

PBG 200A Notes

Sam Fleischer

September 26, 2016

1 Model Selection

Consider a time series y_1, y_2, \dots, y_T of log densities. Recall process error vs. observational error.

1.1 Process Error

$$x_{t+1} = g(x_t, a) + \underbrace{E_{t+1}^p}_{\text{process error}} \quad (1)$$

$$y_t = x_t \quad (\text{no observational error}) \quad (2)$$

We assume the random variables E_{t+1}^p are IID (independent, identically distributed) Normal with mean 0 and variance σ^2 .

We run the model and ask..

- What value of a (parameter or vector of parameters) is most likely to generate the observed data y_t ?
 - For example, for a given a , and given y_1 , what is the likelihood, what is the probability that the model produce y_2 ?
 - This is the same as asking: what is the likelihood a normal with mean 0 and variance σ^2 yields a $y_2 - g(y_1, a)$?
 - The answer is

$$p(y_2 - g(y_1, a)) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left[-\frac{(y_2 - g(y_1, a))^2}{2\sigma^2}\right] \quad (3)$$

and we'd like to maximize this value with respect to a (optimization problem..)

Now we ask:

- What is the likelihood that the random variables $E_{t+1}^p = y_{t+1} - g(y_t, a)$ for $1 \leq t \leq T-1$?
- By independence, the likelihood a produces the data, denoted $L(a)$, is

$$L(a) = \prod_{t=1}^{T-1} \left[\frac{1}{\sqrt{2\pi}\sigma} \exp\left[-\frac{(y_{t+1} - g(y_t, a))^2}{2\sigma^2}\right] \right] \quad (4)$$

$$\implies \log L(a) = \sum_{t=1}^{T-1} \left[\log \frac{1}{\sqrt{2\pi}\sigma} - \frac{(y_{t+1} - g(y_t, a))^2}{2\sigma^2} \right] \quad (5)$$

So maximizing $\log L(a)$ is the same as minimizing the sum

$$\sum_{t=1}^{T-1} (y_{t+1} - g(y_t, a))^2 \quad (6)$$

1.1.1 Chickadee Data

We define the model $g(x, a)$ by the following:

$$N_{t+1} = N_t \exp[a_1 + a_2 N_t], \quad \text{with} \quad x = \log N \quad (7)$$

$$\implies x_{t+1} = x_t + a_1 + a_2 e^{x_t} =: g(x_t, [a_1, a_2]) \quad (8)$$

Off to RStudio... a negative value of a_2 corresponds to some negative density dependence.