

**EE364b Spring 2021 Homework 3**  
Due Friday 4/23 at 11:59pm via Gradescope

3.1 (4 points) *Constrained subgradient method.* Consider the optimization problem

$$\begin{aligned} \text{minimize}_{\{x_j\}_{j=1}^J} \quad & f(x_1, \dots, x_J) := \frac{1}{2} \|b - \sum_{j=1}^J A_j x_j\|_2^2 + \lambda \cdot \sum_{j=1}^J \|x_j\|_2, \\ \text{s.t.} \quad & A_j x_j \geq 0, \forall j \in \{1, 2, \dots, J\} \end{aligned}$$

with variable  $x_1, \dots, x_J \in \mathbf{R}^n$  and problem data  $A_1, \dots, A_J \in \mathbf{R}^{m \times n}$ ,  $b \in \mathbf{R}^m$  and  $\lambda > 0$ . We will apply the subgradient method for constrained optimization given on page 11 of [the lecture slides for subgradient methods for constrained problems](#).

Let  $J = 3$ ,  $n = 100$ ,  $m = 10$ , and  $\lambda = .5$ . Generate random matrices  $A_1, \dots, A_J \in \mathbf{R}^{m \times n}$  with independent uniformly distributed entries in the interval  $\left[0, \frac{1}{\sqrt{m}}\right)$  and, random vectors  $x_1, \dots, x_J \in \mathbf{R}^n$  with independent uniformly distributed entries in the interval  $\left[0, \frac{1}{\sqrt{n}}\right)$ , then set  $b = \sum_{j=1}^J A_j x_j$ . Plot convergence in terms of the objective  $f(x_1^{(k)}, \dots, x_J^{(k)})$ . Try different step length schedules. Also, plot the maximal violation for the linear constraints at each step.

3.2 (4 points) *A stochastic linear system solver.* Consider the Least Squares minimization problem

$$\begin{aligned} \text{minimize} \quad & \underbrace{\frac{1}{2m} \sum_{i=1}^m (b_i - a_i^T x)^2}_{f(x)}, \\ \text{subject to} \quad & x \in \mathbf{R}^n \end{aligned}$$

where  $a_1, \dots, a_m$  are the rows of a data matrix  $A$ . We will consider the stochastic subgradient descent iterates

$$x^{t+1} = x^t - \alpha_t g_t, \tag{1}$$

where  $g_t$  is a noisy unbiased subgradient of the objective function, i.e.,  $\mathbf{E}[g^t | x^t] \in \partial f(x^t)$ .

(a) (1 point) Let  $j$  be a random index chosen from  $\{1, \dots, m\}$  such that for every index  $i \in \{1, \dots, m\}$  the probability that  $j = i$  is  $p_i$ , i.e.,

$$\mathbb{P}[j = i] = p_i,$$

for a given discrete probability distribution  $p_1, \dots, p_m \geq 0$ ,  $\sum_{i=1}^m p_i = 1$ . Show that  $\frac{(a_j^T x - b_j)}{mp_j} a_j$  is an unbiased subgradient, i.e.,

$$\mathbf{E} \frac{(a_j^T x - b_j)}{mp_j} a_j \in \partial f(x),$$

where the expectation is taken over the random variable  $j$ .

- (b) (1 point) Assume that  $b = Ax^*$  for some vector  $x^*$ , i.e.,  $x^* \in \arg \min f(x)$ . Define the error vector  $e_t = x_t - x^*$ , where  $x_t$  is the subgradient descent iterate in (1). Consider the constant step size  $\alpha_t = \frac{m}{\|A\|_F^2}$ , the unbiased subgradient from part (a) sampled i.i.d. at every iteration, and the probability distribution

$$p_i = \frac{\|a_i\|_2^2}{\sum_k \|a_k\|_2^2} = \frac{\|a_i\|_2^2}{\|A\|_F^2}.$$

Show that the error vector  $e_t$  obeys the time-varying linear dynamical system

$$e_{t+1} = P_t e_t,$$

where  $P_t$  is a (random) symmetric projection matrix, i.e.,  $P_t^T P_t = P_t^2 = P_t$  obeying  $\mathbf{E} P_t = I - \frac{1}{\|A\|_F^2} A^T A$ .

- (c) (1 point) Show that

$$\mathbf{E} \|e_{t+1}\|_2^2 \leq \left(1 - \frac{\sigma_{\min}(A)^2}{\|A\|_F^2}\right) \mathbf{E} \|e_t\|_2^2,$$

where  $\sigma_{\min}(A)$  is the smallest singular value of  $A$ . *Hint: Note that  $\mathbf{E}[\|e_{t+1}\|_2^2 | e_t] = \mathbf{E}[e_t^T P_t^T P_t e_t | e_t] = \mathbf{E}[e_t^T P_t e_t | e_t] = e_t^T \mathbf{E}[P_t] e_t$ , and*

$$e^T A^T A e \geq \sigma_{\min}(A)^2 e^T e$$

for every vector  $e \in \mathbf{R}^n$ . Apply this bound recursively to obtain a bound on  $\mathbf{E} \|e_t\|_2^2$  involving only  $\mathbf{E} \|e_0\|_2^2$ ,  $\|A\|_F$ ,  $\sigma_{\min}(A)$ .

- (d) (1 point) Assuming zero initialization,  $x_0 = 0$ , how many iterations are needed to obtain  $\mathbf{E} \|x_t - x^*\|_2^2 \leq 10^{-5}$ ? Your answer should depend on  $\|x^*\|_2$ ,  $\|A\|_F$ ,  $\sigma_{\min}(A)$ . What is the computational complexity (number of real number multiplications) in Big O notation?

3.3 (3 points) *Stochastic Log-optimal portfolio optimization using return oracle.* We consider the portfolio optimization problem

$$\begin{aligned} & \text{maximize} && \mathbf{E}_r \log(r^T x) \\ & \text{subject to} && \mathbf{1}^T x = 1, \quad x \succeq 0, \end{aligned}$$

with variable (portfolio weights)  $x \in \mathbf{R}^n$ . The expectation is over the distribution of the (total) return vector  $r \in \mathbf{R}_{++}^n$ , which is a random variable. (Although not relevant in this problem, the log-optimal portfolio maximizes the long-term growth of an initial investment, assuming the investments are re-balanced to the log-optimal portfolio after each investment period, and ignoring transaction costs.)

In this problem we assume that we do not know the distribution of  $r$  (other than that we have  $r \succ 0$  almost surely). However, we have access to an oracle that will generate independent samples from the return distribution. (Although not relevant, these samples could come from historical data, or stochastic simulations, or a known or assumed distribution.)

- (a) (1 point) Explain how to use the (projected) stochastic subgradient method, using one return sample for each iteration, to find (in the limit) a log-optimal portfolio. Describe how to carry out the projection required, and how to update the portfolio in each iteration.

*Hint.* Note that projecting  $x^{(k)}$  onto the constraints involves projecting onto a simplex, or solving the optimization problem

$$\begin{aligned} & \text{minimize} && (1/2)\|z - x^{(k)}\|_2^2 \\ & \text{subject to} && \mathbf{1}^T z = 1, \quad z \succeq 0, \end{aligned} \tag{2}$$

with variable  $z$ . One way to solve the problem is to introduce a dual variable  $\nu$  for the equality constraint and write the (partial) Lagrangian as

$$L(z, \nu) = (1/2)\|z - x^{(k)}\|_2^2 + \nu(\mathbf{1}^T z - 1),$$

with  $\text{dom } L(z, \nu) = \mathbf{R}_+^n \times \mathbf{R}$  (in other words, the inequality constraint  $z \succeq 0$  is implicit). Consider the single variable function  $g(\nu)$  obtained by minimizing  $L(z, \nu)$  over  $z$ . The value  $\nu^*$  that maximizes  $g(\nu)$  can be found using bisection, and the solution  $z^*$  to problem (2) can be found given  $\nu^*$ .

- (b) (1 point) Implement the method and run it on the problem with  $n = 10$  assets, with return sample oracle `log_opt_return_sample` in the file `log_opt_return_sample.m`. This function called with argument  $m$  returns an  $n \times m$  matrix whose columns are independent return samples. We have also provided a function to project onto the simplex in `projToSmplx.m`.

You are welcome to look inside `log_opt_return_sample.m` to see how we are generating the sample. The distribution is a mixture of two log-normal distributions; you can think of one as the standard return model and the other as the return model in some abnormal regime. However, your stochastic subgradient algorithm can only call `log_opt_return_sample(1)`, once per iteration; you cannot use any information found inside the file in your implementation.

To get a Monte Carlo approximation of the objective function value, you can generate a block of, say,  $10^5$  samples (using `R_emp=log_opt_return_sample(1e5)`, which only needs to be done once), and then use `obj_hat = mean(log(R_emp'*x))` as your estimate of the objective function. Plot the (approximate) objective value versus iteration, as well as the best approximate objective value obtained up to that iteration. (Note that evaluating the objective will require far more computation than each stochastic subgradient step.)

You may need to play around with the step size selection in your method to get reasonable convergence. Remember that your objective value evaluation is only an approximation.

- (c) (1 point) Repeat part (b) without the constraint  $x \geq 0$ . In other words, solve the optimization problem

$$\begin{aligned} & \text{maximize} && \mathbf{E}_r \log(r^T x) \\ & \text{subject to} && \mathbf{1}^T x = 1, \end{aligned}$$

using the same algorithm as in part (b) (though the projection onto the constraints will be different, because the constraints are different). As in part (b), plot the (approximate) objective value versus iteration, as well as the best approximate objective value obtained up to that iteration.