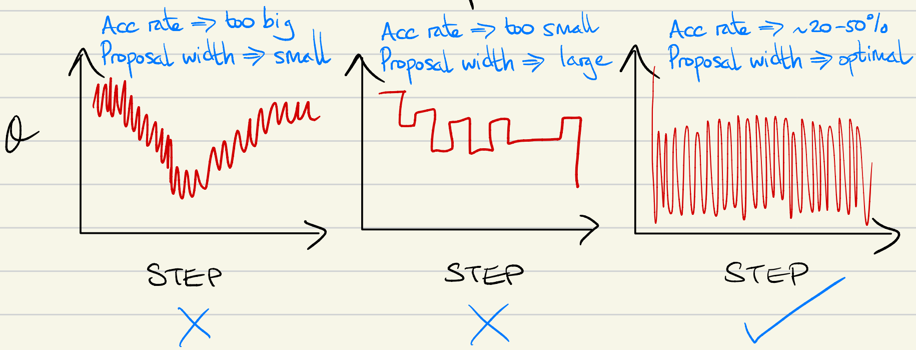
Lecture 11

1 Check acceptance rate

↳ ~20 -50% is OPTIMAL.

2 Check traceplots

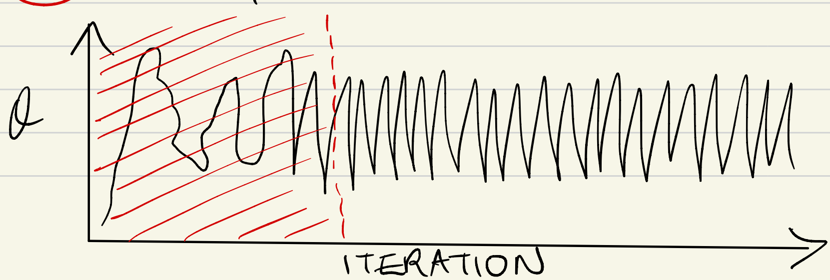


3 Check chain autocorrelation length

↳ measures the number between independent samples in the chain.

↳ we want independent samples from the POSTERIOR for MC integration.

4 Dump the burn-in



Optimizing sampling

(i) Adaptive Metropolis

* Use the chain to tune the width of the proposal distribution.

⇒ Estimate $N_p \times N_p$ covariance matrix, C

⇒ Factorize to take square root, $C = LL^T$.

⇒ $$\theta_{i+1} = \theta_i + \alpha L U$$

$\alpha = 2.38/d_{param}$

U = N_p-vector of draws from $N(0,1)$.

(ii) Single Component Adaptive Metropolis (SCAM)

* PCA on chain to identify important directions in parameter space!

⇒ $$C = \underbrace{D}_{\text{eigen-matrix}} \, \underbrace{\Lambda}_{\text{diag}(\sigma_\Lambda^2)} \, D^T$$

eigenvalues.

⇒ $$\theta_{i+1} = \theta_i + 2.38 \, D_j \, u_j$$

randomly chosen column of D.

$u_j \sim N(0, \sigma_\Lambda^j)$

(iii) Differential Evolution (DE)

$$\theta_{i+1} = \theta_i + \beta \left(x_{r1} - x_{r2} \right)$$

usually α

2 randomly chosen points from chain history.

- Practical MCMC

⇒ emcee — v. popular
- good for small problems
- not great in high-D.

⇒ PyMC — super fancy
- lots of automated optimizations
- overkill for many situations

⇒ PTMCMCSampler — bare-bones
- manual control
- can use parallel tempering
- built for PTA GW searches

Experience and trial/error is a great teacher
MCMC can be an art form.