

Calculate mean and variance:

- $E(\sum_{i=1}^n a_i X_i) = a_1 E(X_1) + a_2 E(X_2) + \dots + a_n E(X_n)$ .
  1.  $E(\bar{X}) = \mu$ ;
- $V(a_1 X_1 + \dots + a_n X_n) = \sum_{i=1}^n \sum_{j=1}^n a_i a_j Cov(X_i, X_j)$ .
  1.  $Cov(X_i, X_i) = V(X_i)$ ;
  2. If  $X_1, \dots, X_n$  are mutually independent are independent,  $V(\sum_{i=1}^n a_i X_i) = \sum_{i=1}^n a_i^2 V(X_i)$ .
  3. If  $X_1, \dots, X_n$  is random sample,  $V(\bar{X}) = \frac{\sigma^2}{n}$
- When  $X_1, \dots, X_n$  are independent and normally distributed, suppose  $X_i \sim N(\mu_i, \sigma_i^2)$ , then for any linear combination  $Y = a_1 X_1 + \dots + a_n X_n = \sum_{i=1}^n a_i X_i$ ,

$$Y \sim N\left(\sum_{i=1}^n a_i \mu_i, \sum_{i=1}^n a_i^2 \sigma_i^2\right).$$

1. A random sample  $X_1, X_2, \dots, X_n$  from a normal distribution with mean  $\mu$  and variance  $\sigma^2$  ( $X_i \sim N(\mu, \sigma^2)$ ) then  $\bar{X} \sim N\left(\mu, \frac{\sigma^2}{n}\right)$

Tools:

Let  $X_1, X_2, \dots, X_n$  independent random variables with mgfs  $M_{X_i}(t)$  and  $Y$  then for any linear combination  $Y = a_1 X_1 + \dots + a_n X_n = \sum_{i=1}^n a_i X_i$ , then

$$M_Y(t) = M_{X_1}(a_1 t) \times M_{X_2}(a_2 t) \times \dots \times M_{X_n}(a_n t)$$

**LLN:** If  $X_1, \dots, X_n$  is a random sample from a distribution with mean  $\mu$  and variance  $\sigma^2$ , then as  $n \rightarrow \infty$ ,  $\bar{X}_n$  converges to  $\mu$  :

- In mean square  $E[(\bar{X} - \mu)^2] \rightarrow 0$
- In probability  $P(|\bar{X} - \mu| \geq \epsilon) \rightarrow 0$

**CLT:** If  $X_1, \dots, X_n$  is a random sample with mean  $\mu$  and variance  $\sigma^2$ , then as  $n \rightarrow \infty$ , the limiting distribution of  $\sqrt{n}(\bar{X}_n - \mu)/\sigma$  is standard normal, written as

$$\frac{\sqrt{n}(\bar{X}_n - \mu)}{\sigma} \rightarrow_d N(0, 1).$$

Distributions:

- $\chi^2_\nu$  distribution.

- If  $Z \sim N(0, 1)$ , then  $X = Z^2 \sim \chi^2_1$

- If  $Z_1, \dots, Z_n$  are i.i.d and  $Z_1 \sim N(0, 1)$ , then  $X = \sum_{i=1}^n Z_i^2 \sim \chi^2_n$ .

- 1. If  $X_1 \sim \chi^2_{\nu_1}$  and  $X_2 \sim \chi^2_{\nu_2}$  and  $X_1, X_2$  independent, then  $X_1 + X_2 \sim \chi^2_{\nu_1 + \nu_2}$

- 2. If  $X_3 = X_1 + X_2$ , with  $X_1 \sim \chi^2_{\nu_1}$ ,  $X_3 \sim \chi^2_{\nu_3}$ ,  $\nu_3 > \nu_1$  and  $X_1, X_2$  independent, then  $X_2 \sim \chi^2_{\nu_3 - \nu_1}$

- Let a random sample  $X_1, \dots, X_n \sim N(\mu, \sigma^2)$ , then

- 1.  $\bar{X} \sim N(\mu, \frac{\sigma^2}{n})$

- 2.  $\bar{X}$  and  $S^2$  are independent

- 3.  $\frac{(n-1)S^2}{\sigma^2} \sim \chi^2_{n-1}$

- $t_\nu$  distribution.

If  $Z \sim N(0, 1)$ ,  $X \sim \chi^2_\nu$  and  $X, Z$  are independent then

$$T = \frac{Z}{\sqrt{\frac{X}{\nu}}} \sim t_\nu$$

- 1. If  $X_1, \dots, X_n$  are i.i.d with  $X_1 \sim N(\mu, \sigma^2)$ , then

$$\frac{\sqrt{n}(\bar{X} - \mu)}{S} \sim t_{n-1}.$$

- $F_{df_1, df_2}$  distribution.

If  $X_1 \sim \chi^2_{\nu_1}$ ,  $X_2 \sim \chi^2_{\nu_2}$  and  $X_1, X_2$  are independent, then:

$$F = \frac{\frac{X_1}{\nu_1}}{\frac{X_2}{\nu_2}} \sim F_{\nu_1, \nu_2}$$