On Asymptotically Optimal Methods of Prediction and Adaptive Coding for Markov Sources with Unknown Memory

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Abstract - The asymptotically optimal methods of prediction for Markov sources with unknown memory are suggested. The methods are based on modified twice universal scheme.

I. Introduction

The problem of prediction and the closely related problem of adaptive coding of time series is well known in Information Theory, Probability Theory and Statistics [1].

We consider a source with unknown statistics which generates sequences $x_1x_2...$ of letters from a finite alphabet $A = \{a_1, \ldots, a_n\}$. We imagine that we have at our disposal a computer for solving the prediction problem. As input we consider any finite string $x_1x_2...x_t$ of letters from A and as output we receive at each time instant t non-negative numbers $p^*(a_1|x_1...x_t),...,p^*(a_n|x_1...x_t)$ which are estimates of the unknown conditional probabilities $p(a_1|x_1...x_t),...,p(a_n|x_1...x_t)$, i.e., of the probabilities $p(x_{t+1} = a_i|x_1...x_t); i = 1,...,n.$ The set $p^*(a_i|x_1...x_t);$ $i \leq n$ is called the prediction.

The precision of a prediction method is measured by the divergence between p and p^* and the complexity of a method is characterized by two numbers: the average time of calculation at each time instant in bit operations and the memory size in bits of the program defining the method. Let us denote the set of Markov sources of memory (or connectivity) k as $M_k(A)$ and let $M_0(A)$ be the set of all Bernoulli sources.

In this report we consider the prediction problem for Markov sources with unknown statistics and memory.

II. THE MAIN RESULTS

We will use two asymptotically optimal prediction methods for $M_i(A)$, i = 0, 1, ..., which were suggested in [2]. The method α_i is asymptotically optimal in average and β_i with probability one.

According to twice universal scheme, at each time instant t a computer compares the average precision of all methods $\beta_0, \beta_1, \dots, \beta_N$ on the interval $t = 1, 2, \dots, T-1$ and finds j_0 for which β_{j_0} gives the best precision on the interval t= $1, 2, \ldots, T-1$. Then the computer uses β_{j_0} in order to predict for the next moment T. (It looks like the likelihood principle).

It is clear that the computer should calculate (N+1) prediction sets (for $\beta_0, \beta_1, \dots, \beta_N$) instead of one set as it does in case of known memory of the source. So the time of calculation increases (N+1) times. Similarly, the memory space of the computer should be divided into (N+1) parts in order to store statistics for $\beta_0, \beta_1, \ldots, \beta_N$.

The new methods are based on a simplified twice universal scheme (STUS). According to STUS, a computer which is used for the implementation of the suggested method compares two methods β_{i_1} and β_{i_2} at each time instant t. First, at t = 1, 2, ..., T the computer compares β_0 and β_1 which are optimal for $M_0(A)$ and $M_1(A)$ (T is a parameter of the method). Then the computer removes the worst method and includes β_2 instead of it. After that both methods are compared during the period of $[T+1,\ldots,2T]$, the worst of them is removed and so on. At each time instant t the computer uses the best method $\beta_{i,j}$ for prediction. (At the first interval [1, ..., T] β_0 is used). At the moment (N+1)T+1 the computer again includes β_0 instead of removed β_{i_1} . And so on. It is quite obvious that the computer will find the best β_i and will use it almost all time for prediction if T is quite large. On the other hand, this universal scheme is fast and space-efficient because at every moment only two methods are compared instead of N in the "conventional" twice universal scheme. We designate this method as β_{stu}^1 and describe two other modifications.

The β_{stu}^1 is effective with probability 1. We obtain the method β_{stu}^2 which is simpler if the computer stops to look for the best method β^1_{stu} after the moment (N+1)T and uses for prediction at the moments (N+1)T+1, (N+1)T2, ... the $\beta_{i,j}$ which was the best during $[NT+1,\ldots,(N+1)T]$. The new method β_{stu}^2 is effective in average only. (For simplification of the method it is possible to use optimal in average α_{i_i} instead of $\beta_{i,j}$). The last modification β_{stu}^3 may be used when N is infinite or when it is known only that a source is ergodic. The method β_{stu}^3 looks like β_{stu}^2 but the computer includes randomly chosen method β_i from the $\beta_0, \beta_1, ...$ (Recall, that β_i is included instead of the worst method β_{i_j} at the moments T+1, 2T+1, 3T+1, ...).

The main property of the suggested STUS may be formulated as follows: if β_{stu}^1 is used with $T(r) = \left\lceil \left(\log \frac{1}{r}\right)^2\right\rceil$, where r is the precision, then for every $M_i(A)$ its precision is asymptotically equal to the precision of the method which is optimal for $M_i(A)$, when r goes to 0.

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¹This work was supported by RFBR Grant 99-01-00586.