

GAUSSIAN MODEL

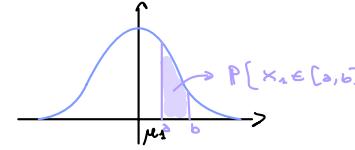
$$\mu \in \mathbb{R}^p, \quad \Sigma \text{ } p \times p \text{ positive def}$$

$$\mu = \begin{pmatrix} \mu_1 \\ \vdots \\ \mu_p \end{pmatrix}, \quad \Sigma = [\sigma_{ij}] \quad i,j = 1, \dots, p$$

$$p=1 \quad \mu_i \in \mathbb{R} \quad \sigma_{ii} > 0$$

$$\mathbb{R} \ni x_i \sim N_1(\mu_i, \sigma_{ii})$$

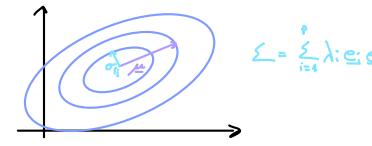
$$\text{if density of } x_i \text{ is } \phi(t) = \frac{1}{\sqrt{2\pi\sigma_{ii}}} e^{-\frac{(t-\mu_i)^2}{2\sigma_{ii}}} \quad t \in \mathbb{R}$$



General p

$$\mathbb{R}^p \ni x \sim N_p(\mu, \Sigma)$$

$$\text{if } \phi(t) = \frac{1}{\sqrt{(2\pi)^p \det(\Sigma)}} \exp \left[-\frac{1}{2} (t - \mu)^T \Sigma^{-1} (t - \mu) \right]$$



Proposition

$$x \sim N_p(\mu, \Sigma) \iff \forall a \in \mathbb{R}^p, \quad a^T x \sim N_1(a^T \mu, a^T \Sigma a)$$

Corollary

$$x \sim N_p(\mu, \Sigma) \implies x_i \sim N_1(\mu_i, \sigma_{ii}) \quad i = 1, \dots, p$$

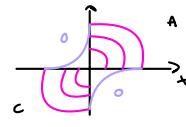
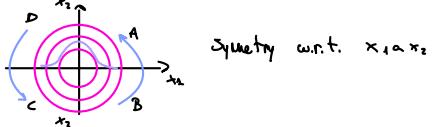
Proof: $\underline{u}_i = (0 \dots 0 \ 1 \ 0 \dots 0)^T$

$$\underline{u}_i^T x \sim N_1(\underline{u}_i^T \mu, \underline{u}_i^T \Sigma \underline{u}_i) = N_1(\mu_i, \sigma_{ii})$$

Explanation $\not\Rightarrow$

$$\text{i.e. } x_i \sim N_1(\mu_i, \sigma_{ii}) \quad \forall i = 1, \dots, p \not\Rightarrow x \sim N_p(\mu, ?)$$

Take $x \sim N_p(\mu, I)$



Same marginal, different mean
NOT GAUSSIAN!
(same variance as before)

Corollary

$$\begin{aligned} x \sim N_p(\mu, \Sigma) \\ A \text{ } q \times p \text{ matrix} \end{aligned} \implies Ax \sim N_q(A\mu, A\Sigma A^T)$$

Proof: Need to prove: $\forall a \in \mathbb{R}^q \quad a^T (Ax) \sim N_1(a^T A \mu, a^T A \Sigma A^T a)$

$$\text{but, } a^T (Ax) = (a^T A)x = (A^T a)^T x \stackrel{\substack{\text{Prop} \\ \text{CR}}}{} \sim N_1((A^T a)^T \mu, (A^T a)^T \Sigma (A^T a)) = N_1(a^T (A\mu), a^T A \Sigma A^T a)$$

Corollary

$$\det \Sigma \in \mathbb{R}^p, \quad \Sigma \sim N_p(\mu, \Sigma) \implies x + d \sim N_p(\mu + d, \Sigma)$$

Obs

$$z_1, \dots, z_p \text{ iid } \sim N_1(0, 1) \quad \text{density of } z_i: \quad \phi(t) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2} t^2}$$

$$\underline{z} = (z_1, \dots, z_p)^T \quad \text{density of } \underline{z}: \quad \phi_p(\underline{t}) = \phi_1(t_1)\phi_2(t_2)\dots\phi_p(t_p) = \frac{1}{\sqrt{(2\pi)^p}} \prod_{i=1}^p e^{-\frac{1}{2} t_i^2} = \frac{1}{\sqrt{(2\pi)^p}} e^{-\frac{1}{2} \sum_{i=1}^p t_i^2} = \frac{1}{\sqrt{(2\pi)^p}} e^{-\frac{1}{2} \underline{t}^T \underline{t}}$$

$$\Sigma \text{ } p \times p \quad \Sigma^{\frac{1}{2}} \underline{z} \sim N_p(\underline{0}, \Sigma^{\frac{1}{2}} \Sigma \Sigma^{\frac{1}{2}})$$

$$\Sigma^{\frac{1}{2}} \underline{z} + \mu \sim N_p(\mu, \Sigma)$$

$$\text{If } x \sim N_p(\mu, \Sigma) \implies \underline{z} = \Sigma^{-\frac{1}{2}}(x - \mu) \sim N_p(\underline{0}, \Sigma)$$

$$\begin{pmatrix} z_1 \\ z_2 \\ \vdots \\ z_p \end{pmatrix} \implies \text{i.e. } z_1, \dots, z_p \text{ iid } \sim N_1(0, 1)$$

$$\Sigma = \sum_{i=1}^p \lambda_i \underline{e}_i \underline{e}_i^T \implies \Sigma^{\frac{1}{2}} = \sum_{i=1}^p \lambda_i^{\frac{1}{2}} \underline{e}_i \underline{e}_i^T$$

$$\implies \underline{z} = \sum_{i=1}^p \frac{1}{\sqrt{\lambda_i}} \underline{e}_i \underline{e}_i^T$$



Obs

$$\underline{x} \sim N_p(\mu, \Sigma)$$

$$w = d_{\Sigma}^{-1}(\underline{x}, \mu) = (\underline{x} - \mu)^T \Sigma^{-1} (\underline{x} - \mu) = (\underline{x} - \mu)^T \underbrace{\Sigma^{-1/2}}_{\Sigma^{-1}} \underbrace{\Sigma^{-1/2}(\underline{x} - \mu)}_{\underline{z}}$$

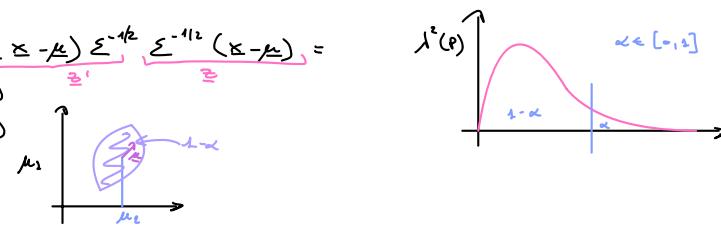
$$= \sum_i z_i^2 \sim \chi^2(p)$$

$$z_i \sim N_1(0, 1)$$

$$z_i^2 \sim \chi^2(1)$$

$$P[d_{\Sigma}^{-1}(\underline{x}, \mu) \leq \lambda_{1-\alpha}(p)] = 1-\alpha$$

$$P[(\underline{x} - \mu)^T \Sigma^{-1} (\underline{x} - \mu) \leq \lambda^2(p)] = 1-\alpha$$



$$R^p \geq \underline{x} = \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} \in \mathbb{R}^2 \quad q < p$$

$$\mu = \begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix} \in \mathbb{R}^{p-q}$$

$$\Sigma = \begin{bmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{bmatrix} \quad \begin{array}{l} \text{Cov between comp of } \\ \underline{x}_1 \text{ and comp of } \underline{x}_2 \end{array}$$

$\Sigma_{11} = \frac{q}{q-p+1} \Sigma_{11}$
 $\Sigma_{22} = \frac{p-q}{q-p+1} \Sigma_{22}$
 $\Sigma_{12} = \Sigma_{21} = \frac{1}{q-p+1} (\Sigma_{11} + \Sigma_{22})$
 $\text{Cov}(\underline{x}_1) = \Sigma_{11}$
 $\text{Cov}(\underline{x}_2) = \Sigma_{22}$

Corollary

$$\underline{x} = \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} \sim N_p \left(\begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix}, \begin{pmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{pmatrix} \right) \implies x_1 \sim N_q(\mu_1, \Sigma_{11})$$

$$\text{Proof: } A = \begin{bmatrix} I_q & 0 \\ 0 & I_{p-q} \end{bmatrix} \quad q > p$$

$$\implies A \underline{x} = x_1 \sim N_q(\mu_1, A \Sigma A^T)$$

Proposition

$$\underline{x} = \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} \sim N_p \left(\begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix}, \begin{pmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{pmatrix} \right)$$

$$\text{i.e. } \Sigma_{12} \times \Sigma_{21} = 0 \implies x_1 \perp\!\!\!\perp x_2$$

$$\phi_{\underline{x}}(\underline{t}) = \phi_{x_1}(t_1) \phi_{x_2}(t_2) \implies \underline{t} = \begin{pmatrix} t_1 \\ t_2 \end{pmatrix} \in \mathbb{R}^{p-q}$$

Theorem

$$\underline{x} = \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} \sim N_p \left(\begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix}, \begin{pmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{pmatrix} \right)$$

$$\implies x_1 | x_2 = x_2 \sim N_q(\mu_1 + \Sigma_{12} \Sigma_{22}^{-1} (x_2 - \mu_2), \Sigma_{11} - \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21})$$

Observation

$$x_1 \sim N_q(\mu_1, \Sigma_{11})$$

$$x_1 | x_2 = x_2 \sim N_p(\mu_1 + \Sigma_{12} \Sigma_{22}^{-1} (x_2 - \mu_2), \Sigma_{11} - \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21}) \quad \begin{array}{l} \text{partial cov.} \\ \text{known before knowing } x_2 \end{array}$$

Note: if $\Sigma_{12} = 0 \implies x_1 | x_2 = x_2 \sim N_q(\mu_1, \Sigma_{11})$

$$E[x_1 | x_2 = x_2] = \mu_1 + \Sigma_{12} \Sigma_{22}^{-1} (x_2 - \mu_2) \quad \text{regulation factor}$$

$$\text{Proof: Let } A = \begin{bmatrix} I_q & -\Sigma_{12} \Sigma_{22}^{-1} \\ 0 & I_{p-q} \end{bmatrix} \quad p \times p$$

$$A \begin{pmatrix} x_1 - \mu_1 \\ x_2 - \mu_2 \end{pmatrix} = \begin{pmatrix} x_1 - \mu_1 - \Sigma_{12} \Sigma_{22}^{-1} (x_2 - \mu_2) \\ x_2 - \mu_2 \end{pmatrix} \sim N_p \left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 0 & \Sigma_{11} - \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21} \\ 0 & 0 \end{pmatrix} \right)$$

$$\implies x_1 - \mu_1 - \Sigma_{12} \Sigma_{22}^{-1} (x_2 - \mu_2) \perp\!\!\!\perp x_2 - \mu_2 \implies x_1 - \mu_1 - \Sigma_{12} \Sigma_{22}^{-1} (x_2 - \mu_2) | x_2 = x_2 \sim N_q(0, \Sigma_{11} - \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21})$$

$$\implies x_1 | x_2 = x_2 \sim N_q(\mu_1 + \Sigma_{12} \Sigma_{22}^{-1} (x_2 - \mu_2), \Sigma_{11} - \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21})$$

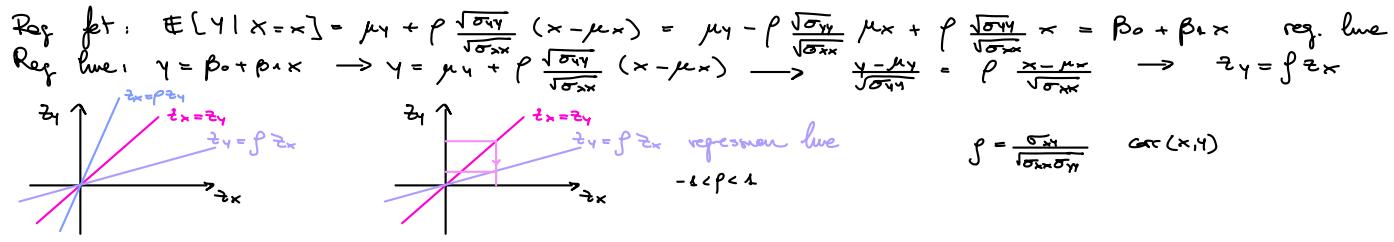
Example

$$\begin{pmatrix} x \\ y \end{pmatrix} \sim N_2 \left(\begin{pmatrix} \mu_x \\ \mu_y \end{pmatrix}, \begin{bmatrix} \sigma_{yy} & \sigma_{yx} \\ \sigma_{xy} & \sigma_{xx} \end{bmatrix} \right)$$

Before obs. $x: y \sim N_1(\mu_y, \sigma_{yy})$

$$\text{After obs. } x = x: y | x = x \sim N_1 \left(\mu_y + \frac{\sigma_{xy}}{\sigma_{xx}} (x - \mu_x), \sigma_{yy} - \frac{\sigma_{xy}^2}{\sigma_{xx}} \right) = N_1(\mu_y + \rho \frac{\sigma_{yy}}{\sigma_{xx}} (x - \mu_x), \sigma_{yy}(1 - \rho^2))$$





Estimators for μ and Σ of a $N_p(\mu, \Sigma)$

Data

$$\mathbf{X} = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} \quad \begin{array}{l} x_1 \in \mathbb{R}^k \text{ or realis. } \underline{x}_1 \\ \vdots \\ x_n \in \mathbb{R}^k \text{ or realis. } \underline{x}_n \end{array} \quad \begin{array}{l} \underline{x}_1, \dots, \underline{x}_n \text{ iid } N_p(\mu, \Sigma) \\ \mu, \Sigma \text{ unknown} \end{array}$$

Obvious estimates: $\bar{\Sigma} = \frac{1}{n} \sum_{i=1}^n \underline{x}_i \underline{x}_i'$ sample mean for μ
 $S = \frac{1}{n-1} \sum_{i=1}^n (\underline{x}_i - \bar{\Sigma})(\underline{x}_i - \bar{\Sigma})'$ for Σ

Short excursion on MLE

x_1, x_2, \dots, x_n iid Bernoulli(p), $p \in [0, 1]$
 $P[x_i=1] = p \quad P[x_i=0] = 1-p$

Data: $x_1=1, x_2=1, x_3=0, x_4=1, x_5=0$

$$\hat{p} = 3/5$$

$$P[x_1=1, x_2=1, x_3=0, x_4=1, x_5=0] = p^3(1-p)^2$$

$$L(p) = p^3(1-p)^2$$

$$l(p) = 3 \log p + 2 \log(1-p) \quad \text{Maximizing this}$$

$$\hat{p} = \arg \max L(p) = \arg \max l(p) = \frac{3}{5}$$

Exercise

x_1, \dots, x_n iid $\sim \text{Bern}(p)$

$p \in [0, 1]$ unknown

x_1, \dots, x_n data

$$L(p | x_1, \dots, x_n) = p^{\sum x_i} (1-p)^{n-\sum x_i}$$

$$l(p) = \sum x_i \log p + (n - \sum x_i) \log(1-p)$$

$$\arg \max_{p \in [0, 1]} L(p) = \frac{1}{n} \sum x_i$$

Invariance property of MLE

$$\theta \in \mathbb{R}^k \quad \hat{\theta} = \hat{\theta}(x_1, \dots, x_n) \quad \text{MLE}$$

Data $x_1, \dots, x_n \implies h: \mathbb{R}^k \rightarrow \mathbb{R}^d$
 Model

$$\eta = h(\theta) \quad \text{function of interest} \quad \hat{\eta} \quad \text{MLE} \implies \hat{\eta} = \eta(\hat{\theta}) \implies \widehat{h}(\hat{\theta}) = h(\hat{\theta})$$

EXAMPLE

Assume $\hat{\Sigma} = \frac{1}{n} \sum_{i=1}^n (\underline{x}_i - \bar{\Sigma})(\underline{x}_i - \bar{\Sigma})'$ MLE for Σ

$\Sigma = \Sigma \lambda_i e_i e_i'$ estimate λ_i, e_i ?

$\hat{\Sigma} = \hat{\Sigma} \hat{\lambda}_i \hat{e}_i \hat{e}_i'$ estimate λ_i with $\hat{\lambda}_i$ and e_i with \hat{e}_i

Back to x_1, \dots, x_n iid $\sim N_p(\mu, \Sigma)$

$$L(\mu, \Sigma | x_1, \dots, x_n) = \prod_{i=1}^n \frac{1}{\sqrt{(2\pi)^p \det(\Sigma)}} \exp\left(-\frac{1}{2} (\underline{x}_i - \mu)' \Sigma^{-1} (\underline{x}_i - \mu)\right)$$

$$l(\mu, \Sigma) = -\frac{p}{2} \log \det(\Sigma) - \frac{1}{2} \sum_{i=1}^n (\underline{x}_i - \mu)' \Sigma^{-1} (\underline{x}_i - \mu)$$

$$\arg \max_{\substack{\mu \in \mathbb{R}^p \\ \Sigma \in \mathbb{R}^{p \times p}}} l(\mu, \Sigma) = (\hat{\mu}, \hat{\Sigma})$$

$\hat{\Sigma}$ $\propto \hat{\Sigma}$ result

Theoreme

$$\underline{x}_1, \dots, \underline{x}_n \text{ iid } N_p(\mu, \Sigma)$$

HLE for μ : $\hat{\mu} = \frac{1}{n} \sum_{i=1}^n \underline{x}_i$ (unbiased)

HLE for Σ : $\hat{\Sigma} = \frac{1}{n} \sum_{i=1}^n (\underline{x}_i - \bar{\underline{x}})(\underline{x}_i - \bar{\underline{x}})^T$ (unbiased)

What dist's for $\bar{\underline{x}}$, $\hat{\Sigma}$, S' if $\underline{x}_1, \dots, \underline{x}_n$ iid $N_p(\mu, \Sigma)$

Proposition

$$\underline{x}_1, \dots, \underline{x}_n \text{ iid } N_p(\mu, \Sigma) \implies \bar{\underline{x}} \sim N_p(\mu, \frac{1}{n} \Sigma)$$

Proof:

$$\begin{aligned} \bar{\underline{x}} &= \begin{pmatrix} \underline{x}_1 \\ \underline{x}_2 \\ \vdots \\ \underline{x}_n \end{pmatrix} \in \mathbb{R}^{np} & \bar{\underline{x}} \sim N_p \left(\begin{pmatrix} \mu \\ \mu \\ \vdots \\ \mu \end{pmatrix}, \begin{pmatrix} \Sigma & 0 \\ 0 & \Sigma \end{pmatrix} \right) \\ A &= \underbrace{\begin{bmatrix} 1 & \dots & 1 & \dots & 1 \\ 0 & \dots & 0 & \dots & 0 \\ \vdots & & \vdots & & \vdots \\ 0 & \dots & 0 & \dots & 1 \end{bmatrix}}_{np} & A \text{ p} \times \text{np} & \frac{1}{n} A \bar{\underline{x}} = \begin{bmatrix} \frac{1}{n} \sum_{i=1}^n x_{i1} \\ \frac{1}{n} \sum_{i=1}^n x_{i2} \\ \vdots \\ \frac{1}{n} \sum_{i=1}^n x_{ip} \end{bmatrix} \\ \hat{\Sigma} &\sim N_p \left(\frac{1}{n} A \begin{pmatrix} \mu \\ \vdots \\ \mu \end{pmatrix}, \frac{1}{n^2} A \begin{pmatrix} \Sigma & 0 \\ 0 & \Sigma \end{pmatrix} A^T \right) = N_p \left(\mu, \frac{1}{n} \Sigma \right) \end{aligned}$$

Distr's of S or $\hat{\Sigma}$

Definition

$$\text{Let } \underline{z}_1, \dots, \underline{z}_m \text{ iid } N_p(\underline{0}, \Sigma). \quad A = \sum_{i=1}^m \underline{z}_i \underline{z}_i^T \sim \text{Wishart}(\Sigma, m)$$

Proposition 1

$$A_1 \sim \text{Wish}(\Sigma, m_1) \quad \text{if} \quad A_1 \perp\!\!\!\perp A_2 \implies A_1 + A_2 \sim \text{Wish}(\Sigma, m_1 + m_2)$$

$$A_2 \sim \text{Wish}(\Sigma, m_2)$$

Proof:

$$\begin{aligned} A_1 &= \sum_{i=1}^{m_1} \underline{z}_i \underline{z}_i^T & \underline{z}_1, \dots, \underline{z}_{m_1} \text{ iid } N_p(\underline{0}, \Sigma) \\ A_2 &= \sum_{i=1}^{m_2} \underline{z}_i \underline{z}_i^T & \underline{z}_1, \dots, \underline{z}_{m_2} \text{ iid } N_p(\underline{0}, \Sigma) \\ \underline{w}_1, \dots, \underline{w}_{m_1}, \underline{w}_{m_1+1}, \dots, \underline{w}_{m_1+m_2} &\text{ iid } N_p(\underline{0}, \Sigma) \\ \underline{z}_1 &\quad \underline{z}_{m_1} \quad \underline{z}_1 & \underline{z}_{m_1+m_2} \\ A_1 + A_2 &= \sum_{i=1}^{m_1+m_2} \underline{w}_i \underline{w}_i^T \sim \text{Wish}(\Sigma, m_1 + m_2) \end{aligned}$$

Proposition 2

$$A \sim \text{Wish}(\Sigma, m) \quad C \text{ k} \times \text{p} \text{ matrix} \implies C A C^T \sim \text{Wish}(C \Sigma C^T, m)$$

Proof:

$$A = \sum_{i=1}^m \underline{z}_i \underline{z}_i^T \quad \underline{z}_1, \dots, \underline{z}_m \text{ iid } N_p(\underline{0}, \Sigma)$$

$$C A C^T = \sum_{i=1}^m \underbrace{C \underline{z}_i \underline{z}_i^T C^T}_{\underline{w}_i \underline{w}_i^T} \quad \underline{w}_i \sim N_p(\underline{0}, C \Sigma C^T) \text{ indep.} \implies C A C^T \sim \text{Wish}(C \Sigma C^T, m)$$

Proposition 3

$$A \sim \text{Wish}(\Sigma, m) \quad \sigma^2 \mathbf{I} \implies \sigma^2 A \sim \text{Wish}(\sigma^2 \Sigma, m)$$

Proof:

$$\sigma^2 A = \sigma^2 \sum_{i=1}^m \underline{z}_i \underline{z}_i^T = \sum_{i=1}^m \underbrace{\sigma \underline{z}_i \underline{z}_i^T \sigma}_{\underline{w}_i \underline{w}_i^T} \quad \underline{w}_1, \dots, \underline{w}_m \text{ iid } N_p(\underline{0}, \sigma^2 \Sigma)$$

Proposition 4

$$\text{Let } p = s \implies \text{Wishart}(\Sigma, m) = \sigma^2 \chi^2_{(m)}$$

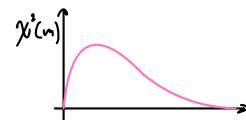
Proof:

$$\begin{aligned} p = s, \Sigma = [\sigma^2] &\implies A \sim \text{Wish}(\Sigma, m) & A = \sum_{i=1}^m \underline{z}_i \underline{z}_i^T & \underline{z}_1, \dots, \underline{z}_m \text{ iid } N_p(\underline{0}, \sigma^2 \mathbf{I}) \\ \frac{1}{\sigma^2} A = \sum_{i=1}^m \frac{\underline{z}_i \underline{z}_i^T}{\sigma^2} &= \sum_{i=1}^m \left(\frac{\underline{z}_i}{\sigma} \right)^2 & \frac{\underline{z}_i}{\sigma} \sim N_p(\underline{0}, \mathbf{I}) & \left(\frac{\underline{z}_i}{\sigma} \right)^2 \sim \chi^2(s) \end{aligned}$$



$$\frac{1}{\sigma^2} A \sim \mathcal{N}^2(\mu)$$

$$A \sim \sigma^2 \mathcal{N}^2(\mu) = W \sim \sigma \cdot N_2(0, I) \Leftrightarrow \frac{W}{\sigma} \sim N^2(0, I)$$



Exercise

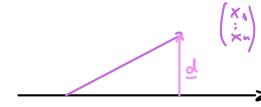
$$A \sim \text{Wish}(\Sigma, m) \quad p \times p \quad \Sigma \in \mathbb{R}^p \quad ? \quad \Sigma' A \Sigma$$

$$\Sigma' A \Sigma \sim \text{Wish}(\Sigma' \Sigma, m) \quad (\text{prop: take } C = [\Sigma']) \quad 1 \times p$$

$$\Sigma' \Sigma \geq 0 \quad \Sigma' A \Sigma \sim (\Sigma' \Sigma) \mathcal{N}^2(m) \quad \text{i.e. } \frac{\Sigma' A \Sigma}{\Sigma' \Sigma} \sim \chi^2(m)$$

Theorem

$$x_1, \dots, x_n \text{ iid } \sim N_p(\mu, \Sigma) \implies \sum_{i=1}^n (x_i - \bar{x})(x_i - \bar{x})' \sim \text{Wish}(\Sigma, n-1)$$



Corollary

$$x_1, \dots, x_n \text{ iid } \sim N_p(\mu, \Sigma)$$

$$\hat{\Sigma} = \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})(x_i - \bar{x})' \sim \text{Wish}(\frac{1}{n}\Sigma, n-1)$$

$$\hat{S} = \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})(x_i - \bar{x})' \sim \text{Wish}(\frac{1}{n-1}\Sigma, n-1)$$

Theorem

$$x_1, \dots, x_n \text{ iid } \sim N_p(\mu, \Sigma)$$

$$1. \bar{x} \sim N_p(\mu, \frac{1}{n}\Sigma)$$

$$2. (n-1)S \sim \text{Wish}(\Sigma, n-1)$$

$$3. \bar{x} \perp S$$

Recall

CLT: $\mathbb{R}^p \ni x_1, \dots, x_n \text{ iid } \sim F \quad (\text{s.t. } \mathbb{E}[x_i] = \mu, \Sigma = \text{cov}(x_i) \text{ exist})$

then $\sqrt{n}(\bar{x} - \mu) \sim A N_p(\Sigma, \Sigma)$

In particular, for n large $\bar{x} \sim N_p(\mu, \frac{1}{n}\Sigma)$

LLN: $x_1, \dots, x_n \text{ iid } \sim F(\mu, \Sigma)$

$$\begin{aligned} \bar{x} &\xrightarrow{P} \mu \\ S &\xrightarrow{P} \Sigma \end{aligned} \quad \text{as } n \rightarrow +\infty$$

Inference for the mean $\mu \in \mathbb{R}^p$

$$x_1, \dots, x_n \text{ iid } \sim F(\mu, \Sigma)$$

$$\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i$$

- n is very large ($n \gg p$): $\mathbb{R}^p \ni \sqrt{n}(\bar{x} - \mu) \sim A N_p(\Sigma, \Sigma) \quad \text{i.e. } \bar{x} \sim N_p(\mu, \frac{1}{n}\Sigma) \quad (\text{approx})$
 $\implies (\bar{x} - \mu)' (\frac{1}{n}\Sigma)^{-1} (\bar{x} - \mu) \sim \chi^2(p)$
 $\circledast n(\bar{x} - \mu)' \Sigma^{-1} (\bar{x} - \mu) \sim \chi^2(p)$

Obs: if Σ is known \circledast is precise

if Σ is unknown $S \xrightarrow{P} \Sigma$ (LLN) $\implies n(\bar{x} - \mu)' S^{-1} (\bar{x} - \mu) \sim \chi^2(p)$

$$\text{For } \alpha \in [0, 1]. \quad \Pr[n(\bar{x} - \mu)' S^{-1} (\bar{x} - \mu) \leq \chi^2_{1-\alpha}(p)] = 1 - \alpha$$

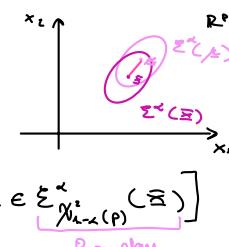
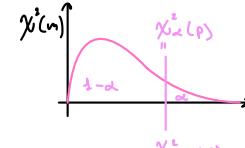
$\Pr[n(\bar{x} - \mu)' (\frac{1}{n}S)^{-1} (\bar{x} - \mu) \leq \chi^2_{1-\alpha}(p)] = 1 - \alpha$

$$\text{Consider: } \Sigma^{\chi^2_{1-\alpha}(p)}(\mu) = \{ \bar{x} \in \mathbb{R}^p : d_{(\frac{1}{n}S)^{-1}}(\bar{x}, \mu) \leq \chi^2_{1-\alpha}(p) \}$$

$$\Sigma^{\chi^2_{1-\alpha}(p)}(\bar{x}) = \{ \bar{x}' \in \mathbb{R}^p : d_{(\frac{1}{n}S)^{-1}}(\bar{x}', \bar{x}) \leq \chi^2_{1-\alpha}(p) \}$$

$$\text{Equivalent formulations for } \circledast: \quad \Pr[\bar{x} \in \Sigma^{\chi^2_{1-\alpha}(p)}(\mu)] = 1 - \alpha = \Pr[\mu \in \Sigma^{\chi^2_{1-\alpha}(p)}(\bar{x})]$$

Random Random



$$\begin{aligned} \bar{x} \in \Sigma^{\chi^2_{1-\alpha}(p)}(\mu) \\ \downarrow \\ \mu \in \Sigma^{\chi^2_{1-\alpha}(p)}(\bar{x}) \end{aligned}$$



Definition (confidence region)

$$CR_{1-\alpha}(\mu) = \{ \mu \in \mathbb{R}^p : n(\bar{\mu} - \mu)^T S^{-1} (\bar{\mu} - \mu) \leq \chi^2_{1-\alpha}(p) \}$$

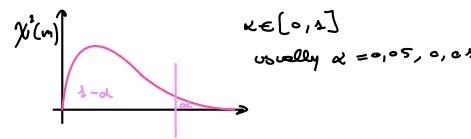


Test

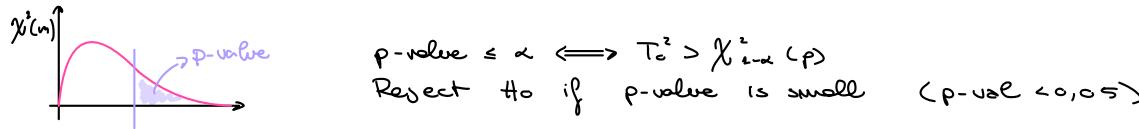
$$\begin{cases} H_0: \mu = \mu_0 & n(\bar{\mu} - \mu_0)^T S^{-1} (\bar{\mu} - \mu_0) = T_0^2 \\ H_1: \mu \neq \mu_0 & \end{cases}$$

Reject H_0 if T_0^2 is large. How large?

Reject if $\{ T_0^2 > \chi^2_{1-\alpha}(p) \}$



Let T_0^2 observed volume



Observation

$H_0: \mu = \mu_0$ is rejected if $T_0^2 > \chi^2_{1-\alpha}(p)$

$n(\bar{\mu} - \mu_0)^T S^{-1} (\bar{\mu} - \mu_0) > \chi^2_{1-\alpha}(p)$

$d^2(\frac{1}{n}S)^{-1} (\bar{\mu}, \mu_0) > \chi^2_{1-\alpha}(p) \iff \mu_0 \notin CR_{1-\alpha}(\mu)$

i.e. $CR_{1-\alpha}(\mu)$ identifies all values of μ_0 for which you cannot reject $H_0: \mu = \mu_0$

If n is not large?

X_1, \dots, X_n iid $\sim N_p(\mu, \Sigma)$

? $n(\bar{\mu} - \mu)^T S^{-1} (\bar{\mu} - \mu) \sim ?$

Definition

$Y \sim \chi^2(u)$, $W \sim \chi^2(m)$, $Y \perp\!\!\!\perp W$

Distribution of $\frac{Y/u}{W/m} \sim F(u, m)$

Observation

$$\begin{aligned} 1. \quad t &\sim t(n) \quad t = \frac{Z}{\sqrt{\frac{W}{m}}} \quad Z \sim N(0, 1) \quad Z \perp\!\!\!\perp W \\ &t^2 = \frac{Z^2}{\frac{W}{m}} \sim \chi^2_m \sim F(1, m) \quad W \sim \chi^2_m \end{aligned}$$

$$\begin{aligned} 2. \quad F(n, m) &\xrightarrow[m \rightarrow \infty]{} \frac{1}{n} \chi^2(n) \\ \frac{Y/n}{W/m} &\sim F(n, m) \quad \frac{W}{m} \xrightarrow[m \rightarrow \infty]{} ? \quad W \sim \chi^2_m \\ &\frac{1}{m} \sum_i z_i^2 \xrightarrow[m \rightarrow \infty]{} \mathbb{E}[z_i^2] = 1 \end{aligned}$$

$$\text{hence } \frac{Y/n}{W/m} \xrightarrow[m \rightarrow \infty]{\text{indistr.}} Y/n \sim \frac{1}{n} \chi^2(n)$$

Theorem (Hotelling)

- $X \sim N_p(\mu, \Sigma)$
- $mW \sim \text{Wishart}(\Sigma, m)$
- $X \perp\!\!\!\perp W$

$$\implies \frac{m-p+1}{mp} (\bar{\mu} - \mu)^T W^{-1} (\bar{\mu} - \mu) \sim F(p, m-p)$$

Corollary

$$X_1, \dots, X_n \text{ iid } \sim N_p(\mu, \Sigma) \implies n(\bar{\mu} - \mu)^T S^{-1} (\bar{\mu} - \mu) \sim \frac{(n-1)p}{n-p} F(p, n-p)$$

$$d^2(\frac{1}{n}S)^{-1} (\bar{\mu}, \mu)$$



Proof: $\sqrt{n}(\bar{\Sigma} - \mu) \sim N_p(\underline{0}, \Sigma)$
 $(n-1)S \sim \text{Wishart}(\Sigma, n-1)$ \iff with $n\mu = n-\alpha$
 $\sqrt{n}(\bar{\Sigma} - \mu) \perp\!\!\!\perp S$ $\frac{(n-1)S}{n-\alpha} \sim F_{1-\alpha}(p, n-p)$ (Practical)

$\alpha \in [0, 1]: CR_{1-\alpha}(\mu) = \left\{ \eta \in \mathbb{R}^p: n(\bar{\Sigma} - \eta)^T S^{-1}(\bar{\Sigma} - \eta) \leq \frac{(n-1)p}{n-p} F_{1-\alpha}(p, n-p) \right\}$

n large: radius² = $\chi^2_{1-\alpha}(p)$

n small, Gaussian dist.: radius² = $\frac{(n-1)p}{n-p} F_{1-\alpha}(p, n-p)$

Obs: For $n \rightarrow +\infty$ $\frac{(n-1)p}{n-p} F_{1-\alpha}(p, n-p) \xrightarrow{1} \frac{1}{p} \chi^2(p)$

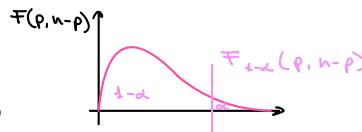
Test

$H_0: \mu = \mu_0$ test statistic $T_0^2 = n(\bar{\Sigma} - \mu_0)^T S^{-1}(\bar{\Sigma} - \mu_0)$
 $H_1: \mu \neq \mu_0$

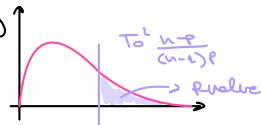
$\alpha \in [0, 1]$ Reject H_0 if:

If H_0 is true: $T_0^2 \sim \frac{(n-1)p}{n-p} F(p, n-p)$

hence reject if: $T_0^2 > \frac{(n-1)p}{n-p} F_{1-\alpha}(p, n-p)$



p-value: observed T_0^2



Obs: $CR_{1-\alpha}(\mu)$ is the set of μ_0 that you cannot reject at level α

Exercise

$n=10 \quad x_1, \dots, x_n$ iid $\sim N_2(\mu, \Sigma)$

$$\bar{\Sigma} = \underline{0}, \quad S = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

$$CR_{1-\alpha}(\mu) = \left\{ \eta \in \mathbb{R}^2: 10(\bar{\Sigma} - \eta)^T(\bar{\Sigma} - \eta) \leq \frac{(10-1)2}{10-2} F_{1-\alpha}(2, 8) \right\}$$

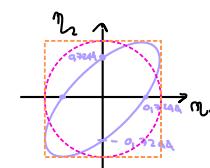
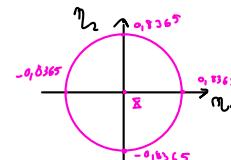
$$\alpha = 0, 1 \quad F_{0.5}(2, 8) = 3, 11$$

$$CR_{0.5}(\mu) = \left\{ \eta \in \mathbb{R}^2: 10\eta^T \eta \leq \frac{18}{8} (3, 11) \right\} = \left\{ \eta: \eta_1^2 + \eta_2^2 \leq 0, 6527 \right\}$$

Now suppose

$$\bar{\Sigma} = \underline{0}, \quad S = \begin{bmatrix} 1 & 0.5 \\ 0.5 & 1 \end{bmatrix}$$

$$\begin{aligned} CR_{0.5}(\mu) &= \left\{ \eta: \eta^T S^{-1} \eta \leq 0, 6527 \right\} \\ &= \left\{ \eta: \frac{4}{3} \eta_1^2 - \frac{4}{3} \eta_1 \eta_2 + \frac{4}{3} \eta_2^2 \leq 0, 6527 \right\} \end{aligned}$$



Inference for linear combination of μ

$\Sigma_1, \dots, \Sigma_n$ iid $\sim N_p(\mu, \Sigma)$, μ estimator is $\bar{\Sigma}$

Which can be estimated for $\alpha^T \mu = \alpha_1 \mu_1 + \alpha_2 \mu_2 + \dots + \alpha_p \mu_p$ for $\alpha \in \mathbb{R}^p$?

It can be: $\alpha^T \bar{\Sigma}$ but I want to consider uncertainty, I need an interval.

- $\alpha^T \bar{\Sigma} \sim N_1(\alpha^T \mu, \frac{1}{n} \alpha^T \Sigma \alpha)$
- $\frac{\sqrt{n}(\alpha^T \bar{\Sigma} - \alpha^T \mu)}{\sqrt{\alpha^T \Sigma \alpha}} \sim N_1(0, 1)$ $\perp\!\!\!\perp \frac{(n-1)\alpha^T S \alpha}{\alpha^T \Sigma \alpha} \sim \chi^2(p)$

- $(n-1)S \sim \text{Wish}(\Sigma, n-1)$
 $(n-1)\alpha^T S \alpha \sim \text{Wish}(\alpha^T \Sigma \alpha, n-1) \sim (\alpha^T \Sigma \alpha) \chi^2(p)$

- $N(0, 1) \sim \frac{\sqrt{n}(\alpha^T \bar{\Sigma} - \alpha^T \mu)}{\sqrt{\alpha^T \Sigma \alpha}}$
 $\perp\!\!\!\perp \frac{\sqrt{\chi^2(p)}}{\sqrt{\frac{(n-1)\alpha^T S \alpha}{\alpha^T \Sigma \alpha}}} \sim t(n-1)$

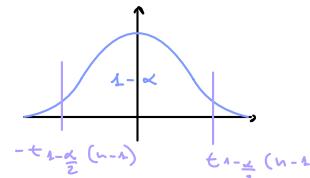
we can rewrite $\frac{\sqrt{n}(\alpha^T \bar{\Sigma} - \alpha^T \mu)}{\sqrt{\alpha^T \Sigma \alpha}} \sim t(n-1)$
(Pactical)



$$\alpha \in [0, 1] \\ \Pr \left[\frac{\sqrt{n} |\bar{x} - \mu|}{\sqrt{\sigma^2 / n}} < t_{1-\frac{\alpha}{2}}(n-1) \right] = 1 - \alpha$$

$$\Pr \left[|\bar{x} - \mu| < t_{1-\frac{\alpha}{2}}(n-1) \cdot \sqrt{\frac{\sigma^2}{n}} \right] = 1 - \alpha$$

$$CI_{1-\alpha}(\bar{x}, \mu) = \left[\bar{x} \pm t_{1-\frac{\alpha}{2}}(n-1) \sqrt{\frac{\sigma^2}{n}} \right]$$



Ex: $\underline{x} = [0 \dots 0 1 0 \dots 0] \quad i=1, \dots, p$

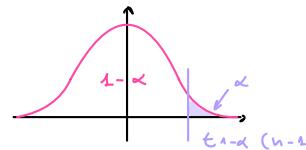
$$CI_{1-\alpha}(\mu_i) = [\bar{x}_i \pm t_{1-\frac{\alpha}{2}}(n-1) \sqrt{\frac{s_{ii}}{n}}]$$

$$CI_{1-\alpha}(\mu_i - \mu_j) = [\bar{x}_i - \bar{x}_j \pm t_{1-\frac{\alpha}{2}}(n-1) \sqrt{\frac{s_{ii} + s_{jj} - 2s_{ij}}{n}}]$$

Test

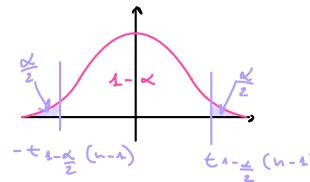
$$\begin{cases} H_0: \bar{x} - \mu \leq \delta_0 & \text{test stat: } \frac{\bar{x} - \mu}{\sqrt{\sigma^2 / n}} \sim t_{n-1} \\ H_1: \bar{x} - \mu > \delta_0 \end{cases}$$

Reject H_0 if: $t_0 > t_{1-\alpha}(n-1)$



$$\begin{cases} H_0: \bar{x} - \mu = \delta_0 & t_0 = \frac{\bar{x} - \mu}{\sqrt{\sigma^2 / n}} \sim t_{n-1} \\ H_1: \bar{x} - \mu \neq \delta_0 \end{cases}$$

Reject H_0 if: $t_0 > t_{1-\frac{\alpha}{2}}(n-1)$
or $t_0 < -t_{1-\frac{\alpha}{2}}(n-1)$



$$\alpha \in [0, 1] \quad \forall \underline{a} \in \mathbb{R}^p : CI_{1-\alpha}(\bar{x}, \mu) = \left[\bar{x} \pm t_{1-\frac{\alpha}{2}}(n-1) \sqrt{\frac{\sigma^2}{n}} \right] \\ \forall \underline{a} \in \mathbb{R}^p : \Pr \left[\underline{a}' \underline{\mu} \in \left[\bar{x} \pm t_{1-\frac{\alpha}{2}}(n-1) \sqrt{\frac{\sigma^2}{n}} \right] \right] = 1 - \alpha$$

$$? \Pr \left[\underline{a}' \underline{\mu} \in \left[\bar{x} \pm t_{1-\frac{\alpha}{2}}(n-1) \sqrt{\frac{\sigma^2}{n}} \right], \forall \underline{a} \in \mathbb{R}^p \right] = 1 - \alpha \\ \hookrightarrow \text{it can't be this distribution}$$

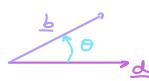
"given an interval, its prob is"

"given all intervals, thus prob is
for all possible trial simultaneously"

A bit of Algebra

$$b, d \in \mathbb{R}^p$$

$$\cos \theta = \frac{\underline{b}' \underline{d}}{\|\underline{b}\| \|\underline{d}\|}$$



$$(\underline{b}' \underline{d})^2 = \|\underline{b}\|^2 \|\underline{d}\|^2 \cos^2 \theta$$

$$(\underline{b}' \underline{d})^2 \leq \|\underline{b}\|^2 \|\underline{d}\|^2 \quad (\text{equality if } \theta = 0, \text{ meaning } \underline{b} = k \underline{d})$$

$$(\sum_i b_i d_i)^2 \leq (\sum_i b_i)(\sum_i d_i) \quad \text{CAUCHY-SCHWARTZ}$$

EXTENDED C.S. INEQUALITY

$$B: \text{pos. def.}, \forall b, d \in \mathbb{R}^p \implies (\underline{b}' \underline{d})^2 \leq (\underline{b}' B \underline{b})(\underline{d}' B^{-1} \underline{d}) \quad (\text{with equality if } b \in \mathcal{L}(B^{-1} d))$$

$$(\underline{b}' \underline{d})^2 = (\underline{b}' B^{1/2} B^{-1/2} \underline{d})^2 \leq \|\underline{B}^{1/2} \underline{b}\|^2 \|\underline{B}^{-1/2} \underline{d}\|^2 = \frac{(\underline{b}' B^{1/2} B^{-1/2} \underline{b})(\underline{d}' B^{-1/2} B^{1/2} \underline{d})}{\underline{b}' B^{1/2} B^{-1/2} \underline{b}} = \frac{1}{2} (\underline{b}' B \underline{b})(\underline{d}' B^{-1} \underline{d})$$

Lemma

$$B \text{ pos. def. } \underline{d} \in \mathbb{R}^p \quad \max_{\substack{\underline{x} \in \mathbb{R}^p \\ \underline{x} \neq \underline{0}}} \frac{(\underline{x}' \underline{d})^2}{\underline{x}' B \underline{x}} = \underline{d}' B^{-1} \underline{d}$$

Proof: $(\underline{x}' \underline{d})^2 \leq (\underline{x}' B \underline{x})(\underline{d}' B^{-1} \underline{d})$ c.s. eq holds if $\underline{x} \in \mathcal{L}(B^{-1} \underline{d})$

Since $\underline{x} \neq \underline{0} \Rightarrow \underline{x}' B \underline{x} > 0 \Rightarrow \frac{(\underline{x}' \underline{d})^2}{\underline{x}' B \underline{x}} \leq (\underline{d}' B^{-1} \underline{d}) \quad \forall \underline{x} \neq \underline{0}$

$$\implies \max_{\underline{x} \in \mathbb{R}^p} \frac{(\underline{x}' \underline{d})^2}{\underline{x}' B \underline{x}} = \underline{d}' B^{-1} \underline{d}$$



$$\underline{\alpha} \in \mathbb{R}^p \quad \frac{\underline{\alpha}' \bar{x} - \underline{\alpha}' \mu}{\sqrt{\underline{\alpha}' S \underline{\alpha}}} \sqrt{n} \quad \text{Let's square it and minimize}$$

$$\max_{\underline{\alpha} \in \mathbb{R}^p} \frac{(\underline{\alpha}' \bar{x} - \underline{\alpha}' \mu)^2}{\underline{\alpha}' S \underline{\alpha}} \quad n = n(\bar{x} - \mu)' S^{-1} (\bar{x} - \mu)$$

$$\Pr \left[\underline{\alpha}' \mu \in \left[\underline{\alpha}' \bar{x} \pm c \sqrt{\frac{\underline{\alpha}' S \underline{\alpha}}{n}} \right], \forall \underline{\alpha} \in \mathbb{R}^p \right] = 1 - \alpha \quad \alpha \in [0, 1]$$

$$\Pr \left[\frac{(\underline{\alpha}' (\bar{x} - \mu))^2}{\underline{\alpha}' S \underline{\alpha}} n \leq c^2, \forall \underline{\alpha} \in \mathbb{R}^p \right] = \Pr \left[\max_{\underline{\alpha} \in \mathbb{R}^p} \frac{(\underline{\alpha}' (\bar{x} - \mu))^2}{\underline{\alpha}' S \underline{\alpha}} n \leq c^2 \right] = 1 - \alpha$$

$$\Rightarrow c^2 = \frac{(n-1)\rho}{n-\rho} F_{1-\alpha}(\rho, n-\rho)$$

Hence $\boxed{\Pr \left[\underline{\alpha}' \mu \in \left[\underline{\alpha}' \bar{x} \pm \sqrt{\frac{(n-1)\rho}{n-\rho} F_{1-\alpha}(\rho, n-\rho)} \sqrt{\frac{\underline{\alpha}' S \underline{\alpha}}{n}} \right], \forall \underline{\alpha} \in \mathbb{R}^p \right] = 1 - \alpha}$

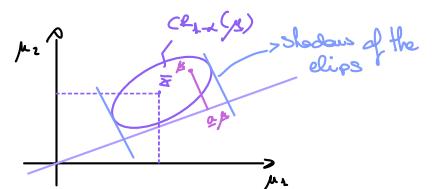
$$\alpha \in [0, 1]$$

For $\underline{\alpha} \in \mathbb{R}^p$ $CI_{1-\alpha}(\underline{\alpha}' \mu) = \left[\underline{\alpha}' \bar{x} \pm t_{1-\frac{\alpha}{2}}(n-1) \sqrt{\frac{\underline{\alpha}' S \underline{\alpha}}{n}} \right]$ Smaller one-at-the-time

Simultaneously-interval-conf: $Sim CI_{1-\alpha}(\underline{\alpha}' \mu) = \left[\underline{\alpha}' \bar{x} \pm \sqrt{\frac{(n-1)\rho}{n-\rho} F_{1-\alpha}(\rho, n-\rho)} \sqrt{\frac{\underline{\alpha}' S \underline{\alpha}}{n}} \right]$ Bigger

$$\alpha \in [0, 1]$$

$$CR_{1-\alpha}(\mu) = \left[\mu \in \mathbb{R}^p : n(\bar{x} - \mu)' S^{-1} (\bar{x} - \mu) \leq \frac{(n-1)\rho}{n-\rho} F_{1-\alpha}(\rho, n-\rho) \right]$$



$$\text{Let } \underline{\alpha}_1, \dots, \underline{\alpha}_k \in \mathbb{R}^p$$

$$\beta \in [0, 1] \quad CI_{1-\beta} \left[\underline{\alpha}_i' \bar{x} \pm t_{1-\frac{\beta}{2}}(n-1) \sqrt{\frac{\underline{\alpha}_i' S \underline{\alpha}_i}{n}} \right] \text{ for all } i=1, \dots, k \text{ is an one-at-time CI for } \underline{\alpha}_i' \mu \text{ of level } 1-\beta$$

$$\alpha \in [0, 1] \quad \Pr \left[\bigcap_{i=1}^k [\underline{\alpha}_i' \mu \in CI_{1-\beta}(\underline{\alpha}_i' \mu)] \right] = 1 - \alpha = 1 - \Pr \left[\bigcup_{i=1}^k [\underline{\alpha}_i' \mu \notin CI_{1-\beta}(\underline{\alpha}_i' \mu)] \right] = 1 - \sum_{i=1}^k \Pr \left[\underline{\alpha}_i' \mu \notin CI_{1-\beta}(\underline{\alpha}_i' \mu) \right] = 1 - k\beta$$

$$\text{Hence take } \beta = \alpha/k$$

$$\text{Bonferroni sim conf int for } \underline{\alpha}_i' \mu \quad i=1, \dots, k: \quad BCI(\underline{\alpha}_i' \mu) = \left[\underline{\alpha}_i' \bar{x} \pm t_{1-\frac{\alpha}{2k}}(n-1) \sqrt{\frac{\underline{\alpha}_i' S \underline{\alpha}_i}{n}} \right]$$

$$\text{Testing } \underline{\alpha}_1, \dots, \underline{\alpha}_k \in \mathbb{R}^p$$

$$H_0: \begin{cases} \underline{\alpha}_1' \mu = \delta_1 \\ \underline{\alpha}_2' \mu = \delta_2 \\ \vdots \\ \underline{\alpha}_k' \mu = \delta_k \end{cases} \quad \text{vs} \quad H_A: \exists i \in \{1, \dots, k\} \quad \text{s.t. } \underline{\alpha}_i' \mu \neq \delta_i$$

$$\alpha \in [0, 1] \quad \text{Reject } H_0 \text{ at level } \alpha \text{ if for at least one } i \in \{1, \dots, k\}$$

$$\frac{|\underline{\alpha}_i' \bar{x} - \delta_i|}{\sqrt{\underline{\alpha}_i' S \underline{\alpha}_i}} \sqrt{n} > t_{1-\frac{\alpha}{2k}}(n-1) \quad (\text{Bonferroni})$$

$$\begin{aligned} \Pr \left[\text{reject } H_0 \mid H_0 \text{ is true} \right] &= \Pr \left[\bigcup_{i=1}^k \left\{ \frac{|\underline{\alpha}_i' \bar{x} - \delta_i|}{\sqrt{\underline{\alpha}_i' S \underline{\alpha}_i}} \sqrt{n} > t_{1-\frac{\alpha}{2k}}(n-1) \right\} \mid H_0 \right] \\ &\leq \sum_{i=1}^k \Pr \left[\frac{|\underline{\alpha}_i' \bar{x} - \delta_i|}{\sqrt{\underline{\alpha}_i' S \underline{\alpha}_i}} \sqrt{n} > t_{1-\frac{\alpha}{2k}}(n-1) \mid H_0 \right] = \alpha \end{aligned}$$