

$$\begin{aligned}
\frac{\partial(\mathbf{b}^T \mathbf{a})}{\partial \mathbf{a}} &= \mathbf{b} \\
\frac{\partial(\mathbf{a}^T \mathbf{A} \mathbf{a})}{\partial \mathbf{a}} &= (\mathbf{A} + \mathbf{A}^T) \mathbf{a} \\
\frac{\partial}{\partial \mathbf{A}} \text{tr}(\mathbf{B} \mathbf{A}) &= \mathbf{B}^T \\
\frac{\partial}{\partial \mathbf{A}} \log |\mathbf{A}| &= \mathbf{A}^{-T} \triangleq (\mathbf{A}^{-1})^T \\
\text{tr}(\mathbf{A} \mathbf{B} \mathbf{C}) &= \text{tr}(\mathbf{C} \mathbf{A} \mathbf{B}) = \text{tr}(\mathbf{B} \mathbf{C} \mathbf{A})
\end{aligned}$$

Figure 1: important formulas

Mahalanobis distance

Eigendecomposition:

Equation of Ellipse:  $(\mathbf{x} - \mathbf{c})^T \mathbf{A} (\mathbf{x} - \mathbf{c})$

Orthonormal Matrices:  $\mathbf{U}^T = \mathbf{U}^{-1} \Rightarrow \mathbf{U}^{-T} = \mathbf{U}$

Trace of a Matrix  $\mathbf{A}$ :  $\text{tr}(\mathbf{A}) = \sum_{i=1}^n a_{ii} = a_{11} + a_{22} + \dots + a_{nn}$

Discriminant Analysis  $p(y = c | \mathbf{x}, \theta) = p(\mathbf{x} | y = c, \theta) \times p(y = c | \theta)$