

## ST102 Week 13

### Common sampling distributions

Def. Let  $Z_1, Z_2, \dots, Z_k$  be independent  $N(0, 1)$ , if  
$$\underline{X} = \sum_{i=1}^k Z_i^2,$$
then  $\underline{X} \sim \chi_k^2$ , with degree of freedom  $k$ .

RK.  $E(\underline{X}) = k$ ,  $\text{Var}(\underline{X}) = 2k$

Prop. 1) If  $\underline{X}_1, \dots, \underline{X}_n$  are independent, with  
 $\underline{X}_i \sim \chi_{k_i}^2$ , then  
$$\sum_{i=1}^n \underline{X}_i \sim \chi_{\sum_{i=1}^n k_i}^2$$

2) For i.i.d. random sample  $\{\underline{X}_i\}_1^n$  from  $N(\mu, \sigma^2)$ ,  
and sample variance  $S^2$ , then

$$\frac{(n-1)S^2}{\sigma^2} \sim \chi_{n-1}^2$$

Reason?

Def. ( $t$  distribution)

Let  $Z \sim N(0, 1)$ ,  $\underline{X} \sim \chi_k^2$ ,  $Z \perp \underline{X}$ , then

$$T = \frac{Z}{\sqrt{\underline{X}/k}} \sim t_k$$

with degree of freedom  $k$ .

RK.  $E(T) = 0$  for  $k > 1$ ;  
 $Var(T) = \frac{k}{k-2}$  for  $k > 2$ ;  
otherwise not exists.

RK.  $t_k$  has heavier tail than  $N(0, 1)$ ;  
 $t_k$  tends to  $N(0, 1)$  as  $k \rightarrow +\infty$ .

Prop.  $\{X_i\}_1^n$  &  $\{Y_j\}_1^m$  all i.i.d. from  $N(\mu, \sigma^2)$ ,  
then

$$\frac{\sqrt{\frac{n+m-2}{\frac{1}{n} + \frac{1}{m}}}}{\sqrt{(n-1)S_X^2 + (m-1)S_Y^2}} \cdot \frac{\bar{X} - \bar{Y}}{\sqrt{(n-1)S_X^2 + (m-1)S_Y^2}} \sim t_{n+m-2}$$

Def.  $U \perp V$  with  $U \sim \chi_p^2$  and  $V \sim \chi_k^2$ . Then

$$F = \frac{U/p}{V/k} \sim F_{p,k}$$

i.e.,  $F$  distribution with degree of freedom  $(p, k)$ .

RK.  $E(F) = \frac{k}{k-2}$  for  $k > 2$ ,

Prop. 1) If  $F \sim F_{p,k} \Rightarrow \frac{1}{F} \sim F_{k,p}$

2) If  $T \sim t_k \Rightarrow T^2 \sim F_{1,k}$

3)  $\frac{S_X^2}{S_Y^2} \sim F_{n-1, m-1}$

for i.i.d.  $\{X_i\}_1^n$  &  $\{Y_j\}_1^m$  from  $N(\mu, \sigma^2)$