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Overview of Machine Learning and Essential Mathematic Skills for Machine Learning

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seek LIGHT

Summation and Product

- Commonly used operations in Statistic Machine Learning
- Summation notations
 - Summation

$$\sum_{i=1}^N a_i = \sum_i a_i = \sum_j a_j$$

- Summation with two indices

$$\sum_{i=1}^M \sum_{j=1}^N a_{ij} = \sum_{i,j} a_{ij}$$

Summation and Product

- A useful formula (a little bit counter-intuitive)

$$\sum_{i=1}^M \sum_{j=1}^N a_i b_j = \left(\sum_i a_i \right) \left(\sum_j b_j \right) = \left(\sum_i a_i \right) \left(\sum_i b_i \right)$$

Summation and Product

- A useful formula (a little bit counter-intuitive)

$$\sum_{i=1}^M \sum_{j=1}^N a_i b_j = (\sum_i a_i) \left(\sum_j b_j \right) = (\sum_i a_i) (\sum_i b_i)$$

- Proof

$$\sum_{i=1}^M \sum_{j=1}^N a_i b_j = \sum_i a_i \left(\sum_j b_j \right) = (\sum_i b_i) (\sum_i a_i)$$

Linear algebra: vector, matrix and basic matrix operations

- Vectors and matrix

Scalar Vector Matrix

$$1 \quad \begin{bmatrix} 1 \\ 2 \end{bmatrix} \quad \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix}$$

- Basic operations

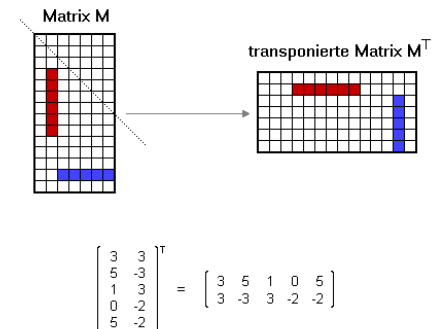
- Multiplication

$$\begin{bmatrix} a_1 & a_2 & a_3 \\ a_4 & a_5 & a_6 \\ a_7 & a_8 & a_9 \end{bmatrix} \begin{bmatrix} b_1 & b_2 & b_3 \\ b_4 & b_5 & b_6 \\ b_7 & b_8 & b_9 \end{bmatrix} = \begin{bmatrix} c_1 & c_2 & c_3 \\ c_4 & c_5 & c_6 \\ c_7 & c_8 & c_9 \end{bmatrix}$$

- Transpose

- Inverse

$$\mathbf{A}\mathbf{A}^{-1} = \mathbf{I}$$



Matrix multiplication

- View matrix as a set of vectors

$$\mathbf{A}\mathbf{b} = \underbrace{[\mathbf{a}_1, \mathbf{a}_2, \dots, \mathbf{a}_n]^T}_{\text{Row vectors}} \mathbf{b} = [\mathbf{a}_1^\top \mathbf{b}, \mathbf{a}_2^\top \mathbf{b}, \dots, \mathbf{a}_n^\top \mathbf{b}]^\top$$

$$\mathbf{A}\mathbf{\Lambda} = \underbrace{[\mathbf{a}_1, \mathbf{a}_2, \dots, \mathbf{a}_n]}_{\text{Column vectors}} \begin{bmatrix} \lambda_1 & & \\ & \ddots & \\ & & \lambda_n \end{bmatrix} = [\lambda_1 \mathbf{a}_1, \lambda_2 \mathbf{a}_2, \dots, \lambda_n \mathbf{a}_n]$$

Matrix product (example)

- Multiply row value by corresponding col value and add to make one value of the product, located at the intersection of row and col.
- Generally not commutative

- $\mathbf{x} \qquad \qquad \mathbf{y} \qquad \qquad \mathbf{z} = \mathbf{x} * \mathbf{y}$
- $\begin{bmatrix} 1 & 2 & 3 \end{bmatrix} \qquad \begin{bmatrix} 1 & \mathbf{2} & 3 \end{bmatrix} \qquad \begin{bmatrix} . & . & . \end{bmatrix}$
- $\begin{bmatrix} \mathbf{2} & \mathbf{2} & \mathbf{3} \end{bmatrix} * \begin{bmatrix} 2 & \mathbf{2} & 3 \end{bmatrix} = \begin{bmatrix} . & \mathbf{17} & . \end{bmatrix}$
- $\begin{bmatrix} 3 & 3 & 3 \end{bmatrix} \qquad \begin{bmatrix} 3 & \mathbf{3} & 3 \end{bmatrix} \qquad \begin{bmatrix} . & . & . \end{bmatrix}$

- $z_{22} = x_{21} * y_{12} + x_{22} * y_{22} + x_{23} * y_{32}$

Inner product and norms

- Inner product between two vectors

$$\langle \mathbf{x}, \mathbf{y} \rangle = \mathbf{x}^T \mathbf{y} = \sum_i x_i y_i$$

- Vector Norms
 - Measure the length of the vector
 - Not unique: could have infinite number of definitions
 - Commonly used ones

$$l_2 \text{ norm: } \|x\|_2 = \sqrt{\sum_i x_i^2} \qquad l_1 \text{ norm: } \|x\|_1 = \sum_i |x_i|$$

$$l_p \text{ norm: } \|x\|_p = (\sum_i |x_i|^p)^{1/p}$$

Trace and Matrix Norm

- Definition $Tr(A) = \sum_i a_{ii}$ $Tr(a) = a$
- Properties

$$Tr(X^\top Y) = Tr(XY^\top) = Tr(Y^\top X) = Tr(YX^\top)$$

$$Tr(A) + Tr(B) = Tr(A + B)$$

- Frobenius norm

$$\|A\|_F = \sqrt{\sum_{ij} a_{ij}^2}$$

- Relationship to Trace

$$\|A\|_F = \sqrt{\sum_{ij} a_{ij}^2} = \sqrt{Tr(AA^\top)} = \sqrt{Tr(A^\top A)}$$

Matrix calculus

- For functions that involve matrices or vectors
 - Case 1: Vector/Matrix variable and scalar output
 - Case 2: Vector/Matrix variable and vector output
- Definition
- Application
 - Similar

$$\frac{\partial y}{\partial \mathbf{x}} \stackrel{\text{def}}{=} \begin{bmatrix} \frac{\partial y}{\partial x_1} \\ \frac{\partial y}{\partial x_2} \\ \vdots \\ \frac{\partial y}{\partial x_n} \end{bmatrix}.$$

Matrix calculus

- Properties
- More info
 - [Matrix Calculus](#)
- Trick to memorize
 - Analogy to scalar case
 - Check dimensions

Identities: vector-by-vector $\frac{\partial \mathbf{y}}{\partial \mathbf{x}}$

Condition	Expression	Numerator layout, i.e. by \mathbf{y} and \mathbf{x}^\top	Denominator layout, i.e. by \mathbf{y}^\top and \mathbf{x}
\mathbf{a} is not a function of \mathbf{x}	$\frac{\partial \mathbf{a}}{\partial \mathbf{x}} =$	$\mathbf{0}$	
	$\frac{\partial \mathbf{x}}{\partial \mathbf{x}} =$	\mathbf{I}	
\mathbf{A} is not a function of \mathbf{x}	$\frac{\partial \mathbf{A} \mathbf{x}}{\partial \mathbf{x}} =$	\mathbf{A}	\mathbf{A}^\top
\mathbf{A} is not a function of \mathbf{x}	$\frac{\partial \mathbf{x}^\top \mathbf{A}}{\partial \mathbf{x}} =$	\mathbf{A}^\top	\mathbf{A}
\mathbf{a} is not a function of \mathbf{x} , $\mathbf{u} = \mathbf{u}(\mathbf{x})$	$\frac{\partial \mathbf{a} \mathbf{u}}{\partial \mathbf{x}} =$	$\mathbf{a} \frac{\partial \mathbf{u}}{\partial \mathbf{x}}$	
$v = v(\mathbf{x}), \mathbf{u} = \mathbf{u}(\mathbf{x})$	$\frac{\partial v \mathbf{u}}{\partial \mathbf{x}} =$	$v \frac{\partial \mathbf{u}}{\partial \mathbf{x}} + \mathbf{u} \frac{\partial v}{\partial \mathbf{x}}$	$v \frac{\partial \mathbf{u}}{\partial \mathbf{x}} + \frac{\partial v}{\partial \mathbf{x}} \mathbf{u}^\top$
\mathbf{A} is not a function of \mathbf{x} , $\mathbf{u} = \mathbf{u}(\mathbf{x})$	$\frac{\partial \mathbf{A} \mathbf{u}}{\partial \mathbf{x}} =$	$\mathbf{A} \frac{\partial \mathbf{u}}{\partial \mathbf{x}}$	$\frac{\partial \mathbf{u}}{\partial \mathbf{x}} \mathbf{A}^\top$
$\mathbf{u} = \mathbf{u}(\mathbf{x}), \mathbf{v} = \mathbf{v}(\mathbf{x})$	$\frac{\partial (\mathbf{u} + \mathbf{v})}{\partial \mathbf{x}} =$	$\frac{\partial \mathbf{u}}{\partial \mathbf{x}} + \frac{\partial \mathbf{v}}{\partial \mathbf{x}}$	
$\mathbf{u} = \mathbf{u}(\mathbf{x})$	$\frac{\partial \mathbf{g}(\mathbf{u})}{\partial \mathbf{x}} =$	$\frac{\partial \mathbf{g}(\mathbf{u})}{\partial \mathbf{u}} \frac{\partial \mathbf{u}}{\partial \mathbf{x}}$	$\frac{\partial \mathbf{u}}{\partial \mathbf{x}} \frac{\partial \mathbf{g}(\mathbf{u})}{\partial \mathbf{u}}$
$\mathbf{u} = \mathbf{u}(\mathbf{x})$	$\frac{\partial \mathbf{f}(\mathbf{g}(\mathbf{u}))}{\partial \mathbf{x}} =$	$\frac{\partial \mathbf{f}(\mathbf{g})}{\partial \mathbf{g}} \frac{\partial \mathbf{g}(\mathbf{u})}{\partial \mathbf{u}} \frac{\partial \mathbf{u}}{\partial \mathbf{x}}$	$\frac{\partial \mathbf{u}}{\partial \mathbf{x}} \frac{\partial \mathbf{g}(\mathbf{u})}{\partial \mathbf{u}} \frac{\partial \mathbf{f}(\mathbf{g})}{\partial \mathbf{g}}$

Matrix calculus

- More information
- Exercise

$$\min_{\mathbf{x}} \|Ax - b\|_2^2$$

- Hint

$$\|Ax - b\|_2^2 = (Ax - b)^\top (Ax - b)$$

Matrix calculus

- More information
- Exercise

$$\min_{\mathbf{x}} \|Ax - b\|_2^2$$

- Hint

$$\|Ax - b\|_2^2 = (Ax - b)^\top (Ax - b)$$

$$\frac{\partial \|Ax - b\|_2^2}{\partial x} = 2A^\top (Ax - b) = 2A^\top Ax - 2A^\top b$$

$$\text{Solve } \frac{\partial \|Ax - b\|_2^2}{\partial x} = 2A^\top Ax - 2A^\top b = 0$$

$$x = (A^\top A)^{-1} A^\top b$$