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A New Prediction Model Based on Web Access Behavior

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Abstract

In order to predict network users' access behavior accurately, this paper proposes a new prediction model based on Web access behavior. To improve prediction performance and reduce the state-space complexity, the model uses hybrid-order Markov chain structure and stores the sequences which share the same prefix. The problems that lower-order models have poor prediction performance and higher-order models result in high state-space complexity are solved in this paper. Simulation results have shown that the prediction model based on Web access behavior can improve the precision and recall to some extent.

Keywords*: Markov chain, prediction model, Web access behavior, state-space complexity, prediction performance.*

1. Introduction

The development of computer technology and communication technology, as well as the continuous growing of the demands for people connecting to the Internet, prompt the Internet to develop rapidly. In China, for example, the number of people using Internet is 668 million, and Internet penetration rate is 48.8 percent and 18.94 million people become new Internet users in half a year up to June 2015, said the thirty-sixth "statistics report of China Internet development"[1]released by CNNIC. Moreover, up to November 15, 2015, the number of people using Internet all of world is 3345832772 and Internet penetration rate is 46.4 percent according to the latest statistics [2]. It is obvious that the number of computers connecting to Internet and people using Internet presents a faster growth trend. From a user's perspective, the current Internet has become an information ocean in which we can develop and use data resources. The Internet prompts the transmission of network information extremely. People pay more attention to developing and making full use of information resources and these requirements play an immeasurable role in promoting the development of science, culture, economy and society.

With the massive increase in the number of Internet users, more and more users access the Internet resulting in the heavy internet traffic and the Web's popularity has significantly increased user-perceived latency. The obvious solution—to increase the bandwidth—is not viable, because we cannot easily change the Web infrastructure (the Internet) without significant economic cost. However, if we could predict future user requests, we could put those pages into the client-side cache when the browser is free. When a user requests one of the pages, the browser could retrieve it directly from cache. Thus, user-perceived latency can be reduced. It makes use of the combination of caching and prefetching. Caching and prefetching techniques both reduce the user-perceived latency through predicting users' access behavior. But the cache mechanism only uses the time locality of WWW access

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pattern, it can't cache the documents which are not accessed before, so the quality of response can't be improved much yet. As a complement way, Web prefetching is the most effective method to break the upper bound of caching performance. And prefetching is one kind of the active caches that can cache the pages which are still not requested by the user, which is an expansion from the time locality to the space locality.

Markov model is a statistical model proposed by Andrei A. Markov. Markov models are widely used to model sequential processes, and have achieved many practical successes in areas such as web log mining, computational biology, speech recognition, natural language processing, robotics, and fault diagnosis. In Web domain, Markov models are used to predict users' access behavior. In general, they use the sequence of Web pages a user has accessed as input, with the goal of building Markov models with which they can predict the page the user will most possibly access next.

Presently Markov models have a lot of variations. The PPM (Prediction by Partial Match) prediction models[3-14] based on tree-like structure belong to multiple high-order Markov models; the DG(Dependency Graph) models [15-20]based on graph-like structure belong to 1-order Markov models. In many applications, first-order Markov models are not very accurate in predicting the user's browsing behaviors, since these models do not look far into the past to correctly discriminate the different observed patterns. As a result, higher-order models are often used. Unfortunately, these higher-order models have a number of limitations associated with high space complexity, reduced coverage, and sometimes even the worse prediction precision. Higher-order model states are different combinations of the actions observed in the data set, so the number of states tends to rise exponentially as the model order increases. This dramatic increase can significantly limit the applicability of Markov models for applications in which fast predictions are critical for real-time performance or for applications with tight memory constraints. Furthermore, many examples in the test set might not have corresponding states in higher-order Markov models, thus reduce their coverage.

A new hybrid-order Markov prediction model (NPM) is proposed in the paper. NPM stores the sequences which share the same prefix so as to reduce the state-space complexity. And its performance is assessed from many aspects.

2. NPM Model

Definition 1.Sequence Prefix: Given sequences Sequ1=< $a_1\ a_2\ \cdots\ a_n$ >, Sequ2=<$b_1\ b_2\ \cdots\ b_m$>, ($m<n$), the sequence Sequ2 is the prefix of the sequence Sequ1; iff $i<m$, $b_i = a_i$, all items of $b_m \subseteq a_m$and ($a_m - b_m$) rank after the item bm. The sequence Sequ2 can also be called prefixal sequence.

The first step of the model is to turn the event sequence into the tree-like model to store in order to the following mining. First of all, scan and access the sequence database, then construct the head table. The following is the algorithm of constructing the tree-like model.

Input: historical access sequence database DB
Output: k-order Tree
MSS_Generate(DB)
{ for each sequence s do
current=root
for each event e of sequence s do
if URL of current node's child nodes=URL of event e then

count of this child node++
current=this child node
else
current=Generate_New_Node (current event e)
endif
endfor
endfor
}Return Tree

In general, given the three sequences of three users: x1, x2; y1, y2, y3, y4, y5; z1, z2, z3, they are stored with PPM model and tree-like model respectively as shown in figure 1.

As figure 1 shows, they only need the space expenses of 11 nodes when they are stored with tree-like model; however, they need the space expenses of 56 nodes when they are stored with PPM model. Assuming the sessions which are formed with n different nodes, they only need the space expenses of (n+1) nodes when they are stored with tree-like model and the space complexity is O(n); however, they need the space expenses of $(0.5n^2+0.5n+1)$ nodes when they are stored with PPM model and the space complexity is $O(n^2)$ as shown as figure 2. For the sequences which have the same prefix, PPM models far exceed tree-like models on space complexity. The tree-like models have reduced the space complexity of the model greatly and saved the space expenses.

Definition 2 The header table is a hash table. Each item stores the name and the pointer of the header node of header-table queue.

Definition 3 The header table queue consists of a queue and another queue links all nodes of the same event.

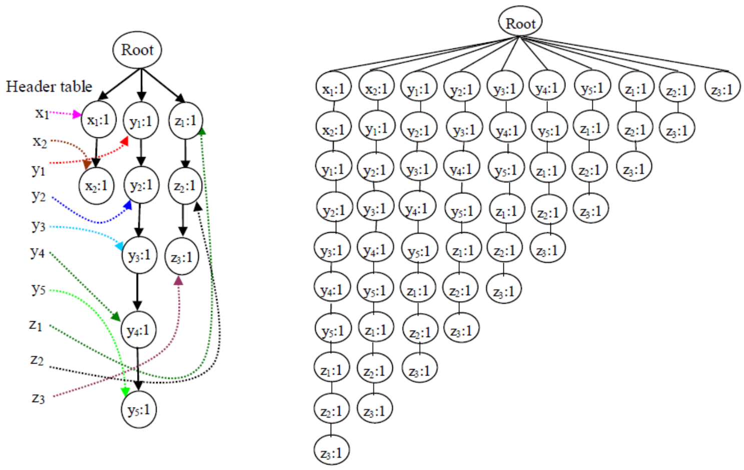


Figure 1. The Tree-like Structure and PPM Tree

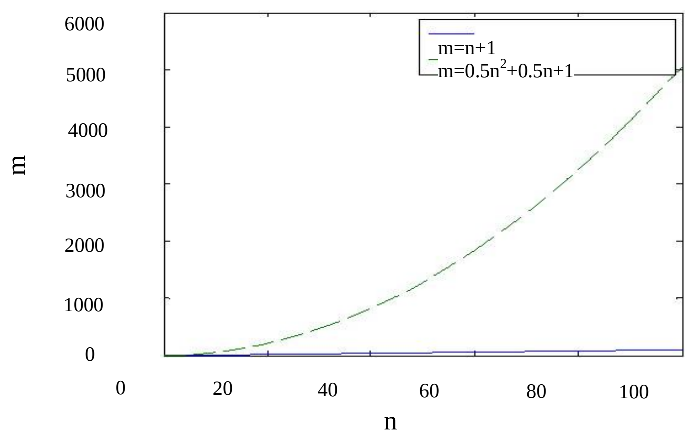


Figure 2. The Number of Note

Definition 4 Given a tree-like model G= (V, E), V is the aggregate of nodes and E is the aggregate of borders thereinto. Node contains the event name, counts and two quotations. The quotation of Next Header Queue Item points to the next node of header-table queue of the event; the quotation of Next Session Item points to next item of event sequence. The branch from the root node to the leaf node along with the quotation Next Session Item is a session.

After building the tree-like model, prediction algorithm is used to predict the result of hybrid-order model. The following is the prediction algorithm.

Input：The n-order tree-like structure Tree; a set of the last k requests, Requ[i], $0 \le i \le k \le n$; and the confidence threshold for each order, confth [j], $0 \le j \le n$

```
Output: prediction object ObjSetj
Method:
for(j=1;j<=maxOrder;j++){
for every header in Tree.HeaderTable{
for every node en in the header-queue{
Queue qu =Tree.JUnion(en,j-1);
if (qu.count>0)
AddToLink(en,qu.Dequeue(),Sqlist Lj);
Insert (child of qu.Dequeue(),Lj);}
}
  }
current_context[j]←node of depth j, representing the access sequence{Requ[k-j+1],…,Requ[k]};
ObjSetj←NULL;
for (length j=k;j>=1;j--){
  for every child_node chd of Current_context[j]
    if(occurrence_count of chd)/(occurrent_count of parent)>=conf th [j]
          ObjSetj←ObjSetj+chd;}
Return ObjSetj;
```

3. Simulations and Results Analysis

The NPM offers three methods for combining models: the accuracy voting method, selecting top value method and the top order method. To test performance, we compare the prediction results of our NPM with the results of HTMM [21].

NPM improves the accuracy voting method of HTMM. From Formula 1 to formula 3has shown how the prefetching value can be got from each order model. Firstly, choose the prediction page with the maximum prefetching value of j-order model as the prediction result, then get the prediction set PS={ P1, P2, …, PmaxOrder }, maxOrder∈N. Finally, compute the recommendation value of each page in PS using formula 3, where *Rec_j(PageX)* is j-order recommendation value of *PageX* in the current session.

Different from HTMM, the weight of each order isn't static and is computed using formula 2. The weight varies with the order. Order accuracy determines prediction weight. The precision of j-order model is computed using formula 1, where *rec(row)* is the prediction value and *row* is the row mark. The process of computing the precision of each order is dynamic. All the above operations are processed off-line.

Forluma 1: prediction accuracy.

$$Accuracy(j) = \frac{\sum_{row} rec^2(row)}{the number of row} \tag{1}$$

Forluma 2: prediction weight.

$$Weight(j) = \frac{Accuracy(j)}{\sum_k Accuracy(j)} \tag{2}$$

Forluma 3: recommendation value.

$$R(PageX) = \sum_{j=1}^{|PS|} rec_j(PageX) * Weight(j) \tag{3}$$

We have tested the precision, recall, prediction time and PRS of the two models. We coded all algorithms in Microsoft Visual C# and performed experiments on Pentium PC with 256 Mbytes RAM, 2.40GHZ CPU and Winxp operation system. We examined 1000000 records of Berkeley Trace and 98 World Cup trace respectively. After cleaning the original data, the URL of every requested page is coded according to the frequency, then forms the sessions.

3.1 Performance Parameters

We have evaluate the model in terms of precision, recall and PRS. Precision and recall which were proposed by Cleverdon in 1968[22] and have been used so far are the most commonly used metrics in the field of information retrieval field. Precision and recall were used for recommendation system by Billsus and Pazzani[23] in 1998 at the earliest , then are widely used in the field of recommendation gradually[24-33].

Definition 5: precision.

$$precision = P^+ / (P^+ + P^-) \tag{4}$$

where P^+ is the number of rightly predicted pages and P^- is the number of wrongly predicted pages.

Definition 6: recall.

$$recall = R^+ / |R| \tag{5}$$

where R^+ is the number of requests which is predicted by the model and $|R|$ is the number of all requests.

Precision and recall is often used as the valid metrics of Web prefetching. With the increase of prefetching data, it brings the high recall and low precision. It is necessary to use the metric PRS to weight the validity of prefetching synthetically.

Definition 7: PRS.

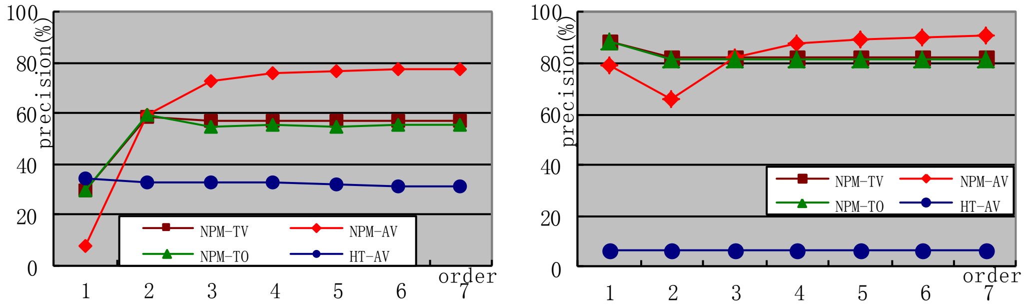
$$PRS = \frac{1}{\frac{1}{recall} + \frac{1}{precision}} = \frac{precision * recall}{precision + recall} \tag{6}$$

3.2 Results and Analysis

Table 1. English Name-English ab. Comparison table

English Name	Ab. English
top value method of NPM	NPM-TV
accuracy voting method of NPM	NPM-AV
top order method of NPM	NPM-TO
accuracy voting method of HTMM	HT-AV

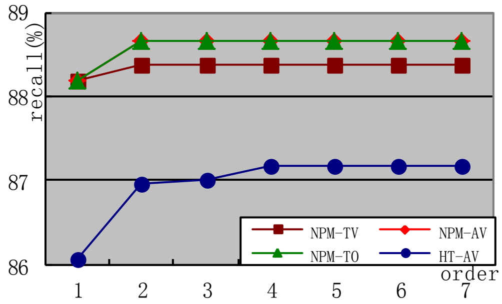
Figure 3 shows the relationship between precision and order. As figure 3 shows, of the three NPM combination methods, accuracy voting is more accurate as the order rises, the other two methods have similar precision regardless of order. From the second order, the three NPM combination methods are more accurate than HTMM combination method, while the HTMM combination method remains unchangeable nearly as the order increases. To all the combination methods, the precision remains unchangeable when the order reaches a certain value.



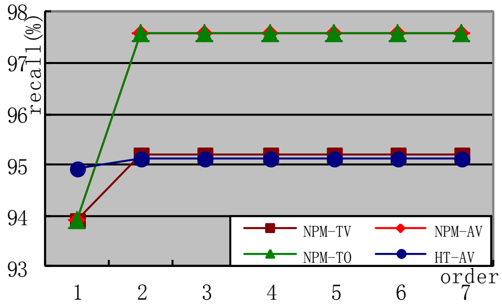
(a) Berkeley trace (b) 98 WC trace

Figure 3. Precision Comparison Curves

Figure 4 shows the relationship between recall and order. The performance of the three NPM combinations improves appreciably than that of the HTMM combination. Of the three NPM combination methods, accuracy voting and top order are better than top value, while the difference between accuracy voting and top order is very small as order increases. To all the combination methods, the recall remains unchangeable when the order reaches a certain value.



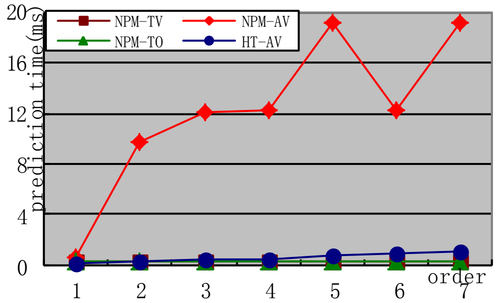
(a) Berkeley trace



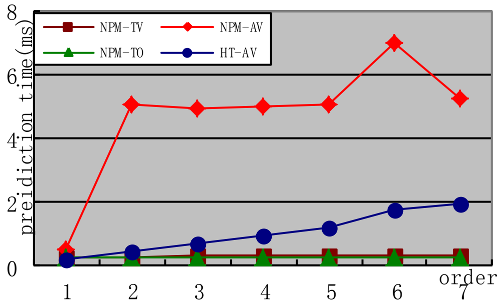
(b) 98 WC trace

Figure 4. Recall Comparison Curves

Figure 5 shows the relationship between the prediction time and order. As figure 5 shows, the variable set of the accuracy voting method of NPM is larger, while other three combinations change gently. Of the three NPM combination methods, top value and top order have similar prediction time, and, as the order rises, the time increases linearly and is shorter than the time for the HTMM combination method. We can see the prediction time for the accuracy voting method of NPM is the longest in all orders for all combination methods.



(a) Berkeley trace



(b) 98 WC trace

Figure 5. Prediction Time Comparison Curves

Figure 6 shows the relationship between PRS and order. PRS weights the validity of prefetching synthetically. As figure 6 shows, of the three NPM combination methods, accuracy voting is higher as the order rises, and the other two methods have similar PRS regardless of order. From the second order, the performance of the three NPM combination methods all improves compared with HTMM combination method, while the HTMM combination method remains unchangeable nearly as the order increases. To all the combination methods, PRS remains unchangeable when the order reaches a certain value.

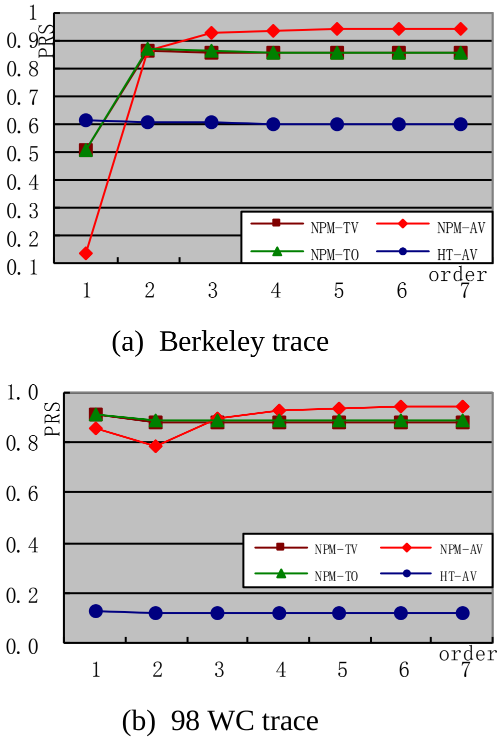


Figure 6. PRS Comparison Curves

4. Summary

Predicting users' access behavior precisely plays an important role in website design, E-commerce and personalized recommendation and so on. A new hybrid-order Markov prefetching model(NPM) is proposed in the paper. NPM stores the sequences which share the same prefix so as to reduce the space complexity. The NPM model integrated with diversified recommendation methods improves the quality of predicting users' access behavior, and enhances the quality of Intelligent Service such as Web prefetching and so on effectively and reduces the user-perceived latency.

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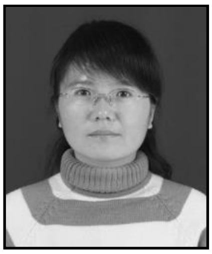

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