

# 50.039 Theory and Practice of Deep Learning

## Theory Homework 2

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February 13, 2019

### 1 Linear Algebra

#### Matrix inverse

$$XA + A^\top = I$$

$$XA = I - A^\top$$

Taking the inverse of  $A$  on both sides,

$$XAA^{-1} = (I - A^\top)A^{-1}$$

$$XI = IA^{-1} - A^\top A^{-1}$$

$$X = (I - A^\top)A^{-1}$$

#### Matrix inverse and transpose

$C - 2A^\top$  is invertible.

$$X^\top C = [2A(X + B)]^\top$$

$$X^\top C = 2A^\top X^\top + 2A^\top B^\top$$

$$X^\top C - 2A^\top X^\top = 2A^\top B^\top$$

$$X^\top (C - 2A^\top) = 2(AB)^\top$$

$$X^\top (C - 2A^\top)(C - 2A^\top)^{-1} = 2(AB)^\top (C - 2A^\top)^{-1}$$

$$X = (2(AB)^\top (C - 2A^\top)^{-1})^\top$$

#### Matrix inverse

$$(Ax - y)^\top A = 0$$

$$(Ax - y)^\top = 0^\top$$

$$Ax = y$$

In order to remove  $A$  from the left side, the inverse of  $A$  must be defined,  $A^{-1}$ .

$$x = A^{-1}y$$

#### Positive definiteness and invertibility

Any positive definite matrix is invertible.

$$(Ax - y)^\top A = -x^\top B$$

$$x^\top A^\top A - y^\top A = -x^\top B$$

$$x^\top A^\top A + x^\top B = y^\top A$$

$$x^\top (A^\top A + B) = y^\top A$$

In the case where  $A$  is invertible,

$$Ax \neq 0$$

Necessarily,  $A^\top A$  is positive definite, as per the definition of a positive definite matrix:

$$x^\top A^\top A z > 0$$

$$(Ax)^\top (Ax) > 0$$

Since  $A^\top A$  is positive definite, and  $B$  is positive definite, then  $(A^\top A + B)$  is also positive definite, and therefore invertible.

$$x^\top (A^\top A + B)(A^\top A + B)^{-1} = y^\top A(A^\top A + B)^{-1}$$

$$x^\top = y^\top A(A^\top A + B)^{-1}$$

$$x = (y^\top A(A^\top A + B)^{-1})^\top$$

### 2 Directional derivative

For a function  $f : \mathbb{R}^n \mapsto \mathbb{R}^1$ , and some arbitrary direction  $v$ , the directional derivative  $\nabla f(x) \cdot v$  can be seen as a projection along  $v$ . We need to choose the right  $v$  such that the maximum value of  $\nabla f(x) \cdot v$  is achieved. Using the geometric definition of the dot product,

$$\nabla f(x) \cdot v = \|\nabla f(x)\| \|v\| \cos(\theta)$$

where  $\theta$  is the angle between the gradient and  $v$ . This function is at its maximum when  $\cos(\theta) = 1$ , which implies  $\theta = 0^\circ$ .  $\nabla f(x)$  is indeed codirectional with  $v$ .