach that uses data mining techniques to systematically mine traversal paths in a virtual environment to infer object correlation. More specifically, we have designed a frequent projection-based sequential pattern mining algorithm to find correlations among objects. Using synthetic datasets and actual virtual environments traces, our experiments show that *VSPM* is an efficient algorithm. We have also scaled our experiments on *VSPM* for testing its scalability. Besides, we have evaluated correlation-directed prefetching and data layout. Our experimental results with virtual environments traces have shown that correlation-directed prefetching and data layout can improve I/O average response time by 35.6% to 1.249 seconds compared to no prefetching, and 33.3% to 2.625 seconds compared to the number of retrieved files. Finally, we have also designed two criteria to verify the validity of clustering method.

Our study still has limitations. First, even though this paper focuses on how to obtain object correlations, our

evaluation of the object correlation-directed prefetching and disk layout was not designed for the extra long frequent sequential patterns. Since the problem of long sequential patterns should be customized, we are in the process of implementing another long-based correlation-directed prefetching mechanism. Second, the sequential order is not maintained in clustering units. As this problem is concerned, we are in the processing of designing several clustering criteria and verifying their validity. Finally, the disk layout should consider not only the temporal locality, but also the spatial locality (shown in the traversal database). This direction will enhance the system performance.

REFERENCES

[1] S. Christodoulakis, P. Triantafillou, and F. Zioga, "Principles of optimally placing data in tertiary storage libraries," in *Proceedings of the 23rd International Conference on Very Large Data Bases (VLDB '97)*, pp. 236–245, Athens, Greece, August 1997.

[2] S. More, S. Muthukrishnan, and E. A. M. Shriver, "Efficiently sequencing tape-resident jobs," in *Proceedings of the 18th ACM SIGACT-SIGMOD-SIGART Symposium on Principles of Database Systems (PODS '99)*, pp. 33–43, Philadelphia, Pa, USA, May-June 1999.

[3] S. Sarawagi, "Database systems for efficient access to tertiary memory," in *Proceedings of the 14th IEEE Symposium on Mass Storage Systems (MSS '95)*, pp. 120–126, Monterey, Calif, USA, September 1995.

[4] J. Yu and D. J. Dewitt, "Processing satellite images on tertiary storage: a study of the impact of tile size on performance," in *Proceedings of the 5th NASA Goddard Conference on Mass Storage Systems and Technologies*, pp. 460–476, College Park, Md, USA, September 1996.

[5] E. Thereska, M. Abd-El-Malek, J. J. Wylie, D. Narayanan, and G. R. Ganger, "Informed data distribution selection in a self-predicting storage system," in *Proceedings of the 3rd IEEE International Conference on Autonomic Computing (ICAC '06)*, pp. 187–198, Dublin, Ireland, June 2006.

[6] A. Amer, D. D. E. Long, J.-F. Paris, and R. C. Burns, "File access prediction with adjustable accuracy," in *Proceedings of 21st IEEE International Performance, Computing, and Communications Conference (IPCCC '02)*, pp. 131–140, Phoenix, Ariz, USA, April 2002.

[7] J. Yang, M. O. Ward, E. A. Rundensteiner, and S. Huang, "Visual hierarchical dimension reduction for exploration of high dimensional datasets," in *Proceedings of Symposium on Visualization (VisSym '03)*, pp. 19–28, Grenoble, France, May 2003.

[8] P. Cignoni, C. Montani, C. Rocchini, and R. Scopigno, "External memory management and simplification of huge meshes," *IEEE Transactions on Visualization and Computer Graphics*, vol. 9, no. 4, pp. 525–537, 2003.

[9] H. Hoppe, "Progressive meshes," in *Proceedings of the 23rd Annual Conference on Computer Graphics (SIGGRAPH '96)*, pp. 99–108, New Orleans, La, USA, August 1996.

[10] S.-E. Yoon and D. Manocha, "Cache-efficient layouts of bounding volume hierarchies," *Computer Graphics Forum*, vol. 25, no. 3, pp. 507–516, 2006.

[11] S.-E. Yoon, P. Lindstrom, V. Pascucci, and D. Manocha, "Cache-oblivious mesh layouts," *ACM Transactions on Graphics*, vol. 24, no. 3, pp. 886–893, 2005.

[12] S.-E. Yoon and P. Lindstrom, "Mesh layouts for block-based caches," *IEEE Transactions on Visualization and Computer Graphics*, vol. 12, no. 5, pp. 1213–1220, 2006.

[13] S. Chakrabarti, *Mining the Web: Discovering Knowledge from Hypertext Data*, Morgan Kaufmann, San Francisco, Calif, USA, 2003.

[14] M.-S. Chen, J. S. Park, and P. S. Yu, "Efficient data mining for path traversal patterns," *IEEE Transactions on Knowledge and Data Engineering*, vol. 10, no. 2, pp. 209–221, 1998.

[15] J. Pei, J. Han, B. Mortazavi-Asl, et al., "PrefixSpan: mining sequential patterns efficiently by prefix-projected pattern growth," in *Proceedings of the 17th International Conference on Data Engineering (ICDE '01)*, pp. 215–224, Heidelberg, Germany, April 2001.

[16] J. Han, J. Pei, B. Mortazavi-Asl, Q. Chen, U. Dayal, and M. Hsu, "FreeSpan: frequent pattern-projected sequential pattern mining," in *Proceedings of the 6th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD '00)*, pp. 355–359, Boston, Mass, USA, August 2000.

[17] R. Kohavi, C. E. Brodley, B. Frasca, L. Mason, and Z. Zheng, "KDD-Cup 2000 organizers' report: peeling the onion," *SIGKDD Explorations*, vol. 2, no. 2, pp. 86–98, 2000.

[18] S. Sarawagi and M. Stonebraker, "Efficient organization of large multidimensional arrays," in *Proceedings of the 10th International Conference Data Engineering (ICDE '94)*, pp. 328–336, Houston, Tex, USA, February 1994.

[19] S. More and A. Choudhary, "Tertiary storage organization for large multidimensional datasets," in *Proceedings of the 8th NASA Goddard Space Flight Center Conference on Mass Storage Systems and Technologies in Cooperation with the 17th IEEE Symposium on Mass Storage Systems*, pp. 203–210, College Park, Md, USA, March 2000.

[20] P. J. Rhodes and S. Ramakrishnan, "Iteration aware prefetching for remote data access," in *Proceedings of the 1st International Conference on e-Science and Grid Computing*, pp. 279–286, Melbourne, Australia, December 2005.

[21] W. T. Correa, J. T. Klosowski, and C. T. Silva, "Visibility-based prefetching for interactive out-of-core rendering," in *Proceedings of the IEEE Symposium on Parallel and Large-Data Visualization and Graphics (PVG '03)*, pp. 1–8, Seattle, Wash, USA, October 2003.

[22] P. J. Rhodes, X. Tang, R. D. Bergeron, and T. M. Sparr, "Out-of-core visualization using iterator-aware multidimensional prefetching," in *Visualization and Data Analysis*, vol. 5669 of *Proceedings of SPIE*, pp. 295–306, San Jose, Calif, USA, January 2005.

[23] D. Chisnall, M. Chen, and C. Hansen, "Knowledge-based out-of-core algorithms for data management in visualization," in *Eurographics/IEEE-VGTC Symposium on Visualization (EuroVis '06)*, Lisbon, Portugal, May 2006.

[24] H. Samet, *The Design of Analysis of Spatial Data Structure*, Addison Wesley, Reading, Mass, USA, 1990.

[25] L. De Floriani, P. Magillo, and E. Puppo, "Multi-resolution mesh representation: models and data structures," in *Principle of Multi-Resolution in Geometric Modeling*, Lecture Notes in Mathematics, pp. 363–418, Springler, Berlin, Germany, 2002.

[26] R. Pajarola and J. Rossignac, "Compressed progressive meshes," *IEEE Transactions on Visualization and Computer Graphics*, vol. 6, no. 1, pp. 79–93, 2000.

[27] G. M. Nielson, "Tools for triangulations and tetrahedralizations and constructing functions defined over them," in *Scientific Visualization: Overviews, Methodologies and Techniques*, chapter 20, pp. 429–525, IEEE Computer Society, Silver Spring, Md, USA, 1997.

[28] R. Lario, R. Pajarola, and F. Tirado, "Cached geometry manager for view-dependent LOD rendering," in *Proceedings of the*

13th International Conference in Central Europe on Computer Graphics, Visualization and Computer Vision (WSCG '05), pp. 9–16, Plzen-Bory, Czech Republic, January-February 2005.

[29] K. Hilbert and G. Brunnett, "A hybrid LOD based rendering approach for dynamic scenes," in *Proceedings of Computer Graphics International Conference (CGI '04)*, pp. 274–277, Crete, Greece, June 2004.

[30] D. Bartz, M. Meißner, and T. Hüttner, "OpenGL-assisted occlusion culling for large polygonal models," *Computers & Graphics*, vol. 23, no. 5, pp. 667–679, 1999.

[31] N. Greene, M. Kass, and G. Miller, "Hierarchical Z-buffer visibility," in *Proceedings of the 20th Annual Conference on Computer Graphics and Interactive Techniques (SIGGRAPH '93)*, pp. 231–238, Anaheim, Calif, USA, August 1993.

[32] H. Zhang, D. Manocha, T. Hudson, and K. E. Hoff III, "Visibility culling using hierarchical occlusion maps," in *Proceedings of the 24th Annual Conference on Computer Graphics and Interactive Techniques (SIGGRAPH '97)*, pp. 77–88, Los Angeles, Calif, USA, August 1997.

[33] W. T. Correa, J. T. Klosowski, and C. T. Silva, "iWalk: interactive out-of-core rendering of large models," Tech. Rep. TR-653-02, Princeton University, Princeton, NJ, USA, 2002.

[34] L. Sobierajski and W. Schroeder, "Interactive visualization of aircraft and power generation engines," in *Proceedings of IEEE Conference on Information Visualization*, pp. 483–486, Phoenix, Ariz, USA, October 1997.

[35] J. El-Sana and Y.-J. Chiang, "External memory view-dependent simplication," *Computer Graphics Forum*, vol. 19, no. 3, pp. 139–150, 2000.

[36] T. Tamada, Y. Nakamura, and S. Takeda, "An efficient 3D object management and interactive walkthrough for the 3D facility management system," in *Proceedings of the 20th International Conference on Industrial Electronics, Control and Instrumentation (IECON '94)*, vol. 3, pp. 1937–1941, Bologna, Italy, September 1994.

[37] S. J. Teller and C. H. Sequin, "Visibility preprocessing for interactive walkthroughs," in *Proceedings of the 18th Annual Conference on Computer Graphics and Interactive Techniques (SIGGRAPH '91)*, pp. 61–70, Las Vegas, Nev, USA, July-August 1991.

[38] D. Cohen-Or, Y. Chrysanthou, and C. T. Silva, "A survey of visibility for walkthrough applications," in *Proceedings of the 27th Annual Conference on Computer Graphics (SIGGRAPH '00)*, pp. 61–69, New Orleans, La, USA, July 2000, courses notes.

[39] J. Airey, J. Rohlf, and F. P. Brooks Jr., "Towards image realism with interactive update rates in complex virtual building environments," in *Proceedings of Symposium on Interactive 3D Graphics*, vol. 24, no. 2, pp. 41–50, Snowbird, Utah, USA, March 1990.

[40] E. Ohbuchi, "A real-time refraction renderer for volume objects using a polygon-rendering scheme," in *Proceedings of Computer Graphics International (CGI '03)*, pp. 190–195, Tokyo, Japan, July 2003.

[41] D. P. Luebke, "A developer's survey of polygonal simplification algorithms," *IEEE Computer Graphics and Applications*, vol. 21, no. 3, pp. 24–35, 2001.

[42] R. Agrawal and R. Srikant, "Mining sequential patterns," in *Proceedings of the 11th International Conference on Data Engineering (ICDE '95)*, pp. 3–14, Taipei, Taiwan, March 1995.

[43] R. Srikant and R. Agrawal, "Mining quantitative association rules in large relational tables," in *Proceedings of the ACM SIGMOD International Conference on Management of Data*, vol. 25, no. 2, pp. 1–12, Montreal, Canada, June 1996.

[44] M. Zaki, "SPADE: an efficient algorithm for mining frequent sequences," *Machine Learning*, vol. 42, no. 1-2, pp. 31–60, 2001.

[45] S.-S. Hung, T.-C. Kuo, and D. S.-M. Liu, "PrefixUnion: mining traversal patterns efficiently in virtual environments," in *Proceedings of the 5th International Conference International Conference on Computational Science (ICCS '05)*, vol. 3516 of *Lecture Notes in Computer Science*, pp. 830–833, Atlanta, Ga, USA, May 2005.

[46] J. Choi, S. H. Noh, S. L. Min, and Y. Cho, "Towards application/file-level characterization of block references: a case for fine-grained buffer management," in *Proceedings of the ACM SIGMETRICS International Conference on Measurement and Modeling of Computer Systems*, pp. 286–295, Santa Clara, Calif, USA, June 2000.

[47] J. B. MacQueen, "Some methods for classification and analysis of multivariate observations," in *Proceedings of the 5th Berkeley Symposium on Mathematical Statistics and Probability*, vol. 1, pp. 281–297, Berkeley, Calif, USA, 1967.

[48] L. Kaufman and P. J. Rousseuw, *Finding Groups in Data*, John Wiley & Sons, New York, NY, USA, 1990.

[49] Z. Wu and R. Leahy, "An optimal graph theoretic approach to data clustering: theory and its application to image segmentation," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 15, no. 11, pp. 1101–1113, 1993.

[50] G. Karypis, E. Han, and V. Kumar, "Chameleon: a hierarchical clustering algorithm using dynamic modeling," Tech. Rep. 432, University of Minnesota, Minneapolis, Minn, USA, 1999.

[51] S. Goil, H. Nagesh, and A. Choudhary, "MAFIA: efficient and scalable subspace clustering for very large data sets," Tech. Rep. CPDC-TR-9906-010, Northwestern University, Evanston, Ill, USA, June 1999.

[52] G. Karypis, "CLUTO—a clustering toolkit," Tech. Rep. 02-017, University of Minnesota, Minneapolis, Minn, USA, 2002.

[53] P. Jaccard, "The distribution of the flora in the Alpine zone," *New Phytologist*, vol. 11, no. 2, pp. 37–50, 1912.

[54] C.-M. Ng, C.-T. Nguyen, D.-N. Tran, T.-S. Tan, and S.-W. Yeow, "Analyzing pre-fetching in large-scale visual simulation," in *Proceedings of Computer Graphic International Conference*, pp. 100–107, New York, NY, USA, June 2005.

[55] J. Schindler, J. L. Griffin, C. R. Lumb, and G. R. Ganger, "Track-aligned extents: matching access patterns to disk drive characteristics," in *Proceedings of the 1st USENIX Conference on File and Storage Technologies (FAST '02)*, pp. 259–274, Monterey, Calif, USA, January 2002.

[56] M. Sivathanu, V. Prabhakaran, F. I. Popovici, T. E. Denehy, A. C. Arpaci-Dusseau, and R. H. Arpaci-Dusseau, "Semantically-smart disk systems," in *Proceedings of the 2nd USENIX Conference on File and Storage Technologies (FAST '03)*, pp. 73–88, San Francisco, Calif, USA, March-April 2003.

[57] A. J. Smith, "Sequentiality and prefetching in database systems," *ACM Transactions on Database Systems*, vol. 3, no. 3, pp. 223–247, 1978.

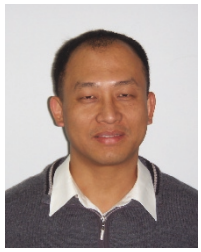
[58] J. M. Kim, J. Choi, J. Kim, et al., "A low-overhead, high-performance unified buffer management scheme that exploits sequential and looping references," in *Proceedings of the 4th Symposium on Operating System Design and Implementation (OSDI '00)*, pp. 119–134, San Diego, Calif, USA, October 2000.

[59] R. Srikant and R. Agrawal, "Mining sequential patterns: generalizations and performance improvements," in *Proceeding of the 5th International Conference on Extending Database Technology (EDBT '96)*, pp. 3–17, Avignon, France, March 1996.

[60] A. Joshi and R. Krishnapuram, "On mining web access logs," in *Proceedings of the SIGMOD Workshop on Research Issues in Data Mining and Knowledge Discovery (DMKD '00)*, pp. 63–69, Dallas, Tex, USA, May 2000.

[61] R. Agrawal, T. Imielinski, and A. N. Swami, "Mining association rules between sets of items in large databases," in *Proceedings of ACM SIGMOD International Conference on Management of Data*, pp. 207–216, Washington, DC, USA, May 1993.

[62] R. Agarwal, C. C. Aggarwal, and V. V. V. Prasad, "Depth first generation of long patterns," in *Proceedings of the 6th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD '00)*, pp. 108–118, Boston, Mass, USA, August 2000.



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