

**Reading:** See resources page - handouts and bibliography on ODE methods and SA.

**Exercises:**

13. Compute the conditional distribution of  $X_1$  and  $X_2$  for the Gaussian two-armed bandit problem introduced in class. Recall that the observations are given by,

$$Y(t) = U(t)X_1 + (1 - U(t))X_2 + N(t)$$

where  $\{X_i\}$  are independent Gaussian,  $N(0, \sigma_i^2)$ ,  $\mathbf{N}$  is i.i.d.,  $N(0, \sigma_N^2)$ , and  $U(t) \in \{0, 1\}$  is adapted to  $\mathbf{Y}$ .

14. *Avoidance of traps.*

In this exercise you will try out the SA algorithm to minimize a function  $f(x)$  over  $x \in \mathbb{R}$ . You will consider  $f(x) = x^2(1 + (x + 10)^2)$ . We have access only to noisy measurements of its normalized gradient: If at time  $t$  the value  $x$  is selected, then  $Y(t)$  is observed,

$$Y(t) = \frac{1}{1 + (x + 5)^2} \nabla f(x) + N(t)$$

where  $\mathbf{N}$  is i.i.d., with zero mean, and unit variance.

- (i) Apply the stochastic approximation algorithm repeatedly, from various initial conditions, to obtain estimates  $\{X(t)\}$  of  $x^* = 0$ . Obtain an estimate of the probability that  $X(\infty) = 0$  when  $X(0) = 20$ . Repeat, with  $X(0) = -20$ .
  - (ii) Compare the sample path behavior of the standard SA algorithm, with the algorithm obtained using Polyak's averaging technique (again for  $X(0) = 20$ , and  $X(0) = -20$ ).
  - (iii) Propose a modification the SA algorithm to ensure that your estimates converge to  $x^* = 0$  with probability one, from each initial condition. Lai & Robbins' exploration should provide some inspiration.
15. *Variance analysis of stochastic approximation.* Consider the standard SA recursion in  $d$  dimensions,

$$X(t+1) = X(t) + \frac{G}{t+1} \left( f(X(t)) + N(t+1) \right), \quad X(0) \in \mathbb{R}^d,$$

where  $\mathbf{N}$  is i.i.d., with zero mean, and finite variance. The  $d \times d$  matrix  $G$  is to be optimized as part of this exercise.

Suppose that the recursion  $\mathbf{X}$  is globally convergent to the origin. To analyze the variance of the algorithm, we might consider a linearization,

$$\mathcal{E}(t+1) = \mathcal{E}(t) + \frac{G}{t+1} \left( A\mathcal{E}(t) + N(t+1) \right), \quad \mathcal{E}(0) = 0.$$

where  $A = \nabla f(0)$ .

- (i) Obtain a recursive formula for  $\Sigma_G(t) = \mathbb{E}[\mathcal{E}(t)\mathcal{E}(t)^\top]$ .
- (ii) Find conditions on  $A$  and  $G$  such that the asymptotic variance exists,

$$\Sigma_G^\infty = \lim_{t \rightarrow \infty} t \Sigma_G(t)$$

- (iii) Obtain the matrix  $G$  that minimizes trace  $\Sigma_G^\infty$ .