

Stanford CS229 ps0 sol

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1 Gradients and Hessians

(a) Note that A is symmetric, we have

$$\frac{\partial}{\partial x_i} \frac{1}{2} x^T A x = \frac{\partial}{\partial x_i} \left(\sum_{j \neq i} (a_{ij} + a_{ji}) x_i x_j + a_{ii} x_i^2 \right) / 2 = \sum_{j=1}^n a_{ij} x_j,$$

$$\nabla f(x) = Ax + b.$$

(b)

$$\frac{\partial}{\partial x_i} g(h(x)) = \frac{\partial g(h(x))}{\partial h(x)} \frac{\partial h(x)}{\partial x_i} = g'(h(x)) \frac{\partial h(x)}{\partial x_i},$$

$$\nabla f(x) = g'(h(x)) \nabla h(x).$$

(c)

$$\frac{\partial^2}{\partial x_i^2} f(x) = a_{ii}, \frac{\partial^2}{\partial x_i \partial x_j} f(x) = \frac{a_{ij} + a_{ji}}{2} = a_{ij}, \nabla^2 f(x) = A$$

(d)

$$\nabla f(x) = g'(a^T x) a.$$

$$\frac{\partial^2}{\partial x_i^2} f(x) = \frac{\partial}{\partial x_i} g'(a^T x) a_i = g''(a^T x) a_i^2, \frac{\partial^2}{\partial x_j \partial x_i} f(x) = \frac{\partial}{\partial x_j} g'(a^T x) a_i = g''(a^T x) a_i a_j,$$

$$\nabla^2 f(x) = g''(a^T x) a a^T.$$

2 Positive definite matrices

(a) Since $x^T z z^T x = x^T z (x^T z)^T = (x^T z)^2 \geq 0$ for any x , $A = z z^T$ is positive semi-definite.

(b) $\mathcal{N}(A) = \{x \in \mathbb{R}^n : Ax = 0\} = \{x \in \mathbb{R}^n : z z^T x = 0\} = \{x \in \mathbb{R}^n : z^T x = 0\}$,
 $\text{rank}(A) = n - \dim(\mathcal{N}(A)) = 1$

(c) Since $BAB^T = BA^T B^T = (BAB^T)^T$, $B^T A B$ is symmetric. Then $x^T B A B^T x = (B^T x)^T A (B^T x) \geq 0$ and BAB^T is PSD.

3 Eigenvectors, eigenvalues, and the spectral theorem

(a)

$$A[t^{(1)} \dots t^{(n)}] = AT = T\Lambda = [t^{(1)} \dots t^{(n)}]\text{diag}(\lambda_1, \dots, \lambda_n),$$

So that $At^{(i)} = \lambda_i t^{(i)}, i = 1, \dots, n$ and they form eigenvalues/eigenvector pairs.

(b) Since $U^T U = I$, $U^{-1} = U^T$. Follow (a) we can derive the result.

(c) Since $Au^{(i)} = \lambda u^{(i)}$, A is PSD, $\lambda_i = \lambda_i (u^{(i)})^T u^{(i)} = (u^{(i)})^T A u^{(i)} \geq 0$.