ELE 520: Mathematics of Data Science

Fall 2020

Homework 2

Due date: Tuesday, Nov. 10, 2020 (11am) (at the beginning of class)

You are allowed to drop 1 subproblem without penalty. In addition, up to 1 bonus point will be awarded to each subproblem for clean, well-organized, and elegant solutions.

1. Mutual coherence (40 points)

For an arbitrary pair of orthonormal bases $\Psi = [\psi_1, \dots, \psi_n] \in \mathbb{R}^{n \times n}$ and $\Phi = [\phi_1, \dots, \phi_n] \in \mathbb{R}^{n \times n}$, the mutual coherence $\mu(\Psi, \Phi)$ of these two bases is defined by

$$\mu(\mathbf{\Psi}, \mathbf{\Phi}) = \max_{1 \le i, j \le n} \left| \mathbf{\psi}_i^{\top} \mathbf{\phi}_j \right| \tag{1}$$

(a) Show that

$$\frac{1}{\sqrt{n}} \le \mu(\mathbf{\Psi}, \mathbf{\Phi}) \le 1.$$

(b) Let $\Psi = I$, and suppose that $\Phi = [\phi_{i,j}]_{1 \le i,j \le n}$ is a Gaussian random matrix such that the $\phi_{i,j}$'s are i.i.d. random variables drawn from $\phi_{i,j} \sim \mathcal{N}(0,1/n)$. Can you provide an upper estimate on $\mu(\Psi,\Phi)$ as defined in (1)? Since Φ is a random matrix, we expect your answer to be a function f(n) such that $\mathbb{P}\{\mu(\Psi,\Phi) > f(n)\} \to 0$ as n scales.

Hint: to simplify analysis, you are allowed to use the crude approximation $\mathbb{P}\{|z| > \tau\} \approx \exp(-\tau^2/2)$ for large $\tau > 0$, where $z \sim \mathcal{N}(0, 1)$.

- (c) Set n=100. Generate a random matrix Φ as in Part (b), and compute $\mu(\boldsymbol{I}, \Phi)$. Report the empirical distribution (i.e. histogram) of $\mu(\boldsymbol{I}, \Phi)$ out of 1000 simulations. How does your simulation result compare to your estimate in Part (b)?
- (d) We now generalize the mutual coherence measure to accommodate a more general set of vectors beyond two bases. Specifically, for any given matrix $\mathbf{A} = [\mathbf{a}_1, \cdots, \mathbf{a}_p] \in \mathbb{R}^{n \times p}$ obeying $n \leq p$, define the mutual coherence of \mathbf{A} as

$$\mu(\boldsymbol{A}) = \max_{1 \le i, j \le p, \ i \ne j} \left| \frac{\boldsymbol{a}_i^{\top} \boldsymbol{a}_j}{\|\boldsymbol{a}_i\| \|\boldsymbol{a}_j\|} \right|.$$

Show that

$$\mu(\mathbf{A}) \ge \sqrt{\frac{p-n}{p-1} \cdot \frac{1}{n}}.$$

This is a special case of the Welch bound.

Hint: you may want to use the following inequality: for any positive semidefinite $M \in \mathbb{R}^{n \times n}$, $||M||_{\mathrm{F}}^2 \ge \frac{1}{n} \left(\sum_{i=1}^n \lambda_i(M) \right)^2$.

2. ℓ_1 minimization (30 points)

Suppose that A is an $n \times 2n$ dimensional matrix. Let $x \in \mathbb{R}^{2n}$ be an unknown k-sparse vector, and y = Ax the observed system output. This problem is concerned with ℓ_1 minimization (or basis pursuit) in recovering x, i.e.

$$\min_{z \in \mathbb{R}^{2n}} \|z\|_1 \quad \text{s.t. } Az = y.$$
 (2)

(a) An optimization problem is called a linear program (LP) if it has the form

$$egin{aligned} ext{minimize}_{oldsymbol{z}} & & & c^ op oldsymbol{z} + oldsymbol{d} \ & & & & & Goldsymbol{z} \leq oldsymbol{h} \ & & & & oldsymbol{A}oldsymbol{z} = oldsymbol{b} \end{aligned}$$

where c, d, G, h, A, and b are known. Here, for any two vectors r and s, we say $r \leq s$ if $r_i \leq s_i$ for all i. Show that (2) can be converted to a linear program.

- (b) Set n=256, and let k range between 1 and 128. For each choice of k, run 10 independent numerical experiments: in each experiment, generate $\mathbf{A}=[a_{i,j}]_{1\leq i\leq n, 1\leq j\leq 2n}$ as a random matrix such that the $a_{i,j}$'s are i.i.d. standard Gaussian random variables, generate $\mathbf{x}\in\mathbb{R}^{2n}$ as a random k-sparse signal (e.g. you may generate the support of \mathbf{x} uniformly at random, with each non-zero entry drawn from the standard Gaussian distribution), and solve (2) with $\mathbf{y}=\mathbf{A}\mathbf{x}$. An experiment is claimed successful if the solution \mathbf{z} returned by (2) obeys $\|\mathbf{x}-\mathbf{z}\|_2 \leq 0.001\|\mathbf{x}\|_2$. Report the empirical success rates (averaged over 10 experiments) for each choice of k.
- 3. Restricted isometry properties (30 points)

Recall that the restricted isometry constant $\delta_s \geq 0$ of \boldsymbol{A} is the smallest constant such that

$$(1 - \delta_s) \|\boldsymbol{x}\|_2^2 \le \|\boldsymbol{A}\boldsymbol{x}\|_2^2 \le (1 + \delta_s) \|\boldsymbol{x}\|_2^2$$
(3)

holds for all s-sparse vector $\boldsymbol{x} \in \mathbb{R}^p$.

(a) Show that

$$|\langle Ax_1, Ax_2 \rangle| \le \delta_{s_1 + s_2} ||x_1||_2 ||x_2||_2$$

for all pairs of x_1 and x_2 that are supported on disjoint subsets $S_1, S_2 \subset \{1, \dots, n\}$ with $|S_1| \leq s_1$ and $|S_2| \leq s_2$.

(b) For any \boldsymbol{u} and \boldsymbol{v} , show that

$$|\langle \boldsymbol{u}, \ (\boldsymbol{I} - \boldsymbol{A}^{\top} \boldsymbol{A}) \boldsymbol{v} \rangle| \leq \delta_s \|\boldsymbol{u}\|_2 \cdot \|\boldsymbol{v}\|_2,$$

where s is the cardinality of support $(u) \cup \text{support}(v)$.

(c) Suppose that each column of A has unit norm. Show that $\delta_2 = \mu(A)$, where $\mu(A)$ is the mutual coherence of A.