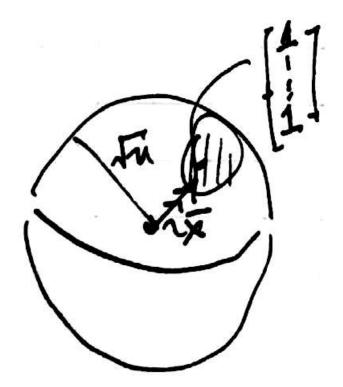
1 Outline

- (a) Testing in General Linear Models
- (b) t, Z, F, χ^2 tests
- (c) Aymptotics: Conv. in Prob.

2 Review

Example 2.1 (1-sample *t*-test). $X_1, \ldots, X_n \stackrel{iid}{\sim} N(\mu, \sigma^2), \sigma^2 > 0$ unknown. Test $H_0: \mu \leq 0$ vs $H_1: \mu > 0$ ($\iff \frac{\mu}{\sigma^2} \leq 0$ vs $\frac{\mu}{\sigma^2} > 0$).

Condition on $\|X\|^2 = u$ ($\Longrightarrow X \stackrel{H_0}{\sim} \mathrm{Unif}(\{z: |z| = \sqrt{u}\})$). Reject when $\frac{\bar{X}}{\|X\|^2 - n\bar{X}^2} > c$ reject when $\frac{\bar{X}}{\sqrt{\frac{\|X\|^2 - n\bar{X}^2}{n-1}}} > c$



Under H_0 , X is uniformly distributed on sphere with radius \sqrt{u} . \bar{X} measures the magnitude of X in the $\begin{bmatrix} 1 & 1 & \cdots & 1 \end{bmatrix}^T$ direction.

3 Basic Setup

Observe $Y \sim N(\theta, \sigma^2 I_n)$. $\theta \in \mathbb{R}^n$, $\sigma^2 > 0$ possibly unknown. Models/hypotheses framed in terms of linear constraints on θ . \mathcal{P} constraints $\theta \in \Theta$, d-dimensional affine space. $H_0: \theta \in \Theta_0 \subset \Theta$ d_0 -dimensional.

Example 3.1. One-sample *t*-test. \mathcal{P} constrains $\theta = \mu 1_n$, $H_0: \theta = 0_n$.

Example 3.2. Two-sample testing $H_0: \mu = \nu \text{ vs } H_1: \mu \neq \nu \ Y_{1,1}, \ldots, Y_{1,n} \overset{iid}{\sim} N(\mu, \sigma^2)$ $Y_{1,1}, \ldots, Y_{1,n} \overset{iid}{\sim} N(\nu, \sigma^2) \ Y = (Y_{1,1}, \ldots, Y_{1,n}, Y_{2,1}, \ldots, Y_{2,n}) \sim N(\theta, \sigma^2 I_{2n}) \ \Theta = \mu(1_n, 0_n) + \nu(0_n, 1_n) \ \Theta_0 = \mu 1_{2n}$

Example 3.3. One-way ANOVA $H_0: \mu_1 = \cdots = \mu_k Y_{k,i} \stackrel{indeed}{\sim} N(\mu_k, \sigma^2) \dim(\Theta) = k \dim(\Theta_0) = 1$

Example 3.4. Linear regression $X \in \mathbb{R}^{n \times d}$, d < n, X full column rank. $Y \sim N(X\beta, \sigma^2 I_n)$, $\beta \in \mathbb{R}^d$. $H_0: \beta_1 = \cdots = \beta_s = 0$, $s \le d$. d = d, $d_0 = d - s$.

4 General Strategy

Rotate Y by some orthogonal matrix Q

$$Q = \begin{bmatrix} d_0 & d_{-s} & n-d \\ Q_0 & Q_1 & Q_r \\ \text{o.n. basis for } \Theta_0 & \text{o.n. basis for } \Theta \cap \Theta_0^\perp \text{ o.n. basis for } \mathbb{R}^d \cap \Theta^\perp \end{bmatrix}$$

$$Z = Q'Y \sim N\left(\begin{pmatrix} Q'_0\theta \\ Q'_1\theta \\ Q'_r\theta \end{pmatrix}, \sigma^2I_n\right) \operatorname{Var}(Q'Y) = Q'\operatorname{Var}(Y)Q = \sigma^2I_n\begin{pmatrix} Z_0 \\ Z_1 \\ Z_r \end{pmatrix} \sim N\left(\begin{pmatrix} \nu_0 \\ \nu_1 \\ \nu_r \end{pmatrix}, \sigma^2I_n \right)$$

$$\operatorname{Model} \implies \nu_r = 0, \quad d, \ H_0: \nu_1 = 0.$$

Example 4.1. $\Theta_0 = \text{span}(X_{s+1}, ..., X_d). \ \Theta = \text{span}(X_1, ..., X_d).$

$$Q_0 = \left\{ \frac{X_{s+1}}{\|X_{s+1}\|}, \frac{\prod_{X_{s+1}^{\perp}} X_{s+2}}{\|\cdot\|}, \dots, \frac{\prod_{(X_{s+1}, \dots, X_d)^{\perp}} X_d}{\|\cdot\|} \right\}$$

Use Gram-Schmidt to get the successive o.n. bases.

We now have the problem in this canonical form:

$$Z_0 \sim N(\nu_0, \sigma^2 I_{d_0})$$

$$Z_1 \sim N(\nu_1, \sigma^2 I_s)$$

$$Z_r \sim N(0, \sigma^2 I_{n-d})$$

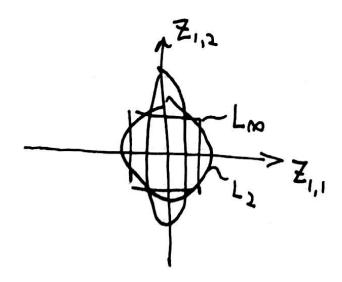
All 3 independent normal random vectors with different means, $H_0: \nu_1 = 0$. How to test H_0 ?

5 χ^2 , t, F distributions

$$\begin{split} Z_1, \dots, Z_d &\overset{iid}{\sim} N(0,1) \implies \|Z\|_2^2 = \sum_{i=1}^n Z_i^2 \sim \chi_d^2. \\ Y \sim N(0,1) \text{ independent of } Z \implies \frac{Z_1}{\sqrt{\|Z\|^2/d}} \sim t_d. \end{split}$$

$$Y_1, \ldots, Y_{d_1} \stackrel{iid}{\sim} N(0,1) \text{ and } Z_1, \ldots, Z_{d_2} \stackrel{\text{viid}}{\sim} N(0,1) \text{ independent} \implies \frac{\|Y\|^2/d_1}{\|Z\|^2/d_2} \sim F_{d_1,d_2}.$$

Case 1: σ^2 known. s=1: reject for $\frac{Z_1}{\sigma}(\stackrel{H_0}{\sim}N(0,1))$ large or extreme. s > 1: reject for $\frac{\|Z_1\|^2}{\sigma^2} 2(\stackrel{H_0}{\sim} \chi_S^2))$ large.



Case 2:
$$\sigma^2$$
 unknown, $\text{Var}(Z_1)$ unknown, $\frac{\|Z_r\|^2}{\sigma^2} \sim \chi_r^2$.

s=1: reject for $\frac{Z_1}{\sqrt{\|Z_r\|^2/(d-s)}} Z_1 \overset{H_0}{\sim} N(0,\sigma^2)$, $\frac{Z_1}{\sigma} \sim N(0,1) \ V = \sqrt{\frac{\|Z_1\|^2}{\sigma^2}} \sim \sqrt{\chi_{n-d}^2}$

$$\frac{Z_r/\sigma}{\sqrt{\frac{\|Z_r\|^2}{\sigma^2}/(d-s)}} = \frac{Z_1}{\sqrt{\frac{\|Z_r\|^2}{n-d}}} \sim t_{n-d}$$

$$\hat{\sigma}^2 = \frac{\|Z_r\|^2}{n-d} E \|Z_r\|^2 = (n-d)E(Z_{r,1}^2) E[\hat{\sigma}^2] = \sigma^2$$

$$\operatorname{Var}(\|Z_r\|^2) = (n-d)\operatorname{Var}(Z_{r,1}^2) = (n-d)2\sigma^4$$

$$Var(||Z_r||^2) = (n-d)Var(Z_{r,1}^2) = (n-d)2\sigma^4$$

The point is that $Var(\hat{\sigma}^2) = \frac{2\sigma^4}{(n-d)^2} \to 0$ so $\hat{\sigma}^2$ is a consistent estimator of σ^2 .

s > 1: reject for
$$\frac{\|Z_1\|^2/s}{\hat{\sigma}^2} = \frac{\|Z_1\|^2/s}{\|Z_r\|^2/(n-d)} \sim F_{s,n-d}$$

Summary

$$\begin{array}{c|cccc} & s = 1 & s > 1 \\ \hline \sigma^2 \text{ known} & \frac{Z_1}{\sigma} \left(Z\text{-test} \right) & \frac{\|Z_1\|^2}{\sigma} \left(\chi_s^2 \text{-test} \right) \\ \hline \sigma^2 \text{ unknown} & \frac{Z_1}{\hat{\sigma}} \left(t_{n-d} \text{-test} \right) & \frac{\|Z_1\|_2^2/s}{\hat{\sigma}^2} \left(F_{s,n-d} \text{-test} \right) \end{array}$$

Example: Regression
$$X \in \mathbb{R}^{n \times d}$$
. $Y \sim N(X\beta, \sigma^2 I_n) H_0 : \beta_d = 0$

$$Q_{0} = \begin{bmatrix} \frac{X_{1}}{\|X_{1}\|} & \frac{X_{2\perp}}{\|X_{2\perp}\|} & \cdots & \frac{X_{d-1\perp}}{\|X_{d-1\perp}\|} \end{bmatrix}$$

$$X_{k\perp} = \prod_{\substack{\text{span}(X_{1}, \dots, X_{k-1})^{\perp}}} (X_{k})$$

$$Q_{1} = \frac{X_{d\perp}}{\|X_{d\perp}\|} = \frac{(I - Q_{0}Q'_{0})X_{d}}{\|\cdot\|}$$

$$Q_{r} = \text{completion of basis}$$

$$Z_{1} = \frac{X'_{d\perp}Y}{\|X_{d\perp}\|} = \frac{\hat{\beta}_{d}}{\text{s.e.}(\hat{\beta}_{d})}$$

$$\|Z_{r}\|^{2} = \|(I - \prod_{\substack{\text{span}(x)}})Y\|^{2} = \sum_{i} (Y_{i} - \hat{Y}_{i})^{2} = \text{RSS}$$