

## CO902

### Supporting Lecture Notes:

### Bernouli, Time-invariant, 1st Order Markov Chain

#### Lecture 2 — 14 Jan 2012

Let  $X_1, X_2, \dots, X_N$  be dependent Bernoulli random variables, such that

$$P(X_i | X_{i-1}, X_{i-2}, \dots, X_1) = P(X_i | X_{i-1}). \quad (1)$$

This is the 1st order Markov property, also known as a “memoryless” property, and we say  $(X_1, X_2, \dots, X_N)$  is a “Markov Chain”. If we further assume that

$$\begin{aligned} P(X_i = 1 | X_{i-1} = 0) &= p_{01} \\ P(X_i = 1 | X_{i-1} = 1) &= p_{11} \end{aligned}$$

for all  $i = 2, 3, \dots, N$ , then the Markov Chain is time-invariant, with  $p_{01}$  being the probability of a success following a failure and  $p_{11}$  being the probability of a success following a success. Specifying the initial success probability

$$P(X_1 = 1) = p_0$$

completes the specification of the process.

The (1st order) Markov property allows the joint likelihood to factor into a concise form:

$$\begin{aligned} P(X_1, X_2, \dots, X_N) &= P(X_N | X_1, X_2, \dots, X_{N-1}) \times \\ &\quad P(X_{N-1} | X_1, X_2, \dots, X_{N-2}) \times \\ &\quad \vdots \\ &\quad P(X_2 | X_1) \times \\ &\quad P(X_1) \\ &= P(X_N | X_{N-1}) \times \\ &\quad P(X_{N-1} | X_{N-2}) \times \\ &\quad \vdots \\ &\quad P(X_2 | X_1) \times \\ &\quad P(X_1) \\ &= P(X_1) \prod_{i=1}^N P(X_i | X_{i-1}) \end{aligned}$$

At the risk of incurring confusion, please realize that the above notation with “big”  $X$  is just shorthand for

$$P(X_1 = x_1, X_2 = x_2, \dots, X_N = x_N) = P(X_1 = x_1) \prod_{i=1}^N P(X_i = x_i | X_{i-1} = x_{i-1}),$$

that is, this expression is the joint probability mass function that tells you the probability (mass) associated with one particular set of realized values  $(x_1, x_2, \dots, x_N)$ .

The log-likelihood can be written

$$\begin{aligned} \mathcal{L}(p_0, p_{01}, p_{11}) = & x_1 \log(p_0) + (1 - x_1) \log(1 - p_0) + \\ & \sum_{i: 2 \leq i \leq N, x_{i-1}=0} (x_i \log(p_{01}) + (1 - x_i) \log(1 - p_{01})) + \\ & \sum_{i: 2 \leq i \leq N, x_{i-1}=1} (x_i \log(p_{11}) + (1 - x_i) \log(1 - p_{11})) \end{aligned}$$

There are three components, one for the initial condition, one for the successes preceded by failure, and one for successes preceded by successes. (Note I have switched to lower case  $x$ , as is often done, reflecting how the likelihood is a function of the parameters *for* a particular value of the observed data.)

Taking derivatives with respect to the parameters, setting to zero and solving gives the Maximum Likelihood Estimators (MLE's). I leave the algebra to your memory of the chalkboard (make sure you can do it!). The MLE's are

$$\begin{aligned} \hat{p}_0 &= x_1 \\ \hat{p}_{01} &= n_{01}/n_0 \\ \hat{p}_{11} &= n_{11}/n_1 \end{aligned}$$

where

$$\begin{aligned} n_0 &= \sum_{i: 2 \leq i \leq N, x_{i-1}=0} 1 && \# \text{ failures } 1, \dots, N - 1 \\ n_1 &= \sum_{i: 2 \leq i \leq N, x_{i-1}=1} 1 && \# \text{ successes } 1, \dots, N - 1 \\ n_{01} &= \sum_{i: 2 \leq i \leq N, x_{i-1}=0} x_i && \# \text{ successes following failures} \\ n_{11} &= \sum_{i: 2 \leq i \leq N, x_{i-1}=1} x_i && \# \text{ successes following successes} \end{aligned}$$

These results will be handy for the lab exercise.