Performance Improvement of Least-Recently-Used Policy in Web Proxy Cache Replacement Using Supervised Machine Learning

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Abstract

Web proxy caching is one of the most successful solutions for improving the performance of Web-based systems. In Web proxy caching, Least-Recently-Used (LRU) policy is the most common proxy cache replacement policy, which is widely used in Web proxy cache management. However, LRU are not efficient enough and may suffer from cache pollution with unwanted Web objects. Therefore, in this paper, LRU policy is enhanced using popular supervised machine learning techniques such as a support vector machine (SVM), a naïve Bayes classifier (NB) and a decision tree (C4.5). SVM, NB and C4.5 are trained from Web proxy logs files to predict the class of objects that would be re-visited. More significantly, the trained SVM, NB and C4.5 classifiers are intelligently incorporated with the traditional LRU algorithm to present three novel intelligent Web proxy caching approaches, namely SVM-LRU, NB-LRU and C4.5-LRU. In the proposed intelligent LRU approaches, unwanted objects classified by machine learning classifier are placed in the middle of the cache stack used, so these objects are efficiently removed at an early stage to make space for new incoming Web objects. The simulation results demonstrated that the average improvement ratios of hit ratio achieved by SVM-LRU, NB-LRU and C4.5-LRU over LRU increased by 30.15%, 32.60% and 31.05 % respectively, while the average improvement ratios of byte hit ratio increased by 32.43%, 69.56% and 28.41%, respectively.

Keywords: *Web proxy server, Cache replacement, Least-Recently-Used (LRU) policy, Classification, Supervised machine learning.*

1   Introduction

The World Wide Web (Web) is the most common and significant service on the Internet. The Web contributes greatly to our life in many fields such as education, entertainment, Internet banking, remote shopping and software downloading. This has led to rapid growth in the number of Internet users, which resulting in an explosive increase in traffic or bottleneck over the Internet performance [1-2]. Consequently, this has resulted in problems during surfing some popular Web sites; for instance, server denials, and greater latency for retrieving and loading data on the browsers [3-5].

Web caching is a well-known strategy for improving the performance of Web-based system. In the Web caching, Web objects that are likely to be used in the near future are kept in a location closer to the user. Web caching mechanisms are implemented at three levels: client level, proxy level and original server level [6-7]. Proxy servers play key roles between users and Web sites in reducing the response time of user requests and saving network bandwidth. In this study, much emphasis is focused on the Web proxy caching because it is still the most common strategy used for caching Web pages [1-4, 8].

Due to cache space limitations, a Web proxy cache replacement is required to manage the Web proxy cache contents efficiently. In the proxy cache replacement, the proxy cache must effectively decide which objects are worth caching or replacing with other objects. The Web cache replacement is the core or heart of Web caching; hence, the design of efficient cache replacement algorithms is crucial for the success of Web caching mechanisms [4, 6-10]. So, the Web cache replacement algorithms are also known as Web caching algorithms [9].

In the Web cache replacement, a few important features or factors of Web objects, such as recency, frequency, size, cost of fetching the object from its origin server and access latency of object, can influence the performance of Web proxy caching [4, 6, 10-12]. These factors can be incorporated into the replacement decision for better performance.

The conventional Web cache replacement approaches consider just some factors and ignore other factors that have an impact on the efficiency of the Web caching [4, 9, 13-15]. Thus, the conventional Web proxy cache replacement policies are no longer efficient enough [4].

Least-Recently-Used (LRU) policy is the most common proxy cache replacement policy among all the conventional Web proxy caching algorithms, which widely used in the real and simulation environments [2-3, 8, 14, 16]. The LRU policy takes into account just the recency factor of the cached objects in cache replacement process. In LRU, by inserting a new object into the cache, it will be located on the top of the cache stack. If the object is not popular (e.g., it is used only once), it will take a long time before it can be moved down to the bottom of the cache stack (namely least recently used object) and will be deleted from the

cache. Therefore, a large portion of objects, which are stored in the cache, are never requested again or requested after a long time. This leads to cache pollution, where the cache is polluted with inactive objects. This causes a reduction of the effective cache size and negatively affects the performance of Web proxy caching.

Even if we can locate a large space for the proxy cache, this will be not helpful since the searching for a Web object in a large cache needs a long response time and an extra processing overhead. Furthermore, a consistency strategy is required to execute frequently to ensure the pages in the cache are the same as pages in the origin Web servers. This cause increase of network traffic, and more loads on the origin servers[1] .

This is motivation to adopt intelligent techniques for solving the Web proxy caching problems. The second motivation behind the development of intelligent approaches in Web caching is availability of proxy logs files that can be exploited as training data. In a Web proxy server, Web proxy logs file records activities of the users and can be considered as complete and prior knowledge of future access.

Several research works have developed intelligent approaches that are smart and adaptive to the Web caching environment. These include adoption of supervised machine learning techniques [8-9, 14, 17-18], fuzzy systems [19], and evolutionary algorithms [12, 20-21] in Web caching and Web cache replacement. Recent studies have reported that the intelligent Web caching approaches based on supervised machine learning techniques are the most common, effective and adaptive Web caching approaches. A multilayer perceptron network (MLP) [9] and back-propagation neural network (BBNN) [8, 14], logistic regression (LR) [22] and multinomial logistic regression(MLR) [23], and adaptive neuro-fuzzy inference system(ANFIS)[15] have been utilized in Web caching. More details about intelligent Web caching approaches are given in our previous work [24].

 Most of these studies have utilized an artificial neural network (ANN) in the Web caching although ANN performance is influenced by the optimal selection of the network topology and its parameters. Furthermore, ANN training may consume more time and require extra computational overhead. More significantly, integration of an intelligent technique in Web cache replacement is still a popular research subject.

In this paper, alternative supervised machine learning techniques are proposed to improve the performance of conventional LRU cache replacement policy. Support vector machine (SVM), naïve Bayes (NB) and decision tree (C4.5) are three popular supervised learning algorithms, which are identified as three of the most influential algorithms in data mining [25]. They perform classifications more accurately and faster than other algorithms in a wide range of applications such as text classification, Web page classification and bioinformatics applications, medical filed, military applications, forecasting, finance and marketing [26-32]. Hence, SVM , C4.5 and NB classifiers can be utilized to produce promising solutions for Web proxy caching.

This study proposes a concrete contribution to the field of Web proxy cache replacement. A new intelligent LRU cache replacement approaches with better performance are designed for use in Web proxy cache. The core of the proposed intelligent cache replacement approaches is to use common supervised machine learning techniques to predict whether Web objects would be needed again in the future. Then, classification decisions are utilized into the conventional LRU method determining what to remove first from the proxy cache.

The remaining parts of this paper are organized as follows. Background and related works are presented in Section 2. Principles of Web proxy caching and replacement are presented in Sections 2.2 and 2.3, while Section 2.4 describes machine learning classifiers used in this study, including support vector machines, decision trees and naïve Bayes classifier. A methodology for improving LRU replacement policy based on machine learning is illustrated in Section 3. Section 4 elucidates implementation and performance evaluation. Finally, Section 5 concludes the paper and discusses possible future works in this area.

2 Web Caching Background and Related Works

2.1 Overview

The term cache has French roots and means, literally, to store [33]. The idea of caching is used in memory architectures of modern computers for improving the performance of CPU speed. In a similar manner to caching in memory system, Web caching stores Web objects in anticipation of future requests. However, the Web caching significantly differs from traditional memory caching in several aspects such as the non-uniformity of Web object sizes, retrieval costs, and cacheability [33]. Significantly, the Web caching has several attractive advantages to Web users [34]. Firstly, the Web caching reduces user perceived latency. Secondly, the Web caching reduces network traffic and therefore reducing network costs for both content provider and consumers. Thirdly, the Web caching reduces loads on the origin servers. Finally, the Web caching increases reliability and availability of Web and application servers.

2.2 Web Proxy Caching

Generally, caches are found in browsers and in any of the Web intermediate between the user agent and the origin server. A Web cache is located in a browser, proxy server and/or origin server. The browser cache is located in the client machine. At the origin server, Web pages can be stored in a server-side cache for reducing the redundant computations and the server load. The proxy cache is found in the proxy server, which is located between the client machines and origin server. The proxy servers are often used to achieve some tasks such as firewalls to provide security, caching, filtering, redirection, and forwarding. They allow and record users' requests from the internal network to the outside Internet. A proxy

server behaves like both a client and a server. It acts like a server to clients, and like a client to servers. A proxy receives requests from clients, processes those requests, and then it forwards them to origin servers.

The Web proxy caching works on the same principle as the browser caching, but on a much larger scale. Unlike the browser cache that deals with only a single user, the proxy server serves hundreds or thousands of users in the same way. When a request is received, the proxy server checks its cache. If the object is available, the proxy server sends the object to the client. If the object is not available, or it has expired, the proxy server will request the object from the origin server and send it to the client. The requested objects are stored in the proxy's local cache for future requests. Hence, the Web proxy caching plays the key roles between users and Web servers in reducing the response time of user requests and saving the network bandwidth.

The Web proxy caching is widely utilized by computer network administrators, technology providers, and businesses to reduce user delays and to reduce Internet congestion [1-3]. In this study, much emphasis are placed on Web proxy caching because it is still the most common strategy used for caching Web pages.

2.3   Web Proxy Cache Replacement

Three popular issues have a profound impact on Web proxy caching, namely cache consistency, cache pre-fetching, and cache replacement [34-36]. The cache consistency is to ensure the pages in the cache are the same as pages in the origin Web server. The pre-fetching is a technique for reducing user Web latency by preloading the Web object that is not requested yet by the user. In other words, the pre-fetching is a technique that downloads the probabilistic pages that are not requested by the user, but that could be requested soon by the same user [34]. The cache replacement refers to the process that takes place when the cache becomes full, and some objects must be removed to make space for new coming objects.

The Web proxy cache replacement plays an extremely important role in Web proxy caching. Hence, the design of efficient cache replacement algorithms is required to achieve highly sophisticated caching mechanism [4, 6-10]. The effective cache replacement algorithm is vital and has a profound impact on Web proxy cache management [7]. Therefore, this study pays attention to improvement of Web proxy cache replacement approaches. In general, cache replacement algorithms are also called Web caching algorithms [9].

As cache size is limited, a cache replacement policy is needed to handle the cache content. If the cache is full when an object needs to be stored, the replacement policy will determine which object is to be evicted to allow space for the new object. The optimal replacement policy aims to make the best use of available cache space, improve cache hit rates, and reduce loads on the origin server.

Most Web proxy servers are still based on conventional replacement policies for Web proxy cache management. In the proxy cache replacement, Least-Recently-Used (LRU), Least-Frequently-Used (LFU), Least-Frequently-Used-Dynamic-Aging (LFU-DA), SIZE, Greedy-Dual-Size (GDS) and Greedy-Dual-Size-Frequency (GDSF) are the most common Web caching approaches, which still used in most of the proxy servers and software like squid software. These conventional Web caching methods form the basis of other Web caching algorithms [8, 14]. However, these conventional approaches still suffer from some limitations as shown in Table 1 [9, 37].

Table 1: Conventional Web cache replacement policies

Policy	Brief Description	Advantage	Disadvantage
LRU	The least recently used objects are removed first.	simple and efficient with uniform size objects, such as the memory cache.	ignores download latency and the size of Web objects
LFU	The least frequently used objects are removed first.	simplicity	ignores download latency and size of objects and may store obsolete Web objects indefinitely.
LFU-DA	Dynamic aging factor (L) is incorporated into LFU.	▪ reduces cache pollution caused by LFU. ▪ high byte hit ratio	may suffer from hit ratio
SIZE	Big objects are removed first	prefers keeping small Web objects in the cache, causing high cachet hit ratio.	▪ stores small Web objects even if these object are never accessed again. ▪ low byte hit ratio.
GDS	It assigns a key value to each cached object g as equation below. The object with the lowest key value is replaced first. $$K(g) = L + \frac{C(g)}{S(g)}$$ where $C(g)$ is the cost of fetching g from the server; $S(g)$ is the size of g; and L is an aging factor.	▪ overcomes the weakness of SIZE policy by removing objects which are no longer requested by users. ▪ high hit ratio	▪ does not take into account the previous frequency of Web objects. ▪ low byte hit ratio.
GDSF	It extends GDS by integrating the frequency factor into the key value	▪ takes into account the previous frequency of Web objects. ▪ very high hit ratio	▪ does not take into account the predicted accesses ▪ low byte hit ratio.

Least-Recently-Used (LRU) algorithm is one of the simplest and most common cache replacement approaches, which removes Web objects from the cache that have not been used for the longest period of time. In other words, LRU policy removes the least recently accessed objects first until there is sufficient space for the new objects. When a Web object is requested by user, the requested Web object is fetched from a server and placed at the top of the cache stack. Consequently, the cache stack pushes down the other objects in the stack so the object in the bottom of the cache stack is evicted from cache. Algorithm of the conventional LRU is shown in Fig. 1.

```
Begin

    For each Web object g requested by user
    Begin
        If g in cache
            Begin
                Cache hit occurs
                Move g to top of the cache stack
            End

        Else
          Begin
                Cache miss occurs
                Fetch g from origin server.
                While no enough space in cache for g
                    Evict q  such that q object in the bottom  of the cache stack
                Insert g at top of the cache stack
          End
    End

End
```
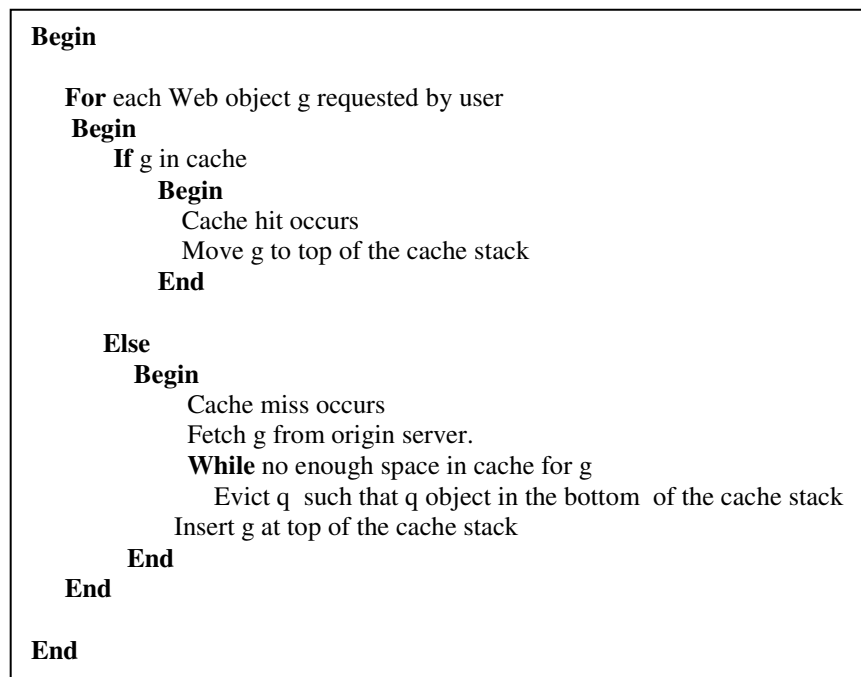
Fig. 1: The algorithm of conventional LRU proxy replacement policy

The reason for the popularity of LRU in the Web proxy caching is the good performance of LRU when requests exhibit temporal locality, i.e., the Web object that have been requested in the recent past are likely to be requested again in the near future. However, if many objects stored by URL in the proxy cache are not requested again or requested after a long time, the cache usage is exploited inappropriately due to the cache pollution with unwanted objects. This causes a low performance of Web proxy caching.

As mentioned earlier, recency, frequency, size, cost of fetching the object and access latency of object are important features of Web objects, which play an essential role in making the wise decisions of Web proxy caching and replacement. In the conventional caching policies, only one factor is considered in cache replacement decision or few factors are combined using mathematical equation to predict revisiting of the Web objects in the future. These conventional approaches are not efficient enough and not adaptive to Web users' interests that change

continuously depending on rapid changes in Web environment. Therefore, alternative approaches are required in Web caching. Many Web cache replacement policies have been proposed to improve the performance of Web caching. However, it is challenging to have an omnipotent policy that performs well in all environments or for all time due to the preference of these factors is still based on the environments [6, 10]. Hence, there is a need for an intelligent and adaptive approach, which can effectively incorporate these factors into Web caching and replacement decisions.

2.4   Supervised machine learning

Machine learning involves adaptive mechanisms that enable computers to learn by example and learn from experience like human learning from experiences. The machine learning can be accomplished in a supervised or an unsupervised learning. In supervised learning, the data (observations) are labeled with pre-defined classes. It is like that a teacher gives the classes. On the other hand, unsupervised learning means that the system acts and observes the consequences of its actions, without referring to any predefined labels.

In this research, supervised machine learning techniques are proposed to improve the performance of Web proxy cache replacement. Support vector machine (SVM), naïve Bayes (NB) and decision tree(C4.5) are three popular supervised learning algorithms, which are identified as three of the most influential algorithms in data mining [25] and perform classifications more accurately and faster than other algorithms in a wide range of applications [26, 30].

Since SVM is formulated as a quadratic programming problem, there is a global optimum solution in SVM training. Besides, SVM is trained to maximize the margin, so the generalization ability can be maximized, especially when training data are scarce and linearly separable. In addition, SVM is robust to outliers because the margin parameter controls the misclassification error [38]. However, the generalization ability in SVM is still controlled by changing a kernel function and its parameters, and the margin parameter. Moreover, SVM may consume quite longer time compared to others in learning process, especially with large dataset. Hence, in addition to SVM, NB and C4.5 are also suggested for improving the performance of Web proxy cache replacement in this study. The NB and C4.5 are two of the most widely used and practical techniques for classification in many applications such as finance, marketing, engineering and medicine [29-32]. In addition to the good classification accuracy in many domains, the NB and C4.5 are efficient, easy to construct without parameters, and simple to understand and interpret [25, 27-28, 31].

2.4.1   Support vector machine

The support vector machine (SVM) was invented by Vapnik [39]. The basic concept of SVM is to use a high dimension space to find a liner boundary or

hyperplane to do binary division (classification) with two classes, positive and negative samples. The SVM attempts to place hyperplane(solid line in Fig. 2) between the two different classes, and orient it in such a way that the margin (dotted lines in Fig. 2) is maximized. The hyperplane is oriented such that the distance between the hyperplane and the nearest data point in each class is maximal. The nearest data points are used to define the margins and are known as support vectors (SVs)(gray circle and square in Fig. 2). The hyperplane can be expressed as in Eq. (1)
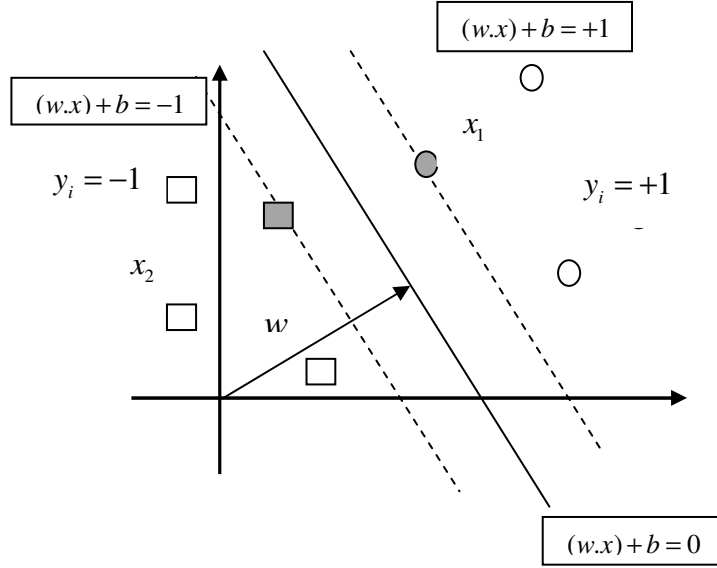

Fig. 2: Classification of data by SVM

$$(w.x) + b = 0, \; w \in R^N, b \in R \tag{1}$$

where the vector w defines the boundary, x is the input vector of dimension N and b is a scalar threshold. At the margins, where the SVs are located, the Eqs.(2) and (3) for positive class and negative class, respectively, are as follows:

$$(w.x) + b = 1 \tag{2}$$

$$(w.x) + b = -1 \tag{3}$$

SVs correspond to the extremities of the data for a given class. Therefore, to classify any data point in either positive or negative class, the following decision Eq. (4) can be used:

$$f(x) = sign((w.x) + b) \tag{4}$$

The optimal hyperplane can be obtained as a solution to the following optimization problem.

Minimize

$$t(w) = \frac{1}{2}\|w\|^2 \qquad (5)$$

Subject to

$$y_i((w.x_i) + b) \geq 1, i = 1,...,l \qquad (6)$$

where l is the number of training sets. The solution of the constrained optimization problem can be obtained using Eq.(7).

$$w = \sum v_i x_i \qquad (7)$$

where x_i are SVs obtained from training. Putting Eq. (7) in Eq. (4), the decision function is obtained in Eq. (8).

$$f(x) = sign\left(\sum_{i=1}^{l} v_i(x.x_i) + b\right) \qquad (8)$$

However, for many real-life problems, it is not easy to find a hyperplane to classify the data such as nonlinearly separable data. The nonlinearly separable data is classified with the same principle of the linear case. However, the input data is only transformed from the original space into much higher dimensional space called the feature space. Then, a hyperplane can separate positive and negative examples in feature space as shown in Fig. 3. Thus, the decision function becomes as in Eq. (9).
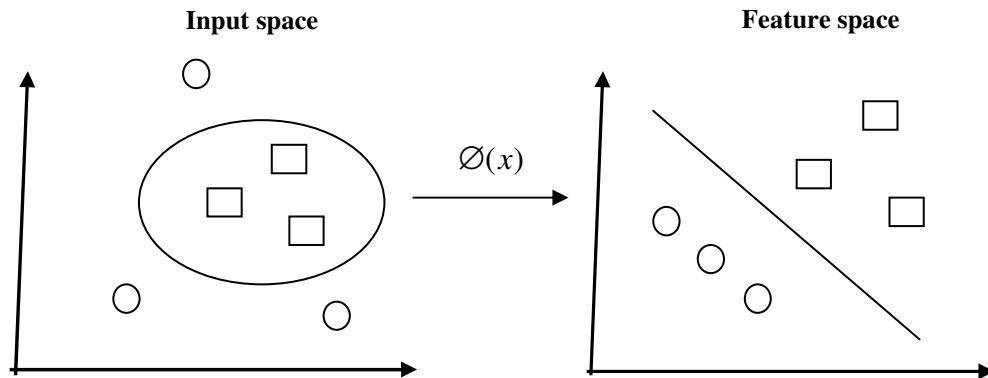

Fig. 3: Transformation from input space to feature space

$$f(x) = sign\left(\sum_{i=1}^{l} v_i (\varnothing(x).\varnothing(x_i)) + b \right) \qquad (9)$$

The transformation from input space to feature space space is relatively computation-intensive. Therefore, a kernel function can be used to perform this transformation and the dot product in a single step. This helps in reducing the computational load and at the same time retaining the effect of higher-dimensional transformation. The kernel function $K(x_i.x_j)$ is defined as Eq.(10).

$$K(x_i.x_j) = \varnothing(x_i).\varnothing(x_j) \qquad (10)$$

After substituting Eq. (10) in the decision function (9), the basic form of SVM is accordingly obtained as Eq. (11).

$$f(x) = sign\left(\sum_{i=1}^{l} v_i K(x.x_i) + b \right) \qquad (11)$$

The parameters v_i are used as weighting factors to determine which of the input vectors are support vectors. Several kernel functions can be used in SVM to solve different problems. In this study, RBF kernel given in Eq. (12) is used as kernel function in SVM training. The parameter γ represents the width of the RBF. In case there is an overlap between the classes with non-separable data, the range of parameters v_i can be limited to reduce the effect of outliers on the boundary defined by SVs. For non-separable cases, the constraint becomes ($0 < v_i < C$). For separable cases, C is infinity while for non-separable cases, it may be varied, depending on the number of allowable errors in the trained solution: high C permits few errors while low C allows a higher proportion of errors in the solution.

$$k(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2), \gamma > 0 \qquad (12)$$

2.4.2   Naïve Bayes classifier

Naïve Bayes(NB) is very simple Bayesian network which has constrained structure of the graph [40]. In NB, all the attributes are assumed to be conditionally independent given the class label. The structure of the NB is illustrated in Fig. 4. In most of the data sets, the performance of the naïve Bayes classifier is surprisingly good even if the independence assumption between

attributes is unrealistic [40-41]**.** Independence between the features ignores any correlation among them.
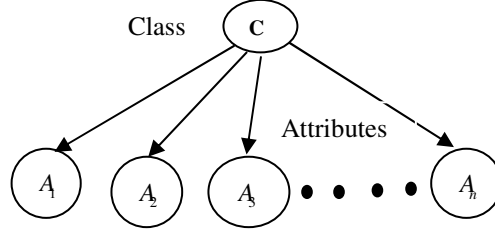

Fig. 4: Structure of a naïve Bayes network

NB depends on probability estimations, called a posterior probability, to assign a class to an observed pattern. The classification can be expressed as estimating the class posterior probabilities given a test example *d* as shown in formula (13). The class with the highest probability is assigned to the example d.

$$\Pr(C = c_j \mid d) \tag{13}$$

Let $A_1, A_2, ..., A_{/A/}$ be the set of attributes with discrete values in the data set D. Let C be the class attribute with |C| values, $c_1, c_2, ..., c_{/C/}$. Given a test example $d = < A_1 = a_1, ..., A_{/A/} = a_{/A/} >$, where a_i is a possible value of A_i. The posterior probability $\Pr(C = c_j \mid d)$ can be expressed using the Bayes theorem as shown in Eq. (14).

$$\Pr(C = c_j \mid A_1 = a_1, ..., A_{/A/} = a_{/A/}) = \frac{\Pr(A_1 = a_1, ..., A_{/A/} = a_{/A/} \mid C = c_j)\Pr(C = c_j)}{\Pr(A_1 = a_1, ..., A_{/A/} = a_{/A/})}$$

$$= \frac{\Pr(A_1 = a_1, ..., A_{/A/} = a_{/A/} \mid C = c_j)\Pr(C = c_j)}{\sum_{k=1}^{/C/}\Pr(A_1 = a_1, ..., A_{/A/} = a_{/A/} \mid C = c_k)\Pr(C = c_j)} \tag{14}$$

NB assumes that all the attributes are conditionally independent given the class $C = c_j$ as in Eq. (15),

$$\Pr(A_1 = a_1, ..., A_{/A/} = a_{/A/} \mid C = c_j) = \prod_{i=1}^{/A/}\Pr(A_i = a_i \mid C = c_j) \tag{15}$$

After putting (15) in (14), the decision function is obtained as shown in Eq. (16)

$$\Pr(C=c_j \mid A_1=a_1,...,A_{/A/}=a_{/A/}) = \frac{\Pr(C=c_j)\prod_{i=1}^{/A/}\Pr(A_i=a_i \mid C=c_j)}{\sum_{k=1}^{C}\Pr(C=c_k)\prod_{i=1}^{/A/}\Pr(A_i=a_i \mid C=c_k)} \qquad (16)$$

In classification tasks, we only need the numerator of Eq. (16) to decide the most probable class for each example since the denominator is the same for each class. Thus we can decide the most probable class for given a test example using formula (17):

$$c = \arg\max_{c_j} \ \Pr(C=c_j)\prod_{i=1}^{/A/}\Pr(A_i=a_i \mid C=c_j) \qquad (17)$$

2.4.3 Decision tree

The most well-know algorithm in the literature for building decision trees is the C4.5 decision tree algorithm , which was proposed by Quinlan [42]. The basic concept of the C4.5 is as follow. The tree begins with a root node that represents the entire given dataset and it recursively splits the data into smaller subsets by testing for a given attribute at each node. The sub-trees denote the partitions of the original dataset that satisfy specified attribute value tests. This process typically continues until the subsets are pure. That means all instances in the subset fall into the same class, at which time the tree growing is terminated.

In the process of constructing the decision tree, the root node is first selected by evaluating each attribute on the basis of an impurity function to determine how well it alone classifies the training examples. The best attribute is selected and used to test at the root node of the tree. A descendant of the root node is created for each possible value of this selected attribute, and the training examples are sorted to the appropriate descendant node. The process is then repeated using the training examples associated with each descendant node to select the best attribute to test at that point in the tree.

In decision tree learning, the most popular impurity functions used for attributes selection are information gain and information gain ratio. In C4.5 algorithm, the gain ratio is employed for better performance achievement [42].

3 A Methodology for Improving Least-Recently-Used Replacement Policy Based on Supervised Machine Learning

A framework for improving Least-Recently-Used replacement (LRU) policy in Web proxy cache replacement based on supervised machine learning classifiers is presented in Fig. 5.
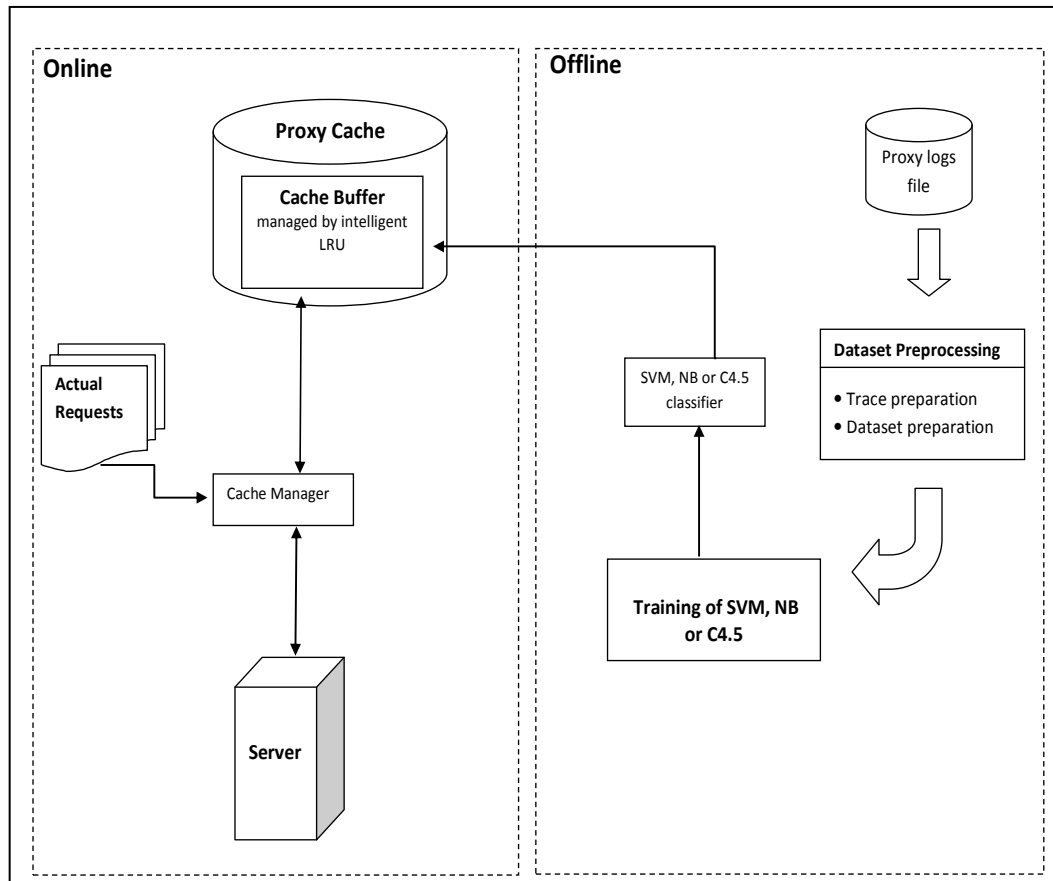
Fig. 5: A framework for improving LRU replacement policy based on supervised machine learning classifiers

As shown in Fig. 5, the framework consists of two functional components: an online component and an offline component. The terms online and offline refer to interactive communications between the users and the proxy server. The offline component does not deal with the user directly, while online connections between the users and the proxy are established in the online component to retrieve the requested object from the proxy cache or the origin server. The offline component is responsible for training a machine learning classifier, while the intelligent LRU replacement approaches based on the trained classifier are utilized to effectively manage the Web proxy cache in the online component.

In the online component, when a user requests a Web page, the user communicates with the proxy, which directly retrieves the requested page from the proxy cache as shown in Fig. 5. However, sometimes the proxy cache miss occurs if the requested object is not in the proxy cache or not fresh. In a cache miss, the proxy server requests the object from the origin server and sends it back to the client. A copy of the requested object is replicated into the proxy cache to reduce the response time and the network bandwidth utilization in future requests. In some situations, a new coming object needs to be stored into the proxy cache; but the proxy cache is full of Web objects. In these cases, the proxy cache manger uses the proposed intelligent LRU replacement approaches to remove the unwanted Web objects in order to release enough space for the new coming object.

3.1   Training of supervised machine learning classifiers

The offline component is responsible for training the machine learning classifiers. In the proxy servers, information about the behaviours of groups of users in accessing many Web servers are recorded in files known as proxy logs files. The proxy logs files can be obtained from proxy servers located in various organizations or universities. The proxy logs files are considered a complete and prior knowledge of the users' interests and can be utilized as training data to effectively predict the next Web objects.

As the raw proxy datasets are collected, these data must be prepared properly in order to obtain more accurate results. Dataset pre-processing involves manipulating the dataset into a suitable form with training of the supervised machine learning techniques. Data pre-processing requires two steps: trace preparation and training dataset preparation. In the trace preparation, irrelevant or not valid requests are removed from log files such as uncacheable and dynamic requests. On the other hand, training dataset preparation step requires extracting the desired information from the logs proxy files, and then selecting the input/output dataset. The important features of Web objects that indicate the users' interests are extracted in order to prepare the training dataset. These features consist of URL ID, timestamp, elapsed time, size and type of Web object. Subsequently, these features are converted to the input/output dataset or training patterns required at the training phase. A training pattern takes the format $<x_1, x_2, x_3, x_4, x_5, x_6, y>$. $x_1, ..., x_6$ represent the input features and y represents the target output of the requested object. Table 2 shows the inputs and their meanings for each training pattern.

4 Table 2: The inputs and their meanings

Input	Meaning
x_1	Recency of Web object access based on backward-looking sliding window
x_2	Frequency of Web object accesses
x_3	Frequency of Web object accesses based on backward-looking sliding window
x_4	Retrieval time of Web object in milliseconds
x_5	Size of Web object in bytes
x_6	Type of Web object

x_1 and x_3 are extracted based on a backward-looking sliding window in a similar manner to [8, 43] as shown in Eqs. (18) and (19). The backward-looking and forward-looking sliding windows of a request are the time before and after when the request was made.

$$x_1 = \begin{cases} Max(SWL, \Delta T) & , if \ object \ g \ was \ requested \ before \\ \\ SWL & , otherwise \end{cases} \tag{18}$$

$$x_{3_i} = \begin{cases} x_{3_{i-1}} + 1 & , if \ \Delta T \ \leq SWL \\ \\ 1 & , otherwise \end{cases} \tag{19}$$

where ΔT is the time in seconds since object g was last request , and *SWL* is sliding window length. If object g is requested for the first time, x_3 will be set to 1.

In a similar way to Foong et al.[22], x_6 is classified into five categories: HTML with value 1, image with value 2, audio with value 3, video with value 4, application with value 5 and others with value 0.y is set based on the forward-looking sliding window. The value of y will be assigned to 1 if the object is re-requested again within the forward-looking sliding window. Otherwise, the target output will be assigned to 0. The idea is to use information about a Web object requested in the past to predict revisiting of such Web object within the forward-looking sliding window.

Once the proxy dataset is prepared properly, the machine learning classifiers can be trained depending on the finalized dataset for Web objects classification. The training phase aims to train SVM, C4.5 and NB to predict the class of a Web

object requested by the user, either as object would be revisited within the forward-looking sliding window or not.

As recommended by Hsu et al. [44], SVM is trained as follows: prepare and normalize the dataset, consider the RBF kernel, use cross-validation to find the best parameters C (margin softness) and γ (RBF width), use the best parameters to train the whole training dataset, and test. In SVM training, several kernel functions like polynomial, sigmoid and RBF can be used. However, in this study, RBF kernel function is used since it is the most often used kernel function and can achieve a better performance in many applications compared to other kernel functions [44]. After training, the obtained SVM uses Eq. (11) to predict the class of a Web objects either objects would be revisited again or not.

Regarding training of NB classifier, the NB classifier assumes that all attributes are categorical. Therefore, the numerical attributes need to be discretized into an interval in order to train or construct the NB classifier. In this study, the dataset is discretized by Minimum Description Length (MDL) given by Fayyad and Irani [45], and then the NB classifier is constructed depending on the finalized proxy dataset in order to classify Web objects as objects would be revisited again or not. In the training phase of NB classifier, it is only required to estimate the prior probabilities $\Pr(C = c_j)$ and the conditional probabilities $\Pr(A_i = a_i \mid C = c_j)$ from the proxy training dataset using Eqs. (20) and (21). Then, the NB classifier can predict class of a Web object using the formula (17), as explained in Section 2.4.2.

$$\Pr(C = c_j) = \frac{\# \, examples \, of \, class \, c_j}{\# \, total \, examples} \tag{20}$$

$$\Pr(A_i = a_i \mid C = c_j) = \frac{\# \, examples \, with \, A_i = a_i \, and \, class \, c_j}{\# \, examples \, of \, class \, c_j} \tag{21}$$

In C4.5 training, the decision tree is constructed in a top-down recursive manner. Initially, all the training patterns are at the root. Then, the training patterns are partitioned recursively based on attributes selected based on an impurity function. Partitioning continues until all patterns for a given node belong to the same class. After the decision tree is trained, a Web object is classified depending on traversing the tree top-down according to the attribute values of the given test pattern until reaching a leaf node. The leaf node represents the predicted class, either as object that would be re-visited (class 1) or not (class 0). In addition, probabilities of classes can be obtained by computing the relative frequency of each class in a leaf. As can be observed from Fig. 6, at the end of each leaf, the numbers in parentheses show the number of examples in this leaf. If one or more leaves were not pure, i.e., not all of the same class, the number of misclassified examples would also be given after a slash.
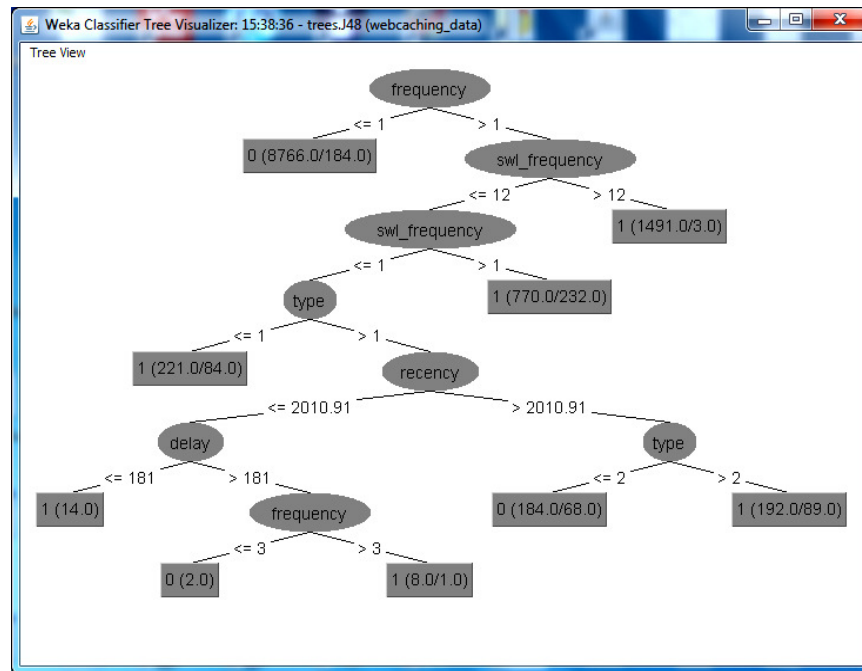
Fig. 6: An example of building C4.5 decision tree for Web proxy dataset

3.2 The proposed intelligent LRU replacement approaches based on machine learning classifiers

LRU policy is the most common proxy cache replacement policy among all the Web proxy caching algorithms [2-3, 8, 14]. However, LRU policy suffers from cold cache pollution, which means that unpopular objects remain in the cache for a long time. In other words, in LRU, a new object is inserted at the top of the cache stack. If the object is not requested again, it will take some time to be moved down to the bottom of the stack before removing it from the cache.

In order to reduce the cache pollution in LRU, the trained SVM, NB and C4.5 classifiers are combined with the traditional LRU to form three new intelligent LRU approaches known as SVM-LRU, NB-LRU and C4.5-LRU.

The proposed intelligent LRU approaches work as follows. When Web object g is requested by the user, the trained SVM, NB or C4.5 classifier predicts whether the class of that object would be revisited again or not. If object g is classified as an object would be re-visited again, object g is placed at the top of the cache stack. Otherwise, object g is placed in the middle of the cache stack used. As a result, the intelligent LRU approaches can efficiently remove unwanted objects at an early stage to make space for new Web objects.

By using this mechanism, cache pollution can be reduced and the available cache space can be utilized effectively. Consequently, the hit ratio and byte hit ratio can

be greatly improved by using the proposed intelligent LRU approaches. The algorithm of the proposed intelligent LRU is shown in Fig. 7.

```
Begin

   For each Web object g requested by user
    Begin
       If g in cache
           Begin
             Cache hit occurs
             Update information of g
           // classify g by SVM, NB or C4.5 classifier
           class of g = classifier.classify ( common features)
              If class of g =1   // g classified as object will be revisited later
                 Move g to top of the cache stack
              Else
                  Move g to the middle of the cache stack used
           End

       Else
          Begin
             Cache miss occurs
             Fetch g from origin server.
             While no enough space in cache for g
             Begin
                Evict q  such that q object in the bottom  of the cache stack
             End
             // classify g by  SVM, NB or C4.5 classifier
             class of g = classifier.classify ( common features)
             If class of g =1   // g classified as object will be revisited later
                Insert g at top of the cache stack
                                 Else
                Insert g in the middle of the cache stack used
          End
    End

End
```

Fig. 7: The algorithm of intelligent LRU approaches

In order to understand the benefits of the proposed intelligent LRU, Fig. 8 illustrates an example of alleviating LRU cache pollution by using the intelligent LRU. Suppose that sequence of Web objects with fixed size is A B C D E F G B H C D requested by the users from left to right. The caching and removing of these objects using LRU policy and the proposed intelligent LRU are illustrated in Fig. 8.
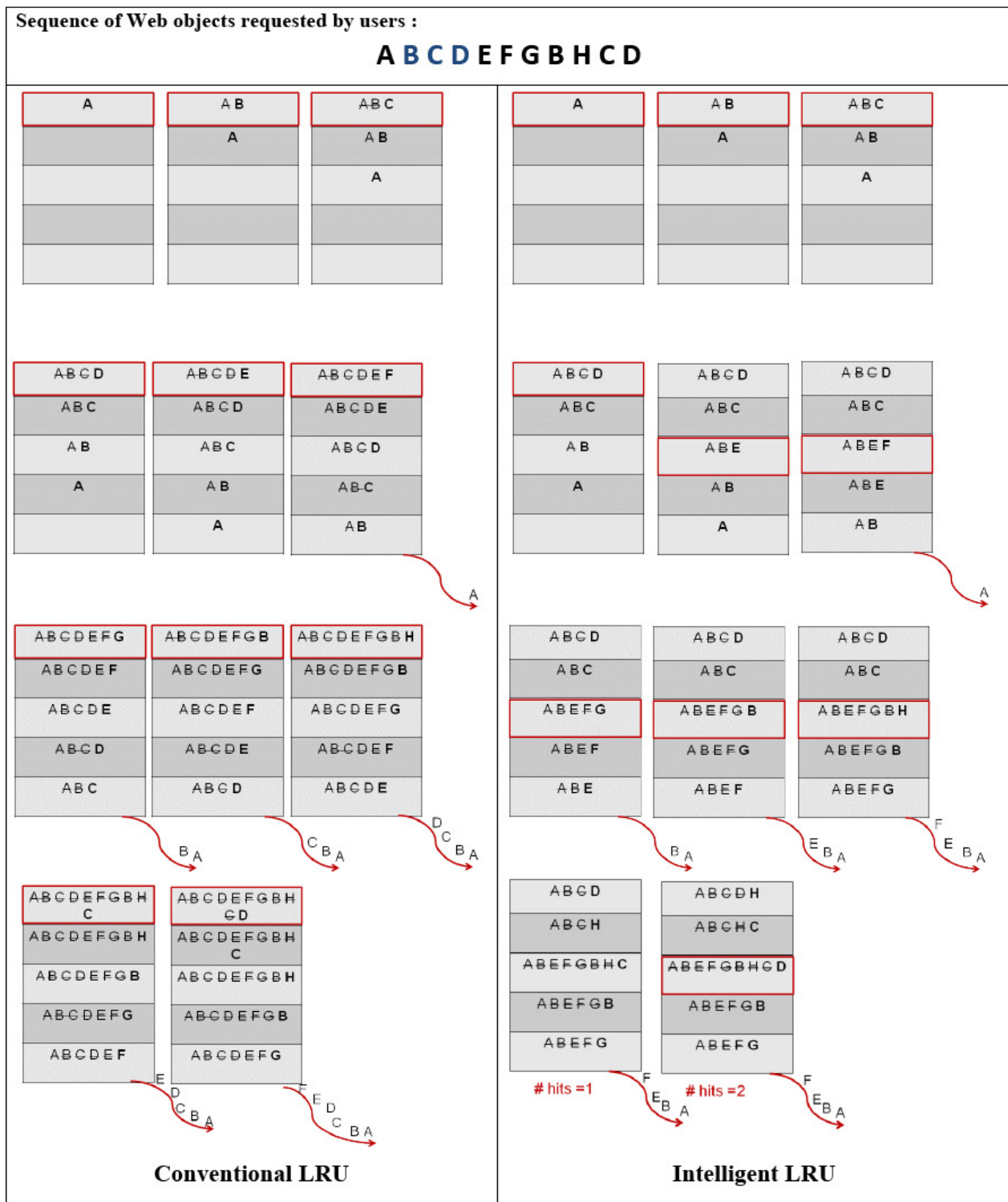
Fig. 8: Example of alleviating the cache pollution by the proposed intelligent LRU

From Fig. 8, it can be observed that objects A, E, F, G, and H are visited only once, while the objects B, C and D are visited twice by user. In the traditional LRU policy, all Web objects are initially stored at the top of the cache, so these objects need longer time to move down to the bottom of the cache (where least recently used objects are stored) for removal from the cache.

By contrast, the proposed intelligent LRU (see Fig. 8) stores the preferred objects B, C and D at the top of the cache if the machine learning classifier predicts correctly revisiting of B, C and D again. On the other hand, if objects A, E, F, and G are properly classified as objects would not be re-visited soon, then these objects will be stored in the middle of the proxy cache used. Therefore, these objects A, E, F and G move down to the bottom of the cache shortly. Hence, the un-preferred objects are removed in a short time by the intelligent LRU to make space for new Web objects.

From the above example, it can be noted that the proposed intelligent LRU approaches efficiently remove unwanted objects early to make space for new Web objects. Therefore, the cache pollution is lessened and the available cache space is exploited efficiently. Moreover, the hit ratio and byte hit ratio can be improved successfully.

4   Performance Evaluation and Discussion

4.1   Raw data collection and pre-processing

The proxy datasets or the proxy logs files were obtained from five proxy servers located in the United States from the IRCache network and covered fifteen days [46]. Four proxy datasets (BO2, NY, UC and SV) were collected between 21st August and 4th September, 2010, while SD proxy dataset was collected between 21st and 28th August, 2010. In this study, the proxy logs files of 21st August, 2010 were used in the training phase, while the proxy logs files of the following days were used in the simulation to evaluate the proposed intelligent Web proxy cache replacement approaches against existing works (see Table 3).

Each line in the proxy logs file represents access proxy log entry, which consists of the ten following fields: timestamp, elapsed time, client address, log tag and HTTP code, size request method, URL, user identification, hierarchy data and hostname and content type.

As the raw datasets were collected, some data pre-processing steps were performed to produce results reflecting the performance of the algorithms. The dataset pre-processing was achieved in three steps:

Table 3: Proxy datasets used for evaluating the proposed intelligent caching approaches

Proxy Dataset	Proxy Server Name	Location	Duration of Collection
UC	uc.us.ircache.net	Urbana-Champaign, Illinois	21/8 – 4/9/2010
BO2	bo.us.ircache.net	Boulder, Colorado	21/8 – 4/9/2010
SV	sv.us.ircache.net	Silicon Valley, California (FIX-West)	21/8 – 4/9/2010
SD	sd.us.ircache.net	San Diego, California	21/8 – 28/8/2010
NY	ny.us.ircache.net	New York, NY	21/8 – 4/9/2010

Parsing: This involves identifying the boundaries between successive records in log files as well as the distinct fields within each record.

Filtering: This includes elimination of irrelevant entries such as un-cacheable requests (i.e., queries with a question mark in the URLs and cgi-bin requests) and entries with unsuccessful HTTP status codes. We only consider successful entries with 200 status codes.

Finalizing: This involves removing unnecessary fields. Moreover, each unique URL is converted to a unique integer identifier for reducing time of simulation.

4.2   Raw data collection and pre-processing

4.2.1   Training phase

Since the trace and logs files were prepared as mentioned earlier; the training datasets were prepared as explained in Section 3.1. Romano and ElAarag [8] recommended one day as enough time for training, especially with a dataset preparation based on SWL. Depending on the recommendations of Romano and ElAarag [8], the proxy log files covering a single day, 21st August 2010, were used in this study for training the supervised machine learning classifiers. Furthermore, Romano and ElAarag [8] have shown the effect of SWL on the performance of the BPNN classifier. The BPNNs were trained by Romano and ElAarag [8] with various values of SWL between 30 minutes and two hours. They concluded that a smaller SWL decreases the training performance. However, a decreasing SWL can increase the training performance when using large training datasets. Thus, Romano and ElAarag [8] considered that SWL with 30 minutes are enough periods on a large dataset. Based on this assumption, in this study, SWL was set to 30 minutes during the training datasets preparation for all intelligent classifiers, since our datasets were large as well.

Once the datasets were properly prepared, the machine learning techniques were implemented using MATLAB and WEKA. The SVM model was trained using the libsvm library [47]. The generalization capability of SVM is controlled through a few parameters such as the term C and the kernel parameter like RBF width γ. To decide which values to choose for parameter C and γ, a grid search algorithm was implemented as suggested by Hsu et al. [44]. The parameters that obtain the best accuracy using a 10-fold cross validation on the training dataset were retained. Next, a SVM model was trained depending on the optimal parameters to predict and classify the Web objects whether the objects would be re-visited or not. Regarding C4.5 training, a J48 learning algorithm was used, which is a Java re-implementation of C4.5 and provided with WEKA tool. The default values of parameters and settings were used as determined in WEKA. In NB training, the datasets were discretized using a MDL method suggested by Fayyad and Irani [45] with default setup in WEKA. Once the training dataset was prepared and discretized, NB was trained using WEKA as well. In WEKA, a NB classifier is available in the Java class "weka.classifiers.bayes.NaiveBayes".

4.2.2   Classifiers evaluation

The main measure for evaluating a classifier is the correct classification rate (CCR), which is the number of correctly classified examples in the dataset divided by the total number of examples in the dataset. In some situations, CCR alone is insufficient for measuring the performance of a classifier, e.g., when the data is imbalanced. Therefore, some accurate measures of the classification evaluation are extracted from a confusion matrix shown in Table 4.

Table 4: Confusion matrix for a two-class problem

	Predicted Positive	**Predicted Negative**
Actual Positive	True Positive (*TP*)	False Negative (*FN*)
Actual Negative	False Positive (*FP*)	True Negative (*TN*)

Table 5: The measures used for evaluating performance of machine learning classifiers

Measure name	Formula
Correct Classification Rate	$CCR = \dfrac{TP+TN}{TP+FP+FN+TN}$ *(%)*
True Positive Rate	$TPR = \dfrac{TP}{TP+FN}$ *(%)*
True Negative Rate	$TNR = \dfrac{TN}{TN+FP}$ *(%)*
Geometric Mean	$G_{mean} = \sqrt{TPR*TNR}$ *(%)*

This study considers that the Web object belongs to the positive class (minority class) if the object is re-requested again. Otherwise, the Web object belongs to the negative class (majority class). It is observed from proxy logs files used in this

study that the training datasets are imbalanced since many Web objects are visited just one time by the users. Therefore, like several research works [23, 48-49], CCR, true positive rate (TPR) or sensitivity, true negative rate (TNR) or specificity, and geometric mean (GM) are used in this study to evaluate the classifiers performance as shown in Table 5.

In this paper, both hold-out validation and n-fold cross validation were used in evaluating the supervised machine learning algorithms. In hold-out validation, each proxy dataset was randomly divided into training data (70%) and testing data (30%). In addition, 10-fold cross validation was used in evaluating the supervised machine learning algorithms since it is commonly used by many researchers.

In order to benchmark the SVM, NB and C4.5, they were compared to both back-propagation neural network (BPNN) and adaptive neuro-fuzzy inference system (ANFIS). This is due to the fact that BPNN and ANFIS have good performance in Web caching area in pervious works [8-9, 14-15, 17-18, 37]. In addition, the SVM, NB and C4.5 were also compared with BPNN as used in the existing caching approach NNPCR-2 [8].

Tables 6 and 7 show comparisons between the performance measures of SVM, NB, C4.5, BPNN, ANFIS and NNPCR-2 for the five proxy datasets in testing phase using hold-out and 10-fold cross-validations. In Tables 6 and 7, the best and the worst values of the measures are highlighted in bold font and underline font, respectively. In hold-out validation shown in Table 6, SVM, NB and C4.5 achieved the averages of CCR around 94.33%, 94.43% and 94.55%, while BPNN, ANFIS, and NNPCR-2 achieved the averages of CCR around 87.39%, 93.93% and 86.37% respectively. In 10-fold cross-validation shown in Table 7, SVM, NB and C4.5 achieved the averages of CCR around 94.53%, 94.59% and 94.79% respectively, while BPNN and ANFIS, and NNPCR-2 achieved the averages of CCR around 87.79%, 93.72% and 85.53% respectively. As can be seen from Tables 6 and 7, SVM, NB, C4.5 and ANFIS produced competitive performances in terms of CCR. However, it is obvious that SVM, NB and C4.5 achieved higher CCR when compared to the CCR of BPNN and NNPCR-2. This was due to the fact that BPNN training could be trapped in a local minimum, while there is a global optimum solution in SVM training.

In terms of GM, Tables 6 and 7 clearly show that SVM, NB, C4.5 performed well for the five proxy datasets. In particular, the SVM achieved the best TPR and GM for all datasets. On the other hand, NNPCR-2 and BPNN achieved the worst TPR and GM for all datasets. This is because that BPNN and NNPCR-2 tended to classify most of the patterns as the majority class, i.e, the negative class. This led to the highest TNR of BPNN and NNPCR-2. On the other hand, SVM was trained with a penalty (weight) option, which was useful in dealing with imbalanced data. A higher weight was set to a positive class, while less weight was set to a negative class. Thus, SVM could predict the positive or minority class, which includes the objects that will be re-visited in the near future. Moreover, NB and C4.5 were less

susceptible to imbalanced data when compared to BPNN and ANFIS, as can be observed from Tables 6 and 7. This indicated that SVM, NB and C4.5 had better GM and TPR when compared to others.

Table 6: Performance measures of machine learning algorithms in hold-out validation

		BO2	NY	UC	SV	SD	Average
	CCR	95.30	91.19	95.54	93.76	95.84	94.326
	TPR	**86.41**	**91.95**	**92.76**	**91.16**	**89.17**	**90.29**
SVM	TNR	<u>96.16</u>	<u>90.95</u>	<u>95.93</u>	<u>94.36</u>	<u>96.83</u>	<u>94.846</u>
	GM	**91.15**	**91.45**	**94.33**	**92.97**	**92.92**	**92.564**
	CCR	95.34	**91.35**	95.74	93.78	**95.93**	94.428
	TPR	82.14	88.22	86.9	82.39	88.94	85.718
NB	TNR	96.61	92.34	96.95	96.95	96.98	95.966
	GM	89.08	90.26	91.79	89.38	92.87	90.676
	CCR	**95.68**	91.26	**95.88**	**94.02**	95.91	**94.55**
	TPR	68.54	89.36	78.27	87.87	83.81	81.57
C4.5	TNR	98.30	91.86	98.29	95.74	97.72	96.382
	GM	82.08	90.60	87.71	91.72	90.50	88.522
	CCR	94.08	<u>75.90</u>	90.36	87.95	88.65	87.388
	TPR	32.62	0.00	20.07	45.69	12.77	22.23
BPNN	TNR	**100.00**	**100.00**	99.99	99.73	99.98	**99.94**
	GM	57.12	<u>0.00</u>	44.79	67.50	35.73	41.028
	CCR	95.30	91.23	94.75	92.94	95.43	93.93
	TPR	61.55	84.94	62.46	76.53	74.77	72.05
ANFIS	TNR	98.56	93.22	99.17	97.52	98.52	97.398
	GM	77.89	88.98	78.71	86.39	85.83	83.56
	CCR	<u>91.41</u>	76.25	<u>90.05</u>	<u>87.11</u>	<u>87.01</u>	<u>86.366</u>
	TPR	<u>7.77</u>	2.49	<u>17.44</u>	<u>40.92</u>	0	<u>13.724</u>
NNPCR-2	TNR	99.48	99.67	**100**	**99.99**	100	99.828
	GM	<u>27.8</u>	15.74	<u>41.76</u>	<u>63.97</u>	<u>0</u>	<u>29.854</u>

Table 7: Performance measures of machine learning algorithms in 10-fold cross validation

		BO2	NY	UC	SV	SD	Average
SVM	CCR	95.5	91.7	95.58	93.88	95.97	94.526
	TPR	**87.61**	**92.57**	**92.62**	**92.02**	**89.28**	**90.82**
	TNR	96.27	91.43	95.98	94.39	96.95	95.004
	GM	**91.82**	**92**	**94.29**	**93.2**	**93.04**	**92.87**
NB	CCR	95.57	91.79	95.71	93.86	96	94.586
	TPR	83.46	88.48	87.73	82.72	88.83	86.244
	TNR	96.76	92.84	96.79	96.89	97.06	96.068
	GM	89.84	90.63	92.15	89.52	92.85	90.998
C4.5	CCR	**95.6**	**92.19**	**96.03**	**94.08**	**96.03**	**94.786**
	TPR	67.09	83.5	80.7	86.7	84.23	80.444
	TNR	98.38	94.95	98.1	96.09	97.77	97.058
	GM	81.2	89.03	88.97	91.27	90.75	88.244
BPNN	CCR	92.21	80.41	90.15	88.06	88.11	87.788
	TPR	12.64	21.19	18.23	45.73	7.91	21.14
	TNR	**99.97**	99.25	99.84	99.54	99.92	99.704
	GM	26.31	45.5	35.61	64.32	22.47	38.842
ANFIS	CCR	94.67	91.11	95.13	92.38	95.32	93.722
	TPR	56.9	84.16	65.26	74.55	73.68	70.91
	TNR	98.37	93.32	99.16	97.22	98.51	97.316
	GM	74.81	88.62	80.44	85.13	85.19	82.838
NNPCR-2	CCR	91.28	76.42	89.34	83.32	87.29	85.53
	TPR	2.36	3.41	10.74	22.43	1.35	8.058
	TNR	99.95	**99.65**	**99.92**	**99.84**	**99.94**	**99.86**
	GM	6.87	16.82	27.97	46.44	6.33	20.886

In addition to above measures, the computational times for training SVM, NB, C4.5, BPNN, ANFIS and NNPCR-2 were calculated using the same computer (PC with processor Intel(R), Core(TM)2 Duo CPU E4500 @2.20GHz,ii, and 2 GB RAM) for the five datasets, as shown in Tables 8 and 9. As expected, NB and C4.5 were faster when compared to the other intelligent techniques used. This is mainly due to nature of the training algorithm of NB and C4.5. NB was the fastest among all algorithms, while SVM was slower than NB and C4.5 but faster than BPNN, NNPCR-2 and ANFIS for all datasets. ANFIS was the slowest among other algorithms since many antecedent (nonlinear) parameters and consequent (linear) parameters required to be optimized in ANFIS training.

Table 8: The computational time for training the supervised machine learning algorithms in hold-out validation

Dataset	Training Time(seconds)					
	SVM	NB	C4.5	BPNN	ANFIS	NNPCR-2
BO2	9.11	**0.12**	0.36	146.59	41436.63	69.50
NY	69.41	**0.35**	0.85	316.34	89057.09	153.62
UC	280.30	**1.59**	3.36	701.18	202033.64	342.61
SV	52.20	**0.33**	0.69	303.40	85753.53	153.30
SD	291.51	**1.32**	2.90	693.36	205294.87	345.068
Average	140.506	**0.742**	1.632	432.174	124715.2	212.8196

Table 9: The computational time for training supervised machine learning algorithms in 10-fold cross validation

Dataset	Training Time(seconds)					
	SVM	NB	C4.5	BPNN	ANFIS	NNPCR-2
BO2	14.55	**0.14**	0.26	188.26	65507.18	79.75
NY	126.92	**0.51**	1.29	385.85	120657.97	167.44
UC	500.15	**1.96**	4.32	865.07	284267.57	376.03
SV	100.02	**0.51**	1.05	375.62	115745.14	163.67
SD	436.76	**1.84**	4.55	851.26	281538.43	764.33
Average	235.68	**0.992**	2.294	533.212	173543.3	310.244

4.3   Evaluation of intelligent LRU approaches

4.3.1   Web proxy cache simulation

The simulator WebTraff [16] was modified to meet the proposed LRU caching approaches. WebTraff is a trace-driven simulator for evaluating different replacement policies such as LRU, LFU, GDS, FIFO, and RAND policies. The trained classifiers were integrated with WebTraff to simulate the proposed intelligent LRU Web proxy cache replacement approaches. The WebTraff simulator receives the prepared log proxy file as input and generates files containing performance measures as outputs. In addition, the maximum cache size should be determined in the simulator. The simulator starts automatically with a cache size of 1 MB, and scales it up by a factor of two for each run until the maximum desired cache size is reached. The output reported by the simulator shows cache size (in MB), hit ratio, and byte hit ratio for each cache size simulated.

4.3.2 Performance Measures

The hit ratio (HR) and byte hit ratio (BHR) are the most widely used metrics in evaluating the performance of Web caching [8-10, 14]. HR is defined as the percentage of requests that can be satisfied by the cache. Note that HR only indicates how many requests hit and does not indicate how much bandwidth can be saved. BHR is the number of bytes satisfied from the cache as a fraction of the total bytes requested by the user. BHR represents the saved network bandwidth achieved by caching approach.

It is important to note that HR and BHR work in somewhat opposite ways. It is very difficult for one strategy to achieve the best performance for both metrics [4, 8, 50-51]. This is due to the fact that the strategies that increase HR typically give preference to small objects, but these strategies tend to decrease BHR by giving less consideration to larger objects. On the contrary, the strategies that do not give preference to small objects tend to increase BHR at the expense of HR.

4.3.3 Performance measures of infinite cache

An infinite cache is a cache with enough space to store all requested objects without the need to replace any object. The infinite cache size is defined as the total size of all unique requests. Therefore, it is unnecessary to consider any replacement policy for an infinite cache. In an infinite cache, HR and BHR reach their maximum values.

In reality, the caches cannot be designed as infinite. A replacement policy is needed when the cache is full, and this has a great effect on the performance of Web caching systems. However, in our simulation the infinite cache is required to determine the maximum cache size in the simulator, which represents the stop point during the simulation. Table 10 shows some statistical information for the maximum HR and BHR for the five proxy datasets used in the simulation.

Table 10: Statistics for different proxy datasets used in simulation

	BO2	NY	UC	SV	SD
#Total requests	1210693	3248452	8891764	2496001	29871204
#Cacheable requests	594989	1518232	2827904	1194098	6059349
#Cacheable bytes	23204930341	68402036319	469362584083	48043794224	230326816876
#Unique requests	530192	1144885	2402406	1012355	5284441
Total size of unique requests (bytes)	18690093450	56147903761	156538171752	38364029432	190539902251
#Hits	64797	373347	425498	181743	774908
#Byte Hits	4514836891	12254132558	312824412331	9679764792	39786914625
Max HR(%)	10.89	24.59	15.05	15.22	12.79
Max BHR(%)	19.46	17.91	66.65	20.15	17.27

4.3.4   Impact of cache size on performance measures

By using the WebTraff simulator, the proposed SVM-LRU, NB-LRU and C4.5-LRU approaches were compared with the conventional LRU algorithm across the five proxy datasets: BO2, NY, UC, SV, and SD. For each dataset, the Web proxy caching algorithms were simulated with varying limits of the cache size starting at 1 MB to 32 GB in order to determine the impact of cache size on the performance measures. The simulation was stopped at 32 GB since the performances of all algorithms became stable and close to the maximum level achieved for a cache of infinite size.

Figs. 9 and 10 show the HR and BHR of different policies for the five proxy datasets with varying cache sizes. As can be seen in Figs. 9 and 10, when the cache size increased, the HR and BHR also provided a boost for all algorithms. However, the percentage of increase was reduced when the cache size increased. When the cache size was close to the size of the infinite cache, the performance became stable and close to its maximum level. On the contrary, when the cache size was small, the replacement of objects was frequently required. Hence, the effect of the performance of replacement policy was clearly noted.

As can be observed from Figs. 9 and 10, SVM-LRU, NB-LRU and C4.5-LRU produced better performances in terms of HR and BHR when compared to the conventional LRU, especially with small sizes of cache. This was mainly due to the capability of intelligent LRU approaches for storing the preferred objects for longer time. Depending on classification decisions, the preferred objects were placed at the top of cache stack, so these objects took longer time to move down to the bottom of the cache stack where they would be removed from the cache. On the other hand, the unwanted objects were removed from the proxy cache at earlier stage. This eventually reduced the cache pollution. Consequently, the performance in terms of HR and BHR of LRU was improved by using SVM-LRU, NB-LRU and C4.5-LRU.

For comparison of intelligent LRU approaches with each other, SVM-LRU, NB-LRU and C4.5-LRU achieved competitive HR in the different cache sizes across the five proxy datasets, as can be seen from Fig. 9. This was due to the equivalent capability of intelligent classifiers to predict the classes of objects, whether objects would be re-visited or not. In general, C4.5-LRU and SVM-LRU achieved slightly higher HR when compared to NB-LRU. In terms of BHR, Fig. 10 shows that SVM-LRU and NB-LRU achieved better BHR when compared to C4.5-LRU in different proxy cache sizes for most the proxy datasets.

It is important to note that the performance of SVM, NB and C4.5 classifiers were equivalent in their ability to predict the classes of objects at training phase. However, the proposed intelligent LRU approaches did not necessarily perform the same performances at the simulation phase. This was due influence of the size factor of the objects classified by the classifiers into the cache replacement decisions and the cache performance, especially the performance in terms of BHR.

Furthermore, the performance in terms of HR and BHR could be influenced by changing the sizes of the proxy cache between 1 MB and 32 GB.

In order to clarify the benefits of the intelligent LRU approaches, the improvement ratio (*IR*) of the performance in terms of HR and BHR in each particular cache size can be calculated using Eq. (22).

$$IR = \frac{(PM - CM)}{CM} \times 100 \; (\%)$$ (22)

where *IR* is the percent of improvement in terms of HR or BHR achieved by the proposed method (*PM*) over the conventional method (*CM*). *CM* refers the performance in terms of HR or BHR of the conventional LRU. *PM* represents the performance in terms of HR or BHR of the proposed intelligent LRU: SVM-LRU, NB-LRU and C4.5-LRU.

The average *IRs* of the performances in terms of HR and BHR of the intelligent LRU approaches for the five proxy datasets in each particular cache are concluded and summarized in Table 11. In Table 11 , the highest and the lowest values of the average *IRs* are highlighted in bold and underline fonts, respectively.

Table 11: The average IRs (%) achieved by intelligent LRU approaches over conventional LRU method

Cache Size (MB)	Average IR of SVM-LRU Over LRU (%)		Average IR of NB-LRU Over LRU (%)		Average IR of C4.5-LRU Over LRU (%)	
	HR	BHR	HR	BHR	HR	BHR
1	30.15	20.84	32.596	**22.966**	31.046	20.84
2	23.26	27.05	23.326	**57.776**	24.14	28.408
4	13.988	29.846	11.722	**69.564**	15.43	28.118
8	12.318	24.208	12.078	**33.312**	14.648	25.946
16	9.692	17.58	10.05	**21.468**	11.452	20.216
32	8.294	14.44	8.408	14.604	9.852	**15.832**
64	10.408	**32.434**	11.244	23.454	11.904	22.802
128	5.08	**15.054**	4.736	10.318	6.568	10.336
256	4.974	**7.596**	4.174	6.188	6.222	6.938
512	5.804	**5.316**	5.206	5.066	6.878	5.276
1024	5.65	2.874	5.142	2.898	6.588	**2.932**
2048	4.422	0.794	3.846	0.794	5.224	**1.07**
4096	2.87	0.81	2.426	**1.104**	3.376	0.81
8192	1.422	0.266	1.186	0.25	1.698	0.284
16384	0.718	0.204	0.548	0.2	0.872	0.206
32768	0.38	**0.124**	0.324	0.112	0.464	0.124

The results in Table 11 show that the average IRs of HR achieved by SVM-LRU, NB-LRU and C4.5-LRU over LRU increased by 30.15%, 32.60% and 31.05%, respectively. In terms of the BHR, the average IRs achieved by SVM-LRU, NB-LRU and C4.5-LRU over LRU increased by 32.43%, 69.56% and 28.41%, respectively. From Figs. 9 and 10, and Table 11, it can be concluded that the proposed SVM-LRU, NB-LRU and C4.5-LRU significantly improved the performance of the conventional LRU method across the five proxy datasets. Furthermore, C4.5-LRU and SVM-LRU achieved slightly higher HR compared to HR of NB-LRU, while NB-LRU and SVM-LRU achieved better BHR compared to BHR of C4.5-LRU for most of the proxy datasets. This means SVM-LRU performed well in both HR and BHR.
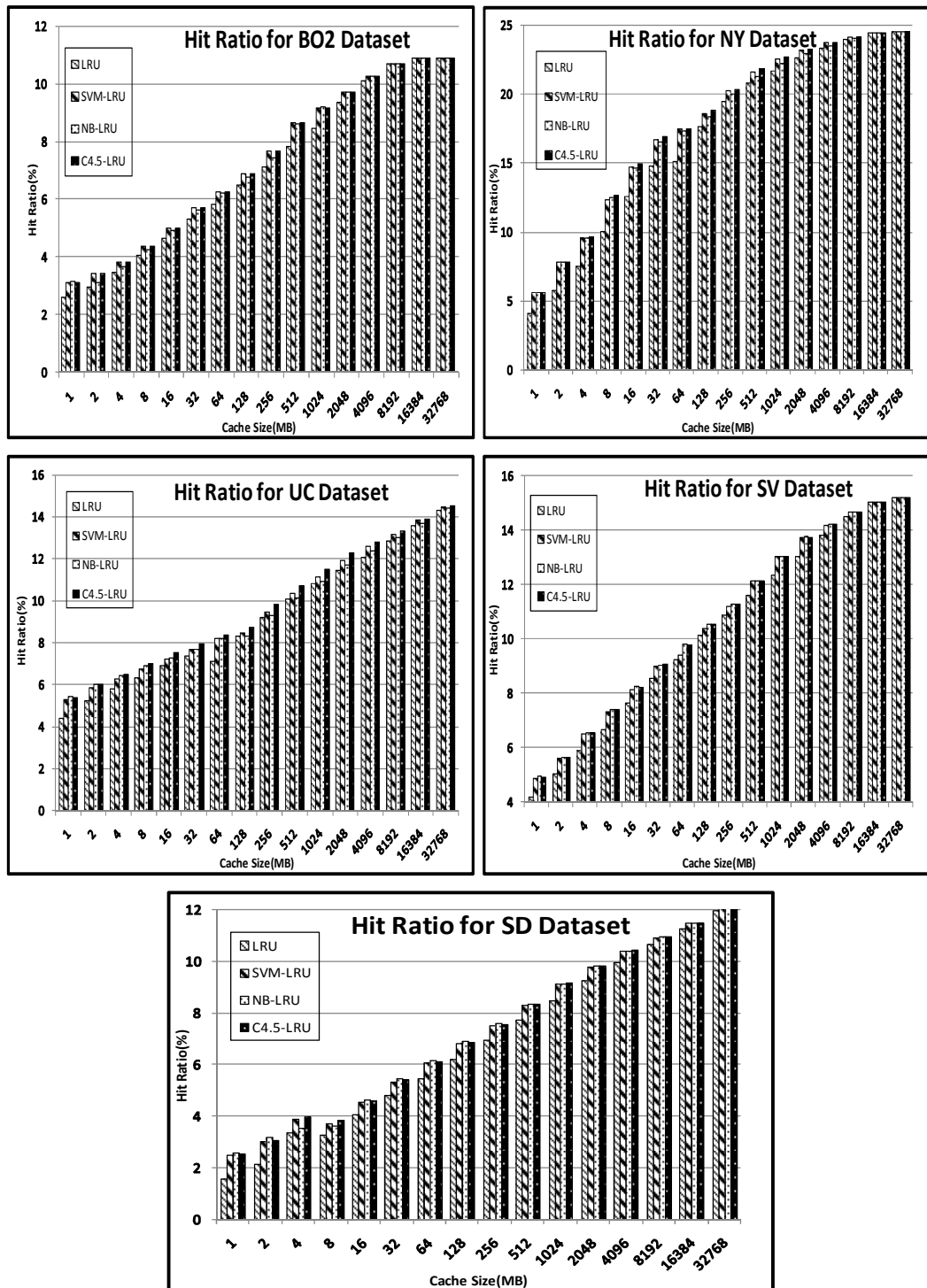
Fig. 9: Comparison of hit ratio between intelligent LRU approaches and LRU
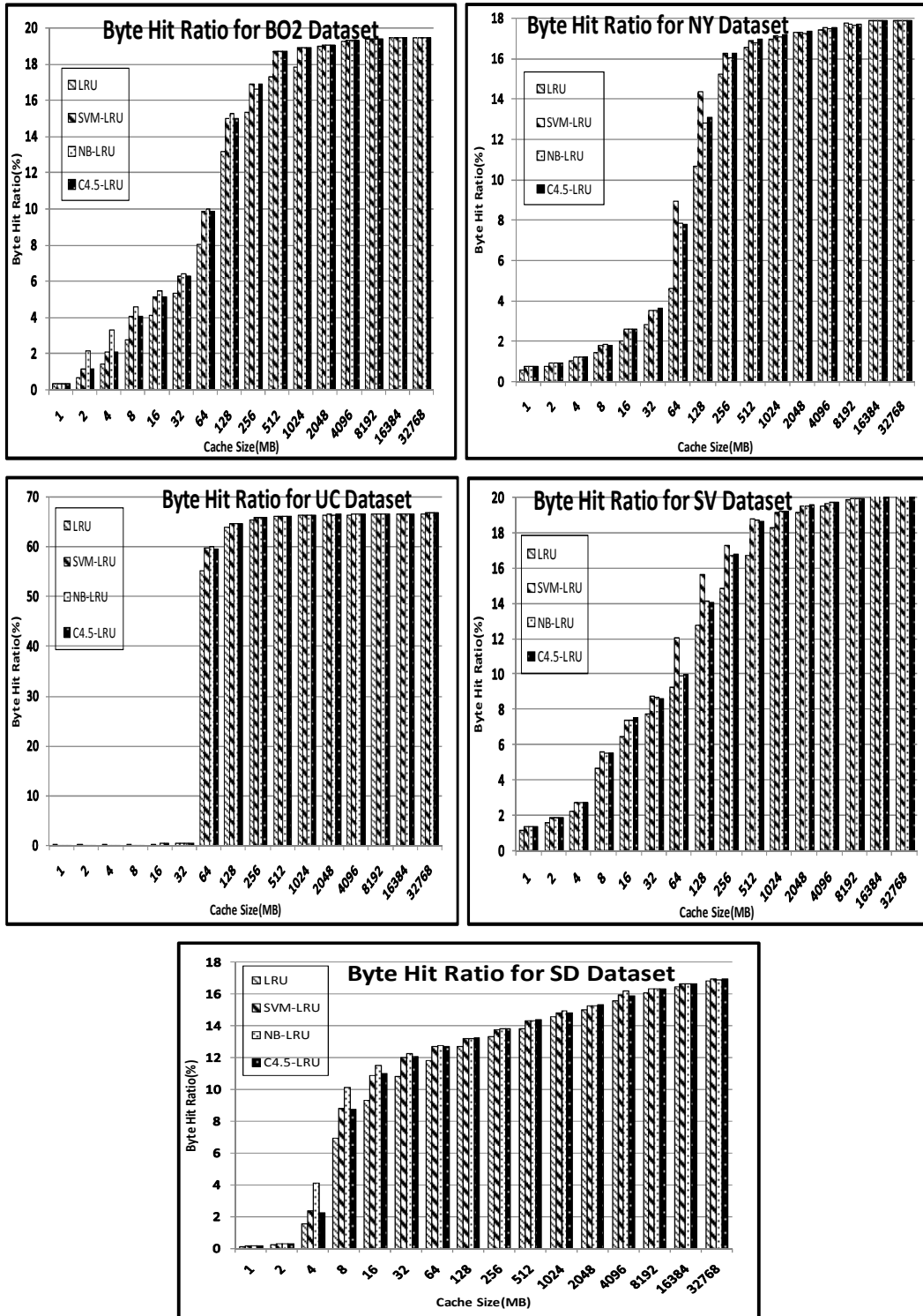
Fig. 10: Comparison of byte hit ratio between intelligent LRU approaches and LRU

5   Conclusion and Future Works

In order to improve the performance of Web proxy caching, this paper presented a framework for improving the conventional LRU replacement policy based on supervised machine learning classifiers. The framework consisted of two functional components: online and offline components. In the offline component, SVM, NB and C4.5 were intelligently trained from proxy logs files to classify the contents of Web proxy cache. In the online component, the trained SVM, NB and C4.5 classifiers were effectively utilized to improve the performance of the conventional LRU policy, which widely used in Web proxy cache replacement. In particular, the conventional LRU technique was extended by efficiently integrating the classification decisions made by the trained SVM, NB and C4.5 classifiers into cache replacement decisions to obtain more efficient and intelligent SVM-LRU, NB-LRU and C4.5-LRU approaches. For testing and evaluating the proposed proxy caching methods, the proxy logs files were obtained from several proxy servers located around the United States of the IRCache network, which are the most common proxy datasets used in the research of Web proxy caching. The experimental results showed that SVM, NB and C4.5 achieved a better accuracy and a much faster than BPNN and ANFIS. Furthermore, the proposed intelligent LRU approaches were evaluated by trace-driven simulation and compared with the conventional LRU policy. The simulation results revealed that the proposed intelligent LRU approaches considerably improved the performance in terms of hit ratio and byte hit ratio of the conventional LRU on a range of datasets.

There are some limitations in this study. One of the limitations is that the classifiers in the proposed intelligent LRU approaches were trained once and then were used to predict the classes of Web object over the next one or two weeks. A regular retraining of classifiers would ensure that the proposed intelligent LRU approaches become more efficient and adaptive. Another limitation is the preparation of the target outputs in training phase that required extra computational overhead when looking for the future requests. Therefore, unsupervised machine learning algorithms can be used for enhancing the performance of Web caching policies since the unsupervised algorithms do not need any preparation for the target outputs. Furthermore, other intelligent classifiers can be also utilized to improve both the hit ratio and the byte hit ratio of traditional Web caching policies.

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