Statistically Speaking Lecture Series

Sponsored by the Biostatistics Collaboration Center

BIOSTATISTICS 101: THE MINOR DETAILS THAT MAKE A MAJOR DIFFERENCE

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Minor Detail #1:

What's the BCC?

Who We Are



Leah J. Welty, PhD Assoc. Professor BCC Director



Masha Kocherginsky, PhD Assoc. Professor



Lauren Balmert, PhD Asst. Professor



Mary J. Kwasny, ScD Assoc. Professor



Jody D. Ciolino, PhD Asst. Professor



Julia Lee, PhD, MPH Assoc. Professor



Amy Yang, MS Senior Stat. Analyst



Kwang-Youn A. Kim, PhD Assoc. Professor



David Aaby, MS Senior Stat. Analyst



Tameka L. Brannon Financial | Research Administrator



Elizabeth Gray, MS Stat. Analyst



Kimberly Koloms, MS Stat. Analyst



Our Mission

Mission: to support investigators in the conduct of high-quality, innovative health-related research by providing expertise in biostatistics, statistical programming, and data management.

How do we accomplish this?

- 1. Every investigator is provided a **FREE** initial consultation of 1-2 hours, subsidized by **FSM Office for Research**. Thereafter:
 - a) Grants
 - b) Subscription
 - c) Re-charge (Hourly) Rates
- 2. Grant writing (e.g. developing analysis plans, power/sample size calculations) is also supported by FSM at **no cost to the investigator**, with the goal of establishing successful collaborations.

What We Do

Many areas of expertise, including:

- Bayesian Methods
- Big Data
- Bioinformatics
- Causal Inference
- Clinical Trials
- Database Design
- Genomics
- Longitudinal Data
- Missing Data
- Reproducibility
- Survival Analysis

Many types of software, including:



An Overview of Shared Statistical Resources

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ROBERT H. LURIE COMPREHENSIVE CANCER CENTER ONDERWESTER UNIVERSITY

Stanley Manne Children's Research Institute Ann & Robert H. Lurie Children's Hospital of Chicago

Biostatistics Collaboration Center (BCC)

- Supports non-cancer research at NU
- Provides investigators an initial 1-2 hour consultation subsidized by the FSM Office of Research
- Grant, Hourly, Subscription

Abilitylab

Quantitative Data Sciences Core (QDSC)

- Supports all cancer-related research at NU
- Provides free support to all Cancer Center members subsidized by RHLCCC
- Grant

Biostatistics Research Core (BRC)

- Supports Lurie Children's Hospital affiliates
- Provides investigators statistical support subsidized by the Stanley Manne Research Institute at Lurie Children's.
- Hourly

Shared Resources Contact Info

- Biostatistics Collaboration Center (BCC)
 - Website: http://www.feinberg.northwestern.edu/sites/bcc/index.html
 - Email: <u>bcc@northwestern.edu</u>
 - Phone: 312.503.2288
- Quantitative Data Sciences Core (QDSC)
 - Website:

http://cancer.northwestern.edu/research/shared_resources/quantitative_data_sciences/inde x.cfm

- Email: <u>qdsc_rhlccc@northwestern.edu</u>
- Phone: 312.503.2288
- Biostatistics Research Core (BRC)
 - Website: <u>https://www.luriechildrens.org/en-us/research/facilities/Pages/biostatistics.aspx</u>
 - Email: mereed@luriechildrens.org
 - Phone: 773.755.6328

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Minor Detail #2:

Assuming observations are independent

Independent Observations: Overview

- Many common statistical methods assume observations are independent (nearly everything taught in a usua
- There are different statistical methods for observations that are not independent
- Examples of paired/not independent data
 - Before and after measurements
 - Case and matched control
 - Longitudinal data
 - Nested samples
 - Spatial data
- Analyses that assume observations are independent, when in reality they're not, can be very wrong

(In)dependence Example: Two Case-Control Studies Hodgkins & Tonsillectomy

- Is Tonsillectomy associated with Hodgkin's?
- Vianna, Greenwald, and Davies (1971)
 - Case-control study (controls unmatched)
- Johnson & Johnson (1972)
 - Case-control study (controls matched)

Adapted from Mathematical Statistics and Data Analysis, John A. Rice, Duxbury (1995)

(In)dependence: Contingency Table Vianna et al. Vianna et al.

	Tonsillectomy	No Tonsillectomy
Hodgkin's (n = 101)	67	34
Control (n = 107)	43	64

- Case-control study
 - Recruit people with Hodgkin's and similar people without
- Look back to see who had exposure (tonsillectomy)
 - In Hodgkin's group, 67/101 = 66%
 - In Control group, 43/107 = 40%
- Is that a big enough difference to conclude that tonsils are protective?

(In)dependence: Odds and Odds Ratios

Vianna et al.

	Tonsillectomy	No Tonsillectomy
Hodgkin's (n = 101)	67	34
Control (n = 107)	43	64

- Odds of tonsillectomy in Hodgkin's group: 67/34
- Odds of tonsillectomy in Control group: 43/64
- Odds ratio comparing tonsillectomy for Hodgkin's versus Control
 - OR = (67/34)/(43/64) = 2.93
 - "Hodgkin's had 2.93 times the odds of tonsillectomy compared to Controls."
- Odds ratios range from 0 to ∞
 - 1 = no difference in groups
- Is 2.93 different enough from 1 to conclude that tonsils are protective?

(In)dependence: Chi-Squared Test

Vianna et al.

	Tonsillectomy	No Tonsillectomy
Hodgkin's (n = 101)	67	34
Control (n = 107)	43	64

- A chi-squared test can be used to compare whether rows and columns in a 2x2 contingency table are associated
- Computed by comparing "expected" versus observed values
 - E.g. Expect 53.4 people to have Hodgkin's and a Tonsillectomy, observe 67
 - 101 * (67+43)/208
- Chi-squared statistics is 14.46 with 1 degree of freedom
- P-value = 0.0002
- Conclude there is evidence for an association between Hodgkin's and Tonsillectomy

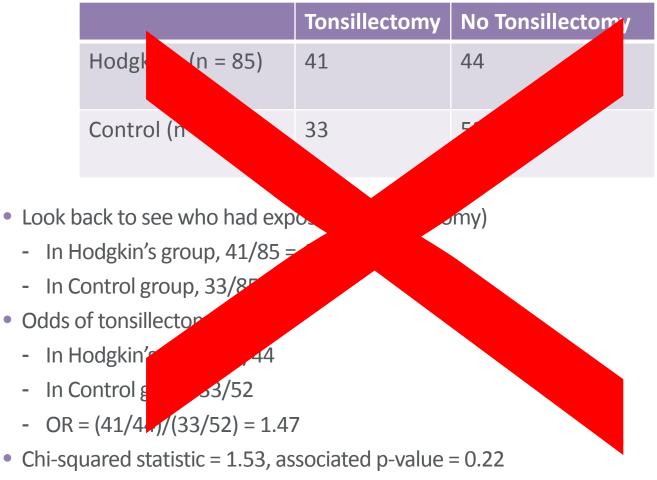
(In)dependence: A second study, Johnson et al. Johnson et al.

	Tonsillectomy	No Tonsillectomy
Hodgkin's (n = 85)	41	44
Control (n = 85)	33	52

- Case-control study (controls matched)
 - 85 Hodgkin's who had sibling w/in 5 yrs age and same sex
 - Sibling was matched control

(In)dependence: What went wrong?

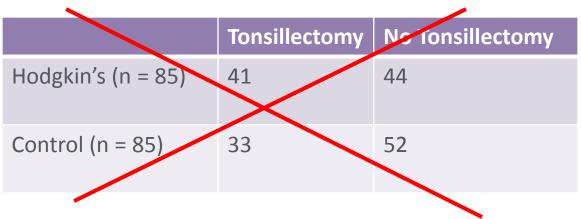
Johnson et al. NEJM



• No evidence that Hodgkin's is associated with Tonsillectomy

(In)dependence: Johnson failed to account for pairing

Johnson et al.



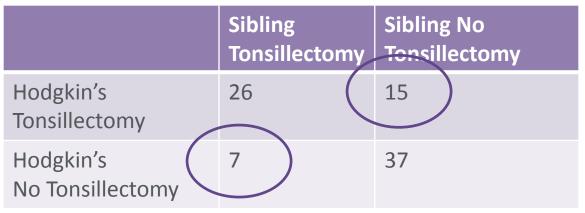
• This analysis IGNORED pairing (siblings and controls were *matched*)

	Sibling Tonsillectomy	Sibling No Tonsillectomy
Hodgkin's Tonsillectomy	26	15
Hodgkin's No Tonsillectomy	7	37

• Correct contingency table shows pairings (treats the unit of analysis as a pair)

(In)dependence: McNemar's Test

Johnson et al.

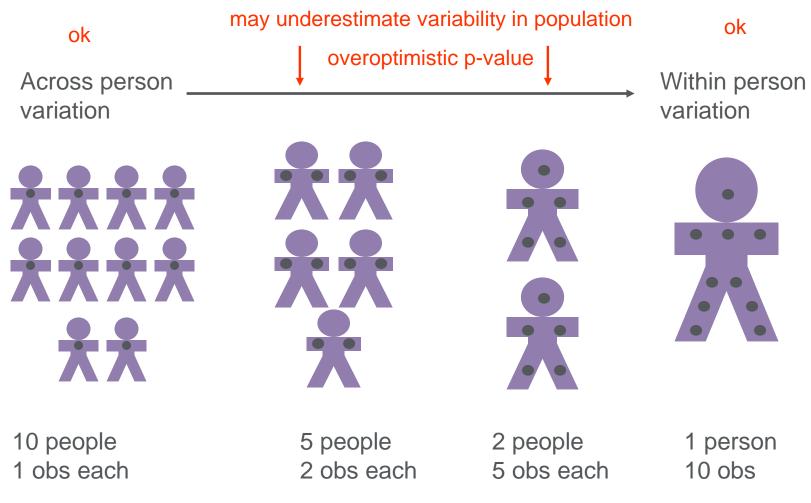


- Chi-squared test WRONG choice
- Compare discordant pairs (McNemar's Test):
- Proportion of pairs in which sibling had tonsillectomy but Hodgkin's did not 7/85 = 8%
- Proportion of pairs in which sibling did not have tonsillectomy but Hodgkin's did 15/85 = 17%
- P-value 0.09
- Less doubt about results of Vianna et al.

(In)dependence: Think about types of variation

Across & Within Person Variation

If assume observations are independent ...



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(In)dependence: Different Statistical Approaches

What you might use for independent data	What you might use for paired/dependent data
Chi-squared test	McNemar's test
Two-sample t-test	Paired t-test
Wilcoxon rank-sum test	Wilcoxon signed rank-sum test
Generalized Linear Model	Generalized Linear Mixed Model

NOTE: This is not a recipe for what to do if your data contains dependence, but rather an illustration of what MIGHT be suitable.

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Minor Detail #3:

Assuming the mean is a good measure of central tendency

Defaulting to the Mean: Mean vs Median Example

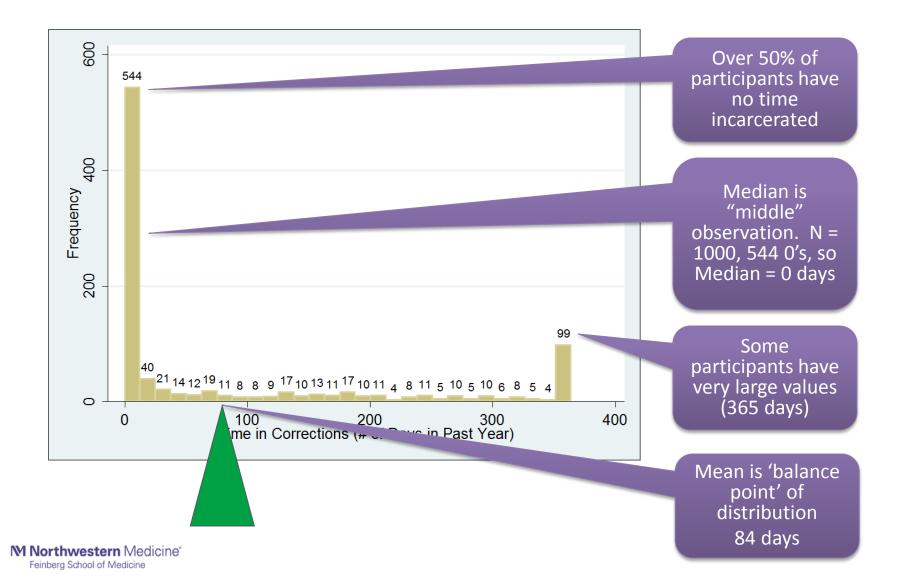
Examining time incarcerated in the past year

- Longitudinal study of juvenile delinquents (Northwestern Juvenile Project)
- Looking at re-incarceration
- Goal is to summarize time incarcerated in the past year
 - Mean time incarcerated = 84 days
 - Median time incarcerated = 0 days

These are really different estimates what's going on?

Defaulting to the Mean: Mean vs Median Example

Look at the data



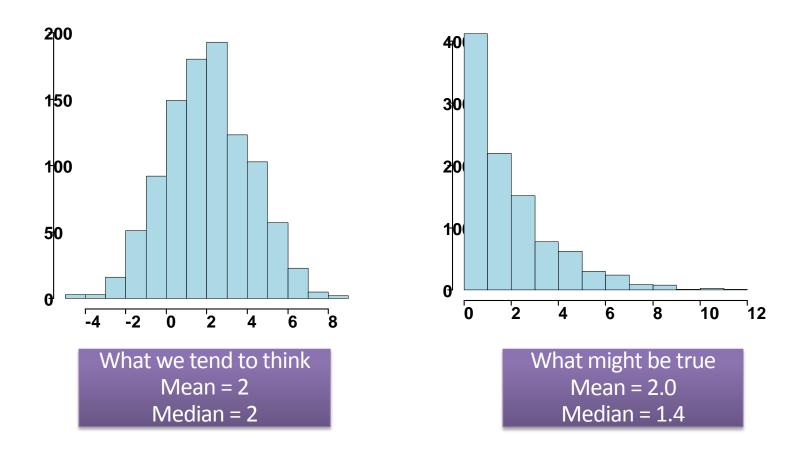
Defaulting to the Mean: Mean vs Median Example

What should you report when data are skewed?

- Longitudinal study of juvenile delinquents (Northwestern Juvenile Project)
- Looking at re-incarceration
- Goal is to summarize time incarcerated in the past year
 - Mean time incarcerated = 84 days
 - Median time incarcerated = 0 days
- What should we report?
 - People expect to see the mean (and the associated standard deviation)
 - I recommend also reporting the median, range, Q1, and Q3
- In this case, it may be better to separately
 - Report the fraction of participants who were never re-incarcerated
 - Report mean/median etc. among the 456 who we re-incarcerated

Defaulting to the Mean: Picture Your Data!

What do you think of when you hear "The mean value was 2.0"?



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Defaulting to the Mean: SD vs SE

Averages are less variable than individual observations

- Standard deviation (SD) describes the variability in a population
- Standard error (SE) describes the *variability of an estimate from a sample*
- American women are on average 5'4", with a standard deviation of about 3"
 - Height is normally distributed, so approx 95% of women +/- 2 SD
 - 95% confidence interval for next woman to walk through the door

(4'10" - 5'10")

- Average height in a sample of 35 American women
 - Average is likely to be around 5'4"; with a standard error of $3/\sqrt{35} = 0.5$
 - 95% confidence interval for AVERAGE height of next 35 women through door

out 3"

Describes variability in the mean of the sample of 35

Describes variability in the

population of American women

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Defaulting to the Mean: Recommendations

- The mean is not robust to outliers
- For skewed distributions, or distributions with outliers, the mean may be misleading
- In a manuscript, don't blindly report mean.
- Why use the mean at all?
 - Mathematically convenient
 - Nice statistical properties
- Standard deviation describes variability in a population, and standard error describes variability in an estimate from a sample

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Minor Detail #4:

Using Excel for data capture, cleaning, or analysis

Using Excel: Potential problems for research

- Excel is available and accessible
- It's not uncommon for use with research data
 - Data capture
 - Data cleaning
 - Data analysis
 - Generating figures
- It's critical that we conduct rigorous and reproducible research
 - Excel not always optimal
- When is it okay to use Excel, and when is it not recommended?

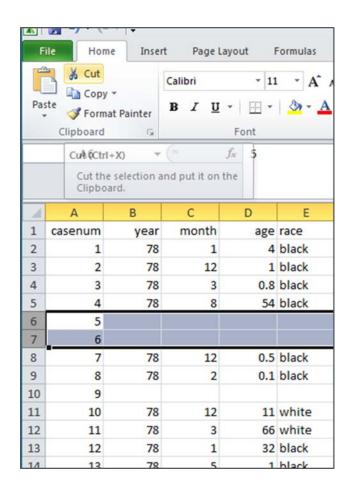


Using Excel: Issues with data capture

Problems with entering data directly in to an Excel spreadsheet

Problems with entering data directly in to an Excel spreadsheet:

- 1. One-off/misalignment errors, especially for wide spreadsheets
- 2. Easy to unknowingly move or delete data
- 3. No explicit version control, traceback, record or date stamp.
- 4. Standardization (e.g., Black vs black, blank vs "missing")



Using Excel: Issues with data coding

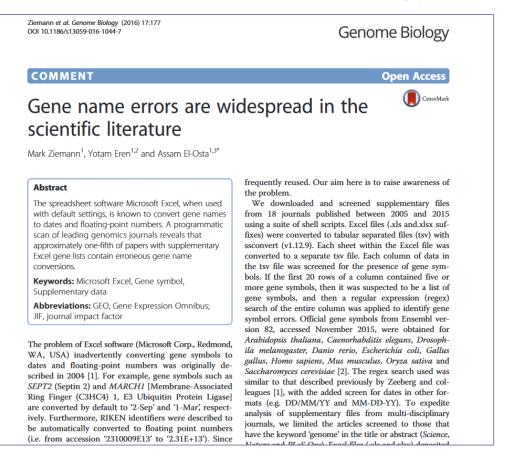
Excel isn't designed for data that's coded, and has features that can lead to poor formatting for analysis

-					
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				Y doubt	Yellow highlighting means something.
214	320368722	1	0	1 adenoma	But it is very hard to translate that in to
				Y, double	a variable for analysis.
215	320368722	2	0	1 adenoma	
216	320440974	1	0		
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218	320469342	1	0		
219	320581700	1	0		This column seems to contain two
220	321248969	1	0	0 N	variables:
221	321248969	2	0	0 N	
222	321302497	1	1		1. Adenoma present (Y/N)
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229	324106248	1	0		not applicable? All have different
230	324421569	1	0		implications for analysis.
				Y, single	implications for analysis.
231	324480106	1	0	1 adenoma	
				Y, single	
232	324480106	2	0	1 adenoma 🥿	Mixing variable codes (Y/N) with plain

Mixing variable codes (Y/N) with plain text. It is very hard to tell a computer what to do with this, especially when you mistype ademona.

Using Excel: Issues with data formatting

Gene names converted to dates or floating point numbers



SEPT2 (Septin 2) converted to "2-Sept" MARCH1 [Membrane-Associated Ring Finger (C3CH4) 1, E3 Ubiquitin Protein Ligase] converted to "1-Mar"

Using Excel: REDCap for capture, coding

Supports robust data capture and consistent data coding, formatting

- Research Electronic Data Capture
- Secure web application
- <u>http://project-redcap.org</u>
- Features:
 - Rapid set-up
 - Web-based data collection
 - Data validation
 - Export to statistical programs
 - Supports HIPAA compliance







Using Excel: REDCap for data capture, coding REDCap vs Excel

Enrollment	Ass	sign record to a Dat
Adding new Study ID 999		
Event Name: Baseline		
Study ID		999
Enrollment Date		[]]
Inclusion Criteria		
Does the participant meet the definition of hypertensive (i.e., SBP/DBP >= 140/90)?		◯ Yes ◯ No
Is the participant 18 years of age or older?		○ Yes ○ No
Is the participant female of childbearing potential (i.e., pre- menopausal)?	H	 No, the partic No, the partic Yes
Is the participant considered obese according to the study criteria (BMI at least 30 kg/m^2)?	H ,	○ Yes ○ No
Does the participant agree to comply with all protocol- required study procedures?		◯ Yes ◯ No
Did the participant sign the study's informed consent document?		○ Yes○ No
Does the participant have any pre-existing condition that, in the investigator's opinion, would preclude participation in the study?		○ Yes ○ No
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9	8	78	2	0.1	black			
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11	10	78	12	11	white			
12	11	78	3	66	white			
13	12	78	1	32	black			
14	12	70	5	1	black			





Using Excel: Issues with data cleaning/analysis

Problems with entering data directly in to an Excel spreadsheet

Problems with cleaning or analyzing data in to an Excel spreadsheet:

- 1. Repeated point-and-click, copy and paste, search and replace
- No record of each step that was taken, and in what sequence (unless you write them all down)
- 3. Not very reproducible if there is a change to the original raw data, or questions about the analysis

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Using Excel: Issues with data analysis

Cleaning/analyzing data in Excel versus statistical program

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				-		22 * keep higer rates in warmer months 23 recode month (12=4) (2=3) (3=2) (4=12) (1=11) (10=9) (9=10) (11=1), gen(month2)
1	casenum	year			race	23 recode month (12=4) (2=3) (3=2) (4=12) (1=11) (10=9) (9=10) (11=1), gen(month2) 24
2	1	78	1	4	black	25 drop year month
3	2	78	12	1	black	26 rename year2 year
4	3	78	3	0.8	black	27 rename month2 month
5	4	78	8	54	black	28 label variable year "Year of admission" 29 label variable month "Month of admission"
6	5					29 label variable month "Month of admission" 30
						31 * replace race to be more up to date
7	6					32 gen raceth = race
8	7	78	12	0.5	black	33 replace raceth = "Hispanic" if race == "black" & rnum < 0.3
9	8	78	2	0.1	black	34 replace raceth = "non-Hispanic white" if race == "white"
10	9					<pre>35 replace raceth = "African American" if race == "black" & rnum >= 0.3 36 label variable raceth "Race/ethnicity"</pre>
11	10	78	12	11	white	37 drop race
12	11	78	3	66	white	38
13	12	78	1	32	black	39 * label main variables of interest 40 label variable casenum "Case number"
14	12	78			black	41 label variable age "Age (years)"
		18				42 label variable wbc "White blood count/1000"
						43 label variable bloodgl "Blood glucose mg/dl"
						44 label variable gl "CSF Glucose mg/dl"

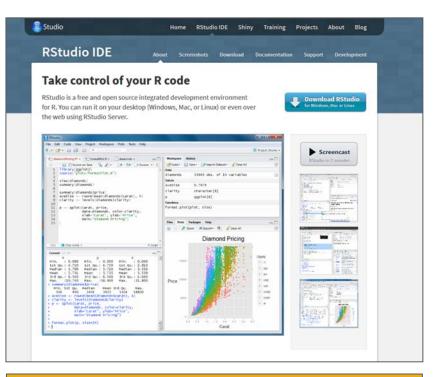
Inefficient and potentially inaccurate to repeat cleaning/analysis in Excel. With scripted code, it's easy to re-run a data cleaning or analysis program.

Using Excel: Alternatives such as R Studio, Stata

Getting more user friendly, and much more robust than Excel

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Stata has menus that you can use to point and click, but it will generate the statistical code file for you and keep a log of all your work!



R Stuido is a way to use R statistical software (free, open source) in a user friendly environment with more pointand-click capability.

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Using Excel: poster child for why not to

Misconduct in science

An array of errors

A disastrous story in why not to use Excel

The Annals of Applied Statistics 2009, Vol. 3, No. 4, 1309-1334 DOI: 10.1214/09-AOAS291 C Institute of Mathematical Statistics, 2009

DERIVING CHEMOSENSITIVITY FROM FORENSIC BIOINFORMATICS AND REP **RESEARCH IN HIGH-THROUGHPUT**

BY KEITH A. BAGGERLY¹ AND KEVIN R. C

University of Texas

High-throughput biological assays such as microarray detailed questions about how diseases operate, and promise alize therapy. Data processing, however, is often not descri to allow for exact reproduction of the results, leading to exer bioinformatics" where aspects of raw data and reported resu fer what methods must have been employed. Unfortunately, tion can shift from an inconvenience to an active danger who

just methods but error porting to use micros cell lines to predict p show in five case stu that may be putting p common errors are si experience that the m

"The most simple problems are common." When using Excel, it is being allocated to tre especially easy to make off-by-one errors (e.g. accidentally deleting a cell in one column), or mixing up group labels (e.g. swapping sensitive/resistant).

are taking to avoid such errors in our own investigations.

that they had developed a similar technique which used gene expression in laboratory cultures of cancer cells, known as cell lines, to predict which chemotherapy would be most effective for an individual patient suffering from lung, breast or ovarian cancer.

At the time, this work looked like a tremendous advance for personalised medicine-the idea that understanding the molecular specifics of an individual's illness will lead to a tailored treatment. The papers drew adulation from other workers in the field, and many newspapers, including this one (see article), wrote about them. The team then started to organise a set of clinical trials of personalised treatments for lung and breast cancer. Unbeknown to most people in the field, however, within a few weeks of the publication of the





Using Excel: Recommendations

- *Try to avoid* capturing, manipulating, and analyzing your data in Excel
- Be careful when 'parking' your data in Excel
 - Data is often passed around in .csv format, which Excel easily reads
 - Excel isn't bad per se for viewing .csv data
- Data cleaning, reshaping can eat up a lot of analysis time, sometimes more than the analysis itself, so the investment of time up front is worth it
- In the conduct of rigorous, reproducible research, Excel can be a weak link



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Minor Detail #5:

Big statistics for little data: Right-sizing the statistical approach to the sample size

Right-sizing the statistics: big ideas, little data

- It's tempting to come up with sophisticated models, but need to think about whether or not you have enough data to explore them.
- Especially relevant when proposing your main hypothesis for a study
- For example, proposing mediation models (see upcoming lecture) for a sample of n = 100
 - Most statisticians will raise their eyebrows
 - Too small unless you're detecting pretty big effects
- Sometimes even simple comparisons require a lot of data.
 - E.g. Comparing prevalence between two groups
 - Expect prevalence in one group is 3%, and other group is 8%
 - Still need more than 300 per group to detect this difference as significant with 80% power



Right sizing the statistics: A (Very) General Rule

If you're comparing a binary (yes/no) outcome, you need at least 10 observations of each type (yes/no) per "degree of freedom" to have a reasonable chance at *estimating* those differences.

Can think of a "degree of freedom" as a variable you will put in your logistic regression model.

This does not guarantee any sort of power!

Independent Variable	Degrees of Freedom	Minimum Sample Size*
Sex (Man, Woman)	1	20
Age (continuous)	1	20
Age (< 20, 20-40, 40-60, 60+)	3	60
Race/Ethnicity (non-Hispanic white, African American, Hispanic, Asian, Other)	4	80
Sex + Race/Ethnicity	5	100



* Assumes an even split, so you probably need a lot more.

Right-sizing the statistics: small samples

Sometimes see 'regular' statistical approaches applied to small data sets

- E.g. Two sample t-test comparing groups of 15 each

There are alternatives:

- Non-parametric approaches
 - Makes fewer distributional assumptions about the data
 - E.g. Fisher's exact test instead of a chi-squared test
- Exact approaches
 - Same models, but estimated differently
 - E.g. "Exact" logistic regression vs (maximum likelihood) logistic regression
- Bootstrapping
 - Resampling your data to obtain better standard errors
 - Doesn't always solve the small sample problem



Right-sizing the statistics: Effect sizes

Effect sizes are *relative*

• Power/sample size considerations often calculated in terms of 'effect size'

Power	Total N	Effect size
0.8	788	0.2 ("small")
0.8	128	0.5 ("medium")
0.8	52	0.8 ("large")
0.8	12	2.0

Two independent samples comparison of means with alpha = 0.05.

- Effect 'size' is relative to the standard deviation of the outcome
- If SD of outcome is 10 units
 - Can detect a "small" difference of 2 units (= 0.2 * 10) with n = 788
 - Can detect a "medium" difference of 5 units (=0.5 * 10) with n = 128
 - Can detect a "large" difference of 8 units (=0.8 * 10) with n = 52
 - Can detect a "huge" difference of 20 units (=2.0 * 10) with n = 12



Your feedback is important to us! (And helps us plan future lectures).

Complete the evaluation survey to be entered in to a drawing to win 2 free hours of biostatistics consultation.

Statistically Speaking: Upcoming Lectures

We hope to see you again!

Monday, October 9	The Impact of Other Factors: Confounding, Mediation, and Effect Modification Amy Yang, MS, Sr. Statistical Analyst, Division of Biostatistics, Department of Preventive Medicine
Monday, October 16	Using REDCap for Data Capture in Clinical Studies: Database Management on a Budget Jody D. Ciolino, PhD, Assistant Professor, Division of Biostatistics, Department of Preventive Medicine
Monday, October 30	Using R for Statistical Graphics: The Do's and Don'ts of Data Visualization David Aaby, MS, Sr. Statistical Analyst, Division of Biostatistics, Department of Preventive Medicine
Wednesday, November 1	Time-to-Event Analysis: A 'Survival' Guide Lauren C. Balmert, PhD , Assistant Professor, Division of Biostatistics, Department of Preventive Medicine

All lectures will be held from noon to 1 pm in Baldwin Auditorium, Robert H. Lurie Medical Research Center, 303 E. Superior St.

Contact Us

- Request an Appointment
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