STATISTICAL FORMULAE

1. CALCULATION FORMULAE

For a sample x_1, x_2, \ldots, x_n

• Sample mean

$$\bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i$$

• Sample variance

$$s^{2} = \frac{1}{n-1} \sum_{i=1}^{n} (x_{i} - \bar{x})^{2} = \frac{1}{n-1} \left(\sum_{i=1}^{n} x_{i}^{2} - n\bar{x}^{2} \right)$$

2. The Binomial distribution

Assume $X \sim Bin(n, \pi)$

- domain of variation : $S_X = \{0, 1, \dots, n\}$
- probability mass function (pmf) :

$$p(x) = \binom{n}{x} \pi^x (1-\pi)^{n-x}, \quad \text{for } x \in S_X$$

Note that $\binom{n}{x} = {}^nC_x = \frac{n!}{x!(n-x)!}$. cumulative distribution function (cdf):

$$F(x) = \sum_{k=0}^{\lfloor x \rfloor} \binom{n}{k} \pi^k (1-\pi)^{n-k}$$

(where |x| denotes the integer part of x).

• expectation :

$$\mathbb{E}(X) = n\pi$$

• variance:

$$Var(X) = n\pi(1-\pi)$$

3. The Poisson distribution

Assume $X \sim \mathcal{P}(\lambda)$

- domain of variation : $S_X = \{0, 1, 2, \ldots\}$
- probability mass function (pmf):

$$p(x) = e^{-\lambda} \frac{\lambda^x}{x!}, \quad \text{for } x \in S_X$$

• cumulative distribution function (cdf):

$$F(x) = e^{-\lambda} \sum_{k=0}^{\lfloor x \rfloor} \frac{\lambda^k}{k!}$$

(where |x| denotes the integer part of x). See also the attached Poisson table.

expectation:

$$\mathbb{E}(X) = \lambda$$

variance:

$$Var(X) = \lambda$$

Assume $X \sim U_{[\alpha,\beta]}$

• domain of variation : $S_X = [\alpha, \beta]$

• probability density function (pdf):

$$f(x) = \frac{1}{\beta - \alpha}, \quad \text{for } x \in S_X$$

• cumulative distribution function (cdf):

$$F(x) = \frac{x - \alpha}{\beta - \alpha}, \quad \text{for } x \in S_X$$

• expectation :

$$\mathbb{E}(X) = \frac{\alpha + \beta}{2}$$

• variance:

$$\mathbb{V}\mathrm{ar}(X) = \frac{(\beta - \alpha)^2}{12}$$

5. The Exponential distribution

Assume $X \sim \text{Exp}(\mu)$

• domain of variation : $S_X = [0, +\infty)$

• probability density function (pdf):

$$f(x) = \frac{1}{\mu} e^{-\frac{x}{\mu}}, \quad \text{for } x \in S_X$$

• cumulative distribution function (cdf):

$$F(x) = 1 - e^{-\frac{x}{\mu}}, \quad \text{for } x \in S_X$$

• expectation :

$$\mathbb{E}(X) = \mu$$

• variance:

$$Var(X) = \mu^2$$

6. The Normal distribution

Assume $X \sim \mathcal{N}(\mu, \sigma)$

• domain of variation : $S_X = (-\infty, +\infty)$ • probability density function (pdf) :

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}\frac{(x-\mu)^2}{\sigma^2}}, \quad \text{for } x \in S_X$$

• cumulative distribution function (cdf):

$$F(x) = \int_{-\infty}^{x} \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2} \frac{(y-\mu)^2}{\sigma^2}} dy, \quad \text{for } x \in S_X$$

(no closed form)

• expectation :

$$\mathbb{E}(X) = \mu$$

• variance:

$$\mathbb{V}\mathrm{ar}(X) = \sigma^2$$

7. Sampling distributions

7.1. Sample mean.

7.1.1. known variance. Let \bar{X} be the sample average from a random sample of size n from a population with mean μ and standard deviation σ . Under appropriate conditions,

$$Z = \sqrt{n} \, \frac{\bar{X} - \mu}{\sigma} \sim \mathcal{N}(0, 1)$$

(exact result if the population distribution is normal, approximate result if the population distribution is not normal but n > 30)

7.1.2. unknown variance. Let \bar{X} and S be the sample average and standard deviation from a random sample of size n from a normal population with mean μ . Under appropriate conditions,

$$T = \sqrt{n} \, \frac{\bar{X} - \mu}{S} \sim t_{n-1}$$

If the population is not normal but n is large enough (n > 40), we can also write

$$T = \sqrt{n} \, \frac{\bar{X} - \mu}{S} \sim \mathcal{N}(0, 1)$$

approximately

7.2. **Sample proportion.** Let \hat{p} be the sample proportion of 'successes' where the number of trials is n and the true probability of a success is π . Under appropriate conditions,

$$\sqrt{n} \frac{\hat{p} - \pi}{\sqrt{\pi(1 - \pi)}} \sim N(0, 1)$$

approximately when $n\pi(1-\pi) > 5$

7.3. Sample variance. Let S^2 be the sample variance from a random sample of size n from a normal population with variance σ . Under appropriate conditions,

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

7.4. Difference in sample means.

7.4.1. variances σ_1^2 and σ_2^2 known. For two independent samples of size n_1 and n_2 from two populations with means μ_1 and μ_2 and standard deviations σ_1 and σ_2 respectively, let \bar{X}_i be the sample average of sample i for i = 1 and 2. Under appropriate conditions,

$$\frac{(\bar{X}_1 - \bar{X}_2) - (\mu_1 - \mu_2)}{\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}} \sim \mathcal{N}(0, 1)$$

(exact result if both population distributions are normal, approximate result if they are not but $n_1, n_2 > 30$)

7.4.2. variances σ_1^2 and σ_2^2 unknown; $\sigma_1^2 = \sigma_2^2$. For two independent samples of size n_1 and n_2 from two normal populations with means μ_1 and μ_2 respectively and common standard deviation σ , let \bar{X}_i and S_i be the sample average and sample standard deviation of sample i for i = 1 and 2. Under appropriate conditions,

$$\frac{(\bar{X}_1 - \bar{X}_2) - (\mu_1 - \mu_2)}{S_p \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}} \sim t_{n_1 + n_2 - 2},$$

where S_p is the pooled sample standard deviation,

$$S_p = \sqrt{\frac{(n_1 - 1)S_1^2 + (n_2 - 1)S_2^2}{n_1 + n_2 - 2}}.$$

7.4.3. variances σ_1^2 and σ_2^2 unknown; $\sigma_1^2 \neq \sigma_2^2$. For two independent samples of size n_1 and n_2 from two normal populations with means μ_1 and μ_2 and standard deviations σ_1 and σ_2 respectively, let \bar{X}_i and S_i be the sample average and sample standard deviation of sample i for i = 1 and 2. Under appropriate conditions,

$$\frac{(\bar{X}_1 - \bar{X}_2) - (\mu_1 - \mu_2)}{\sqrt{\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2}}} \sim t_{\nu},$$

where

$$\nu = \frac{(s_1^2/n_1 + s_2^2/n_2)^2}{\frac{(s_1^2/n_1)^2}{n_1 - 1} + \frac{(s_2^2/n_2)^2}{n_2 - 1}}$$

(rounded down to the nearest integer)

7.5. Ratio of sample variances. Let S_1^2 and S_2^2 be the sample variances from two independent random samples of size n_1 and n_2 from normal populations with variances σ_1^2 and σ_2^2 respectively. Under appropriate conditions,

$$\frac{S_1^2/\sigma_1^2}{S_2^2/\sigma_2^2} \sim \mathbf{F}_{n_1-1,n_2-1}$$

8. SIMPLE LINEAR REGRESSION

Consider the simple linear regression model

$$Y = \beta_0 + \beta_1 X + \epsilon$$

where $\epsilon \sim \mathcal{N}(0, \sigma)$

The least squares estimators $\hat{\beta}_0$ and $\hat{\beta}_1$ of β_0 and β_1 are

$$\hat{\beta}_1 = \frac{S_{XY}}{S_{XX}} \qquad \qquad \hat{\beta}_0 = \bar{Y} - \hat{\beta}_1 \bar{X}$$

where

$$S_{XY} = \sum_{i} (X_i - \bar{X})(Y_i - \bar{Y})$$
 $S_{XX} = \sum_{i} (X_i - \bar{X})^2.$

An estimator of σ is

$$S = \sqrt{\frac{\sum_{i} (Y_i - \hat{\beta}_0 - \hat{\beta}_1 X_i)^2}{n - 2}}.$$

Under fixed design:

$$\sqrt{s_{xx}}\frac{\hat{\beta}_1 - \beta_1}{S} \sim t_{n-2}$$

$$\frac{\hat{\beta}_0 - \beta_0}{S\sqrt{\frac{1}{n} + \frac{\bar{x}^2}{s_{rr}}}} \sim t_{n-2}$$

Let x_0 denote the predictor value for a response yet to be observed :

i) a $100 \times (1-\alpha)\%$ confidence interval for the mean response at x_0 is

$$\hat{y}(x_0) \pm s \, t_{n-2;1-\alpha/2} \sqrt{\frac{1}{n} + \frac{(x_0 - \bar{x})^2}{s_{xx}}}$$

where $\hat{y}(x_0) = \hat{b}_0 + \hat{b}_1 x_0$;

ii) a $100 \times (1-\alpha)\%$ prediction interval for the response at x_0 is

$$\hat{y}(x_0) \pm s \, t_{n-2;1-\alpha/2} \sqrt{1 + \frac{1}{n} + \frac{(x_0 - \bar{x})^2}{s_{xx}}}$$

9. ANOVA

• Total sum of squares :

$$SS_{\text{Tot}} = \sum_{i=1}^{k} \sum_{j=1}^{n_i} (X_{ij} - \bar{\bar{X}})^2$$

• Treatment sum of squares :

$$SS_{\text{Tr}} = \sum_{i=1}^{k} n_i (\bar{X}_i - \bar{\bar{X}})^2$$

• Error sum of squares :

$$SS_{\text{Er}} = \sum_{i=1}^{k} \sum_{j=1}^{n_i} (X_{ij} - \bar{X}_i)^2$$

• Under the assumption of equality of means in each of the k groups of a one-way Analysis of Variance,

$$F = \frac{\text{MS}_{\text{Tr}}}{\text{MS}_{\text{Er}}} \sim \mathbf{F}_{k-1, n-k},$$

where n is the total number of observations.