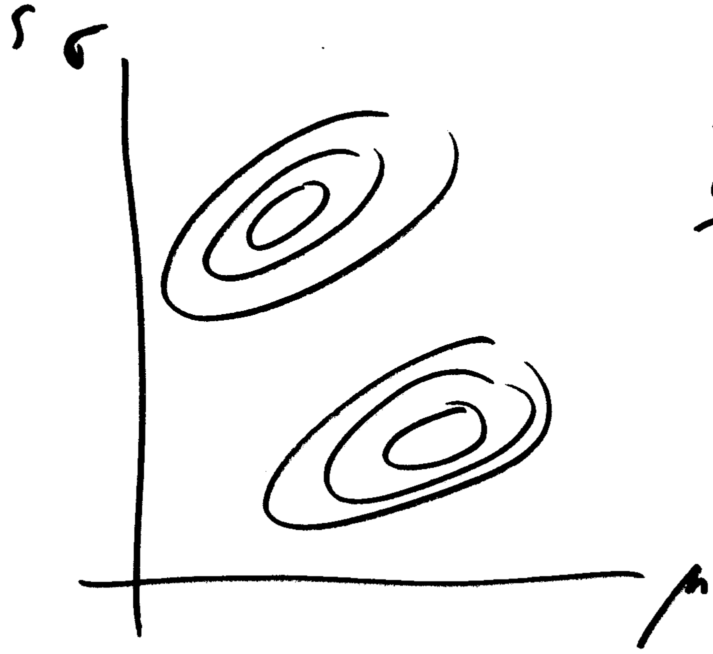


bimodal

ll function

$\underset{k\times 1}{\hat{\underset{\sim}{\theta}}}$ r.v.

constants: $\underset{k\times 1}{\underset{\sim}{a}}$, $\underset{1\times k}{\underset{\sim}{a}^T}$

$$\Big(\underset{k}{\hat{\Sigma}} \quad \underset{k}{\hat{\theta}}\Big)$$

$$\underset{1\times 1}{\hat{\gamma}} = \underset{1\times k}{\underset{\sim}{a}^T} \; \underset{k\times 1}{\hat{\underset{\sim}{\theta}}}$$

$$\underset{k\times 1}{\underset{\sim}{a}} = \begin{pmatrix} a_1 \\ a_2 \\ \vdots \\ a_k \end{pmatrix}$$

$k = 3$

$$\underset{k\times 1}{\hat{\theta}} = \begin{pmatrix} \hat\theta_1 \\ \hat\theta_2 \\ \vdots \\ \hat\theta_k \end{pmatrix}$$

$$\underset{3\times 1}{\hat{\theta}} = \begin{pmatrix} \hat\theta_1 \\ \hat\theta_2 \\ \hat\theta_3 \end{pmatrix} \qquad \underset{3\times 1}{\underset{\sim}{a}} = \begin{pmatrix} a_1 \\ a_2 \\ a_3 \end{pmatrix}$$

$$\underset{1\times 3}{\underset{\sim}{a}^T} \; \underset{3\times 1}{\hat{\underset{\sim}{\theta}}} = (a_1, a_2, a_3) \begin{pmatrix} \hat\theta_1 \\ \hat\theta_2 \\ \hat\theta_3 \end{pmatrix} = a_1 \hat\theta_1 + a_2 \hat\theta_2 + a_3 \hat\theta_3$$

$$\hat{\gamma} = \hat\theta_1 - \hat\theta_2 \qquad \underset{3\times 1}{\underset{\sim}{a}} = \begin{pmatrix} 1 \\ -1 \\ 0 \end{pmatrix} \; ✓$$

$$\hat{\gamma} = \underset{\sim}{a}^T \hat{\underset{\sim}{\theta}}$$

$$\hat{V}(\hat{\gamma}) = \hat{V}(\underset{\sim}{a}^T \underset{\sim}{\hat{\theta}}) = \underset{\sim}{a}^T \hat{\Sigma}\, \underset{\sim}{a} = ?$$

here $\underset{\sim}{a}^T \hat{\Sigma}\, \underset{\sim}{a} = (1, -1, 0) \begin{pmatrix} \frac{\hat{\theta}_1(1-\hat{\theta}_1)}{n} & & \\ & & \\ & & \end{pmatrix} \begin{pmatrix} 1 \\ -1 \\ 0 \end{pmatrix}$

$$\hat{V}(\hat{\gamma}) = \hat{V}(\hat{\theta}_1 - \hat{\theta}_2) = \hat{V}[\hat{\theta}_1 + (-\hat{\theta}_2)]$$

$$= \hat{V}(\hat{\theta}_1) + \hat{V}(-\hat{\theta}_2) + 2\,C(\hat{\theta}_1, -\hat{\theta}_2)$$

$$= \hat{V}(\hat{\theta}_1) + \hat{V}(\hat{\theta}_2) - 2\,C(\hat{\theta}_1, \hat{\theta}_2)$$

$\hat{V}(cX) = c^2 V(X)$

$C(X, X) = V(X)$

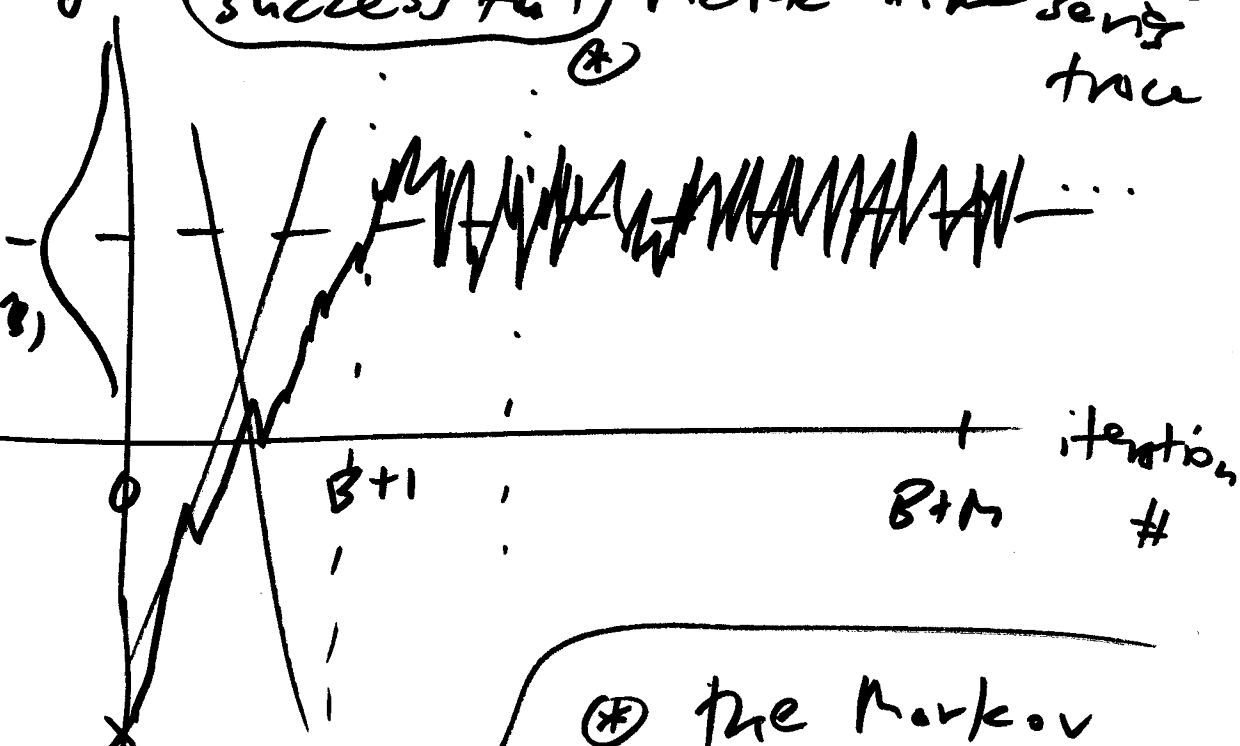
$$\hat{\Sigma} = \begin{array}{c|ccc} & \hat{\theta}_1 & \hat{\theta}_2 & \hat{\theta}_3 \\ \hline \hat{\theta}_1 & C(\hat{\theta}_1, \hat{\theta}_1) & \checkmark & \\ \hat{\theta}_2 & C(\hat{\theta}_1, \hat{\theta}_2) & C(\hat{\theta}_2, \hat{\theta}_2) & \\ \hat{\theta}_3 & & & \end{array}$$

$$\hat{\theta}_1 = \frac{n_1}{n} = \frac{659}{1265} = \vdots$$

$$\widehat{SE}(\hat{\gamma}) = \sqrt{\hat{V}(\hat{\gamma})}$$

THT3
1(J)

successful MCMC time series trace (*)



$p(\theta \mid \mathcal{D}\, \mathcal{B})$ [SM] [PM]

(*) the Markov chain we're sampling from has an equilibrium distribution

(*) it's $p(\theta \mid \mathcal{D}\,[SM]\,[PM]\,\mathcal{B})$

M_{IID}

IID MC draws: $\widehat{MCSE}(\bar{\theta}_j^*) = \frac{s_j}{\sqrt{M_{IID}}}$ MC estimate of posterior SD of θ_j

M_{mcmc} AR(1) MCMC draws: $\widehat{MCSE}(\bar{\theta}_j^*) = \frac{s_j}{\sqrt{M_{mcmc}}} \sqrt{\frac{1+\hat{\rho}_j}{1-\hat{\rho}_j}}$

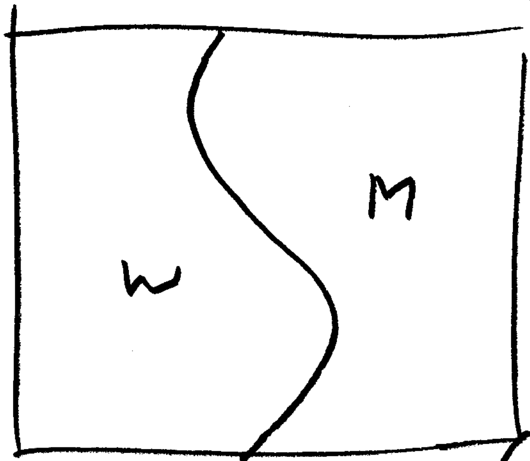
for equal accuracy

$$\frac{\cancel{S_j}}{\sqrt{M_{IID}}} = \frac{\cancel{S_j}}{\sqrt{\underline{\underline{M_{MCMC}}}}}\sqrt{\frac{1+\hat{\rho}_j}{1-\hat{\rho}_j}}$$

$$\frac{M_{MCMC}}{M_{IID}} = \left(\frac{1+\hat{\rho}_j}{1-\hat{\rho}_j}\right) = 249 \doteq 250$$

variance inflation factor (VIF)

max k?



they make use a bounded utility function

simple Loss

truth

poisonous → P

edible → E

what algorithm says	P	E
P	0	$l_1 = 1$
E	$l_2 = c > 1$	0

miss out on eating a good mushroom

people die

$(l_1, l_2 > 0)$

BC: $c = 1000$

$c \to +\infty \to$ alg. always says don't eat