## **Introduction to Statistical Method**

## **Comparing Two Means and Two Variances**

## **Comparing Two Means - A Point Estimator**

We have two populations with different means  $\mu_1$  and  $\mu_2$ , the goal is to estimate the difference  $\mu_1 - \mu_2$  by taking a sample from each population in independent way.

Natural point estimator:  $\mu_1 - \mu_2 := \hat{\mu_1} - \hat{\mu_2} = \overline{X_1} - \overline{X_2}$ 

To determine confidence intervals and to test hypothesis we need to know the distribution  $\overline{X}_1 - \overline{X}_2$ 

#### **Theorem**

The  $\overline{X}_1$  and  $\overline{X}_2$  be the sample means based on independent random samples of size  $n_1$  and  $n_2$  drawn from normal distributions with mean  $\mu_1$  and  $\mu_2$  and variance  $\sigma_1^2$  and  $\sigma_2^2$ .

The  $\overline{X}_1-\overline{X}_2$  is normal with mean  $\mu_1-\mu_2$  and variance  $\sigma_1^2/n_1+\sigma_2^2/n_2$ 

$$rac{\overline{X}_1-\overline{X}_2-(\mu_1-\mu_2)}{\sqrt{\sigma_1^2/n_1+\sigma_2^2/n_2}}$$
 is standard normal random variable.

(Central Limit Theorem allows us to apply this result even to non-normal populations if we have really large sample sizes)

## **OC Curve Application**

$$d=rac{|\mu_1-\mu_2|}{\sqrt{\sigma_1^2+\sigma_2^2}}$$
 , if  $n=n_1=n_2$  , unchanged, else  $n=rac{\sigma_1^2+\sigma_2^2}{\sigma_1^2/n_1+\sigma_2^2/n_2}$ 

If the variances are unknown, we need some more sophisticated methods.

The unknown variances are equal, situation is much easier.

## **Comparing Two Variances**

Consider test types of this:

•  $H_0: \sigma_1^2 = \sigma_2^2$ ,  $H_1: \sigma_1^2 > \sigma_2^2$  (right-tailed test) •  $H_0: \sigma_1^2 = \sigma_2^2$ ,  $H_1: \sigma_1^2 \neq \sigma_2^2$  (two-tailed test)

we move the  $\sigma$  to one side to consider only about the quotient.

 $(n-1)S^2/\sigma^2$  follows a chi-squared distribution with n-1 degree of freedom.

If the variance is put into quotient, it is easier to handle

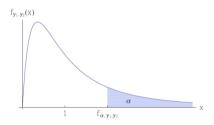
#### F-Distribution

 $X_{\gamma_1}^2$  and  $X_{\gamma_2}^2$  are independent chi-squared random variables with  $\gamma_1$  and  $\gamma_2$  degrees of freedom.

Random variable  $F_{\gamma_1,\gamma_2}=\frac{X_{\gamma_1}^2/\gamma_1}{X_{\gamma_2}^2/\gamma_2}$  is said to follow a F-distribution with  $\gamma_1$  and  $\gamma_2$  degree of freedom.

$$P[F_{\gamma_1,\gamma_2} < x] = P[1/F_{\gamma_1,\gamma_2} > 1/x] = 1 - P[F_{\gamma_2,\gamma_1} < 1/x]$$

Then 
$$f_{\gamma_1,\gamma_2}(x)=\gamma_1^{\gamma_1/2}\gamma_2^{\gamma_2/2}rac{\Gammaig(rac{\gamma_1+\gamma_2}{2}ig)}{\Gammaig(rac{\gamma_1}{2}ig)\Gammaig(rac{\gamma_2}{2}ig)}rac{x^{\gamma_1/2-1}}{(\gamma_1x+\gamma_2)^{(\gamma_1+\gamma_2)/2}}$$
 for  $x\geq 0$ 



Define 
$$f_{lpha,\gamma_1,\gamma_2}$$
 by  $P[F_{\gamma_1,\gamma_2}>f_{lpha,\gamma_1,\gamma_2}]=lpha$ 

Then 
$$\begin{aligned} 1-\alpha &= P[F_{\gamma_1,\gamma_2} \geq f_{1-\alpha,\gamma_1,\gamma_2}] \\ &= 1-P[F_{\gamma_1,\gamma_2} < f_{1-\alpha,\gamma_1,\gamma_2}] \\ &= P[F_{\gamma_2,\gamma_1} < 1/f_{1-\alpha,\gamma_1,\gamma_2}] \\ &= 1-P[F_{\gamma_2,\gamma_1} \geq 1/f_{1-\alpha,\gamma_1,\gamma_2}] \end{aligned} \text{ also we can see } \alpha = P[F_{\gamma_2,\gamma_1} \geq f_{\alpha,\gamma_2,\gamma_1}].$$

So  $f_{1-\alpha,\gamma_1,\gamma_2}\cdot f_{\alpha,\gamma_2,\gamma_1}=1$ .

#### Remark

Let  $S_1^2$  and  $S_2^2$  be sample variance based on independent random samples of size  $n_1$  and  $n_2$  from normal populations with means  $\mu_1$  and  $\mu_2$  and variance  $\sigma_1^2$  and  $\sigma_2^2$ 

If  $\sigma_1^2=\sigma_2^2$  then the statistic  $S_1^2/S_2^2$  follows F-distribution with  $n_1-1$  and  $n_2-1$  distribution.

Since 
$$F_{n_1-1,n_2-1}=rac{[(n_1-1)S_1^2/\sigma_1^2]/(n_1-1)}{[(n_2-1)S_2^2/\sigma_2^2]/(n_2-1)}=rac{\sigma_2^2S_1^2}{\sigma_1^2S_2^2}$$
 , so it is trivial to require  $\sigma_1^2=\sigma_2^2$ 

#### F-Test

We can derive F-Test from F-distribution that:

$$H_0:\sigma_1=\sigma_2$$
 based on  $F_{n_1-1,n_2-1}=rac{S_1^2}{S_2^2}$  is a F-Test

We reject  $H_0$  at significance level lpha

- ullet in favor of  $H_1:\sigma_1>\sigma_2$  if  $rac{S_1^2}{S_2^2}>f_{lpha,n_1-1,n_2-1}$
- ullet in favor of  $H_1:\sigma_1<\sigma_2$  if  $rac{S_2^{\overline{2}}}{S_1^2}>f_{lpha,n_2-1,n_1-1}$
- ullet in favor of  $H_1:\sigma_1
  eq\sigma_2$  if  $rac{\hat{S_1^2}}{\hat{S_2^2}}>f_{lpha/2,n_1-1,n_2-1}$  or  $rac{\hat{S_2^2}}{\hat{S_1^2}}>f_{lpha/2,n_2-1,n_1-1}$

When testing to see whether two population variances are equal for the purpose of comparing their means, one hopes to not reject  $H_0$ .

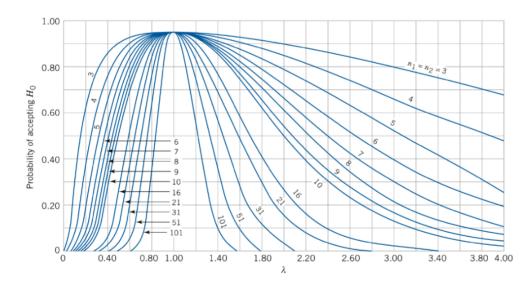
If  $H_0$  is not rejected, one can assume that the variances are in fact equal and continue with the test for equality for means.

In this case, a small Type II error  $\beta$  is more important than  $\alpha$  small.

#### **OC Curves for F-Test**

For case  $n=n_1=n_2$ , the OC curves plotting eta against the parameter  $\lambda=rac{\sigma_1}{\sigma_2}.$ 

The curves are for both one- two- sided alternatives.



# **Comparing Two Means - Equal Variances**