Theoretical Statistics. Lecture 24. Peter Bartlett

- 1. Relative efficiency of tests. [vdv14]
 - (a) Asymptotic power functions.
 - (b) Asymptotic relative efficiency of tests.

Example: Suppose $X_1, \ldots, X_n \sim P_{\theta}$, where

- 1. P_{θ} has density $f(x \theta)$ on \mathbb{R} ,
- 2. *f* is symmetric about zero (so the mean=median of P_{θ} is θ),
- 3. f has a unique median $(f(0) \neq 0)$,
- 4. *f* has a finite variance.

We wish to test $H_0: \theta = 0$ versus $H_1: \theta > 0$.

Example: Candidate tests:

1. Sign test:
$$S_n = \frac{1}{n} \sum_{i=1}^n 1[X_i > 0].$$

2. t-test: $T_n = \frac{1}{n} \sum_{i=1}^n \frac{X_i}{S_n}.$

Which is better?

Recall: Relative efficiency of tests. Sign test

Definition: The power function of a test that rejects the null hypothesis when the statistic T_n falls in the critical region K_n is

$$\pi_n(\theta) = P_\theta(T_n \in K_n).$$

For the sign test,

$$\pi_n(\theta) = 1 - \Phi\left(\frac{\sigma(0)z_\alpha + \sqrt{n}\left(\mu(0) - \mu(\theta)\right)}{\sigma(\theta)}\right) + o(1)$$
$$\rightarrow \begin{cases} \alpha & \text{if } \theta = 0, \\ 1 & \text{if } \theta > 0. \end{cases}$$

So the limiting power function is perfect. (Typical for a reasonable test.)

How do we compare tests? We need to make the problem of discriminating between the null and the alternative more difficult as n increases. It is natural to consider a **shrinking alternative**, that converges to the null.

We wish to test $H_0: \theta = 0$ versus $H_1: \theta_n > 0$, with $\theta_n \to 0$.

For the sign test,

$$\pi_n(\theta_n) = 1 - \Phi\left(\frac{\sigma(0)z_\alpha + \sqrt{n}\left(\mu(0) - \mu(\theta_n)\right)}{\sigma(\theta_n)}\right) + o(1).$$

The power depends on the asymptotics of $\sqrt{n} (\mu(0) - \mu(\theta_n))$. Since F is differentiable at 0,

$$\sqrt{n}\left(\mu(0) - \mu(\theta_n)\right) = \sqrt{n}\left(F(-\theta_n) - F(0)\right) = -\sqrt{n}\theta_n f(0) + o(\sqrt{n}\theta_n).$$

If $\theta_n \to \theta$ faster than $1/\sqrt{n}$, $\sqrt{n} (\mu(0) - \mu(\theta_n)) \to 0$, so $\pi_n(\theta_n) \to \alpha$. The test fails: these alternatives are too hard.

For $\theta_n \to \theta$ slower than $1/\sqrt{n}$, $\sqrt{n} (\mu(0) - \mu(\theta_n)) \to -\infty$, so $\pi_n(\theta_n) \to 1$. These slowly shrinking alternatives are too easy.

Consider an intermediate rate:

 $\sqrt{n}\theta_n \to h.$

If
$$\sqrt{n}\theta_n \to h$$
, then $\sqrt{n} \left(\mu(0) - \mu(\theta_n)\right) \to -hf(0)$, so
 $\pi_n(\theta_n) \to 1 - \Phi\left(\frac{\sigma(0)z_\alpha - hf(0)}{\sigma(0)}\right)$
 $= 1 - \Phi\left(z_\alpha - 2hf(0)\right)$
 $= \Phi\left(2hf(0) - z_\alpha\right).$

This leads to a natural asymptotic comparison of two tests for $H_0: \theta = 0$ versus $H_1: \theta > 0$:

Compare the local limiting power functions,

$$\pi(h) = \lim_{n \to \infty} \pi_n \left(\frac{h}{\sqrt{n}}\right)$$

for $h \ge 0$.

Theorem: Suppose that (1) T_n , μ , and σ are such that, for all h and $\theta_n = h/\sqrt{n}$,

$$\frac{\sqrt{n}\left(T_n - \mu(\theta_n)\right)}{\sigma(\theta_n)} \stackrel{\theta_n}{\rightsquigarrow} N(0, 1),$$

(2) μ is differentiable at 0, (3) σ is continuous at 0. Then a test that rejects $H_0: \theta = 0$ for large values of T_n and is asymptotically of level α satisfies, for all h,

$$\pi_n\left(\frac{h}{\sqrt{n}}\right) \to 1 - \Phi\left(z_\alpha - h\frac{\mu'(0)}{\sigma(0)}\right).$$

Proof:

Substituting h = 0 shows that the asymptotic level of the test is α iff we reject $H_0: \theta = 0$ for

$$\frac{\sqrt{n}\left(T_n - \mu(0)\right)}{\sigma(0)} > z_{\alpha}.$$

Thus,

$$\pi_n(\theta_n) = P_{\theta_n} \left(\sqrt{n} \left(T_n - \mu(0) \right) > \sigma(0) z_\alpha \right)$$

= $P_{\theta_n} \left(\sqrt{n} \frac{\left(T_n - \mu(\theta_n) \right)}{\sigma(\theta_n)} > \frac{\sigma(0) z_\alpha - \sqrt{n} \left(\mu(\theta_n) - \mu(0) \right)}{\sigma(\theta_n)} \right)$
 $\rightarrow 1 - \Phi \left(z_\alpha - h \frac{\mu'(0)}{\sigma(0)} \right).$

So we have an easy comparison between tests based on locally asymptotically normal statistics: compare the **slope** of the tests, $\mu'(0)/\sigma(0)$. The bigger the slope, the faster $\pi_n(h/\sqrt{n})$ increases from α as h increases from 0.

Example: sign test

$$\mu(\theta) = 1 - F(-\theta),$$

$$\mu'(\theta) = f(-\theta),$$

$$\sigma^2(\theta) = (1 - F(-\theta))F(-\theta),$$

$$\frac{\mu'(0)}{\sigma(0)} = 2f(0).$$

Relative efficiency of tests: t-test

$$T_n = \frac{\bar{X}_n}{S_n}.$$
$$\sqrt{n} \frac{\bar{X}_n - \theta}{S_n} \stackrel{\theta}{\leadsto} N(0, 1).$$

Reject H_0 if $\sqrt{n}T_n > z_{\alpha}$.

Relative efficiency of tests: t-test

$$\pi_n(\theta) = P_\theta \left(\sqrt{nT_n} > z_\alpha\right)$$
$$= P_\theta \left(\sqrt{n\frac{X_n - \theta}{S_n}} > z_\alpha - \sqrt{n\frac{\theta}{S_n}}\right)$$
$$= 1 - \Phi \left(z_\alpha - \sqrt{n\frac{\theta}{\sigma}}\right) + o(1).$$

As before,

So

$$\pi_n(\theta) \to \begin{cases} \alpha & \text{if } \theta = 0, \\ 1 & \text{if } \theta > 0. \end{cases}$$

The limiting power function is perfect.

$$\begin{aligned} \mathbf{Relative efficiency of tests: t-test} \\ T_n &= \frac{\bar{X}_n}{S_n}. \\ \sqrt{n} \frac{\bar{X}_n - \theta}{S_n} &\stackrel{\theta}{\rightsquigarrow} N(0, 1). \\ \sqrt{n} \left(\frac{\bar{X}_n}{S_n} - \frac{h/\sqrt{n}}{\sigma}\right) &= \sqrt{n} \left(\frac{\bar{X}_n - h/\sqrt{n}}{S_n}\right) + h\left(\frac{1}{S} - \frac{1}{\sigma}\right) \stackrel{h/\sqrt{n}}{\rightsquigarrow} N(0, 1). \\ \mu(\theta) &= \frac{\theta}{\sigma}, \\ \sigma(\theta) &= 1. \\ \frac{\mu'(0)}{\sigma(0)} &= \frac{1}{\sigma}. \end{aligned}$$

sign test:

t-test:

$$\frac{u'(0)}{\sigma(0)} = 2f(0)$$
$$\frac{u'(0)}{\sigma(0)} = \frac{1}{\sigma}.$$

Laplace: $2f(0)\sigma = 2.$ Logistic: $2f(0)\sigma = \frac{\pi^2}{12} = 0.82246703.$ Normal: $2f(0)\sigma = \frac{2}{\pi} = 0.63661977.$ Uniform: $2f(0)\sigma = \frac{1}{3}.$

But the fact that the local limiting power function for the sign test depends on the density at a single point (0) should raise a red flag! Consider a uniform distribution with its density slightly modified to give a huge, narrow peak at 0. The sign test will have better asymptotics, but unless we have a huge sample, this distribution would be hard to distinguish from a uniform. That is, the asymptotics would need a very large n to be relevant.

Asymptotic relative efficiency of tests

Definition: For level α and power $\gamma \in (\alpha, 1)$, the **asymptotic relative** efficiency or Pitman efficiency of test 1 with respect to test 2 is

$$\lim_{\nu \to \infty} \frac{n_{\nu,1}}{n_{\nu,2}},$$

where $n_{\nu,1}$ is the minimal number of observations such that

 $\pi_{n_{\nu,1}}(0) \le \alpha, \quad \text{and} \quad \pi_{n_{\nu,1}}(\theta_{\nu}) \ge \gamma.$

Asymptotic relative efficiency of tests

Theorem: For a model P_{θ} , suppose $||P_{\theta} - P_0|| \to 0$ as $\theta \to 0$. Suppose tests i = 1, 2 satisfy: (1) Test *i* rejects the null hypothesis $H_0 : \theta = 0$ for large values of a statistic $T_{n,i}$, and $T_{n,i}$ satisfies

$$\frac{\sqrt{n}(T_{n,i} - \mu_i(\theta_n))}{\sigma_i(\theta_n)} \stackrel{\theta_n}{\rightsquigarrow} N(0,1) \qquad \text{for } \sqrt{n}\theta_n \to h$$

(2) μ_i is differentiable at 0, σ_i is continuous at 0, $\mu'_i(0) > 0$, $\sigma_i(0) > 0$. (3) The power function of test *i* is nondecreasing for each *n*. Then the relative efficiency of these tests is

$$\left(\frac{\mu_1'(0)\sigma_2(0)}{\mu_2'(0)\sigma_1(0)}\right)^2$$

Asymptotic relative efficiency of tests: Proof

The condition that P_{θ} approaches P_0 in total variation distance as $\theta \to 0$ implies that the minimal numbers $n_{\nu,i}$ must go to infinity as $\nu \to \infty$.

Then the limiting normal distribution reveals the appropriate threshold to ensure that $\pi_{n_{\nu,1}}(0) = \alpha$:

$$\sqrt{n_{\nu,i}}(T_{n_{\nu,i},i} - \mu_i(0)) > \sigma_i(0)z_\alpha + o(1).$$

Then

$$\pi_{n_{\nu,i}}(\theta_{\nu}) = 1 - \Phi\left(z_{\alpha} - \sqrt{n_{\nu,i}}\theta_{\nu}\frac{\mu_i'(0)}{\sigma_i(0)}\right) + o(1).$$

Asymptotic relative efficiency of tests: Proof

For the power to approach γ as $\nu \to \infty$, the argument of Φ must approach z_{γ} , which means

$$\sqrt{n_{\nu,i}}\theta_{\nu}\frac{\mu_i'(0)}{\sigma_i(0)} \to z_{\alpha} - z_{\gamma}.$$

Hence,

$$\lim_{\nu \to \infty} \frac{n_{\nu,2}}{n_{\nu,1}} = \lim_{\nu \to \infty} \left(\frac{\sqrt{n_{\nu,2}} \theta_{\nu}}{\sqrt{n_{\nu,1}} \theta_{\nu}} \right)^2 = \left(\frac{\mu_1'(0) \sigma_2(0)}{\mu_2'(0) \sigma_1(0)} \right)^2.$$