

CS 229, Fall 2018

Problem Set #0: Linear Algebra and Multivariable Calculus

Notes: (1) These questions require thought, but do not require long answers. Please be as concise as possible. (2) If you have a question about this homework, we encourage you to post your question on our Piazza forum, at <https://piazza.com/stanford/fall2018/cs229>. (3) If you missed the first lecture or are unfamiliar with the collaboration or honor code policy, please read the policy on Handout #1 (available from the course website) before starting work. (4) This specific homework is *not graded*, but we encourage you to solve each of the problems to brush up on your linear algebra. Some of them may even be useful for subsequent problem sets. It also serves as your introduction to using Gradescope for submissions.

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 $f : \mathbb{R}^n \rightarrow \mathbb{R}$, which is the n -vector of partial derivatives

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

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

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

- 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 $\nabla f(x)$?
- Let $f(x) = g(h(x))$, where $g : \mathbb{R} \rightarrow \mathbb{R}$ is differentiable and $h : \mathbb{R}^n \rightarrow \mathbb{R}$ is differentiable. What is $\nabla f(x)$?
- Let $f(x) = \frac{1}{2}x^T A x + b^T x$, where A is symmetric and $b \in \mathbb{R}^n$ is a vector. What is $\nabla^2 f(x)$?
- Let $f(x) = g(a^T x)$, where $g : \mathbb{R} \rightarrow \mathbb{R}$ 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.)

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 $x^T A x \geq 0$ 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 $x \neq 0$, 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 .

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 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 $\text{diag}(\lambda_1, \dots, \lambda_n)$ to denote the diagonal matrix with diagonal entries $\lambda_1, \dots, \lambda_n$, that is,

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

- (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 $\Lambda = \text{diag}(\lambda_1, \dots, \lambda_n)$ 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 symmetric, 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 $\Lambda = \text{diag}(\lambda_1, \dots, \lambda_n)$.
- (c) Show that if A is PSD, then $\lambda_i(A) \geq 0$ for each i .