Statistics & Scientific reporting: Can we do better?

Abhraneel Sarma School of Information University of Michigan Collective

Scientists & researchers can be really bad at interpreting results of statistical analysis.

A simple independent means t-test comparing the means of your control and experimental groups (n = 20 each):

t = 2.7, d.f. = 18, p < 0.01

The probability there is no difference between treatment and control is less t = 2.7, dt has 18, p < 0.01

[Oakes (1986): Statistical inference] [Haller and Krauss (2002): Misinterpretations of significance: A problem students share with their teachers]

True or False?

False!

The probability there is no difference between treatment and control is less than 1%

If there was no difference between the means of the two conditions, there is a less than 1% probability of obtaining the result

[Oakes (1986): Statistical inference] [Haller and Krauss (2002): Misinterpretations of significance: A problem students share with their teachers]

~ 90% people answered at least one such questions incorrectly

[Oakes (1986): Statistical inference] [Haller and Krauss (2002): Misinterpretations of significance: A problem students share with their teachers]

Misinterpretation may lead to overestimation of certainty

Adopt Bayesian statistics Uncertainty representations

Adopt Bayesian statistics Uncertainty representations

factor and self-rated attractiveness (low, average, high) and oral effect of sex of face, F(1, 1276) = 1372, p < .001, η_p^2 = .52. This was p = .94, $n_p^2 < .001$. All other main effects and interactions were nonsignificant and irrelevant to our hypotheses, all F \leq 0.94, p \geq .39, n_p² \leq .001.

A mixed-design ANOVA with sex of face (male, female) as a within-subjects contraceptive use (true, false) as between-subjects factors revealed a main qualified by interactions between sex of face and SRA, F(2, 1276) = 6.90, p = .001, η_p^2 = .011, and between sex of face and oral contraceptive use, F(1, 1276) = 5.02, p = .025, η_p^2 = .004. The predicted interaction among sex of face, SRA and oral contraceptive use was not significant, F(2, 1276) = 0.06,

A mixed-design NOVA with sex of face (male, female) are within-subjects factor and self-rated stractiveness (low, average, high and oral contraceptive use (true, have) as between-subject factors revealed a main effect of sex of face, F(1, 127 c) = 1372, p < 1001, $\eta_p^2 = .52$. This was qualified by interactions between second are and SRA, F(2, 1276) = 6.90, p = .001, $\eta_p^2 = .011$, and between second are and oral contraceptive use, F(1, 1276) = 5.02, p = .025, $\eta_p^2 = .04$. The predicted interaction among sex of face, SRA and oral contraceptive use was not significant, F(2, 1276) = 0.06, p = .94, n_p^2 < .001. All other main effects and interactions were non-significant and interevant to our hypotheses, all F ≤ 0.94, p = .39, n_p^2 ≤ .001.

Alternatives...

Table 7 Stevens et al. 2006, table 2: Determinants of authoritarian aggression

Variable	Coefficient (Standard Error)
Constant	.41 (.93)
Countries	
Argentina	1.31 (.33)** ^{B,M}
Chile	.93 (.32)** ^{B,M}
Colombia	1.46 (.32)** ^{B,M}
Mexico	.07 (.32) ^{A,CH,CO,V}
Venezuela	.96 (.37)** ^{B,M}
Threat	
Retrospective egocentric economic perceptions	.20 (.13)
Prospective egocentric economic perceptions	.22 (.12)#
Retrospective sociotropic	21 (.12)#
Prospective sociotropic	32 (.12)*
Ideological distance from president	27 (.07)**
Ideology	
Ideology Individual Differences	.23 (.07)**
Age	00(01)
Female	03 (.21)
Education	.13 (14)
Academic Sector	.15 (.29)
Business Sector	.31 (.25)
Government Sector	10(.27)
R^2	.15
Adjusted R ²	.12
N	500

[Kastellac and Leoni (2007): Using Graphs Instead of Tables in Political Science]

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Figure 6 Presenting a single regression model using a dot plot with error bars.

Prospective egocentric-Retrospective sociotropic-

Prospective sociotropic-

Distance from president-

[Kastellac and Leoni (2007): Using Graphs Instead of Tables in Political Science]











There is a 95% probability that the mean difference between the experimental and control conditions lie in the interval [0.13, 2.99]



If you were to repeat the experiment over and over, then the fraction of calculated confidence intervals (which would differ for each sample) that encompass the true population parameter would tend towards 95%.



2.

The estimate for the probability of answering a *typical question* correctly given one of our designs, by a typical participant, on average.

This estimate accounts for differences in questions, and therefore will not correspond exactly to the observed proportion. Since this estimate is based on the variance associated with a typical question, it will also be more uncertain.



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[Kay, Kola, Hullman and Munson (2016): When (ish) is my bus?: User-centered visualizations of uncertainty in everyday, mobile predictive systems]

What is the probability of x >= 3 ?

~ 90%



[Kay, Kola, Hullman and Munson (2016): When (ish) is my bus?: User-centered visualizations of uncertainty in everyday, mobile predictive systems]

On average, quantile dotplots with 50 outcomes improve transit decision making.



[Fernandes, Walls, Munson, Hullman, and Kay (2018): Uncertainty Displays Using Quantile Dotplots or CDFs Improve Transit Decision-Making]

Are these better at addressing misinterpretation?



A. Text tables with confidence interval (here, 95%) Textual communication of point estimates and the corresponding 95% confidence interval is still commonly used in NHST which is advocated widely to be used in place of p-values (Cumming et. al.); if the null hypothesis is outside the interval, p < 0.05.

B. 95% interval

The point estimate and 95% confidence interval from (A) represented graphically. Graphical representation of statistical results have been commonly advocated as another way of emphasizing uncertainty.

C. Density + interval plot (here 95%) The density shows the sampling distribution (or Bayesian posterior distribution. The addition of the point estimate and interval adds precision.

D. Quantile dotplot (here100 dots)

A quantile dotplot allows precise estimatio of many intervals and by providing a frequency based framing of the probability of the parameter, may improve understanding of uncertainty through hypothetical outcomes.

Are these better at addressing misinterpretation?

1.5



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A non exhaustive set of statements describing a statistical result

There exists

- strong evidence
 weak evidence
 inconclusive evidence
 no evidence

 - that an effect exists

braces by Sumana Chamrunworakiat from the Noun Project



A non exhaustive set of statements describing a statistical result

There exists

strong evidence
weak evidence
inconclusive evidence
no evidence

that an effect exists

"The lure of incredible certitude"

Existing incentives make it tempting for researchers to maintain assumptions far stronger than they can persuasively defend, in order to draw strong conclusions.

[Manski (2018): The Lure of Incredible Certitude]

Let's step back from strictly probabilistic uncertainty.

[Gelman and Loken (2016)]

data <u>analysis</u> p < 0.05

[Gelman and Loken (2016)]



[Gelman and Loken (2016)]



1

[Gelman and Loken (2016)]



- statistical models

[Gelman and Loken (2016)]



p > 0.05 This is p < 0.05 model/specification uncertainty p > 0.05

- p < 0.05

→ p > 0.05

p > 0.05

[Gelman and Loken (2016)]



statistical models

- p < 0.05 -
- → p > 0.05
- → p > 0.05
- ★ p < 0.05</p> publish! yay!!
- → p > 0.05
- → p < 0.05
- → p > 0.05
- → p > 0.05

[Christie Aschwanden and Ritchie King (2015): Science Isn't Broken in FiveThirtyEight]

Hack Your Way To Scientific Glory

You're a social scientist with a hunch: The U.S. economy is affected by whether Republicans or Democrats are in office. Try to show that a connection exists, using real data going back to 1948. For your results to be publishable in an academic journal, you'll need to prove that they are "statistically significant" by achieving a low enough p-value.



IS YOUR RESULT SIGNIFICANT? 4

If there were no connection between the economy and politics, what is the probability that you'd get results at least as strong as yours? That probability is your p-value, and by convention, you need a p-value of 0.05 or less to get published.

0.05 1.00 0.50

Result: Almost

Your 0.06 p-value is close to the 0.05 threshold. Try tweaking your variables to see if you can push it over the line!

If you're interested in reading real (and more rigorous) studies on the connection between politics and the economy, see the work of Larry Bartels and Alan Blinder and Mark Watson.

Data from The @unitedstates Project, National Governors Association, Bureau of Labor Statistics, Federal Reserve Bank of St. Louis and Yahoo Finance.

Do hurricanes with more feminine names cause more deaths?



Female hurricanes are deadlier than male hurricanes

Kiju Jung^{a,1}, Sharon Shavitt^{a,b,1}, Madhu Viswanathan^{a,c}, and Joseph M. Hilbe^d

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Edited* by Susan T. Fiske, Princeton University, Princeton, NJ, and approved May 14, 2014 (received for review February 13, 2014)

Do people judge hurricane risks in the context of gender-based expectations? We use more than six decades of death rates from US hurricanes to show that feminine-named hurricanes cause significantly more deaths than do masculine-named hurricanes. Laboratory experiments indicate that this is because hurricane names lead to gender-based expectations about severity and this, in turn, guides respondents' preparedness to take protective action. This finding indicates an unfortunate and unintended consequence of the gendered naming of hurricanes, with important implications for policymakers, media practitioners, and the general public concerning hurricane communication and preparedness.

gender stereotypes | implicit bias | risk perception | natural hazard communication | bounded rationality

stimates suggest that hurricanes kill more than 200 people in

violence and destruction (23, 24). We extend these findings hypothesize that the anticipated severity of a hurricane w a masculine name (Victor) will be greater than that of a hun cane with a feminine name (Victoria). This expectation, in tu will affect the protective actions that people take. As a resu a hurricane with a feminine vs. masculine name will lead to lead protective action and more fatalities.

Archival Study

To test this hypothesis, we used archival data on actual fatalit caused by hurricanes in the United States (1950-2012). Nine four Atlantic hurricanes made landfall in the United Sta during this period (25). Nine independent coders who were bli to the hypothesis rated the masculinity vs. femininity of historic hurricane names on two items (1 = very masculine, 11 = very masculine)feminine, and 1 = very man-like, 11 = very woman-like, whi





"If you torture the data long enough, it will confess." - Ronald Chase

Female hurricanes are not deadlier than

male hurricanes

rather than male names. The article has stirred much controversy. Criticisms range from the

inclusion of hurricanes from the era before they were given male names (2) lective interpretation and the over their results from the archival of their hypothesis (3), to the e of their six behavioral experim populations in at-risk situation The criticism of this letter

Za

one: the results of their archi function of the selective incl sors. Using the same data, m variables, I show in Table 1 are not robust to the inclu two-way interaction they or analysis. Model 1 reprodu main results. Models 2–4 s that female- and male-n were equally deadly canne the interaction effect of a metric pressure and its r toll is included. A more letter should have stated Models 2-4 show th

lower barometric pressu tolls and that hurricanes

Table 1. Results from

Jung et al. (1) assert that hurricanes that tolls had smaller death tolls when the hurri- safety infrastruct more people when they had female names higher death tolls when the hurricanes were after 1978. Eve driven by the pre-1978 sample (model 5). In the post-1978 sample, the interaction effect vergence of incignificant and the damage toll



Are female hurricanes really deadlier than male hurricanes?

Jung et al. (1) claim to show that "feminineand invalid statistics.

their table S2, in particular, model 4. However, due to the interaction terms combined the analysis is based on a very fragile model; e.g., the model predicts almost 20,000 deaths more deaths than female ones (Fig. 1). for hurricane Sandy, which actually caused

Now, we explain our claim that the differences between male- or femalenamed hurricanes cause significantly more results are presented in a biased way. named hurricanes for deaths, minimum deaths than do masculine-named hurricanes" By holding the minimum pressure at its pressure, category, and damages. (p. 1). This conclusion is mainly obtained by mean in prediction of counts of deaths, To conclude, the analyses given in ref. 1 analyzing data on fatalities caused by hurri- the authors only report the influence of are examples of the fact that prediction canes in the United States (1950-2012). By MFI and normalized damage (figure 1 in models using interaction terms have to be reanalyzing the same data, we show that the ref. 1). This ignores the influence of the handled and interpreted carefully; in parconclusion is based on biased presentation second interaction term MFI minimum ticular, using insignificant variables is not pressure, which shows an opposite influexpedient and may lead to statistical The reasoning in ref. 1 is fundamentally ence (see the estimated parameters on p. 5, artifacts. based on the regression models reported in first paragraph). By considering the counts To summarize, the data do not contain of deaths under constant normalized damevidence that feminine-named hurricanes age, the results are contrary: male-named cause more deaths than masculine-named with extreme values and weak significance, hurricanes with a low minimum pressure hurricanes. (strong hurricanes) are associated with Björn Christensen^a and In the light of an alternating male-female Sören Christensen^{b,}



on (less than 39 mph), tropical storm (39–73 mph), hurnore than 73 mph), and major hurricane (more than more than 73 mph), and major hurricane (more than more than major hurricane (more than major hurricane (more than major hurricane thurricane than major hurricane thurricane thurricane than Tropical storms and hurricanes are generally given Hurricane Sandy, but tropical depressions are not. Liur reance samuy, vui u oprear ucpressions are not al. (2014) examine a narrowly defined dataset: U.S. a. (COTA) CRAIMING A HALLOWLY OCTING ORGANIZATION OF THE MALE AND THE a strong, surprising conclusion is drawn from reit can be instructive to see whether the conclusion is espect to the myriad decisions used to restrict the lude tropical storms? In 1994 Tropical Storm Alfall near Destin, Florida, with maximum sustained h and caused historic flooding in Alabama and



Pre-registration



statistical models

p < 0.05

Do soccer referees give more red cards to dark-skinned players than light-skinned ones?



Different researchers may create very different pre-registration documents

Same Data, Different Conclusions



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Multiverse analysis

[Steegen, Tuerlinckx, Gelman, and Vanpaemel (2016): Increasing Transparency Through a Multiverse Analysis]



p > 0.05

Performing and reporting all reasonable analysis scenarios.

p > 0.05

p > 0.05

p < 0.05

p > 0.05

p < 0.05

p > 0.05

- p < 0.05
- statistical models

How to report all of these analyses?

Visual summaries?

		R1					R2					<u>R</u> 3					
F1	F2	FB	F4	F5	F1	F2	F3	F4	F5	F1	F2	Fβ	F4	F5			
0	0	0.03	0.02	0.08	0.02	0.02	0.03	0.05	0.06	0	0	0.02	0.01	0.04	EC1	ECL1	
0.01	0	80. 0	0.03	0.16	0.07	0.05	0.18	0.24	0.41	0.01	0	0.09	0.06	0.23	EC2		NM01
0	0	0.06	0.04	0.37	0.02	0.03	0.07	0.08	0.21	0	0	0.05	0.03	0.23	EC1	ECL2	
0.01	0	0 .13	80.0	0.44	0.06	0.03	0.22	0.24	0.52	0.01	0	0.14	0.09	0.43	EC2		
0	0	0.03	0.01	0.08	0.15	0.07	0.17	0.07	0.14	0.02	0.01	0.06	0.02	0.07	EC1	ECL1	
0	0	0.02	0.01	0.06	0.2	0.05	0.42	0.23	0.44	0.03	0	0.14	0.05	0.19	EC2		NM02
0.01	0.01	0.05	0.01	0.1	0.39	0.2	0.45	0.11	0.26	0.08	0.04	0.17	0.03	0.13	EC 1	ECL3	
0.01	0	0 .05	0.02	0.11	0.33	0.09	0.59	0.26	0.55	0.09	0.02	0.26	80.0	0.27	EC 2		
0.01	0.01	0.02	0.1	0.28	0.11	0.09	0.43	0.26	0.85	0.02	0.02	0.12	0.12	0.51	EC1	ECL1	
0.01	0.01	0	0 .07	0.06	0.07	0.1	0.11	0.14	0.23	0.01	0.02	0.02	0.06	0.08	EC2		
0.02	0.01	0.06	0.11	0.36	0.06	0.04	0.3	0.13	0.66	0.02	0.01	0.13	0.07	0.46	EC1	ECL2	NM03
0.02	0.01	0.02	0.15	0.13	0.04	0.05	0.07	0.07	0.16	0.01	0.02	0.03	0.05	0.09	EC2		
0.07	0.04	0.12	0.09	0.16	0.16	0.11	0.54	0.32	0.77	0.07	0.04	0.25	0.13	0.39	EC1	ECL3	
0.02	0.02	0.01	0.06	0.02	0.06	0.1	0.07	0.16	0.17	0.02	0.03	0.02	0.07	0.05	EC2		

Religiosity (Study 2)

[Steegen, Tuerlinckx, Gelman, and Vanpaemel and Loken (2016): Increasing Transparency Through a Multiverse Analysis]



[Simonsohn, Simmons, and Nelson (2015) Specification curve: Descriptive and inferential statistics on all reasonable specifications]

Can we do better?

Explorable Multiverse Analysis Reports (EMARs)

[Dragicevic, Jansen, Sarma, Kay, and Chevalier (2019): Increasing the Transparency of Research Papers with Explorable Multiverse Analyses]

Re-Evaluating the Efficiency of Physical Visualizations: A Simple Multiverse Analysis

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ABSTRACT

A previous study has shown that moving 3D data visualizations to the physical world can improve users' efficiency at information retrieval tasks. Here, we reanalyze a subset of the experimental data using a multiverse analysis approach. Results from this multiverse analysis are presented as explorable explanations, and can be interactively explored in this paper. The study's findings appear to be robust to choices in statistical analysis.

AUTHOR KEYWORDS

Physical visualization; multiverse analysis.

ACM CLASSIFICATION KEYWORDS

H5.2 User Interfaces: Evaluation/Methodology

GENERAL TERMS

Human Factors; Design; Experimentation; Measurement.

INTRODUCTION

Whereas traditional visualizations map data to pixels or ink, physical visualizations (or "data physicalizations")

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Figure 1. 3D bar chart, on-screen and physical.

STUDY

The study consisted of two experiments. In the first experiment, participants were presented with 3D bar charts showing country indicator data, and were asked simple questions about the data. The 3D bar charts were presented both on a screen and in physical form (see Figure 1). The on-screen bar chart could be rotated in all directions with the mouse. Both a regular and a stereoscopic display were tested. An interactive 2D bar chart was also used as a control condition. Accuracy was high across all conditions,

An Explorable Multiverse Analysis of Durante et al. (2013)

Inria

Pierre Dragicevic pierre.dragicevic@inria.fr

ABSTRACT

In this paper, we reproduce a small part of Steegen et al.'s multiverse analysis of Durante et al.'s study using explorable explanations. The data processing options can be selected interactively, which allows us to show the interaction plot reported in Durante et al. in addition to the p-value.

AUTHOR KEYWORDS

Multiverse analysis.

ACM CLASSIFICATION KEYWORDS

H5.2 User Interfaces: Evaluation/Methodology

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Human Factors; Design; Experimentation; Measurement.

INTRODUCTION

Steegen and colleagues [1] introduced the concept of multiverse analysis, which they illustrated by re-analyzing data from a 2013 paper by Durante and colleagues [2] entitled "The fluctuating female vote: Politics, religion, and the ovulatory cycle". Here, we report the initial part of the

 \Box days 9–17 for high fertility and 18–25 for low fertility [5], \Box days 8–14 for high fertility and 1–7 and 15–28 for low fertility [6], and □ days 9–17 for high fertility and 1–8 and 18–28 for low fertility [7].

Second, there are different reasonable ways of estimating a woman's next menstrual onset, which is an intermediate step in determining cycle day. \boxtimes A woman's cycle day can be based on the number of days before next menstrual onset, which in turn is based on cycle length, which is computed as the difference between the start date of the woman's last menstrual period and the start date of the woman's previous menstrual period [2].
Another way to estimate next menstrual onset is based on the women's reported estimate of their typical cycle length [8].

Relationship status

There are at least three options for the dichotomization of women's relationship status into single or committed. ⊠ Women who selected response Option 1 or 2 on the relationship status item can be assigned to the group of single women whereas women who selected response

All these and more examples can be found at:

explorablemultiverse.github.io/

We need to promote and support transparent statistical reporting

Thanks!

And thanks to Matt Kay, Pierre Dragicevic, Yvonne Jansen, Fanny Chevalier



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