

## STA2101 Formulas

Columns of  $\mathbf{A}$  *linearly dependent* means there is a vector  $\mathbf{v} \neq \mathbf{0}$  with  $\mathbf{A}\mathbf{v} = \mathbf{0}$ .

Columns of  $\mathbf{A}$  *linearly independent* means that  $\mathbf{A}\mathbf{v} = \mathbf{0}$  implies  $\mathbf{v} = \mathbf{0}$ .

$\mathbf{A}$  *positive definite* means  $\mathbf{v}^\top \mathbf{A}\mathbf{v} > 0$  for all vectors  $\mathbf{v} \neq \mathbf{0}$ .

$$\Sigma = \mathbf{P}\Lambda\mathbf{P}^\top$$

$$\Sigma^{-1} = \mathbf{P}\Lambda^{-1}\mathbf{P}^\top$$

$$\Sigma^{1/2} = \mathbf{P}\Lambda^{1/2}\mathbf{P}^\top$$

$$\Sigma^{-1/2} = \mathbf{P}\Lambda^{-1/2}\mathbf{P}^\top$$

If  $\lim_{n \rightarrow \infty} E(T_n) = \theta$  and  $\lim_{n \rightarrow \infty} Var(T_n) = 0$ , then  $T_n \xrightarrow{p} \theta$

If  $\sqrt{n}(T_n - \mu) \xrightarrow{d} T \sim N(0, \sigma^2)$ , then  $\sqrt{n}(g(T_n) - g(\mu)) \xrightarrow{d} g'(\mu)T \sim N(0, g'(\mu)^2\sigma^2)$

If  $\mathbf{T}_n \xrightarrow{d} \mathbf{T}$  and  $\mathbf{Y}_n \xrightarrow{p} \mathbf{c}$ , then  $\begin{pmatrix} \mathbf{T}_n \\ \mathbf{Y}_n \end{pmatrix} \xrightarrow{d} \begin{pmatrix} \mathbf{T} \\ \mathbf{c} \end{pmatrix}$   $\sqrt{n}(\bar{\mathbf{x}}_n - \boldsymbol{\mu}) \xrightarrow{d} \mathbf{x} \sim N(\mathbf{0}, \Sigma)$

Let  $g: \mathbb{R}^d \rightarrow \mathbb{R}^k$  etc. If  $\sqrt{n}(\mathbf{T}_n - \boldsymbol{\theta}) \xrightarrow{d} \mathbf{T}$ , then  $\sqrt{n}(g(\mathbf{T}_n) - g(\boldsymbol{\theta})) \xrightarrow{d} \dot{g}(\boldsymbol{\theta})\mathbf{T}$ , where  $\dot{g}(\boldsymbol{\theta}) = \left[ \frac{\partial g_i}{\partial \theta_j} \right]_{k \times d}$

$$cov(\mathbf{w}) = E\{(\mathbf{w} - \boldsymbol{\mu}_w)(\mathbf{w} - \boldsymbol{\mu}_w)^\top\}$$

$$cov(\mathbf{w}, \mathbf{t}) = E\{(\mathbf{w} - \boldsymbol{\mu}_w)(\mathbf{t} - \boldsymbol{\mu}_t)^\top\}$$

$$cov(\mathbf{w}) = E\{\mathbf{w}\mathbf{w}^\top\} - \boldsymbol{\mu}_w\boldsymbol{\mu}_w^\top$$

$$cov(\mathbf{A}\mathbf{w}) = \mathbf{A}cov(\mathbf{w})\mathbf{A}^\top$$

If  $\mathbf{w} \sim N_p(\boldsymbol{\mu}, \Sigma)$ , then  $\mathbf{A}\mathbf{w} + \mathbf{c} \sim N_r(\mathbf{A}\boldsymbol{\mu} + \mathbf{c}, \mathbf{A}\Sigma\mathbf{A}^\top)$

and  $(\mathbf{w} - \boldsymbol{\mu})^\top \Sigma^{-1}(\mathbf{w} - \boldsymbol{\mu}) \sim \chi^2(p)$

$L(\boldsymbol{\mu}, \Sigma) = |\Sigma|^{-n/2} (2\pi)^{-np/2} \exp -\frac{n}{2} \left\{ tr(\widehat{\Sigma}\Sigma^{-1}) + (\bar{\mathbf{y}} - \boldsymbol{\mu})^\top \Sigma^{-1}(\bar{\mathbf{y}} - \boldsymbol{\mu}) \right\}$ , where  $\widehat{\Sigma} = \frac{1}{n} \sum_{i=1}^n (\mathbf{y}_i - \bar{\mathbf{y}})(\mathbf{y}_i - \bar{\mathbf{y}})^\top$

$$y_i = \beta_0 + \beta_1 x_{i,1} + \dots + \beta_{p-1} x_{i,p-1} + \epsilon_i$$

$\epsilon_1, \dots, \epsilon_n$  independent  $N(0, \sigma^2)$

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon}$$

$$\boldsymbol{\epsilon} \sim N_n(\mathbf{0}, \sigma^2 \mathbf{I}_n)$$

$$\widehat{\boldsymbol{\beta}} = (\mathbf{X}^\top \mathbf{X})^{-1} \mathbf{X}^\top \mathbf{y} \sim N_p(\boldsymbol{\beta}, \sigma^2 (\mathbf{X}^\top \mathbf{X})^{-1})$$

$$\widehat{\mathbf{y}} = \mathbf{X}\widehat{\boldsymbol{\beta}} = \mathbf{H}\mathbf{y}, \mathbf{e} = \mathbf{y} - \widehat{\mathbf{y}}$$

$$G^2 = -2 \log \left( \frac{\max_{\theta \in \Theta_0} L(\theta)}{\max_{\theta \in \Theta} L(\theta)} \right) = -2 \log \left( \frac{L(\widehat{\theta}_0)}{L(\widehat{\theta})} \right)$$

$$W_n = (\mathbf{L}\widehat{\boldsymbol{\theta}}_n - \mathbf{h})^\top (\mathbf{L}\widehat{\mathbf{V}}_n \mathbf{L}^\top)^{-1} (\mathbf{L}\widehat{\boldsymbol{\theta}}_n - \mathbf{h})$$

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