

## 1 Matrix equations

1. Let  $X, Y, A$  be arbitrary matrices,  $A$  invertible. Solve for  $X$ :

$$XA + A^T = I$$

2. Let  $X, A, B$  be arbitrary matrices,  $(C - 2A^T)$  invertible. Solve for  $X$ :

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

3. Let  $x \in \mathbb{R}^n, y \in \mathbb{R}^d, A \in \mathbb{R}^{d \times n}, A^T A$  invertible. Solve for  $x$ :

$$(Ax - y)^T A = 0_n^T$$

4. As above, additionally  $B \in \mathbb{R}^{n \times n}, B$  positive-definite. Solve for  $x$ :

$$(Ax - y)^T A + x^T B = 0_n^T$$

$$\begin{aligned} 1. \quad XA + A^T &= I \\ X &= (I - A^T)A^{-1} \\ X &= A^{-1} - A^T A^{-1} \end{aligned}$$

$$\begin{aligned} 2. \quad X^T C &= (X+B)^T 2A^T = (X^T + B^T) 2A^T \\ X^T (C - 2A^T) &= B^T \cdot 2A^T \\ X^T &= 2(AB)^T \cdot (C - 2A^T)^{-1} \\ X &= (2(AB)^T \cdot (C - 2A^T)^{-1})^T \\ X &= 2[(C - 2A^T)^{-1}]^T \cdot AB = 2(C^T - 2A)^{-1} \cdot AB \end{aligned}$$

$$\begin{aligned} 3. \quad (AX - y)^T A &= 0_n^T \\ (X^T A^T - y^T) A &= 0_n^T \\ X^T A^T A &= y^T A \\ X^T &= y^T A (A^T A)^{-1} \\ X &= (A^T A)^{-1} A^T y \end{aligned}$$

$$\begin{aligned} 4. \quad (AX - y)^T A + X^T B &= 0_n^T \\ X^T A^T A - y^T A + X^T B &= 0_n^T \\ X^T (A^T A + B) &= y^T A \\ (A^T A + B^T) X &= A^T y \end{aligned}$$

$\therefore B$  positive definite,  $A^T A$  invertible

$$X^T (A^T A) X = (AX)^T AX \geq 0$$

$$X^T B X > 0$$

$$\therefore X^T (A^T A + B) X > 0$$

$\therefore A^T A + B$  is positive definite

$$\therefore A^T A + B \text{ invertible} \\ X = (A^T A + B^T)^{-1} A^T y$$

## 2 Vector derivatives

Let  $x \in \mathbb{R}^n, y \in \mathbb{R}^d, A \in \mathbb{R}^{d \times n}$ .

1. What is  $\frac{\partial}{\partial x} x$ ? (Of what type/dimension is this thing?)

2. What is  $\frac{\partial}{\partial x} [x^T x]$ ?

3. Let  $B$  be symmetric and positive definite. What is the minimum of  $(Ax - y)^T (Ax - y) + x^T B x$  w.r.t.  $x$ ?

1. identity matrix with  $n$  dimension

$$2. \frac{\partial}{\partial x} [x^T x] = 2x$$

$$3. F(x) = (Ax - y)^T (Ax - y) + x^T Bx$$

$$\text{let } \frac{\partial}{\partial x} F(x) = 2A^T(Ax - y) + 2Bx$$

$$= 2(A^T Ax - A^T y + Bx)$$

$$= 0$$

$$A^T Ax - A^T y + Bx = 0$$

$$(A^T A + B)x = A^T y$$

$A^T A + B$  is positive definite

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

### 3 Error Measures

Let  $y, \hat{y} \in \mathbb{R}^n$  be  $n$  true and predicted values of a regression problem.

1. Formally define the error measures *Mean Squared Error* (MSE) and *Mean Absolute Error* between  $y$  and  $\hat{y}$ .
2. How would choosing MAE or MSE as objective function for a regression problem impact the resulting prediction model? How do MSE and MAE differ?
3. Let  $y, \hat{y} \in \{0, 1\}^n$  be  $n$  true and predicted labels of a binary classification problem. What would the MSE and MAE calculate in this case?

$$1. \text{MSE: } = \frac{1}{n} \sum_{i=1}^n (y - \hat{y})^2$$

$$\text{MAE: } = \frac{1}{n} \sum_{i=1}^n |y - \hat{y}|$$

2. MSE will square the error and thus having a larger result if there is a large error, MSE is more sensitive to the errors so it has higher accuracy but it is not as robust as MAE.
3. the probability of the prediction being false

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