CS229 Fall 2018

Problem Set #0: Linear Algebra and Multivariable Calculus

1. [0 points] Gradients and Hessians

Recall that a matrix $A \in \mathbb{R}^{n \times n}$ is symmetric if $A^T = A$, that is, $A_{ij} = A_{ji}$ for all i, j. Also recall the gradient $\nabla f(x)$ of a function $f : \mathbb{R}^n \to \mathbb{R}$, which is the *n*-vector of partial derivatives

$$\nabla f(x) = \begin{bmatrix} \frac{\partial}{\partial x_1} f(x) \\ \vdots \\ \frac{\partial}{\partial x_n} f(x) \end{bmatrix} \quad \text{where} \quad x = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix}.$$

The hessian $\nabla^2 f(x)$ of a function $f: \mathbb{R}^n \to \mathbb{R}$ is the $n \times n$ symmetric matrix of twice partial derivatives,

$$\nabla^2 f(x) = \begin{bmatrix} \frac{\partial^2}{\partial x_1^2} f(x) & \frac{\partial^2}{\partial x_1 \partial x_2} f(x) & \cdots & \frac{\partial^2}{\partial x_1 \partial x_n} f(x) \\ \frac{\partial^2}{\partial x_2 \partial x_1} f(x) & \frac{\partial^2}{\partial x_2^2} f(x) & \cdots & \frac{\partial^2}{\partial x_2 \partial x_n} f(x) \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial^2}{\partial x_n \partial x_1} f(x) & \frac{\partial^2}{\partial x_n \partial x_2} f(x) & \cdots & \frac{\partial^2}{\partial x_n^2} f(x) \end{bmatrix}.$$

- (a) Let $f(x) = \frac{1}{2}x^T A x + b^T x$, where A is a symmetric matrix and $b \in \mathbb{R}^n$ is a vector. What is $\nabla f(x)$?
- (b) Let f(x) = g(h(x)), where $g : \mathbb{R} \to \mathbb{R}$ is differentiable and $h : \mathbb{R}^n \to \mathbb{R}$ is differentiable. What is $\nabla f(x)$?
- (c) Let $f(x) = \frac{1}{2}x^T Ax + b^T x$, where A is symmetric and $b \in \mathbb{R}^n$ is a vector. What is $\nabla^2 f(x)$?
- (d) Let $f(x) = g(a^T x)$, where $g : \mathbb{R} \to \mathbb{R}$ is continuously differentiable and $a \in \mathbb{R}^n$ is a vector. What are $\nabla f(x)$ and $\nabla^2 f(x)$? (*Hint*: your expression for $\nabla^2 f(x)$ may have as few as 11 symbols, including ' and parentheses.)

(a)
$$\nabla f(x) = \begin{bmatrix} (Ax)_1 + b_1 \\ \vdots \\ (Ax)_n + b_n \end{bmatrix} = \begin{bmatrix} (Ax+b)_1 \\ \vdots \\ (Ax+b)_n \end{bmatrix} = Ax + b$$

(b)
$$\nabla f(x) = \begin{bmatrix} \frac{\partial g(h(x))}{\partial x_1} \\ \vdots \\ \frac{\partial g(h(x))}{\partial x_n} \end{bmatrix} = \begin{bmatrix} \frac{\partial g(h(x))}{\partial h(x)} \cdot \frac{\partial h(x)}{\partial x_1} \\ \vdots \\ \frac{\partial g(h(x))}{\partial h(x)} \cdot \frac{\partial h(x)}{\partial x_n} \end{bmatrix}$$
$$= \frac{\partial g(h(x))}{\partial h(x)} \begin{bmatrix} \frac{\partial h(x)}{\partial x_1} \\ \vdots \\ \frac{\partial h(x)}{\partial x_n} \end{bmatrix} = \frac{\partial g(h(x))}{\partial h(x)} \cdot \nabla h(x)$$

(c)
$$\nabla^2 f(x) = \nabla(\nabla f(x)) = \nabla(Ax + b)\nabla^2 f(x) = \nabla(\nabla f(x)) = \nabla(Ax + b)$$

$$= \begin{bmatrix} \frac{\partial}{\partial x_1}(Ax + b) \\ \vdots \\ \frac{\partial}{\partial x_n}(Ax + b) \end{bmatrix}$$

$$= \begin{bmatrix} A_1^\top \\ \vdots \\ A_n^\top \end{bmatrix} = \begin{bmatrix} A_1 \\ \vdots \\ A_n \end{bmatrix} = A$$

$$(\nabla^{2} f(x))_{ij} = \frac{\partial^{2}}{\partial x_{i} \partial x_{j}} f(x) = \frac{\partial}{\partial x_{i}} \frac{\partial}{\partial x_{j}} g(a^{T} x)$$

$$= \frac{\partial}{\partial x_{i}} \frac{\partial g(a^{T} x)}{\partial a^{T} x} \frac{\partial a^{T} x}{\partial x_{j}} = \frac{\partial}{\partial a^{T} x} \frac{\partial a^{T} x}{\partial x_{i}} \frac{\partial g(a^{T} x)}{\partial a^{T} x} \frac{\partial a^{T} x}{\partial x_{j}}$$

$$= \frac{\partial}{\partial a^{T} x} \frac{\partial g(a^{T} x)}{\partial a^{T} x} \frac{\partial a^{T} x}{\partial x_{i}} \frac{\partial a^{T} x}{\partial x_{j}} = \frac{\partial^{2} g(a^{T} x)}{(\partial a^{T} x)^{2}} \frac{\partial a^{T} x}{\partial x_{i}} \frac{\partial a^{T} x}{\partial x_{j}}$$

$$= \frac{\partial^{2} g(a^{T} x)}{(\partial a^{T} x)^{2}} \cdot a_{i} a_{j}$$

$$\nabla^{2} f(x) = \frac{\partial^{2} g(a^{T} x)}{(\partial a^{T} x)^{2}} \begin{bmatrix} a_{1} a_{1} & \cdots & a_{1} a_{n} \\ \vdots & \ddots & \vdots \\ a_{n} a_{1} & \cdots & a_{n} a_{n} \end{bmatrix}$$

$$= \frac{\partial^{2} g(a^{T} x)}{(\partial a^{T} x)^{2}} \cdot aa^{T}$$

2. [0 points] Positive definite matrices

A matrix $A \in \mathbb{R}^{n \times n}$ is positive semi-definite (PSD), denoted $A \succeq 0$, if $A = A^T$ and $x^T A x \ge 0$ for all $x \in \mathbb{R}^n$. A matrix A is positive definite, denoted $A \succ 0$, if $A = A^T$ and $x^T A x > 0$ for all $x \ne 0$, that is, all non-zero vectors x. The simplest example of a positive definite matrix is the identity I (the diagonal matrix with 1s on the diagonal and 0s elsewhere), which satisfies $x^T I x = \|x\|_2^2 = \sum_{i=1}^n x_i^2$.

- (a) Let $z \in \mathbb{R}^n$ be an *n*-vector. Show that $A = zz^T$ is positive semidefinite.
- (b) Let $z \in \mathbb{R}^n$ be a non-zero n-vector. Let $A = zz^T$. What is the null-space of A? What is the rank of A?
- (c) Let $A \in \mathbb{R}^{n \times n}$ be positive semidefinite and $B \in \mathbb{R}^{m \times n}$ be arbitrary, where $m, n \in \mathbb{N}$. Is BAB^T PSD? If so, prove it. If not, give a counterexample with explicit A, B.

(a)
$$\begin{aligned} \mathbf{1}.\ &(zz^\top)^\top = zz^\top \\ \mathbf{2}.\ &x^\top zz^\top x = (z^\top x)^\top z^\top x = (z^\top x)^2 \text{ (by } z^\top x \in \mathbb{R} \text{)} \geq 0 \end{aligned}$$

$$zz^{\top}x = 0$$

$$\rightarrow \begin{bmatrix} z_1(z_1x_1 + \dots + z_nx_n) \\ \vdots \\ z_n(z_1x_1 + \dots + z_nx_n) \end{bmatrix} = \begin{bmatrix} 0 \\ \vdots \\ 0 \end{bmatrix}$$

$$\rightarrow z^{\top}x = 0$$

$$\therefore \{x \in \mathbb{R}^n : z^{\top}x = 0\}$$

2. Rank of A

$$A = zz^{\top} = \begin{bmatrix} z_1 z_1 & z_1 z_2 & \cdots & z_1 z_n \\ z_2 z_1 & z_2 z_2 & \cdots & z_2 z_n \\ \vdots & \vdots & \ddots & \vdots \\ z_n z_1 & z_n z_2 & \cdots & z_n z_n \end{bmatrix}$$

$$\Rightarrow \begin{bmatrix} z_1 & z_2 & \cdots & z_n \\ 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 0 \end{bmatrix}$$
(by row operation)

$$\therefore rank(A) = 1$$

(c)
$$\mathbf{1}. \ (BAB^\top)^\top = BA^\top B^\top = BAB^\top \text{ (by } A = A^\top \text{)}$$

$$\mathbf{2}. \ x^\top BAB^\top x = (B^\top x)^\top AB^\top x = y^\top Ay \ (y \in \mathbb{R}^n) \geq 0$$
 (by $x^\top Ax \geq 0$, for all x)

3. [0 points] Eigenvectors, eigenvalues, and the spectral theorem

The eigenvalues of an $n \times n$ matrix $A \in \mathbb{R}^{n \times n}$ are the roots of the characteristic polynomial $p_A(\lambda) = \det(\lambda I - A)$, which may (in general) be complex. They are also defined as the the values $\lambda \in \mathbb{C}$ for which there exists a vector $x \in \mathbb{C}^n$ such that $Ax = \lambda x$. We call such a pair (x, λ) an eigenvector, eigenvalue pair. In this question, we use the notation $\operatorname{diag}(\lambda_1, \ldots, \lambda_n)$ to denote the diagonal matrix with diagonal entries $\lambda_1, \ldots, \lambda_n$, that is,

$$\operatorname{diag}(\lambda_1, \dots, \lambda_n) = \begin{bmatrix} \lambda_1 & 0 & 0 & \cdots & 0 \\ 0 & \lambda_2 & 0 & \cdots & 0 \\ 0 & 0 & \lambda_3 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & \lambda_n \end{bmatrix}.$$

(a) Suppose that the matrix $A \in \mathbb{R}^{n \times n}$ is diagonalizable, that is, $A = T\Lambda T^{-1}$ for an invertible matrix $T \in \mathbb{R}^{n \times n}$, where $\Lambda = \operatorname{diag}(\lambda_1, \dots, \lambda_n)$ is diagonal. Use the notation $t^{(i)}$ for the columns of T, so that $T = [t^{(1)} \cdots t^{(n)}]$, where $t^{(i)} \in \mathbb{R}^n$. Show that $At^{(i)} = \lambda_i t^{(i)}$, so that the eigenvalues/eigenvector pairs of A are $(t^{(i)}, \lambda_i)$.

A matrix $U \in \mathbb{R}^{n \times n}$ is orthogonal if $U^T U = I$. The spectral theorem, perhaps one of the most important theorems in linear algebra, states that if $A \in \mathbb{R}^{n \times n}$ is symetric, that is, $A = A^T$, then A is diagonalizable by a real orthogonal matrix. That is, there are a diagonal matrix $\Lambda \in \mathbb{R}^{n \times n}$ and orthogonal matrix $U \in \mathbb{R}^{n \times n}$ such that $U^T A U = \Lambda$, or, equivalently,

$$A = U\Lambda U^T$$
.

Let $\lambda_i = \lambda_i(A)$ denote the *i*th eigenvalue of A.

- (b) Let A be symmetric. Show that if $U = [u^{(1)} \cdots u^{(n)}]$ is orthogonal, where $u^{(i)} \in \mathbb{R}^n$ and $A = U\Lambda U^T$, then $u^{(i)}$ is an eigenvector of A and $Au^{(i)} = \lambda_i u^{(i)}$, where $\Lambda = \operatorname{diag}(\lambda_1, \ldots, \lambda_n)$.
- (c) Show that if A is PSD, then $\lambda_i(A) \geq 0$ for each i.

(a)
$$A = T\Lambda T^{-1}$$

$$AT = T\Lambda$$

$$A \begin{bmatrix} t^{(1)} & \cdots & t^{(n)} \end{bmatrix} = \begin{bmatrix} t^{(1)} & \cdots & t^{(n)} \end{bmatrix} \begin{bmatrix} \lambda_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \lambda_n \end{bmatrix}$$

$$\begin{bmatrix} At^{(1)} & \cdots & At^{(n)} \end{bmatrix} = \begin{bmatrix} \lambda_1 t^{(1)} & \cdots & \lambda_n t^{(n)} \end{bmatrix}$$

$$\Rightarrow At^{(i)} = \lambda_i t^{(i)}$$

(b)
$$A = A^{\top}, U^{\top}U = I$$

$$\rightarrow A = U\Lambda U^{\top}$$

$$AU = U\Lambda$$

$$\Rightarrow Au^{(i)} = \lambda_i u^{(i)}$$
 (by the previous (a))

(c)

$$\begin{split} &A \text{ is PSD} \\ &\to A = A^\top, \ x^\top A x \geq 0 \text{, for all } x \in \mathbb{R}^n \\ &Au^{(i)} = \lambda_i u^{(i)} \text{ (by the previous (b))} \\ &u^{(i)\top} A u^{(i)} = \lambda_i u^{(i)\top} u^{(i)} \\ &u^{(i)\top} A u^{(i)} \geq 0 \to \lambda_i u^{(i)\top} u^{(i)} = \lambda_i \geq 0 \end{split}$$