First Hidden Markov Model in Forecasting-Application

Dr. K. A. Srinath[1], Dr. R. Veerabathiran[2]

[1]*Professor, Department of Mathematics, Sun College of Engineering and Technology,Kanyakumari District, India*

[2]*Asst. Professor, R. D. Govt. Arts College, Sivagangai, India*

[1]kasrinath19@gmail.com

***Abstract*– Hidden Markov Model is a powerful tool in estimating the most probable Hidden state based on the observing signals emitted by the states of a Markov Chain. In this study, the details of the estimation method along with the possible real life situations in which it can be applied are detailed along with the solution for a hypothetical example.**

***Keywords*– Gesture Recognition, Signals, Evaluation problem, Decoding Problem, Learning Problem**

I Introduction

When we have states wherein the behavior at anytime't', Just depend on the Just previous only i.e. t-1, we use Markov Chains. On the other hand in nature, we have instances wherein at a particular state the state emittate some symbols and the problem now is the identification of the most probable state with the help of the emitted symbols. This is done by the Hidden Markov Models (HMMs). HMMs have found greatest use in problems like speech recognition or gesture recognition. HMMs have a number of parameters, whose values are set so as to test, explain patterns for the known category. A test pattern is classified by the model that has the highest potencies probability i.e. that best "explains" the test pattern.

II First–Order Markov Models

We consider a sequence of states at successive times, the state at any time t is denoted by w(t). A particular sequence of length T is denoted by $w^T=\{w(1),w(2),\ldots w(T)\}$ as for instance $w^6=\{w_1,w_2.w_1,w_3,w_2,w_3)$. Note that the system can revisit a state at different steps, and not every state need be visited.

The above model is described by the transmission probabilities $P\{W_j(t+1)/W_i(t)\}=a_{ij}$- the time –independent probability of having state w_j at step t+1 given that the state at time t was w_i. ($a_{iy} \neq a_{yi}$, in general) ($a_{ii}\neq 0$, in general). This can be displayed in diagram as in Fig. 1

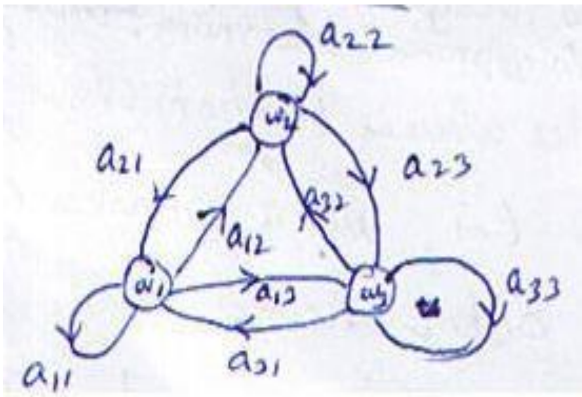

Fig. 1

At any step t the full system is in a particular state w(t). The state at step (t+1) is a random function depends solely on the state at t and the transition probabilities. The above is a first order discrete time markov model. Now we may end up with process which emitt some visible signals only. Now we have the problem of estimating the most probable signal which is the cause of being in that state. For example during the rainy seasons we have: humidity (pressure), wind, and lightning (thunder) and cloud segregation. These symbols cannot be directly measured. But this has the answer thorugh the HMMs.

III First–Order Hidden Markov Models

Let the system at time 't' be in state w(t) and it emits some visible symbol i.e. v(t). For convenience let us suppose that the symbol emitted are discrete.

As in the case of the states, We assume a particular sequence of visible states as $v^T=\{v(1), v(2), \ldots v(T)\}$. Use might have $v^4=\{v_1, v_2, v_1,v_3\}$

Now the model for any state w(t) and emitting signal $v_k(t)$ $P\{v_k(t)/\omega_j(t)\}= b_{jk}$ since we have access to only visible states, if ω(t) are un observable, then the model is called a HMM Fig. 2

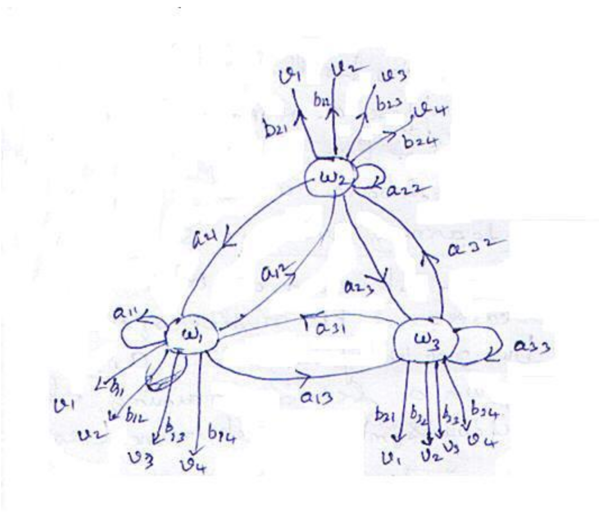

Fig. 2

IV HMM-COMPUTATION

We have $a_{ij}= P(W_j(t+1) / W_i(t))$ ………………(1)

$b_{jk}= P(v_k(t)/w_j(t))$

We suppose that some transition occur from step $t \rightarrow t+1$, and that some visible symbol be emitted after every step, then

$\sum a_{ij} = 1$ for all i and j ………………………(2)

$\sum b_{jk}=1$ for all j

Here the limits for summations are over all hidden states and all visible symbols, respectively.

There are three central issues

(a) The Evaluation Problem:

Suppose we have an HMM, complete with transition probabilities aij and bjk. Find the probability that a particular sequence of visible states V^T was generated by that model.

(b) The Decoding Problem:

Suppose a HMM and the observations v^T. Determine the most likely sequence of hidden states ω^T that lead to those observations.

(c) The learning Problem:

Suppose we are given the coarse structure of a model (the number of states and the number of visible states) but not the probabilities a_{ij} and b_{jk}. Given a set of training observations of visible symbols, determine the parameters.

The decoding problem is the most important for practical life such as

(i) In the case of diseases coming to individuals only symptoms alone will be known. Now if the working algorithm is fixed the physician can use this in determining most probable actual state (disease) which is responsible for these symptoms.

(ii) An automobile Engine in a four wheeler or a pump set used for pumping water may send different types of symptoms in the working before it stops at the end. Here also this problem could find the most probable drawback in the Engine.

Many similar examples can be indicated in day to day life.

A. Algorithm for Evaluating the Decoding Problem:

Given a sequence of visible states v^T. the decoding problem is to find the most probable sequence of hidden states. While we might consider enumerating every possible path and calculating the probability of the visible sequence observed, this is an $O(C^T\ T)$ Calculation and prohibitive. We use a new function to reduce the burden of calculation.

$$\text{Let } \alpha_i(t) = \begin{cases} 0, & t=0 \text{ and } i \neq \text{initial state} \\ 1, & t=0 \text{ and } i=\text{initial state} \\ \sum_j \alpha(t-1)\,.a_{ij}\, b_{jk}\ v(t) & \text{otherwise} \end{cases} \quad \text{-------------------(3)}$$

Algorithm (HMM decodig)

begin initialize Path = { }, t=0

for t $\leftarrow$ t+1

k=0, $\alpha_0 = 0$

for k $\leftarrow$ k+1

$\alpha_k(t) \leftarrow b_{jk}\ \underline{v}(t) \sum_{i=1}^{c} \alpha_i(t-1)a_{ij}$

until k=c

$j' \leftarrow \arg\max \alpha_j(t)$

Append To Path $w_{j'}$

until t=T

return Path

end

We can also use the corresponding logarithms of probabilities and add ; this reduces the complexity to $O(C^2\ T)$

V ILLUSTRATION

We shall assume a hypothetical example the on rainfall. Here there are 4 possible states. w_1,w_2,w_3,w_4

w_1 --- No rainfall

w_2 --- Low rainfall

w_3 --- Medium rainfall

w_4 --- High rainfall

The transition Probability matrix for one station

$$\{a_{ij}\} = \begin{pmatrix} 0.2 & 0.3 & 0.2 & 0.3 \\ 0.2 & 0.3 & 0.1 & 0.4 \\ 0.2 & 0.5 & 0.2 & 0.1 \\ 0.8 & 0.1 & 0.0 & 0.1 \end{pmatrix} \text{ and}$$

$$\{b_{ik}\} = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 0.3 & 0.4 & 0.2 \\ 0.2 & 0.1 & 0.6 & 0.1 \\ 0.1 & 0.5 & 0.2 & 0.1 \end{pmatrix}$$

By solving this solution got from the algorithm is that the most probable states are w_3 next is w_2, w_4 no probability for w_1.

CONCLUSION

In this we have shown the applicability of the probability models in excavating the hidden behavior of the human systems.

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