## Hw11

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#### 1 Find the loglikelihood function

We have  $x_1, x_2, \dots, x_{100}$  data. The likelihood function is

$$L = \delta P(x_1) \Gamma P(x_2) \cdots \Gamma P(x_{100}) I \tag{1.1}$$

Here  $\delta = [0, 1, 0], I = [1, 1, 1]^T$ 

$$\Gamma = \left[ \begin{array}{ccc} 1/2 & 1/2 & 0 \\ 1/3 & 1/3 & 1/3 \\ 0 & 1/2 & 1/2 \end{array} \right]$$

$$P(x) = \begin{bmatrix} p_1(x) & 0 & 0 \\ 0 & p_2(x) & 0 \\ 0 & 0 & p_3(x) \end{bmatrix}$$

$$p_1(x) = \frac{1}{\sqrt{2*\pi}*0.5}e^{-\frac{(x-1)^2}{2*(0.5)^2}}, p_2(x) = \frac{1}{\sqrt{2*\pi}}e^{-\frac{(x-6)^2}{2}}, p_3(x) = \frac{1}{\sqrt{2*\pi}*0.5}e^{-\frac{(x-3)^2}{2*(0.5)^2}}.$$
 Then the

$$loglikelihood = log(L) = -172.66 \tag{1.2}$$

- > da=read.table("~/Downloads/time series analysis/data\_for\_HW11.txt",sep=',',header=F)
- > xt=da\$V2
- > gamma=matrix(c(1/2,1/2,0,1/3,1/3,1/3,0,1/2,1/2),nrow=3,byrow=T)
- > delta=t(c(0,1,0))
- > p=matrix(0,nrow=3,ncol=3)
- > mu=c(1,6,3)
- > sigma=c(0.5,1,0.5)
- > one=rep(1,3)
- > l=matrix(0,nrow=1,ncol=3)
- > alp=matrix(0,nrow=1,ncol=3)
- > beta=matrix(0,nrow=3,ncol=1)
- > bet=matrix(0,nrow=3,ncol=3)
- > state=matrix(0,nrow=1,ncol=3)
- > for (i in c(1:100))
- + {
- + for(j in c(1:3))
- + {p[j,j]=dnorm(xt[i],mean=mu[j],sd=sigma[j])}
- + if(i==1){l=delta%\*%p}
- + else{1=1%\*%gamma%\*%p}
- + if(i==50){alpha=1}

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+ if(i>50){ if(i==51){bet=gamma%*%p}else{bet=bet%*%gamma%*%p} }
+
+ }
> L=log(1%*%one)[1,1]
> L

[1] -172.6599
```

# **2** Find the forward probability $\alpha_{50}(j)$ for j = 1, 2, 3

We know the formula for  $\alpha$  is simple.

$$\alpha_1 = \delta P(x_1), \alpha_t = \alpha_{t-1} * \Gamma * P \tag{2.1}$$

So we can get the result  $\alpha_{50} = [2.5e - 68, 1.87e - 37, 5.68e - 50]$ 

> alpha

[1,] 2.542636e-68 1.187351e-37 5.683856e-50

# 3 Find the backward probability $\beta_{50}(j)$ for j = 1, 2, 3

The definition for  $\beta$  is

$$\beta_t(j) := pr(X_{t+1:T} = x_{t+1:T} | C_t = j) \tag{3.1}$$

And we have a formula for it

$$\beta_t = \prod_{s=t+1}^{T} (\Gamma * P(x_s)) * I \tag{3.2}$$

Then we get the result.  $\beta = [4.17e - 41, 8.71e - 39, 1.31e - 38]^T$ 

- > beta=bet%\*%one
- > beta

- [1,] 4.166726e-41
- [2,] 8.713305e-39
- [3,] 1.306969e-38

# 4 Predict the state of the Markov chain at time T+h,for h=5

The definition of state is

$$Pr(C_{T+h=i}|X_{1:T} = x_{1:T}) = \frac{pr(C_{T+h=i}, X_{1:T} = x_{1:T})}{pr(X_{1:T} = x_{1:T})}$$
(4.1)

The state formula is

$$C_t = \frac{\delta P(x_1) \Gamma P(x_2) \cdots \Gamma P(x_{100}) \Gamma^h}{\delta P(x_1) \Gamma P(x_2) \cdots \Gamma P(x_{100}) I}$$

$$(4.2)$$

So the result is  $C_t = [0.286, 0.428, 0.286]$ 

- > d=1%\*%one
- > state=1%\*%gamma%\*%gamma%\*%gamma%\*%gamma/(d[1,1])
- > state

[1,] 0.2857486 0.428498 0.2857534

## 5 Predict the emission distribution at time T+h,for h=5

$$pr(X_{T+h} = x | X_{1:T} = x_{1:T}) = \frac{\delta P(x_1) \Gamma P(x_2) \cdots \Gamma P(x_{100}) \Gamma^h * P(x)I}{\delta P(x_1) \Gamma P(x_2) \cdots \Gamma P(x_{100})I}$$
(5.1)

So the distribution function is

$$f(x) = 0.286 * p_1(x) + 0.428 * p_2(x) + 0.286 * p_3(x)$$

$$(5.2)$$

$$= \frac{0.286}{\sqrt{2*\pi}*0.5}e^{-\frac{(x-1)^2}{2*(0.5)^2}} + \frac{0.428}{\sqrt{2*\pi}}e^{-\frac{(x-6)^2}{2}} + \frac{0.286}{\sqrt{2*\pi}*0.5}e^{-\frac{(x-3)^2}{2*(0.5)^2}}$$
(5.3)

Here is the graph

```
> tt=seq(-5,15,0.1)
```

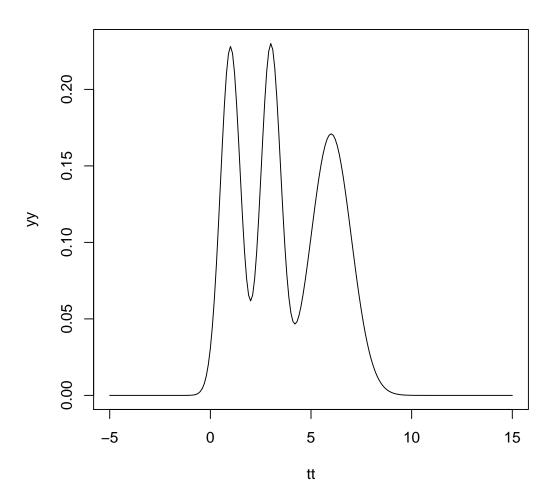


Figure 1: distribution function

<sup>&</sup>gt; yy=rep(0,201)

<sup>&</sup>gt; yy = state[1]\*dnorm(tt,mean=mu[1],sd=sigma[1]) + state[2]\*dnorm(tt,mean=mu[2],sd=sigma[2]) + state[3]\*dnorm(tt,mean=mu[1],sd=sigma[1]) + state[2]\*dnorm(tt,mean=mu[2],sd=sigma[2]) + state[3]\*dnorm(tt,mean=mu[2],sd=sigma[2]) + state[3]\*dnor

<sup>&</sup>gt; plot(tt,yy,type="1")