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## Statistics Notes

Saverio Perugini *University of Dayton*, sperugini1@udayton.edu

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## **Statistics Notes**

## Saverio Perugini

Department of Computer Science University of Dayton 300 College Park Dayton, Ohio 45469–2160 USA

> Tel: +001 (937) 229-4079 Fax: +001 (937) 229-2193

E-mail: saverio@udayton.edu

WWW: http://academic.udayton.edu/SaverioPerugini

## Contents

1	Fun	damentals	3
	1.1	Foundational Statistical Terms, Definitions, and Formulae	3
	1.2	External Reference Distribution	4
	1.3	Normal Distribution	4
		1.3.1 Properties of the Normal Distribution	4
		1.3.2 Empirical Rule for the Normal Distribution	4
	1.4	Student's t Distribution	4
2	Mea	ans, Variances, and Analysis of Variance	5
	2.1	Means	5
		2.1.1 One Population Mean	5
		2.1.2 Two Population Means (unpaired)	5
		2.1.3 Two Population Means (paired)	6
	2.2	Variances	6
		2.2.1 One Population Variance	6
		2.2.2 Two Population Variances	6
	2.3	Analysis of Variance (ANOVA) Table	7
	2.4	Confidence Interval Formulae	7
3	Exp	perimental Design	7
	3.1	Completely Randomized Design	7
	3.2	Randomized Block Design	8
	3.3	Two-Way Factorial Design	8
	3.4	Latin Square Design	8
	3.5	Factorial Design	Q

## 1 Fundamentals

## 1.1 Foundational Statistical Terms, Definitions, and Formulae

Term	Definition	Population	Sample
Mean	a measure of location		
		$\eta = \frac{\sum_{i=1}^{n} y_i}{N} \Rightarrow$	$\overline{y} = \frac{\sum_{i=1}^{n} y_i}{n} \Rightarrow$
		parameter	statistic
Variance	a measure of spread	$\sigma^2 = \frac{\sum_{i=1}^n (y_i - \eta)^2}{N}$	$s^{2} = \frac{\sum_{i=1}^{n} (y_{i} - \overline{y})^{2}}{n-1}$
Other	you use this when you know $\eta$		$\dot{s}^2 = \frac{\sum_{i=1}^n (y_i - \eta)^2}{n}$
Standard Deviation	a measure of spread	$\sigma = \sqrt{\frac{\sum_{i=1}^{n} (y_i - \eta)^2}{N}}$	$s = \sqrt{\frac{\sum_{i=1}^{n} (y_i - \overline{y})^2}{n-1}}$
N (0, 1)	Unit (Standard) Normal Distribution		$z = \frac{y - \eta}{\sigma}$ and $z = \frac{\bar{y} - \eta}{\frac{s}{\sqrt{n}}}$ if $\bar{y}$ is known
Covariance	a measure of linear dependence between two random variables $X$ and $Y$	$\sum_{i=1}^{n} \frac{(x_i - \eta_x)(y_i - \eta_y)}{N} =$	$cov(X,Y) = \sum_{i=1}^{n} \frac{(x_i - \overline{x})(y_i - \overline{y})}{n-1}$
Correlation Coefficient		$corr(X,Y) = \frac{cov(X,Y)}{\sigma_x \sigma_y}$	$corr(X,Y) = \frac{cov(X,Y)}{s_x s_y}$

Mode: most frequently occurring Frequency Histogram: f versus y

**Probability Density Histogram**: p(y) (probability density) versus y

#### 1.2 External Reference Distribution

 $H_0: \eta_B - \eta_A = 0 \ y_B - y_A$  significant evidence  $\Rightarrow$  reject  $H_0$  (null hypothesis) and conclude  $H_A$  (alternate hypothesis)

 $H_A: \eta_B - \eta_A > 0$  insignificant evidence  $\Rightarrow$  fail to reject  $H_0$  (you never accepts  $H_0$ ) use significance level ( $\alpha$ ) to decide (typically  $\alpha = 0.05$  or  $\alpha = 0.01$ )

#### 1.3 Normal Distribution

#### 1.3.1 Properties of the Normal Distribution

- i) an equation
- ii) symmetric about  $\eta$
- iii) infinite tails
- iv) the area under the curve is 1

#### 1.3.2 Empirical Rule for the Normal Distribution

•  $\eta \pm 3\sigma : 99.7\%$  of data

•  $\eta \pm 2\sigma : 95.0\%$  of data

•  $\eta \pm 1\sigma : 68.0\%$  of data

**Central Limit Theorem**: "Averages" (i.e.,  $\bar{y}$ 's) tend to be bell shaped and normally distributed; as  $n \to \infty$ , the distribution of the sample means approaches normality.

#### 1.4 Student's t Distribution

- Use the student's t distribution when you do **NOT** know the standard deviation  $(\sigma)$  of the population.
- Use the fact of whether or not you know the mean  $(\eta)$  of the *population* to determine whether to use  $\mathbf{s}^2$  or  $\dot{\mathbf{s}}^2$ .
- Use  $\dot{\mathbf{s}}^2$  when you **know** the mean  $(\eta)$  of the *population*.
- Use  $s^2$  when you do not know the mean  $(\eta)$  of the population.
- If you use s, then  $t = \frac{y \overline{y}}{s}$ .

• If you use  $\dot{\mathbf{s}}$ , then  $\dot{t} = \frac{y-\eta}{\dot{s}}$ .

As the sample gets larger, the t-distribution approaches the normal distribution.

For a population with mean  $\eta$  and variance  $\sigma^2$ , you take samples of size n. The averages y of all possible samples from this population have mean  $\eta$  and variance  $\frac{\sigma^2}{n}$ .

Standard Error of Mean  $\frac{s}{\sqrt{n}}$ ,  $\frac{\sigma}{\sqrt{n}}$ 

## 2 Means, Variances, and Analysis of Variance

#### 2.1 Means

#### 2.1.1 One Population Mean

Test Type	$H_0$ and $H_A$	Test Statistic	Table
One-Sided	$H_0: \eta = \# H_A: \eta >$	$z = \frac{y-\eta}{\sigma} t = \frac{y-\overline{y}}{s}$	z table: nor-
Hypothesis	#		mal distribution
Test			/ t table: t-
			distribution
Two-Sided	$H_0: \eta = \# H_A: \eta \neq$	$z = \frac{y-\eta}{\sigma} t = \frac{y-\overline{y}}{s}$	z table: nor-
Hypothesis	#		mal distribution
Test			/ t table: t-
			distribution

Note: do not forget to double p.

#### 2.1.2 Two Population Means (unpaired)

Test Type	$H_0$ and $H_A$	Test Statistic	Table
One-Sided Hypothesis Test	$H_0: \eta_B - \eta_A = 0 \Rightarrow \eta_B = \eta_A H_A: \eta_B - \eta_A > 0 \Rightarrow \eta_B > \eta_A$	$z = \frac{(\overline{y_B} - \overline{y}_A) - (\eta_B - \eta_B)}{\sigma \sqrt{\frac{1}{n_B} + \frac{1}{n_A}}}$ $t = \frac{(\overline{y}_B - \overline{y}_A) - (\eta_B - \eta_B)}{s \sqrt{\frac{1}{n_B} + \frac{1}{n_A}}}$	z table: nor- mal distribution / t table: t- distribution
Two-Sided Hypothesis Test	$H_0: \eta_B - \eta_A = 0 \Rightarrow \eta_B = \eta_A H_A: \eta_B - \eta_A \neq 0 \Rightarrow \eta_B \neq \eta_A$	$z = \frac{(\overline{y}_B - \overline{y}_A) - (\eta_B - \eta_B)}{\sigma \sqrt{\frac{1}{n_B} + \frac{1}{n_A}}}$ $t = \frac{(\overline{y}_B - \overline{y}_A) - (\eta_B - \eta_B)}{s \sqrt{\frac{1}{n_B} + \frac{1}{n_A}}}$	z table: nor- mal distribution / t table: t- distribution

Note: do not forget to double p.

#### Notes:

- We must assume that the two populations are independent of each other.
- We must assume that the variances of the populations are equal.

## 2.1.3 Two Population Means (paired)

Test Type	$H_0$ and $H_A$	Test Statistic	Table
One-Sided Hypothesis Test	$H_0: \delta = 0 \ H_A: \delta > 0$	$\overline{d} = \sum_{i=1}^{n} \frac{(x_i - y_i)}{n}$	t table: t-
		$t = \frac{\overline{d} - \delta}{s_{\overline{d}}} = \frac{\overline{d} - \delta}{\frac{s}{\sqrt{n}}}$	distribution
Two-Sided Hypothesis Test	$H_0: \delta = 0 \ H_A: \delta \neq 0$	$\overline{d} = \sum_{i=1}^{n} \frac{(x_i - y_i)}{n}$	t table: t-
		$t = \frac{\overline{d} - \delta}{s_{\overline{d}}} = \frac{\overline{d} - \delta}{\frac{s}{\sqrt{n}}}$	distribution

Note: do not forget to double p.

## 2.2 Variances

### 2.2.1 One Population Variance

Test Type	$H_0$ and $H_A$	Test Statistic	Table
One-Sided Hypothesis Test	$H_0: \sigma^2 = \#$	$\dot{s}^2 =$	$\chi^2$ distribution
		$\frac{\sum_{i=1}^{n} (y-\eta)^2}{N} \sim$	
		$\left  \frac{\sigma^2 \chi^2}{N} \right $	
		$\begin{array}{ccc} \frac{N}{N} & \sim \\ \frac{\sigma^2}{N} \chi_N^2 / s^2 & = \\ \frac{\sum_{i=1}^n (y - \overline{y})^2}{N} & \sim \end{array}$	
		$\frac{\sum_{i=1}^{n}(y-\overline{y})^2}{\sum_{j=1}^{n}(y-\overline{y})^2}$	
		$\begin{bmatrix} \frac{n-1}{n-1} \\ \frac{\sigma^2}{n-1} \chi^2_{n-1} \end{bmatrix}$	
		<i>n</i> 1	
Two-Sided Hypothesis Test			$\chi^2$ distribution

Note: do not forget to double p.

## 2.2.2 Two Population Variances

Test Type	$H_0$ and $H_A$	Test Statistic	Table
One-Sided	$H_0$ : $\sigma_A^2$ =	$\frac{s_A^2}{s_B^2}$	F distribution
Hypothesis	$\sigma_B^2 \Rightarrow \frac{\sigma_A^2}{\sigma_B^2} =$	${}^{\mathcal{S}}B$	
Test	$\left \begin{array}{ccc} I & \sigma_B^{\sigma_B} \\ 1 & H_A & : & \sigma_A^2 \end{array}\right>$		
	$\sigma_B^2 \Rightarrow \frac{\sigma_A^2}{\sigma_B^2} > 1$		

**Y** matrix (data) = **A** matrix (grand average) + **T** matrix ( $\overline{y}$  - grand average) + **R** matrix (residue)

 $\mathbf{D}$  matrix =  $\mathbf{Y}$  matrix -  $\mathbf{A}$  matrix =  $\mathbf{T}$  matrix +  $\mathbf{R}$  matrix

## 2.3 Analysis of Variance (ANOVA) Table

Source	Sum of Squares	Degrees of Freedom	Mean Square
Between (T)	$S_T = \text{Sum of Squares}$	$\nu_T = \# \text{ of columns} - 1$	$S_T^2 = \frac{S_T}{\nu_T}$
Within (R)	$S_R = \text{Sum of Squares}$	$\nu_R = \Sigma(n-1)$ for each column	$S_R^2 = \frac{S_R}{\nu_R}$
Total (D)	$S_D = \text{Sum of Squares}$	$\nu_D = \nu_T + \nu_R$	X
	$=S_T+S_R$		

$\mathbf{F}$	P	Analysis
$\frac{S_T^2}{S_R^2}$		

### 2.4 Confidence Interval Formulae

Population Mean:  $\eta$ 

$\overline{y} \pm z_{\frac{\infty}{2}} \frac{\sigma}{\sqrt{n}}$	$\sigma$ known
$\overline{y} \pm t_{\frac{\infty}{2}} \frac{s}{\sqrt{n}}$	$\sigma$ unknown

Difference in Population Means:  $\eta_B - \eta_A$ 

Mean of Paired Differences:  $\delta$ 

## 3 Experimental Design

## 3.1 Completely Randomized Design

#### 1 Treatment, No Blocks

 $H_0: \eta_A = \eta_B = \eta_C$ 

 $H_A$ : not all population means are equal

Matrix:  $Y = A + T + R \Rightarrow D = T + R$ 

## 3.2 Randomized Block Design

#### 1 Treatment, 1 Block

 $H_0: \eta_A = \eta_B = \eta_C = \eta_D$ 

 $H_A$ : not all population means are equal

 $H_0: \tau_A = \tau_B = \tau_C = \tau_D = 0$ 

 $H_A: \tau_t \neq 0$  for some t

 $H_0: \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = 0$ 

 $H_A: \beta_i \neq 0$  for some i

Matrix:  $Y = A + B + T + R \Rightarrow D = B + T + R$ 

## 3.3 Two-Way Factorial Design

#### 2 Treatments at once, no Blocks, must replicate at least twice

 $H_0: \tau_A = \tau_B = \tau_C = \tau_D = 0$ 

 $H_A: \tau_i \neq 0$  for some i

 $H_0: \tau_1 = \tau_2 = \tau_3 = \tau_4 = \tau_5 = 0$ 

 $H_A: \tau_i \neq 0$  for some j

 $H_0: \forall \omega, \omega = 0$ 

 $H_A: \omega_{ij} \neq 0$  for some ij

**Matrix**:  $Y = A + T_1 + T_2 + I + R \Rightarrow D = T_1 + T_2 + I + R$ 

## 3.4 Latin Square Design

## 1 Treatment, 2 Blocks, No Interactions

 $H_0: \eta_A = \eta_B = \eta_C = \eta_D$ 

 $H_A$ : not all population means are equal

 $H_0: \tau_A = \tau_B = \tau C = \tau D = 0$ 

 $H_A: \tau_t \neq 0$  for some t

 $H_0: \beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$ 

 $H_A:\beta_i\neq 0$  for some i

 $H_0: \beta_I = \beta_{II} = \beta_{III} = \beta_{IV} = 0$ 

 $H_A: \beta_j \neq 0$  for some j

Matrix:  $Y = A + B_1 + B_2 + T + R \Rightarrow D = B_1 + B_2 + T + R$ 

8

## 3.5 Factorial Design

## Any # of Treatments, No Blocks, Must Replicate at least twice

 $H_0: \eta_A = \eta_B = \eta_C$ 

 $H_A$ : not all population means are equal

#### Treatment A

 $H_0: \tau_1 = \tau_2 = 0$ 

 $H_A: \tau_t \neq 0$  for some t

#### Treatment B

 $H_0: \tau_1 = \tau_2 = 0$ 

 $H_A: \tau_t \neq 0$  for some t

#### Treatment C

 $H_0: \tau_1 = \tau_2 = 0$ 

 $H_A: \tau_t \neq 0$  for some t

**Matrix**:  $Y = A + T_1 + T_2 + T_3 + R \Rightarrow D = T_1 + T_2 + T_3 + R$ 

**Tukey Test** is to test which pairs of population means are different. You only perform tukey tests if you rejected the null hypothesis.

$$q_{4,6,0.05} = \frac{4.90}{\sqrt{2}} = 3.46 \text{ abs } (\#) > 3.46$$