Machine Learning Appendix

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Notations

In general, in this class:

• A lowercase, non bold letter is a scalar:

$$x \in \mathbb{R}$$

A lowercase, bold letter is a vector:

$$\mathbf{x} \in \mathbb{R}^N$$

• An uppercase, bold letter is a matrix:

$$\mathbf{X} \in \mathbb{R}^{M \times N}$$



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Expectation and (co)variance

$$\mathrm{cov}[X,Y] = \mathbb{E}[XY] - \mathbb{E}[X]\mathbb{E}[Y]$$

$$\mathbb{E}[X+Y] = \mathbb{E}[X] + \mathbb{E}[Y]$$

 $\mathbb{E}[XY] = \mathbb{E}[X]\mathbb{E}[Y]$ if and only if X and Y are independent, i.e.

$$\mathbb{E}[XY] = \mathbb{E}[X]\mathbb{E}[Y] \iff X \perp\!\!\!\perp Y$$

If X = Y then

$$\operatorname{cov}[X,X] = \operatorname{var}[X] = \mathbb{E}[X^2] - \mathbb{E}[X]^2$$

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Linear algebra

The projection $Proj_{\mathbf{b}}(\mathbf{a})$ of vector \mathbf{a} onto vector \mathbf{b} :

Has amplitude

$$\|\mathbf{a}\|\cos(\theta)$$

where θ is the angle between a and b

Has direction

$$\frac{\mathbf{b}}{\|\mathbf{b}\|}$$

(unit vector in the direction of b)

ullet The dot product between ${f a}$ and ${f b}$ is

$$\mathbf{a}^{\mathsf{T}}\mathbf{b} = \|\mathbf{a}\| \|\mathbf{b}\| \cos(\theta)$$

Consequently,

$$\mathsf{Proj}_{\mathbf{b}}(\mathbf{a}) = \frac{\mathbf{a}^{\top}\mathbf{b}}{\|\mathbf{b}\|^2} \cdot \mathbf{b}$$



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Matrix calculus

We can define:

• Derivatives of scalars with respect to vectors (i.e. gradients):

For
$$a \in \mathbb{R}, \mathbf{x} \in \mathbb{R}^N$$
, $\frac{\partial a}{\partial \mathbf{x}} \in \mathbb{R}^N$ and $\left[\left(\frac{\partial a}{\partial \mathbf{x}}\right)_i = \frac{\partial a}{\partial x_i}\right]$

But also derivatives of vectors with respect to scalars:

For
$$\mathbf{a} \in \mathbb{R}^N, x \in \mathbb{R}, \quad \frac{\partial \mathbf{a}}{\partial x} \in \mathbb{R}^N \quad \text{ and } \quad \left| \left(\frac{\partial \mathbf{a}}{\partial x} \right)_i = \frac{\partial a_i}{\partial x} \right|$$

Or derivatives of vectors w.r.t. vectors:

For
$$\mathbf{a} \in \mathbb{R}^M$$
, $\mathbf{b} \in \mathbb{R}^N$, $\frac{\partial \mathbf{a}}{\partial \mathbf{b}} \in \mathbb{R}^{M \times N}$ and $\left[\left(\frac{\partial \mathbf{a}}{\partial \mathbf{b}} \right)_{ij} = \frac{\partial a_i}{\partial b_j} \right]$

etc



Matrix calculus

We can then prove:

• If a is constant with respect to x ($a \neq a(x)$):

$$\frac{\partial}{\partial \mathbf{x}}(\mathbf{x}^{\top}\mathbf{a}) = \frac{\partial}{\partial \mathbf{x}}(\mathbf{a}^{\top}\mathbf{x}) = \mathbf{a}$$
 (1)

• For matrices A(x) and B(x) that depend on x:

$$\frac{\partial}{\partial x}(\mathbf{A}\mathbf{B}) = \frac{\partial \mathbf{A}}{\partial x}\mathbf{B} + \mathbf{A}\frac{\partial \mathbf{B}}{\partial x}$$
 (2)

Exercise¹: prove that for $\mathbf{A}(x)$:

$$\frac{\partial \mathbf{A}^{-1}}{\partial x} = -\mathbf{A}^{-1} \frac{\partial \mathbf{A}}{\partial x} \mathbf{A}^{-1}$$

¹Hint: use the fact that $A^{-1}A = I$ and equation (2)

Matrix calculus

• For any 3 matrices A, B and C that do not depend on a 4th matrix X, and defined such that the equation below makes sense, we can prove:

Lemma

$$\frac{\partial \|\mathbf{A}\mathbf{W}\mathbf{B} + \mathbf{C}\|_2^2}{\partial \mathbf{X}} = 2\mathbf{A}^{\top}(\mathbf{A}\mathbf{X}\mathbf{B} + \mathbf{C})\mathbf{B}^{\top}$$

 This is a generic result whose special cases we will often be useful in this course.

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Constrained optimization

Coming soon

