Class 4, Chapter 2: Inferences using t-distributions
Chapter 3: A Closer Look at Assumptions [of the *t* tests]

2/9/09 M

Slide 1 Class 4, Chapter 2: Inferences using t-distributions

Chapter 3: A Closer Look at Assumptions [of the t tests]

NOTES:

HW 3 for Thus 2/12/09 11 am

Submit as Myname-HW3.doc (or *.rtf)

- Finish Chapter 2 and start on Chapter 3 "A closer look at assumptions"
  - Read Sterne & Smith (2001) "Sifting the evidence" [Discusses p values & significance testing]
- **Conceptual exercises, Chapter 2**
  - Post ≥1 message & ≥1 reply to a message on the Blackboard Vista 4 discussion section.
- **Chapter 2 computation problems** (SPSS data on Blackboard Vista 4)
  - 2.21Bumpus's data: weights of Bumpus's birds

Slide 2 HW 3 for Thus 2/12/09 11 am

NOTES:

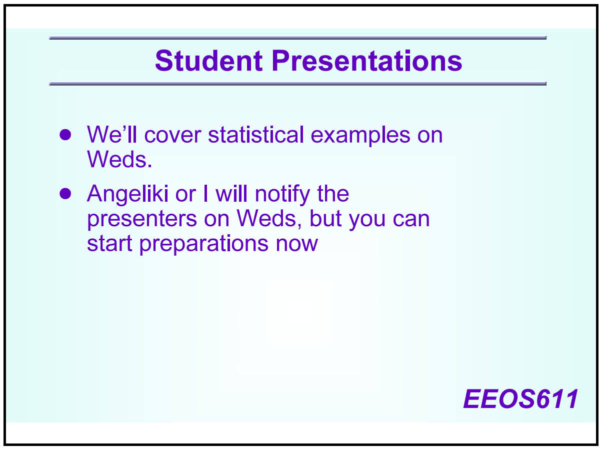
HW 4 due Mon 2/16/09 9:50 am

Submit as Myname-HW4.doc (or *.rtf)

- Finish Ch 3 for Weds' class
  - Chapter 3: A closer look at assumptions
  - Read
    - Hayek & Buzas (1997, on sampling)
    - Hurlbert (1984) on Pseudoreplication
    - **Post one comment and one reply to issues raised in Hayek & Buzas or Hurlbert (1984)**
- Chapter 3 problem due Monday 2/16
  - **3.28 Pollen removal**

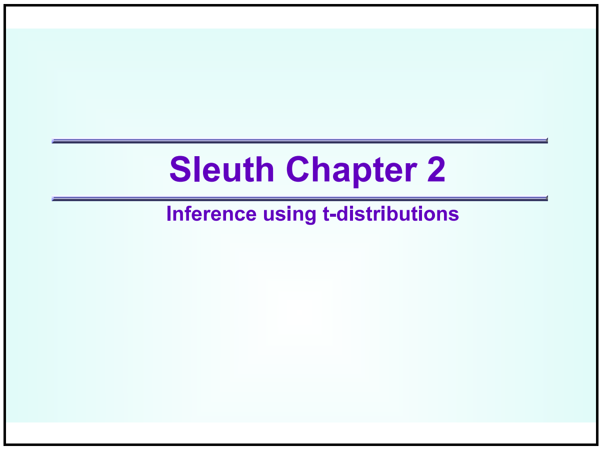
Slide 3 HW 4 due Mon 2/16/09 9:50 am

NOTES:



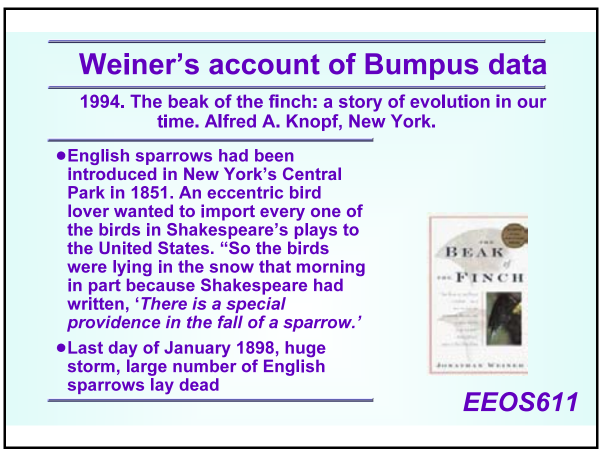
Slide 4 Student Presentations

NOTES:



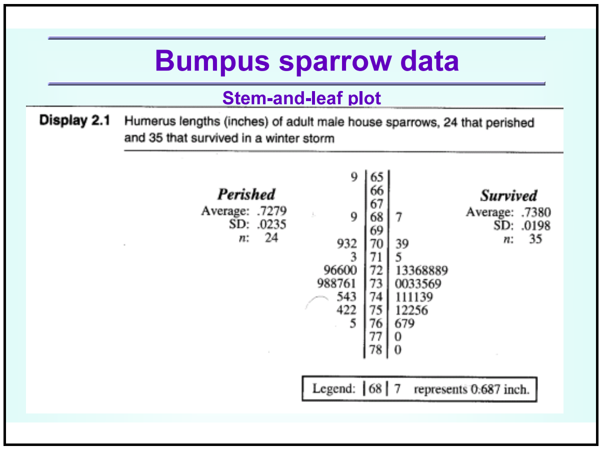
Slide 5 Sleuth Chapter 2

NOTES:



Slide 6 Weiner's account of Bumpus data

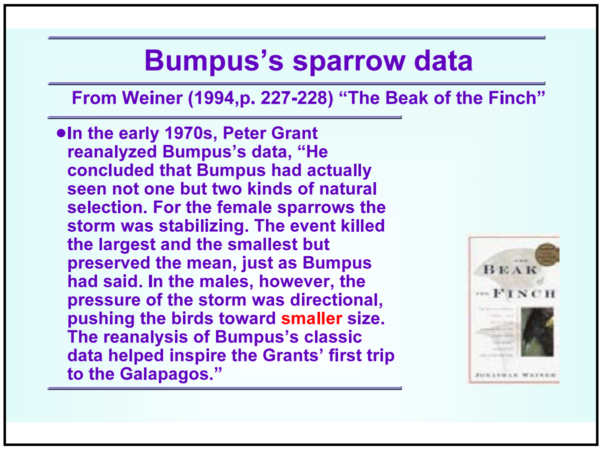
NOTES:



Perished	Stem	Survived
9	65	
	66	
	67	
9	68	7
	69	
932	70	39
3	71	5
96600	72	13368889
988761	73	0033569
543	74	111139
422	75	12256
5	76	679
	77	0
	78	0

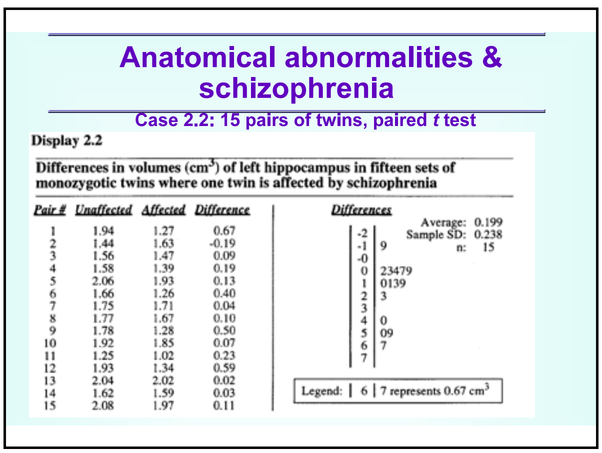
Slide 7 Bumpus sparrow data

NOTES:



Slide 8 Bumpus's sparrow data

NOTES:

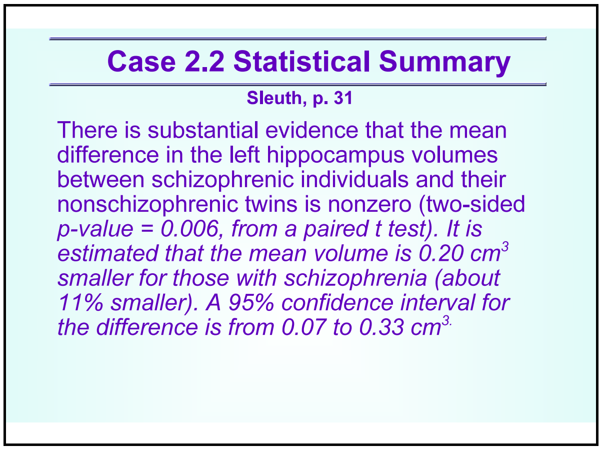


Pair #	Unaffected	Affected	Difference
1	1.94	1.27	0.67
2	1.44	1.63	-0.19
3	1.56	1.47	0.09
4	1.58	1.39	0.19
5	2.06	1.93	0.13
6	1.66	1.26	0.40
7	1.75	1.71	0.04
8	1.77	1.67	0.10
9	1.78	1.28	0.50
10	1.92	1.85	0.07
11	1.25	1.02	0.23
12	1.93	1.34	0.59
13	2.04	2.02	0.02
14	1.62	1.59	0.03
15	2.08	1.97	0.11

Stem	Leaf
-2	
-1	9
-0	
0	23479
1	0139
2	3
3	
4	0
5	09
6	7
7	

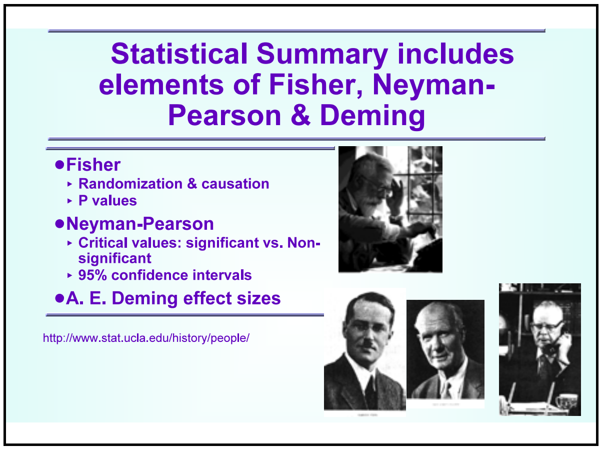
Slide 9 Anatomical abnormalities & schizophrenia

NOTES:



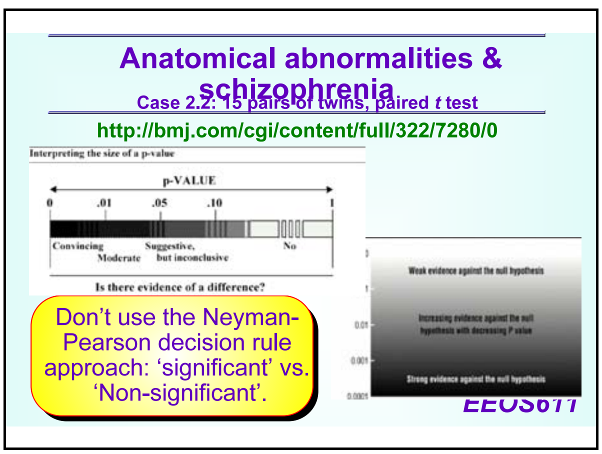
Slide 10 Case 2.2 Statistical Summary

NOTES:



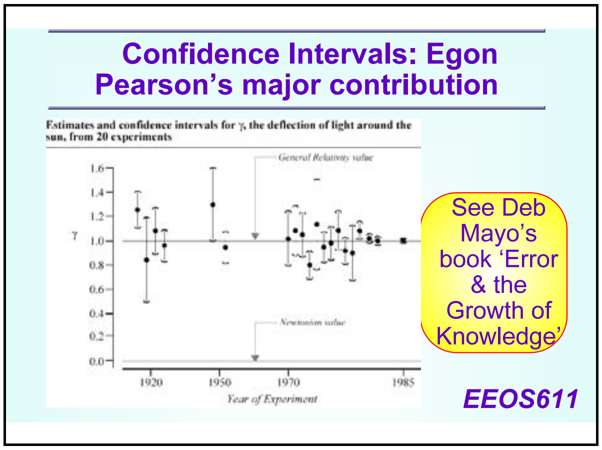
Slide 11 Statistical Summary includes elements of Fisher, Neyman-Pearson & Deming

NOTES:



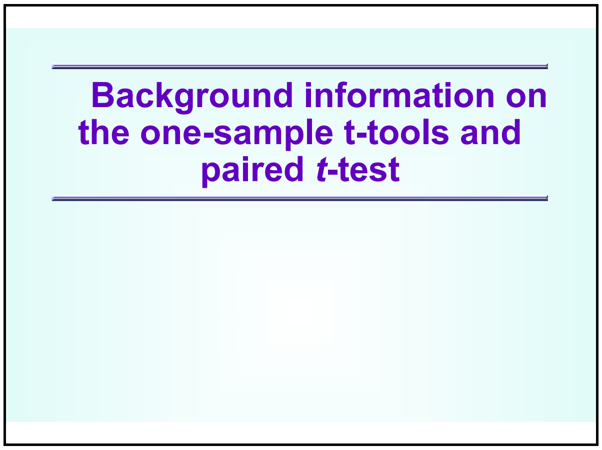
Slide 12 Confidence Intervals: Egon Pearson's major contribution

NOTES:



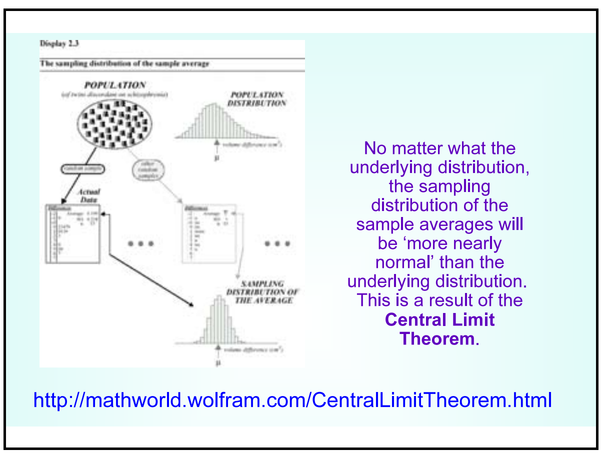
Slide 13 Confidence Intervals: Egon Pearson's major contribution

NOTES:



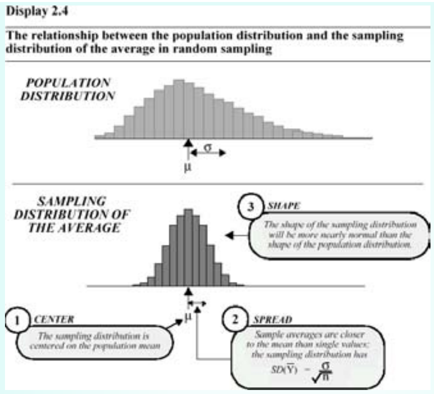
Slide 14 Background information on the one-sample t-tools and paired t-test

NOTES:



Slide 15

NOTES:



Slide 16

NOTES:

Expressing uncertainty

X ± δ, >4 choices for δ {del}

- ± standard deviation
  - Advantage: expressed in the same units as the parameter being estimated
  - Not a good choice, some statisticians argue that it is inappropriate for a sample statistic
- ± standard error, also called the standard deviation of the average or sd of the mean or the standard error of the mean
  - SE($\bar{x}$) = s/ √n, d.f.=(n-1)
  - Advantage: statistically appropriate
  - Needs the sample size for interpretation
- ± half the 95% confidence interval
  - Assumes an underlying model for the data
  - For asymmetric 95% CI's in the statistics natural scale, provide the upper and lower 95% CI (for transformed data and results of Monte Carlo simulations
- Analytical precision of the instrument or technique
  - E.g., the Chl *a* method has a certain analytical precision. This is rarely acceptable.
  - Hurlbert's E(S_{100}), a measure of species richness, has an analytical precision based on the sampling properties of the hypergeometric distribution.
  - Polling data has an analytical precision based on var=p*(1-p), but this rarely expresses the other sources of variability in a poll

Slide 17 Expressing uncertainty

NOTES:

The Z-ratio & t-ratio based on a sample average

- Z-ratio = (Estimate - Parameter)/ SD(Estimate)
  - If the sampling distribution is normal, than the sampling distribution of Z is standard normal
  - Mean zero and standard deviation of 1
  - Z distribution provided in Appendix A.1
  - t-ratio = (Estimate - Parameter)/SE (Estimate)
  - If $\bar{x}$ is the average in a random sample of size n from a normally distributed population, the sampling distribution of *t* is described by the Student's *t* distribution on *n-1* degrees of freedom

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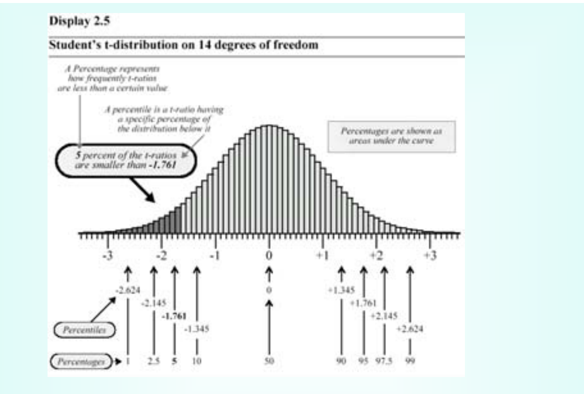
Slide 18 The Z-ratio & t-ratio based on a sample average

NOTES:



Slide 19

NOTES:

Degrees of freedom **Box 1.2**

Statistical tests of significance often call upon the concept of degrees of freedom. A formal definition is the following: "The degrees of freedom of a model for expected values of random variables is the excess of the number of variables [observations] over the number of parameters in the model" (Kotz & Johnson, 1982).

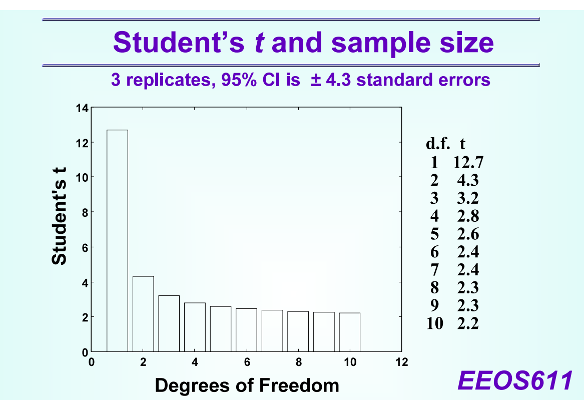
In practical terms, the number of degrees of freedom associated with a statistic is equal to the number of its independent components, i.e. the total number of components used in the calculation minus the number of parameters one had to estimate from the data before computing the statistic. For example, the number of degrees of freedom associated with a variance is the number of observations minus one (noted $\nu = n - 1$): n components $(x_i - \bar{x})$ are used in the calculation, but one degree of freedom is lost because the mean of the statistical population is estimated from the sample data; this is a prerequisite before estimating the variance.

There is a different t distribution for each number of degrees of freedom. The same is true for the F and χ^2 families of distributions, for example. So, the number of degrees of freedom determines which statistical distribution, in these families (t, F, or χ^2), should be used as the reference for a given test of significance. Degrees of freedom are discussed again in Chapter 6 with respect to the analysis of contingency tables.

Legendre & Legendre (1989) Numerical Ecology 2nd Ed.

Slide 20

NOTES:



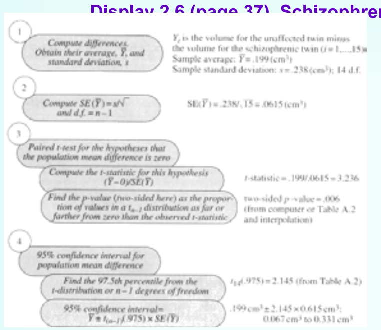
d.f.	t
1	12.7
2	4.3
3	3.2
4	2.8
5	2.6
6	2.4
7	2.4
8	2.3
9	2.3
10	2.2

Slide 21 Student's t and sample size

NOTES:

95% CI for the mean difference

Display 2.6 (page 37). Schizophrenia study



Slide 22 95% CI for the mean difference

NOTES:

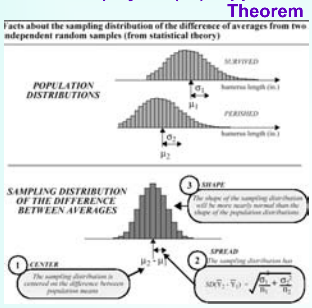
A *t*-ratio for two-sample inference

Slide 23 A t-ratio for two-sample inference

NOTES:

Sampling distribution of the difference of averages

Display 2.7 (38): Application of the Central Limit Theorem



Slide 24 Sampling distribution of the difference of averages

NOTES:

Pooled standard deviation

& standard error for the difference
This estimate assumes equal variances (Sleuth p 39)

$$s_p = \sqrt{\frac{(n_1-1)s_1^2 + (n_2-1)s_2^2}{(n_1+n_2-2)}}, \qquad \text{d.f.} = n_1 + n_2 - 2.$$

$$SE(\bar{Y}_2 - \bar{Y}_1) = s_p\sqrt{\frac{1}{n_1} + \frac{1}{n_2}}.$$

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Slide 25 Pooled standard deviation

NOTES:

SE of difference

Calculation of the pooled estimate of SD and the standard error for the difference between two sample averages; Bumpus' data

(1) SUMMARY STATISTICS

Group	n	Average (in.)	Sample SD (in.)
1: Died	24	.72792	.02354
2: Survived	35	.73800	.01984

(2) THE POOLED SD

$$s_p = \sqrt{\frac{(24-1)(.02354)^2 + (35-1)(.01984)^2}{(24+35-2)}}$$

$$= \sqrt{\frac{.026128}{57}}$$ ← These are the degrees of freedom associated with the pooled SD

$$= \sqrt{.0004584}$$ ← This is the pooled variance

Answer → $s_p = 0.02141$ inches

(3) THE STANDARD ERROR

$$SE(\bar{Y}_2 - \bar{Y}_1) = 0.02141\sqrt{\frac{1}{24} + \frac{1}{35}}$$

$$= 0.00567$$ inches ← Answer

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lay 2.8
40) *EEOS611*

Slide 26 SE of difference

NOTES:

95% Confidence Limits

For the difference between means

100(1 − α)% Confidence Limits for the Difference Between Means

$$(\bar{Y}_2 - \bar{Y}_1) \pm t_{df}(1-\alpha/2)SE(\bar{Y}_2 - \bar{Y}_1).$$

"A 95% confidence interval will contain the parameter if the t-ratio from the observed data happens to be one of those in the middle 95% of the sampling distribution. Since 95% of all possible pairs of samples lead to such t-ratios, **it is safe to say that the procedure of constructing a 95% CI is successful in 95% of its applications."**

It is incorrect to say that there is a 95% probability that the true parameter is within the 95% CI. **That** probability is either 0 or 1. Bayesians have a different interpretation of p values.

Slide 27 95% Confidence Limits

NOTES:

CI for difference of means

Sleuth 2e Display 2.9 (41)

Construction of a 95% confidence interval for the difference between the mean humerus lengths of sparrows that died and that survived

Group	n	Average (in.)	SD (in.)
1: Died	24	.72792	.02354
2: Survived	35	.73800	.01984

$\bar{Y}_2 - \bar{Y}_1$ = .73800 - .72792 = 0.01008

$SE(\bar{Y}_2 - \bar{Y}_1)$ = 0.00567 inches

degrees of freedom = 24 + 35 - 2 = 57

$t_{57}(.975) = 2.002$

Half-width = (2.002)(0.00567) = 0.01136

Lower 95% confidence limit = 0.01008 - 0.01136 = -0.00128 inches

Upper 95% confidence limit = 0.01008 + 0.01136 = 0.02144 inches

From Display 2.8

from tables of the t-distribution with 57 degrees of freedom

Slide 28 CI for difference of means

NOTES:

Testing a hypotheses about the difference of means

$$t\text{-statistic} = \frac{(\bar{Y}_2 - \bar{Y}_1) - [\text{Hypothesized value for } (\mu_2 - \mu_1)]}{SE(\bar{Y}_2 - \bar{Y}_1)}.$$

"The p value for a *t* test is a probability of obtaining a t ratio as extreme or more extreme than the t statistic in its evidence against the null hypothesis, if the null hypothesis is correct." (Sleuth 2nd ed. p. 42) [Bayesians do not use this interpretation.] A large p value means that the study is not capable of excluding the null hypothesis as a possible explanation. **It's wrong to conclude that the null hypothesis is true."**

Slide 29 Testing a hypotheses about the difference of means

NOTES:

Display 2.10

Was the difference consistent with chance?

The t-test for the hypothesis that the mean humerus lengths of sparrows that died is the same as the mean for sparrows that survived

Group	n	Average (in.)	SD (in.)
1: Died	24	.72792	.02354
2: Survived	35	.73800	.01984

$\bar{Y}_2 - \bar{Y}_1$ = .73800 - .72792 = 0.01008

$SE(\bar{Y}_2 - \bar{Y}_1)$ = 0.00567 inches

degrees of freedom = 24 + 35 - 2 = 57

From Display 2.8

Hypothesized Difference

$$t\text{-statistic} = \frac{0.01008 - \mathbf{0.0}}{0.00567} = 1.778$$

P = .960

from tables of the t-distribution with 57 degrees of freedom: $1.778 = t_{57}(.960)$

1-sided p-value = .040 *or* 2-sided p-value = 2(.040) = .080

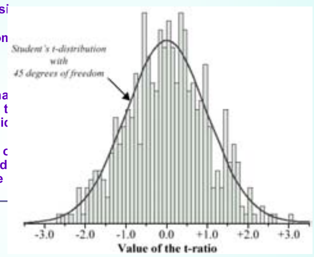
Slide 30 Display 2.10

NOTES:

Randomization distribution

Can be done with Matlab & R, not SPSS
Display 2.11, page 46

- Creativity data
  - Randomly shuffle (500 times) the membership in intrinsic and extrinsi[c] groups
  - Calculate the t-ratio for each randon[m] shuffle
  - Order the value of the t ratios from smallest to largest
  - For a 1-sided test, calculate how ma[ny] the t ratios were larger (or smaller) t[han] the observed t ratio, add 1, and divi[de by] the number of randomizations
  - For a 2-sided test, find the number o[f] ratios whose absolute value exceed[s] observed t ratios, add 1, and divide number of randomizations

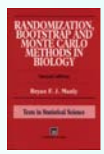


Slide 31 Randomization distribution

NOTES:

Randomization doesn't solve problems with unequal variance

- Randomization is often superior to the t-distribution for 2-sample problems
- Randomization does not remedy violations of the assumptions of the t test.
  - The most common problem with Student's t test is the so-called Fisher-Behrens problem, testing the difference in the average if the distributions have different variances
  - This is an open question
  - Neither nonparametric approaches (see Chapter 4) nor randomization provide a clear solution



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Slide 32 Randomization doesn't solve problems with unequal variance

NOTES:

Chapter 3: A closer look at assumptions

Slide 33 Randomization doesn't solve problems with unequal variance

NOTES:

Randomization doesn't solve problems with unequal variance

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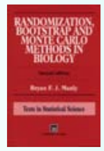

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Slide 34 Chapter 3: A closer look at assumptions

NOTES:

Case study 3.1

Cloud seeding to increase rainfall — A randomized experiment

- 52-day experiment
- Random selection each day to seed or not to seed a cloud; pilot 'blind' to treatment
- Rainfall measured
- Data highly skewed

Display 3.1

Rainfall (acre-feet) for days with and without cloud seeding

Rainfall from unseeded days (n = 26)

1202.6	830.1	372.4	345.5	321.2	244.3	163.0	147.8	95.0
87.0	81.2	68.5	47.3	41.1	36.6	29.0	28.6	26.3
26.1	24.4	21.7	17.3	11.5	4.9	4.9	1.0	

Rainfall from seeded days (n = 26)

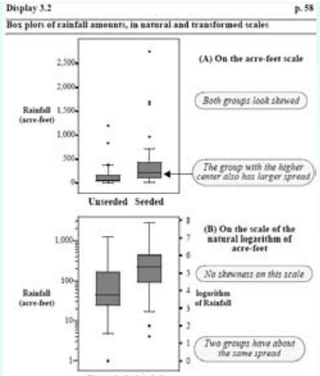
2745.6	1697.8	1656.0	978.0	703.4	489.1	430.0	334.1	302.8
274.7	274.7	255.0	242.5	200.7	198.6	129.6	119.0	118.3
115.3	92.4	40.6	32.7	31.4	17.5	7.7	4.1	

Slide 35 Case study 3.1

NOTES:

Display 3.2 p. 58

Box plots of rainfall amounts, in natural and transformed scales

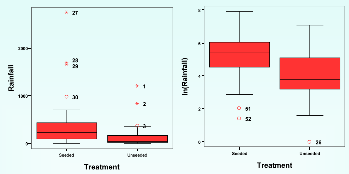


Statistical inference

[Median or geometric mean] volume of rain after seeding was 3.1 times unseeded (95%CI: 1.3 to 7.7). Since randomization used, seeding **caused** a larger rainfall amount.

Slide 36

NOTES:



Independent Samples Test

t-test for Equality of Means

	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference Lower	Upper
ln(Rainfall)	2.5	50	.014	1.14	.450	.241	2.047

Exp(1.14)≈3.1;exp(0.241)≈1.3;exp(2.047)≈**7.7**

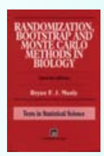
[Median or geometric mean] volume of rain after seeding was **3.1** times unseeded (95%CI: **1.3** to **7.7**). Since randomization used, seeding **caused** a larger rainfall amount.

Slide 37

NOTES:

Randomization doesn't solve problems with unequal variance

- Randomization is often superior to the nominal p values from the t-distribution for 2-sample problems, but randomization does not remedy the most important problem with the t distribution: unequal variance
- The most common problem with Student's t test is the so-called Fisher-Behrens problem, testing the difference between averages from distributions with different variances
  - This is an open question
  - Neither nonparametric approaches (see Chapter 4) nor randomization provide a clear solution



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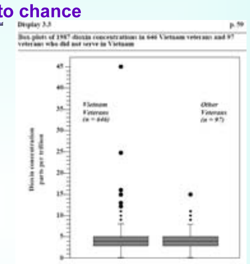
Slide 38 Randomization doesn't solve problems with unequal variance

NOTES:

Case 3.2: Dioxin study

Differences between veteran dioxin concentrations could be due to chance

- 646 Veterans who served in Viet Nam during 1967 & 1968 in areas treated with Agent Orange
- 97 other veterans served between 1965-1971 in US or Germany
- Serum dioxin levels measured
- Statistical Summary:
  - No evidence that the mean dioxin levels differ (1-sided p value=0.4)
  - Extrapolation speculative; dioxin-affected vets may not have participated in the survey



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Slide 39 Case 3.2: Dioxin study

NOTES:

Robustness of the two-sample *t* tools

Slide 40 Robustness of the two-sample t tools

NOTES:

Assumptions of *t* test

- Two major assumptions
  - Both samples are independent samples from normally distributed populations
  - Both samples have identical standard deviations
- The *t* tests are usually robust to modest violations of the assumptions
  - These assumptions are never strictly met, but the *t* test is remarkably robust to violations of the assumptions
  - Robust means the conclusions from test — *e.g., p* values, confidence limits — are valid even when the assumptions aren't strictly met, especially if sample sizes nearly equal
  - Transformations of the data are often used

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Slide 41 Assumptions of t test

NOTES:

Violations of assumptions that matter

- With equal sample sizes, the *t*-test is affected moderately by long-tailedness (leptokurtic or peaked distribution) and very little by skewness (the symmetry of the distribution)
  - Kurtosis: peakedness, platykurtic (flat distribution), leptokurtic (peaked)
  - **Skewness: symmetry**
- If the two populations have the same standard deviations and approximately the same shape, with unequal sample size, the *t* tests are affected moderately by long tailedness (leptokurtic) and **substantially by skewness**
- If the **skewness** differs considerably, the **tools can be misleading with small and moderate sample sizes**

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Slide 42 Violations of assumptions that matter

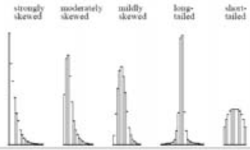
NOTES:

Monte Carlo simulations of violations on p values

really matter?

Display 3.4

Percentage of 95% confidence intervals that are successful when the two populations are non-normal (but same shape and SD, and equal sample sizes); each percentage is based on 1,000 computer simulations



n_1, n_2	strongly skewed	moderately skewed	mildly skewed	long-tailed	short-tailed
5	95.5	95.4	95.2	98.3	94.5
10	95.5	95.4	95.2	98.3	94.6
25	95.3	95.3	95.1	98.2	94.9
50	95.1	95.3	95.1	98.1	95.2
100	94.8	95.3	95.0	98.0	95.6

When 2 populations are the same shape with equal n, the *t* test is only affected moderately (conservative for leptokurtic [peaked] distributions)

Slide 43 Monte Carlo simulations of violations on p values

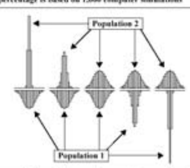
NOTES:

Different standard deviations & sample sizes

Robust if sample sizes the same, nonconservative if smaller group has bigger s.d.

Display 3.5

Percentage of successful 95% confidence intervals when the two populations have different standard deviations (but are normal) with possibly different sample sizes; each percentage is based on 1,000 computer simulations



n_1	n_2	$\sigma_2 / \sigma_1 =$	1/4	1/2	1	2	4
10	10		95.2	94.2	94.7	95.2	94.5
10	20	Success	83.0	89.3	94.4	98.7	99.1
10	40	Rates	71.0	82.6	95.2	99.5	99.9
100	100	for 95%	94.8	96.2	95.4	95.3	95.1
100	200	Intervals	86.5	88.3	94.8	98.8	99.4
100	400		71.6	81.5	95.0	99.5	99.9

P (Type I error) >> stated value (e.g., 0.05) if sd of smaller group larger than larger group

P (Type I error) << stated value (e.g., 0.05) if sd of smaller group smaller than larger group

EEOS611

Slide 44 Different standard deviations & sample sizes

NOTES:

Departures from independence

Cluster, serial & spatial effects can be serious and are more difficult to account for in statistical analysis

- Cluster effects
  - Mice from litters
  - Copepods from net hauls
  - Technician-to-technician variability in sample analysis
- Serial effects (an explicit time or space term)
  - Temporal autocorrelation
- Spatial effects: positive autocorrelation (Ellen Douglas's research on flood frequency, Chen & Ferguson on MCAS scores)
- Check residuals (observed-expected) for spatial or temporal pattern
- Inferences based on Student's *t* tests can be very misleading or wrong if there are spatial or temporal correlations in residuals

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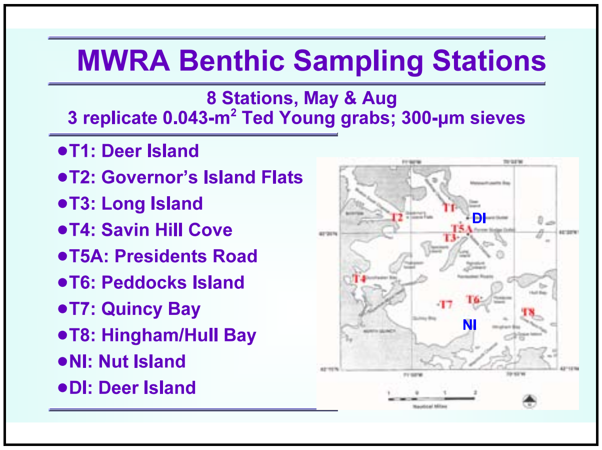
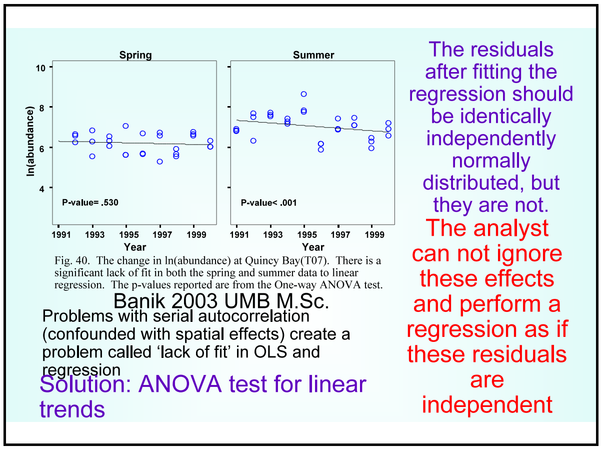
Slide 45 Departures from independence

NOTES:



Slide 46 MWRA Benthic Sampling Stations

NOTES:



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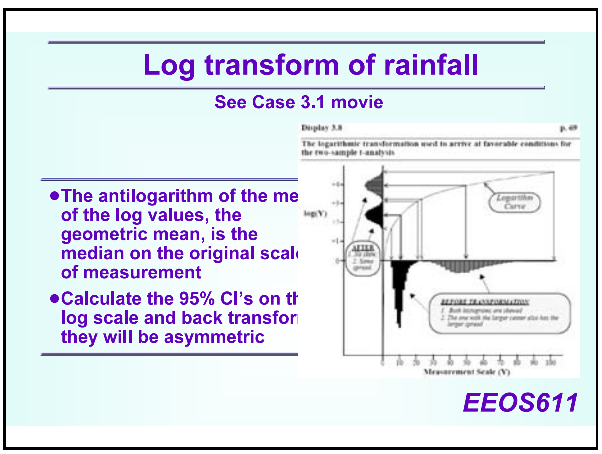
NOTES:



Slide 48 Log transform of rainfall

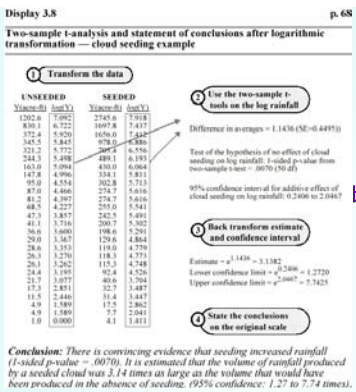
NOTES:

3.5.3 Transformations

- Log (x+1) transform
  - Most biological data, but not usually diversity
  - Needed when there is a multiplicative process in action: growth, bank account interest
  - Marine pollutants: polynuclear aromatic hydrocarbons, fecal coliform bacteria, but not usually metals
  - Calculate the mean and 95% CI and then back-transform. For symmetric data, the mean of the log-transformed data ≈median. Label as the geometric mean
- Many other transforms
  - Arcsin (√Y) for frequency data ranging between 0 and 1 (but the logit transform may be better)
  - % silt clay, but the data must be on the interval 0 to1
  - Logit transform: log [Y/(1-Y)]
  - Square roots for counts, reciprocal for waiting times, logit transforms for proportions between 0 and 1 (log (P/(1-P))
  - "... it is recommended here that a trial-and error approach, with graphical analysis, be used instead."

Slide 49 3.5.3 Transformations

NOTES:



Display 3.8 p. 68

Two-sample t-analysis and statement of conclusions after logarithmic transformation — cloud seeding example

① Transform the data

UNSEEDED Y(acre-ft)	UNSEEDED log(Y)	SEEDED Y(acre-ft)	SEEDED log(Y)
1202.6	7.092	2745.6	7.918
830.1	6.722	1697.8	7.437
372.4	5.920	1656.0	7.412
345.5	5.845	978.0	6.886
321.2	5.772	703.4	6.556
244.3	5.498	489.1	6.193
163.0	5.094	430.0	6.064
147.8	4.996	334.1	5.811
95.0	4.554	302.8	5.713
87.0	4.466	274.7	5.616
81.2	4.397	274.7	5.616
68.5	4.227	255.0	5.541
47.3	3.857	242.5	5.491
41.1	3.716	200.7	5.302
36.6	3.600	198.6	5.291
29.0	3.367	129.6	4.864
28.6	3.353	119.0	4.779
26.3	3.270	118.3	4.773
26.1	3.262	115.3	4.748
24.4	3.195	92.4	4.526
21.7	3.077	40.6	3.704
17.3	2.851	32.7	3.487
11.5	2.446	31.4	3.447
4.9	1.589	17.5	2.862
4.9	1.589	7.7	2.041
1.0	0.000	4.1	1.411

② Use the two-sample t-tools on the log rainfall

Difference in averages = 1.1436 (SE=0.4495)

Test of the hypothesis of no effect of cloud seeding on log rainfall: 1-sided p-value from two-sample t-test = .0070 (50 df)

95% confidence interval for additive effect of cloud seeding on log rainfall: 0.2406 to 2.0467

③ Back transform estimate and confidence interval

Estimate = $e^{1.1436}$ = 3.1382
Lower confidence limit = $e^{0.2406}$ = 1.2720
Upper confidence limit = $e^{2.0467}$ = 7.7425

④ State the conclusions on the original scale

Conclusion: *There is convincing evidence that seeding increased rainfall (1-sided p-value = .0070). It is estimated that the volume of rainfall produced by a seeded cloud was 3.14 times as large as the volume that would have been produced in the absence of seeding. (95% confidence: 1.27 to 7.74 times).*

Do the test and calculate the 95% CI on transformed data and then back transform the effect size and confidence limits. Report as ratio of geometric means (Sleuth: ratio of medians).

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NOTES:

http://www.cdc.gov/exposurereport/

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NOTES:

Table 16. Lead in blood

Geometric mean and selected percentiles of blood concentrations (in µg/dL) for the U.S. population aged 1 year and older, National Health and Nutrition Examination Survey, 1999-2002.

	Survey years	Geometric mean (95% conf. interval)	Selected percentiles (95% confidence interval) 50th	75th	90th	95th	Sample size
Total, age 1 and older	99-00	1.66 (1.60-1.72)	1.60 (1.50-1.60)	2.40 (2.30-2.60)	3.80 (3.60-3.90)	4.90 (4.60-5.30)	7970
	01-02	1.45 (1.39-1.51)	1.40 (1.30-1.40)	2.20 (2.10-2.20)	3.40 (3.10-3.60)	4.40 (4.20-4.70)	8945
Age group							
1-5 years	99-00	2.23 (1.96-2.53)	2.20 (1.90-2.50)	3.30 (2.90-3.60)	4.80 (4.00-5.60)	7.00 (6.10-8.30)	723
	01-02	1.70 (1.55-1.87)	1.50 (1.40-1.70)	2.50 (2.20-2.60)	4.10 (3.40-5.00)	5.80 (4.70-6.90)	898
6-11 years	99-00	1.51 (1.36-1.66)	1.30 (1.20-1.50)	2.00 (1.70-2.40)	3.30 (2.70-3.60)	4.50 (3.40-6.20)	905
	01-02	1.25 (1.14-1.38)	1.10 (1.00-1.30)	1.60 (1.50-1.80)	2.70 (2.40-3.00)	3.70 (3.00-4.70)	1044
12-19 years	99-00	1.10 (1.04-1.17)	1.00 (.900-1.10)	1.40 (1.30-1.60)	2.30 (2.10-2.30)	2.80 (2.60-3.00)	2135
	01-02	.942 (.899-.986)	.800 (.800-.900)	1.20 (1.20-1.30)	1.90 (1.80-2.00)	2.70 (2.30-2.90)	2231
20 years and older	99-00	1.75 (1.68-1.81)	1.70 (1.60-1.70)	2.50 (2.50-2.60)	3.90 (3.70-4.00)	5.20 (4.80-5.50)	4207
	01-02	1.56 (1.49-1.62)	1.60 (1.50-1.60)	2.20 (2.20-2.30)	3.60 (3.30-3.70)	4.60 (4.20-4.90)	4772
Gender							
Males	99-00	2.01 (1.93-2.09)	1.80 (1.80-1.90)	2.90 (2.80-3.00)	4.40 (4.10-4.80)	6.00 (5.40-6.40)	3913
	01-02	1.78 (1.71-1.86)	1.70 (1.70-1.80)	2.70 (2.50-2.80)	3.90 (3.70-4.10)	5.30 (5.00-5.50)	4339
Females	99-00	1.37 (1.32-1.43)	1.20 (1.20-1.30)	1.90 (1.90-2.10)	3.00 (2.90-3.20)	4.00 (3.70-4.20)	4057
	01-02	1.19 (1.14-1.25)	1.10 (1.10-1.20)	1.80 (1.70-1.80)	2.60 (2.40-2.70)	3.60 (3.00-3.80)	4606
Race/ethnicity							
Mexican Americans	99-00	1.83 (1.75-1.91)	1.80 (1.60-1.80)	2.70 (2.60-2.90)	4.20 (3.90-4.50)	5.80 (5.10-6.60)	2742
	01-02	1.46 (1.34-1.60)	1.50 (1.30-1.60)	2.20 (2.00-2.50)	3.60 (3.30-4.00)	5.40 (4.45-6.60)	2268
Non-Hispanic blacks	99-00	1.87 (1.75-2.00)	1.70 (1.60-1.90)	2.80 (2.50-2.90)	4.20 (4.00-4.60)	5.70 (5.20-6.10)	1842
	01-02	1.65 (1.52-1.80)	1.60 (1.40-1.70)	2.50 (2.30-2.80)	4.20 (3.80-4.60)	5.70 (5.30-6.50)	2219
Non-Hispanic whites	99-00	1.62 (1.55-1.69)	1.60 (1.50-1.60)	2.40 (2.30-2.40)	3.60 (3.40-3.70)	5.00 (4.45-5.70)	2716
	01-02	1.43 (1.37-1.48)	1.40 (1.30-1.40)	2.10 (2.10-2.20)	3.10 (3.00-3.40)	4.10 (3.90-4.50)	3806

http://www.cdc.gov/exposurereport/3rd/pdf/thirdreport.pdf

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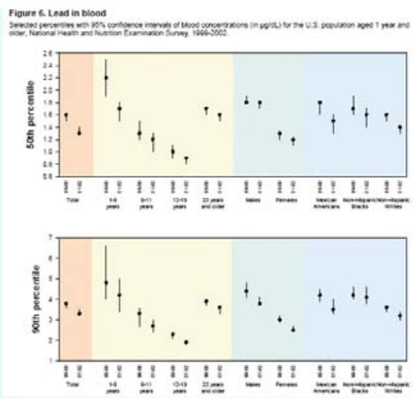
NOTES:



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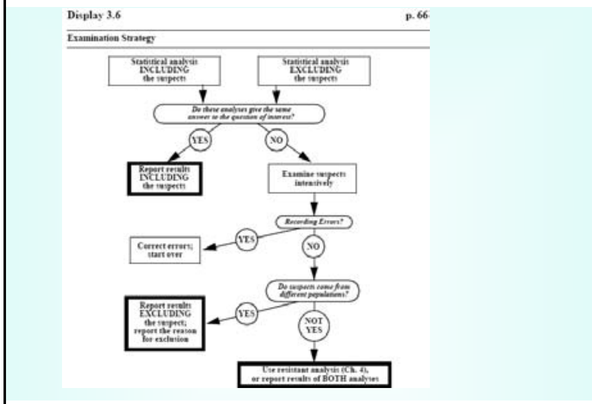
NOTES:

Outliers and resistant procedures

- A procedure is resistant if it doesn't change much when a small part of the data changes, perhaps drastically.
- *t* tools are based on averages and are strongly affected by outliers
  - Chapter 4 introduces tests based on ranks, which protect against outliers (but not against unequal variance)
- Practical strategies
  - Do side-by-side box plots to analyze departures from assumptions
    - Check for patterns in residuals with box plots
  - Consider & test for serial spatial and cluster effects
    - Analyze spatial patterns in the residuals, use more sophisticated tools
    - Legendre & Legendre: if pos. Spatial autocorrelation, decrease the p value. Test for differences at the 0.001 level instead of the 0.05 level

Slide 54 Outliers and resistant procedures

NOTES:



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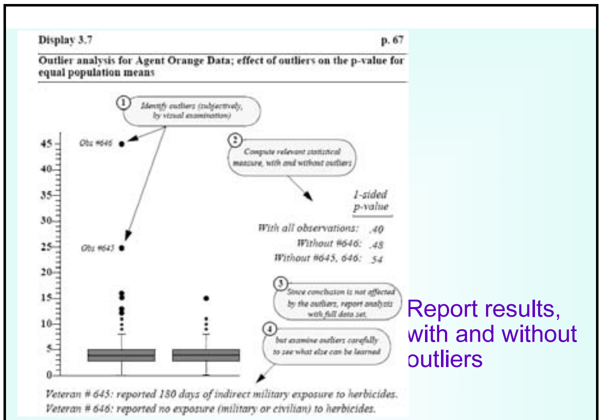


Slide 56 Identifying outliers with boxplots

NOTES:

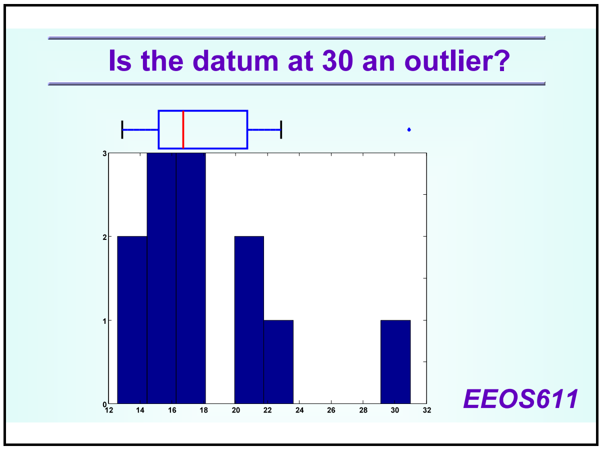
Practical strategies for outliers

Be wary of outlier deletion!

- Outlier strategy
  - Run analysis with and without outliers
  - Throw-out outliers only if there is very compelling evidence to do so, and document this data paring or culling
- Note that outlier removal has created tremendous problems:
  - POC flux to the deep sea
  - The ozone hole
  - Mendel's data: 1:2:1 ratios and the chi-square test; documented by Fisher
  - Milliken's study of the charge of the electron

Slide 57 Practical strategies for outliers

NOTES:



Slide 58 Is the datum at 30 an outlier?
NOTES: