## 实验2. 隐马尔科夫模型实践

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#### 综述

本次实验是一步一步实现隐马尔科夫模型(Hidden Markov Model, HMM),并应用到金融时序数据分析与预测方面。一般而言,对于一个HMM模型 $\lambda$ =[A,B, $\pi$ ],能根据观察序列推断出隐状态序列,简单的方法计算所有可能的状态序列时间复杂度太高,一种更有效率的利用动态规划的思想是Viterbi算法,Viterbi算法定义一个 $\delta_t(i)$ ,指在时间t时,HMM沿着某一条路径到达 $S_i$ ,并输出序列为 $W_1W_2...W_t$ 的最大概率。如果HMM的参数未知,则需要通过数据进行学习与训练,对于有监督学习,使用最大似然估计可求出所需参数,对于无监督学习使用Baum—Welch\_algorithm进行求解。

$$\delta_t(i) = \max P(Pos_1 \cdots Pos_{t-1}, Pos_t = s_i, w_1 \cdots w_t)$$
(1)

初始化:  $\delta_1(i) = maxP(Pos_1 = s_i, w_1) = \pi_i b_i(w_1), 1 \le i \le N$ 

迭代:  $\delta_{t+1}(j) = maxP(Pos_1 \cdots Pos_t, Pos_{t+1} = s_j, w_1 w_2 \cdots w_{t+1})$   $1 \le j \le N, 1 \le t \le T-1$ 

迭代结束:  $max_i[\delta_T(i)]$ 

回溯记录最优路径

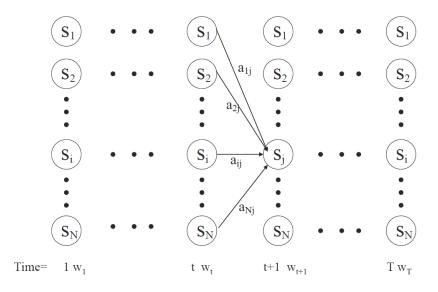


图 1: HMM

#### 实验一.维特比算法

```
本实验实现维特比算法。
输入: a,b,o,pi
输出: path
function VITERBI(O,S,II,Y,A,B):X
       for each state i \in \{1, 2, \dots, K\} do
              T_1[i,1] = \pi_i \cdot B_{iy_1}
               T_2[i,1] = 0
       end for
       for each observation i=2,3,\cdots,T do
               for each state j \in \{1, 2, \dots, K\} do
                      \begin{split} T_1[j,i] \leftarrow \max_{k} \left( T_1[k,i-1] \cdot A_{kj} \cdot B_{jy_i} \right) \\ T_2[j,i] \leftarrow \arg\max_{k} \left( T_1[k,i-1] \cdot A_{kj} \cdot B_{jy_i} \right) \end{split}
              end for
       end for
       z_T \leftarrow \arg\max_k \left( T_1[k, T] \right)
       x_T \leftarrow s_{z_T}
       for i \leftarrow T, T-1, ..., 2 do
              z_{i-1} \leftarrow T_2[z_i, i]
               x_{i-1} \leftarrow s_{z_{i-1}}
       end for
       return X
end function
```

### 实验二.Forward Algorithm

本实验实现 Forward Algorithm

输入: a,b,o,π

输出:  $\alpha$ 

Let  $\alpha_i(t) = P(Y_1 = y_1, ..., Y_t = y_t, X_t = i | \theta)$ , the probability of seeing the  $y_1, y_2, ..., y_t$  and being in state at state i time t. This is found recursively:

$$1.\alpha_i(1) = \pi_i b_i(y_1),$$

$$2.\alpha_i(t+1) = b_i(y_{t+1}) \sum_{j=1}^{N} \alpha_j(t) a_{ji}.$$

## 实验三.Backward Algorithm

本实验实现 Backward Algorithm

Let  $\beta_i(t) = P(Y_{t+1} = y_{t+1}, ..., Y_T = y_T | X_t = i, \theta)$  that is the probability of the ending partial sequence  $y_{t+1}, ..., y_T$  given starting state i at time t. We calculate  $\beta_i(t)$  as,

$$1.\beta_i(T) = 1,$$
  

$$2.\beta_i(t) = \sum_{j=1}^{N} \beta_j(t+1)a_{ij}b_j(y_{t+1}).$$

# 运行结果.

F:\tools\anaconda\python.exe F:/codes/py\_space/ml\_project/HMM/HMM\_test.py 0.6470588235294118

Process finished with exit code 0

图 2: HMM