

**MATH20802: Statistical Methods  
Semester 2**

**Formulas to remember for the final exam in May / June 2018**

The moment generating function of a random variable  $X$  is  $M_X(t) = E[\exp(tX)]$ .

The fact that  $E(X^n) = M_X^{(n)}(0)$ .

$\hat{\theta}$  is an unbiased estimator of  $\theta$  if  $E(\hat{\theta}) = \theta$ .

$\hat{\theta}$  is an asymptotically unbiased estimator of  $\theta$  if  $\lim_{n \rightarrow \infty} E(\hat{\theta}) = \theta$ .

The bias of  $\hat{\theta}$  is  $E(\hat{\theta}) - \theta$ .

The mean squared error of  $\hat{\theta}$  is  $E[(\hat{\theta} - \theta)^2]$ .

$\hat{\theta}$  is a consistent estimator of  $\theta$  if  $\lim_{n \rightarrow \infty} E[(\hat{\theta} - \theta)^2] = 0$ .

The Cauchy distribution has its probability density function specified by  $f(x) = \frac{1}{\pi} \frac{1}{1+x^2}$  for  $-\infty < x < +\infty$ .

The gamma function is defined by  $\Gamma(a) = \int_0^{\infty} t^{a-1} \exp(-t) dt$ .

The fact that  $\Gamma(n) = (n-1)!$ .

The fact that  $\Gamma(x+1) = x\Gamma(x)$ .

The beta function is defined by  $B(a, b) = \int_0^1 t^{a-1} (1-t)^{b-1} dt$ .

The fact that  $B(a, b) = \frac{\Gamma(a)\Gamma(b)}{\Gamma(a+b)}$ .

The probability density function of  $X \sim \text{Exp}(\lambda)$  is  $f_X(x) = \lambda \exp(-\lambda x)$ .

The cumulative distribution function of  $X \sim \text{Exp}(\lambda)$  is  $F_X(x) = 1 - \exp(-\lambda x)$ .

The probability density function of  $X \sim \text{Uni}(a, b)$  is  $f_X(x) = \frac{1}{b-a}$ .

The probability density function of an inverse Gaussian random variable is

$$f_X(x) = \sqrt{\frac{\lambda}{2\pi x^3}} \exp\left[-\frac{\lambda(x-\mu)^2}{2\mu^2 x}\right]$$

for  $x > 0$ ,  $\mu > 0$  and  $\lambda > 0$ . The mean and variance are  $E(X) = \mu$  and  $\text{Var}(X) = \frac{\mu^3}{\lambda}$ .

The mean and variance of  $X \sim \chi_{\nu}^2$  are  $E(X) = \nu$  and  $\text{Var}(X) = 2\nu$ .

If  $X_1, X_2, \dots, X_n$  is a random sample from  $N(\mu, \sigma^2)$  then  $\frac{1}{\sigma^2} \sum_{i=1}^n (X_i - \bar{X})^2 \sim \chi_{n-1}^2$ , where  $\bar{X}$  denotes the sample mean.

The Type I error of  $H_0 : \mu = \mu_0$  versus  $H_1 : \mu \neq \mu_0$  occurs if  $H_0$  is rejected when in fact  $\mu = \mu_0$ .

The Type II error of  $H_0 : \mu = \mu_0$  versus  $H_1 : \mu \neq \mu_0$  occurs if  $H_0$  is accepted when in fact  $\mu \neq \mu_0$ .

The significance level of  $H_0 : \mu = \mu_0$  versus  $H_1 : \mu \neq \mu_0$  is the probability of type I error.

The power function of  $H_0 : \mu = \mu_0$  versus  $H_1 : \mu \neq \mu_0$  is  $\Pi(\mu) = \Pr(\text{Reject } H_0 \mid \mu)$ .

Suppose  $X_1, X_2, \dots, X_n$  is a random sample from  $N(\theta, \sigma^2)$ , where  $\sigma$  is not known.

The rejection region for  $H_0 : \sigma = \sigma_0$  versus  $H_1 : \sigma \neq \sigma_0$  is

$$\frac{(n-1)S^2}{\sigma_0^2} < \chi_{n-1, 1-\alpha/2}^2 \text{ or } \frac{(n-1)S^2}{\sigma_0^2} > \chi_{n-1, \alpha/2}^2.$$

The rejection region for  $H_0 : \sigma = \sigma_0$  versus  $H_1 : \sigma < \sigma_0$  is

$$\frac{(n-1)S^2}{\sigma_0^2} < \chi_{n-1, 1-\alpha}^2.$$

The rejection region for  $H_0 : \sigma = \sigma_0$  versus  $H_1 : \sigma > \sigma_0$  is

$$\frac{(n-1)S^2}{\sigma_0^2} > \chi_{n-1, \alpha}^2.$$

The method of mathematical induction.

Based on a random sample  $X_1, X_2, \dots, X_n$  from a distribution with the probability density function  $f(x; \theta)$ , the Neyman-Pearson test rejects  $H_0 : \theta = \theta_1$  versus  $H_1 : \theta = \theta_2$  if

$$\frac{L(\theta_1)}{L(\theta_2)} = \frac{\prod_{i=1}^n f(X_i; \theta_1)}{\prod_{i=1}^n f(X_i; \theta_2)} < k$$

for some  $k$ .