

Stat 771 Spring 09, UW Madison, MW.

①

Notes on Nelder-Mead algorithm for maximizing a log likelihood $l(\theta)$, with parameter $\theta \in \mathbb{R}^p$

The algorithm produces a sequence of sets $S_1, S_2, \dots, S_m, \dots$ with any $S = \{\theta_1, \dots, \theta_{p+1}\}$, $p+1$ points in \mathbb{R}^p

Assume that we start with S not a hyperplane.

Update until stopping condition:

1. θ_j 's sufficiently close within S
 2. $l(\theta_j)$'s " " " " " "
 3. reach maximum number of iterations
- } or

Updates proceed by trying to improve the $l(\theta)$ value of points in current $S_m = S$

Reflect step

First identify three points in S

$\theta_A =$ value with smallest $l(\theta)$

$\theta_B =$ " " best (largest) $l(\theta)$

$\theta_{A+1} =$ " " 2nd smallest $l(\theta)$

and form $\theta_0 = \frac{1}{p} \sum_{\theta_j \neq \theta_A} \theta_j$ [mean of non-worst]

Construct

$$Q_r = (1+\alpha)Q_0 - \alpha Q_d$$

for some $\alpha > 0$

$$Q_0 = \frac{1}{P} \sum_{Q_j \neq Q_d} Q_j$$

Expansion Step:

$$\text{If } l(Q_r) \geq l(Q_0)$$

[~~expansion~~ reflection improves things]

expand further to

$$Q_e = Q_0 + \gamma(Q_r - Q_0)$$

for some $\gamma > 1$

$$\text{if } l(Q_e) > l(Q_r)$$

Return

$$S_{m+1} = \{S_m \setminus Q_d\} + \{Q_e\}$$

[i.e. drop Q_d and include Q_e]

$$\text{if } l(Q_e) \leq l(Q_r)$$

Return

$$S_{m+1} = \{S_m \setminus Q_d\} + \{Q_r\}$$

i.e., if reflection improves things, try further improvement and take the better of Q_r , Q_e .

Intermediate Case

[reflection not too bad]

(3)

if

$$l(a_{n+1}) \leq l(a_r) < l(a_b)$$

then set

$$S_{n+1} = \{S_n \setminus a_b\} + \{a_r\}$$

Contraction Cases

1. External $l(a_b) \leq l(a_r) < l(a_{n+1})$

form

$$a_c = a_0 + \beta(a_r - a_0) \quad \left. \begin{array}{l} \leftarrow a_r - a_0 \\ \text{for some } \beta \in (0,1) \end{array} \right\}$$

if $l(a_c) > l(a_b)$

$$S_{n+1} = \{S_n \setminus a_b\} + \{a_c\}$$

else "shrink" [see below]

2. Internal

$$l(a_r) < l(a_b) \quad \left[\text{reflected point very bad} \right]$$

form

$$a_{cc} = a_0 + \beta(a_b - a_0)$$

if $l(\theta_{cc}) > l(\theta_a)$

$$S_{m+1} = \{S_m | \theta_a\} + \{\theta_{cc}\}.$$

else "shrink"

Shrink step. if no luck above, and directed here,

$$S_{m+1} = \{ \theta_b, \forall j=b, \theta_b + \delta(\theta_j - \theta_b) \}$$

for some $\delta \in (0, 1)$

Note: in constrained parameter spaces, some adjustment is required to keep all points $\theta_a, \theta_b, \theta_c, \theta_{cc}$ in the parameter space

