

Indian Institute of Technology Kharagpur

Class Test I: 2020-21

Date: 19 Jan. 2021

Subject No.: CS60010

Subject: Deep Learning

1. (a) (4 points) The trace of a square matrix $\mathbf{A} \in \mathbb{R}^{n \times n}$ is defined as the sum of its diagonal entries, or $\text{tr} \mathbf{A} = \sum_{i=1}^n \mathbf{A}_{ii}$. Prove the following fact.

$$\|\mathbf{A}\|_F = \sqrt{\sum_{i=1}^n \sum_{j=1}^n \mathbf{A}_{ij}^2} = \sqrt{\text{tr}(\mathbf{A}^T \mathbf{A})}$$

where, $\|\mathbf{A}\|_F$, is the Frobenius norm. Show all your steps.

Solution: Let $\mathbf{C} = \mathbf{A}^T \mathbf{A}$. Then the j^{th} diagonal element of \mathbf{C} , i.e., $\mathbf{C}_{j,j}$ is given by, $\sum_{i=1}^n \mathbf{A}_{ij} \mathbf{A}_{ij} = \sum_{i=1}^n \mathbf{A}_{ij}^2$. Now, trace of \mathbf{C} , i.e., $\text{tr}(\mathbf{C})$ is the sum of all diagonal elements, i.e. $\text{tr}(\mathbf{C}) = \sum_{j=1}^n \mathbf{C}_{jj} = \sum_{j=1}^n \sum_{i=1}^n \mathbf{A}_{ij}^2 = \sum_{i=1}^n \sum_{j=1}^n \mathbf{A}_{ij}^2$. This implies that,

$$\|\mathbf{A}\|_F = \sqrt{\sum_{i=1}^n \sum_{j=1}^n \mathbf{A}_{ij}^2} = \sqrt{\text{tr}(\mathbf{C})} = \sqrt{\text{tr}(\mathbf{A}^T \mathbf{A})}$$

- (b) (3 points) Show that for a matrix \mathbf{A} and vector \mathbf{x} , $\frac{\partial}{\partial \mathbf{x}}(\mathbf{A}^{-1}) = -\mathbf{A}^{-1} \left(\frac{\partial \mathbf{A}}{\partial \mathbf{x}} \right) \mathbf{A}^{-1}$. **Hint:** Use the fact that for any two matrices \mathbf{A} and \mathbf{B} , $\frac{\partial \mathbf{A} \mathbf{B}}{\partial \mathbf{x}} = \frac{\partial \mathbf{A}}{\partial \mathbf{x}} \mathbf{B} + \mathbf{A} \frac{\partial \mathbf{B}}{\partial \mathbf{x}}$.

Solution:

$$\begin{aligned} \frac{\partial}{\partial \mathbf{x}}(\mathbf{A} \mathbf{A}^{-1}) &= 0 \quad [\mathbf{A} \mathbf{A}^{-1} = \mathbf{I}] \\ \frac{\partial \mathbf{A}}{\partial \mathbf{x}} \mathbf{A}^{-1} + \mathbf{A} \frac{\partial \mathbf{A}^{-1}}{\partial \mathbf{x}} &= 0 \\ \mathbf{A}^{-1} \frac{\partial \mathbf{A}}{\partial \mathbf{x}} \mathbf{A}^{-1} + \frac{\partial \mathbf{A}^{-1}}{\partial \mathbf{x}} &= 0 \\ \frac{\partial \mathbf{A}^{-1}}{\partial \mathbf{x}} &= -\mathbf{A}^{-1} \frac{\partial \mathbf{A}}{\partial \mathbf{x}} \mathbf{A}^{-1} \end{aligned}$$

2. (a) (3 points) Suppose we have a cost function

$$J(\boldsymbol{\theta}) = \frac{1}{N} \sum_{i=1}^N \boldsymbol{\theta}^T \mathbf{x}^{(i)} + b y^{(i)} + \frac{1}{2} \boldsymbol{\theta}^T \mathbf{A} \boldsymbol{\theta}$$

where $\boldsymbol{\theta} \in \mathbb{R}^d$ is the parameter vector $\mathbf{x}^{(i)} \in \mathbb{R}^d$, $y^{(i)} \in \mathbb{R}$, $\{\mathbf{x}^{(i)}, y^{(i)}\}$ are N training data points, $\mathbf{A} \in \mathbb{R}^{d \times d}$ is a symmetric matrix and $b \in \mathbb{R}$. We want to find parameters $\boldsymbol{\theta}$ using gradient descent. Find the vector of partial gradients of the cost function.

Solution: $\frac{\partial}{\partial \boldsymbol{\theta}} J(\boldsymbol{\theta}) = \frac{1}{N} \sum_{i=1}^N \mathbf{x}^{(i)} + 0 + \mathbf{A}\boldsymbol{\theta}$

- (b) (1 point) Give the closed-form solution of $\boldsymbol{\theta}$ from the above expression you found.

Solution: $\frac{1}{N} \sum_{i=1}^N \mathbf{x}^{(i)} + \mathbf{A}\boldsymbol{\theta} = 0, \implies \boldsymbol{\theta} = -\frac{1}{N} \mathbf{A}^{-1} \sum_{i=1}^N \mathbf{x}^{(i)}$

- (c) (4 points) Let λ and \mathbf{x} are respectively the eigenvalue and eigenvector of a square matrix \mathbf{A} . Prove that \mathbf{x} is also an eigenvector of \mathbf{A}^k where k is a positive integer. Also prove that λ^k is the eigenvalue of \mathbf{A}^k .

Solution:

$$\mathbf{A}\mathbf{x} = \lambda\mathbf{x}$$

$$\mathbf{A}\mathbf{A}\mathbf{x} = \mathbf{A}\lambda\mathbf{x}$$

$$\mathbf{A}^2\mathbf{x} = \lambda\mathbf{A}\mathbf{x} = \lambda\lambda\mathbf{x} = \lambda^2\mathbf{x}$$

The eigenvalues of \mathbf{A}^2 are the squares of the eigenvalues of \mathbf{A} . The eigenvectors of \mathbf{A}^2 are the same as the eigenvectors of \mathbf{A} . Similarly, it can be proved for a generic positive integer k also.