FORMULAE FOR BASIC STATISTICS

A. Descriptive Statistics (for Samples)

***A.1 Mean** and **variance** are*

$$\bar{y} = \sum y / n;\ \ s^2 = TSS/(n-1)\ ,\ TSS = \sum (y-\bar{y})^2 = \sum y^2 - \left(\sum y\right)^2 / n\ .$$

***A.2 Quartiles**:* $R_\alpha = \alpha\ (1+n)/4 = i + d\ ,\quad \alpha = 1,\ 2,\ 3;\ \ Q_\alpha = (1-d)y_{(i)} + dy_{(i+1)}$
where i *is the largest integer not exceeding* R_α.

***A.3 Mean** and the **variance** for **grouped data**:*

$$\bar{y} = \sum yf\ / n;\ \ \ s^2 = TSS/(n-1),\ \ TSS = \sum y^2 f\ \ - \left(\sum yf\ \right)^2 / n\ .$$

***A.4 Coefficient of Variation** :* $\quad CV = s/\bar{y}$.

***A.5 Coefficient of Skewness** :* $\ CS = 3(\bar{y} - \tilde{y})/s$.

B. Glossary of Probability of Set Events (Two Sets)

	Verbal Description of Event	*Probability*
B.1	A *but not* B *(=Only* $A = A$ *alone)*	$P(A \cap \overline{B}) = P(A) - P(A \cap B)$
B.2	B *but not* A *(=Only* $B = B$ *alone)*	$P(\overline{A} \cap B) = P(B) - P(A \cap B)$
B.3	*None (=Neither* A *nor* B*)*	$P(\overline{A} \cap \overline{B}) = P(\overline{A \cup B}) = 1 - P(A \cup B)$
B.4	*Exactly one*	$P(A \cap \overline{B}) + P(\overline{A} \cap B)$
B.5	*Both* *(=Exactly two = Two)*	$P(A \cap B) = 1 - P(\overline{A \cap B}\ ) = 1 - P(\overline{A} \cup \overline{B})$ $P(A \cap B) = P(B)P(A \mid B) = P(A)P(B \mid A)$ $P(A \cap B) = P(A)P(B)$ iff A and B are independent
B.6	*Not both*	$P(\overline{A \cap B}\ ) = 1 - P(A \cap B)$
B.7	A given B	$P(A \mid B) = \dfrac{P(A \cap B)}{P(B)}$ if $P(B) \neq 0$ $P(A \mid B) = P(A)$ iff A and B are independent
B.8	*At least one of the two* *(=* A or B *)*	$P(A \cup B) = P(\text{exactly one}) + P(\text{exactly two})$ $= P(A \cap \overline{B}) + P(\overline{A} \cap B) + P(A \cap B)$ $= P(A) + P(B) - P(A \cap B)$ $= 1 - P(\overline{A \cup B}\ ) = 1 - P(\overline{A} \cap \overline{B})$

Independence: $P(A \mid \overline{B}) = P(A \mid B) = P(A),$ or, $P(B \mid \overline{A}) = P(B \mid A) = P(B)$

For intersection of three sets A, B and C, the following results are important:

B.9 $P(\text{none}) + P(\text{at least one}) = 1$

B.10 $P(\text{none}) = P(\bar{A} \cap \bar{B} \cap \bar{C}) = \left(P(\bar{A})P(\bar{B})P(\bar{C}) \text{ by independence}\right)$

B.11 $P(\text{at least one}) = P(A \cup B \cup C)$

$= P(A) + P(B) + P(C) - [P(A \cap B) + P(A \cap C) + P(B \cap C)] + P(A \cap B \cap C)$

C. Discrete Probability Distributions

C.1 $P(a \le Y \le b) = \sum_{y} f(y),\ F(b) = \sum_{y \le b} f(y)$

C.2 $\mu = E(Y) = \sum_{y} y\ f(y), \qquad (p89)$

C.3 $E\left(Y^2\right) = \sum y^2 f(y),\ \ \sigma^2 = E(Y-\mu)^2 = E\left(Y^2\right) - \mu^2,\ (p96)$

	Probability Density function $p(x)$	*Mean* (μ) *and Variance* (σ^2)
C.4	*The Binomial Distribution:* $B(n,p)$ *(p119)* $f(y) = \binom{n}{y} p^y (1-p)^{n-y};\quad y = 0,\ 1,\ \ldots,\ n$	$\mu = E(Y) = np$ $\sigma^2 = V(Y) = np(1-p).$
C.5	*The Geometric Distribution* $f(y) = q^{y-1}p;\ y = 1, 2, \cdots$	$\mu = E(Y) = 1/p$ $\sigma^2 = V(Y) = q/p^2$
C.6	*The Hypergeometric Distribution (p128)* $f(y) = \binom{K}{y}\binom{N-K}{n-y} \div \binom{N}{n},$ $\max\{0, n-(N-K)\} \le y \le \min\{n, K\}$	$\mu = E(Y) = n\ (K/N)$ $\sigma^2 = V(Y) = (1-c)\ n\left(K/N\right)(1-k/N)$ *where* $(N-1)\ c = n-1$
C.7	*The Poisson Distribution (p136)* $f(y) = \dfrac{e^{-\lambda t}(\lambda t)^y}{y!};\ y = 0,\ 1,\ \ldots$	$\mu = E(Y) = \lambda t$ $\sigma^2 = V(Y) = \lambda t$

D. Continuous Probability Distributions

For a continuous random variable Y with pdf $f(y)$

$D.1\ \ P(a < Y < b) = \int_a^b f(y)dy,\ \ F(u) = \int_{-\infty}^{u} f(y)dy$

$D.2\ \ \mu = E(Y) = \int_{-\infty}^{\infty} y\ f(y)dy,\ \ (p89)$

$D.3\ \ E\left(Y^2\right) = \int_{-\infty}^{\infty} y^2 f(y)dx,\ \ \sigma^2 = E(Y-\mu)^2 = E\left(Y^2\right) - \mu^2,\ \ (p96)$

	Probability Density function	Mean and Variance
D.4	The Normal Distribution: $N(\mu,\sigma^2)$	Mean = $E(Y)=\mu$ Variance = $V(Y)=\sigma^2$
D.5	The Exponential Distribution $f(y)=\frac{1}{\beta}\,e^{-y/\beta},\ \ 0<y$	Mean = $E(Y)=\beta$ Variance = $V(Y)=\beta^2$
D.6	Waiting Time Distribution $f(t)=\lambda e^{-\lambda t},\ \ 0<t$	Mean = $E(T)=1/\lambda$ Variance = $V(T)=1/\lambda^2$
D.7	The Gamma Distribution $f(y)=\frac{1}{\beta^{\alpha}\Gamma(\alpha)}\,y^{\alpha-1}\,e^{-y/\beta},\ \ 0<y,\ 0<\alpha,\ 0<\beta$	Mean = $E(Y)=\alpha\beta$ Variance = $V(Y)=\alpha\beta^2$

E. Sampling Distributions

E.1 Suppose that Y has a distribution with mean μ and variance σ^2. Additionally if the distribution is ***normal*** *then* $\frac{\sum Y-n\mu}{\sqrt{n\sigma^2}}=\frac{\overline{Y}-\mu}{\sqrt{\sigma^2/n}}=Z$.

E.2 Suppose that Y has a distribution with mean μ and variance σ^2. However if the distribution is not normal but $n\geq 30$, then $\frac{\sum Y-n\mu}{\sqrt{nS^2}}=\frac{\overline{Y}-\mu}{\sqrt{S^2/n}}\approx Z$ *(p210). This is known as* ***Central Limit Theorem****. Note S^2 converges to σ^2 in probability (WLLN).*

E.3 The ***Student T- statistic*** *is defined by* $T=\frac{\overline{Y}-\mu}{S/\sqrt{n}}$, *with* $\nu=n-1$ *(p220)*

E.4 ***The Sampling Distribution of the Proportion*** *(p258)*

$$\frac{Y-np}{\sqrt{np(1-p)}}=\frac{Y/n-p}{\sqrt{p(1-p)/n}}\approx Z$$

F. Statistical Estimation (with Random Sample / Samples)

F.1 Confidence Interval Estimates of the Mean μ

F.1.0 CI for μ, (σ known, any n, normal): $\overline{y}\mp z_{\alpha/2}\left(\sigma/\sqrt{n}\right)$ *for (235)*

F.1.1 ACI for μ, (σ known, nonnormal, large n): $\overline{y}\mp z_{\alpha/2}\left(\sigma/\sqrt{n}\right)$ *(cf. p235).*

F.1.1(a) sample size for estimating μ : $n=z_{\alpha/2}^2\,\sigma^2/e^2$ *(p237).*

F.1.2 ACI for μ, (σ unknown, large n, nonnormal): $\bar{y} \mp z_{\alpha/2}\left(s/\sqrt{n}\right)$ *(cf. p235).*

F.1.3 CI for μ, (σ unknown, $n \geq 2$, normal): $\bar{y} \mp t_{\alpha/2}\left(s/\sqrt{n}\right)$ *for any* $n \geq 2$ *(p239).*

F.2 Confidence Interval for $\mu_1 - \mu_2$ (Based on Random and Independent Samples)

F.2.0 CI for $\mu_1 - \mu_2$, (σ_i^2 known, normal): $(\bar{y}_1 - \bar{y}_2) \mp z_{\alpha/2}\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}$ *(cf. p247)*

F.2.1 ACI for $\mu_1 - \mu_2$, (σ_i^2 known, large n_i, nonnormal):

$(\bar{y}_1 - \bar{y}_2) \mp z_{\alpha/2}\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}$ *(cf. p247)*

F.2.2 CI for $\mu_1 - \mu_2$, (σ_i^2 unknown, large n_i, nonnormal):

$(\bar{y}_1 - \bar{y}_2) \mp z_{\alpha/2}\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}$ ***(p247)***

F.2.3 CI for $\mu_1 - \mu_2$, (small n_i, unknown $\sigma_1^2 = \sigma_2^2$ but unknown, normal):

$$(\bar{y}_1 - \bar{y}_2) \mp t_{\alpha/2}\sqrt{\frac{s^2}{n_1} + \frac{s^2}{n_2}}, \quad s^2 = \frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{(n_1 - 1) + (n_2 - 1)}, \quad \nu = (n_1 - 1) + (n_2 - 1),$$

where s^2 is the combined variance $\left(s_1^2 \leq s^2 \leq s_2^2\right)$, (p249)

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F.2.4 CI for $\mu_1 - \mu_2$, (small $n_1 = n_2$, $\sigma_1^2 \neq \sigma_2^2$, normal):

$$(\bar{y}_1 - \bar{y}_2) \mp t_{\alpha/2}\sqrt{\frac{s_1^2}{n} + \frac{s_2^2}{n}}, \quad \nu = (n - 1) + (n - 1) \quad \textbf{(p249)}$$

F.2.5 ACI for $\mu_1 - \mu_2$, (small $n_1 \neq n_2$, $\sigma_1^2 \neq \sigma_2^2$, normal):

$$(\bar{y}_1 - \bar{y}_2) \mp t_{\alpha/2}\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}, \quad \nu = \frac{(s_1^2/n_1 + s_2^2/n_2)^2}{(s_1^2/n_1)^2/(n_1 - 1) + (s_2^2/n_2)^2/(n_2 - 1)}, \quad \textbf{(p251)}$$

F.2.6 CI for $\mu_1 - \mu_2$ using matched pairs): $\bar{d} \mp t_{\alpha/2}\sqrt{s_d^2/n}$, ***($df = n - 1$), (p254)***

F.3 Confidence Interval for Proportion p

F.3.1 CI for p when n large: $\hat{p} \mp z_{\alpha/2}\sqrt{\hat{p}(1 - \hat{p})/n}$ *, (p258)*

F.3.1 (a) Large sample size for estimating p: $n = z_{\alpha/2}^2\,\hat{p}(1 - \hat{p})/e^2$. *(p 259)*

F.3.2 CI for $p_1 - p_2$ with large sample sizes :

$$\hat{p}_1 - \hat{p}_2 \mp z_{\alpha/2} \sqrt{\frac{\hat{p}_1(1-\hat{p}_1)}{n_1} + \frac{\hat{p}_2(1-\hat{p}_2)}{n_2}}$$

F.4 Confidence Interval for Variance σ^2 : $[(n-1)s^2/u, \quad (n-1)s^2/l]$
where $l = \chi^2_{1-\alpha/2} << u = \chi^2_{\alpha/2}$

G. Testing of Hypotheses (with Random Sample/ Samples)

Reject H_0 for $p\text{-value} \le \alpha <$; Don't reject H_0 for $0 \le \alpha < p\text{-value}$.

G.1 Testing of a Mean μ

G.1.0 σ known, normal: $z = \dfrac{\bar{y} - \mu_0}{\sqrt{\sigma^2/n}}$ *(p300)*

G.1.1 σ known, large n, nonnormal: $z \approx \dfrac{\bar{y} - \mu_0}{\sqrt{\sigma^2/n}}$

G.1.2 σ unknown, large sample: $z \approx \dfrac{\bar{y} - \mu_0}{\sqrt{s^2/n}}$ *(p300)*

H_0	H_a	RR (for H_0)	p-value
$\mu = \mu_0$	$\mu < \mu_0$	$z < -z_\alpha$	$P(Z < z)$
$\mu = \mu_0$	$\mu > \mu_0$	$z > z_\alpha$	$P(Z > z)$
$\mu = \mu_0$	$\mu \ne \mu_0$	$z < -z_{\alpha/2}$ or $z > z_{\alpha/2}$	$2\,P(Z > \lvert z \rvert)$

G.1.3 σ unknown, normal population : $t = \dfrac{\bar{y} - \mu_0}{\sqrt{s^2/n}}$, $(\nu = n - 1 \ge 1)$ *(p304)*

H_0	H_a	RR (for H_0)	p-value
$\mu = \mu_0$	$\mu < \mu_0$	$t < -t_\alpha$	$P(T < t)$
$\mu = \mu_0$	$\mu > \mu_0$	$t > t_\alpha$	$P(T > t)$
$\mu = \mu_0$	$\mu \ne \mu_0$	$t < -t_{\alpha/2}$ or $t > t_{\alpha/2}$	$2\,P(T > \lvert t \rvert)$

G.2 Testing $\mu_1 - \mu_2 = \delta$ (Random and Independent Samples)

G.2.0 known σ_i , any n_i , normal: $z = \dfrac{\bar{y}_1 - \bar{y}_2 - \delta_0}{\sqrt{\left(\sigma_1^2 / n_1\right) + \left(\sigma_2^2 / n_2\right)}}$

G.2.1 known σ_i , large n_i , nonnormal: $z \approx \dfrac{\bar{y}_1 - \bar{y}_2 - \delta_0}{\sqrt{\left(\sigma_1^2 / n_1\right) + \left(\sigma_2^2 / n_2\right)}}$

G.2.2 unknown σ_i , large n_i , nonnormal: $z \approx \dfrac{\bar{y}_1 - \bar{y}_2 - \delta_0}{\sqrt{\left(s_1^2 / n_1\right) + \left(s_2^2 / n_2\right)}}$

Table for the above three tests are given below:

H_0	H_a	RR (for H_0)	p-value
$\mu_1 - \mu_2 = \delta_0$	$\mu_1 - \mu_2 < \delta_0$	$z < -z_\alpha$	$P(Z < z)$
$\mu_1 - \mu_2 = \delta_0$	$\mu_1 - \mu_2 > \delta_0$	$z > z_\alpha$	$P(Z > z)$
$\mu_1 - \mu_2 = \delta_0$	$\mu_1 - \mu_2 \neq \delta_0$	$z < -z_{\alpha/2}$ or $z > z_{\alpha/2}$	$2\ P(Z > \lvert z \rvert)$

G.2.3 Small n_i , unknown $\sigma_1^2 = \sigma_2^2$, normal)

$$t = \frac{\bar{y}_1 - \bar{y}_2 - \delta_0}{\sqrt{\left(s^2 / n_1\right) + \left(s^2 / n_2\right)}} \ , \quad s^2 = \frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{n_1 + n_2 - 2} \ , \quad \nu = (n_1 - 1) + (n_2 - 1) \ ,$$

where s^2 is the combined variance $\left(s_1^2 \le s^2 \le s_2^2\right)$,(p308).

G.2.4 Small $n_1 = n_2$, $\sigma_1^2 \neq \sigma_2^2$, normal)

$$t \approx \frac{\bar{y}_1 - \bar{y}_2 - \delta_0}{\sqrt{\left(s_1^2 / n\right) + \left(s_2^2 / n\right)}} \ , \quad \nu = (n - 1) + (n - 1)$$

G.2.5 Small $n_1 \neq n_2$, $\sigma_1^2 \neq \sigma_2^2$, normal)

$$t \approx \frac{\bar{y}_1 - \bar{y}_2 - \delta_0}{\sqrt{\left(s_1^2 / n_1\right) + \left(s_2^2 / n_2\right)}} \ , \quad \nu = \frac{(s_1^2 / n_1 + s_2^2 / n_2)^2}{(s_1^2 / n_1)^2 / (n_1 - 1) + (s_2^2 / n_2)^2 / (n_2 - 1)} \ , \ \textit{(p309).}$$

Tables for the above three tests are provided below:

H_0	H_a	RR (for H_0)	p-value
$\mu_1 - \mu_2 = \delta$	$\mu_1 - \mu_2 < \delta$	$t < -t_\alpha$	$P(T < t)$
$\mu_1 - \mu_2 = \delta$	$\mu_1 - \mu_2 > \delta$	$t > t_\alpha$	$P(T > t)$
$\mu_1 - \mu_2 = \delta$	$\mu_1 - \mu_2 \neq \delta$	$t < -t_{\alpha/2}$ or $t > t_{\alpha/2}$	$2\ P(T > \lvert t \rvert)$

G.2.6 Testing $\mu_1 - \mu_2$ using matched pairs): $t = \bar{d} / \sqrt{s_d^2 / n}$, $(df = n-1)$, *(p310)*

G.3.1 Testing of a proportion (p)

Large sample: $z \approx \dfrac{\hat{p} - p_0}{\sqrt{p_0(1-p_0)/n}}$.

H_0	H_a	RR (for H_0)	p-value
$p = p_0$	$p < p_0$	$z < -z_\alpha$	$P(Z < z)$
$p = p_0$	$p > p_0$	$z > z_\alpha$	$P(Z > z)$
$p = p_0$	$p \neq p_0$	$z < -z_{\alpha/2}$ or $z > z_{\alpha/2}$	$2\ P(Z > \lvert z \rvert)$

G.3.2 Testing the difference of two proportions $p_1 - p_2 = \delta$

Large n_i: $z \approx \dfrac{\hat{p}_1 - \hat{p}_2 - \delta_0}{\sqrt{\hat{p}(1-\hat{p})/n_1 + \hat{p}(1-\hat{p})/n_2}}$ *where* $\hat{p} = \dfrac{n_1\hat{p}_1 + n_2\hat{p}_2}{n_1 + n_2} = \dfrac{y_1 + y_2}{n_1 + n_2}$

H_0	H_a	RR (for H_0)	p-value
$p_1 = p_2$	$p_1 < p_2$	$z < -z_\alpha$	$P(Z < z)$
$p_1 = p_2$	$p_1 > p_2$	$z > z_\alpha$	$P(Z > z)$
$p_1 = p_2$	$p_1 \neq p_2$	$z < -z_{\alpha/2}$ or $z > z_{\alpha/2}$	$2\ P(Z > \lvert z \rvert)$

G.4.1 Testing a variance $\chi^2 = (n-1)s^2 / \sigma_0^2$

To test $H_0 : \sigma^2 = \sigma_0^2,\ H_0 : \sigma^2 > \sigma_0^2$ ***use*** $\chi^2 > \chi_\alpha^2$
To test $H_0 : \sigma^2 = \sigma_0^2,\ H_0 : \sigma^2 < \sigma_0^2$ ***use*** $\chi^2 < \chi_{1-\alpha}^2$
To test $H_0 : \sigma^2 = \sigma_0^2,\ H_0 : \sigma^2 \neq \sigma_0^2$ ***use*** $\chi^2 < \chi_{1-\alpha/2}^2$ or $\chi^2 < \chi_{\alpha/2}^2$

H. Linear Regression Analysis (Degrees of Freedom: $\nu = n-2$)

H.1 Line of Best Fit

H.1.0 Model : $y = \beta_0 + \beta_1 x + \varepsilon$ *for a given* x, $Y \sim N(\mu,\ \sigma^2)$ *where* $\mu = \beta_0 + \beta_1 x$
Fitted Model: $\hat{y} = \hat{\mu} = \hat{\beta}_0 + \hat{\beta}_1 x$ *for a given* x

H.1.1 $\hat{\beta}_1 = \dfrac{s_{xy}}{s_{xx}};\ s_{xy} = \sum xy - \left(\sum x\right)\left(\sum y\right)/n;\ s_{xx} = \sum x^2 - \left(\sum x\right)^2 / n;\ \hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x}$ ***.(p536)***

H.1.2 *Pearson product moment* ***coefficient of correlation:*** $r = \dfrac{s_{xy}}{\sqrt{s_{xx}\ s_{yy}}}$ *(p392)*

H.1.3 Standard error of the estimate: $s = \sqrt{SSE\ /(n-2)} = \sqrt{MSE}$

H.1.4 $TSS = \sum (y - \bar{y})^2 = \sum y^2 - \left(\sum y\right)^2 / n;\ SSR = \hat{\beta}_1 s_{xy};\ SSE = TSS - SSR$

H.1.5 $R^2 = \dfrac{Explained\ \text{var}iation}{Total\ \text{var}iation} = \dfrac{SSR}{TSS}$

H.2 Inference Regarding the Regression Coefficients

H.2.1 100 $(1-\alpha)\%$ ***confidence interval for*** β_0 ***:*** $\hat{\beta}_0 \mp t_{\alpha/2} \sqrt{\left(\dfrac{1}{n} + \dfrac{\bar{x}^2}{s_{xx}}\right) MSE}$.

H.2.2 Testing the hypothesis $H_0 : \beta_0 = c$ ***:*** $t = \dfrac{\hat{\beta}_0 - c}{\sqrt{\left(\dfrac{1}{n} + \dfrac{\bar{x}^2}{s_{xx}}\right) MSE}}$ *(p364)*

H.2.3 100(1-α)% confidence interval for β_1 ***:*** $\hat{\beta}_1 \mp t_{\alpha/2} \sqrt{MSE / s_{xx}}$

H.2.4 Testing the hypothesis $H_0 : \beta_1 = c$ ***:*** $t = \dfrac{\hat{\beta}_1 - c}{\sqrt{MSE / s_{xx}}}$ *(p364)*

Inference Regarding the Response Variable

H.2.5 Confidence Interval for Mean for a given x :

$\hat{y} \pm t_{\alpha/2} \sqrt{\left(\dfrac{1}{n} + \dfrac{(x - \bar{x})^2}{s_{xx}}\right) MSE}$,

H.2.6 Prediction Interval for an Individual Y ***Given*** x ***:***

$\hat{y} \pm t_{\alpha/2} \sqrt{\left(1 + \dfrac{1}{n} + \dfrac{(x - \bar{x})^2}{s_{xx}}\right) MSE}$ *(p368)*

Table for Estimation or Tests of Hypotheses on Mean or Difference in Means (In this table sample is always drawn randomly, and two samples considered are always independent)

σ_i^2		n_i	Y	CI	z/t	TEST	page
KNOWN	1	Any, Normal		F.1.0	z	G.1.0	235
	1	Large $(n \geq 30)$, nonnormal		F.1.1	$\approx z$	G1.1	235
	2	Any, Normal		F.2.0	z	G.2.0	247
	2	Each large $(n \geq 30)$, nonnormal		F.2.1	$\approx z$	G.2.1	247
UNKNOWN	1	Large $(n \geq 30)$, Nonnormal		F.1.2	$\approx z$	G.1.2	239
	1	At least 2, Normal		F.1.3	t	G.1.3	239
	2	Large $(n \geq 30)$, Nonnormal		F.2.2	$\approx z$	G.2.2	251
	2	Each at least 2, Normal $(\sigma_1^2 = \sigma_2^2)$		F.2.3	t	G.2.3	249
	2	Small $(n_1 = n_2)$, Normal		F.2.4	$\approx t$	G.2.4	251
	2	Each at least 2, Normal		F.2.5	$\approx\approx t$	G.2.5	251