

# Using data to confuse and deceive

Matthew Brett

## Handout

Available at [https://github.com/matthew-brett/lans-workshop/blob/master/data\\_confuse\\_deceive\\_handout.pdf](https://github.com/matthew-brett/lans-workshop/blob/master/data_confuse_deceive_handout.pdf)

## How to lie with statistics

If you can't prove what you want to prove, demonstrate something else and pretend that they are the same thing. In the daze that follows the collision of statistics with the human mind, hardly anybody will notice the difference.

(Huff 1954)

## “Research Excellence” Framework

Over thirty years the RAE / REF has supported a sustained improvement in the quality and productivity of the UK research base. It is used by universities to attract students, staff and external funding.

Research Excellence Framework (REF) review: Building on success and learning from experience by Lord Nicholas Stern.

## What is improvement?

|    | 1947–66 | 1967–86 | 1987–2006 |
|----|---------|---------|-----------|
| US | 50      | 88      | 126       |
| UK | 20      | 25      | 9         |

Number of science Nobel prizes by country and time period. REA / REF started in 1986.

(Charlton 2007)

## **What is improvement?**

In contrast to the picture of long term decline in Nobel-prize-winning revolutionary science; UK and European scientific production (also that of Chinese science) is probably catching up with the USA in terms of scientometric measures such as numbers of publications and citations.

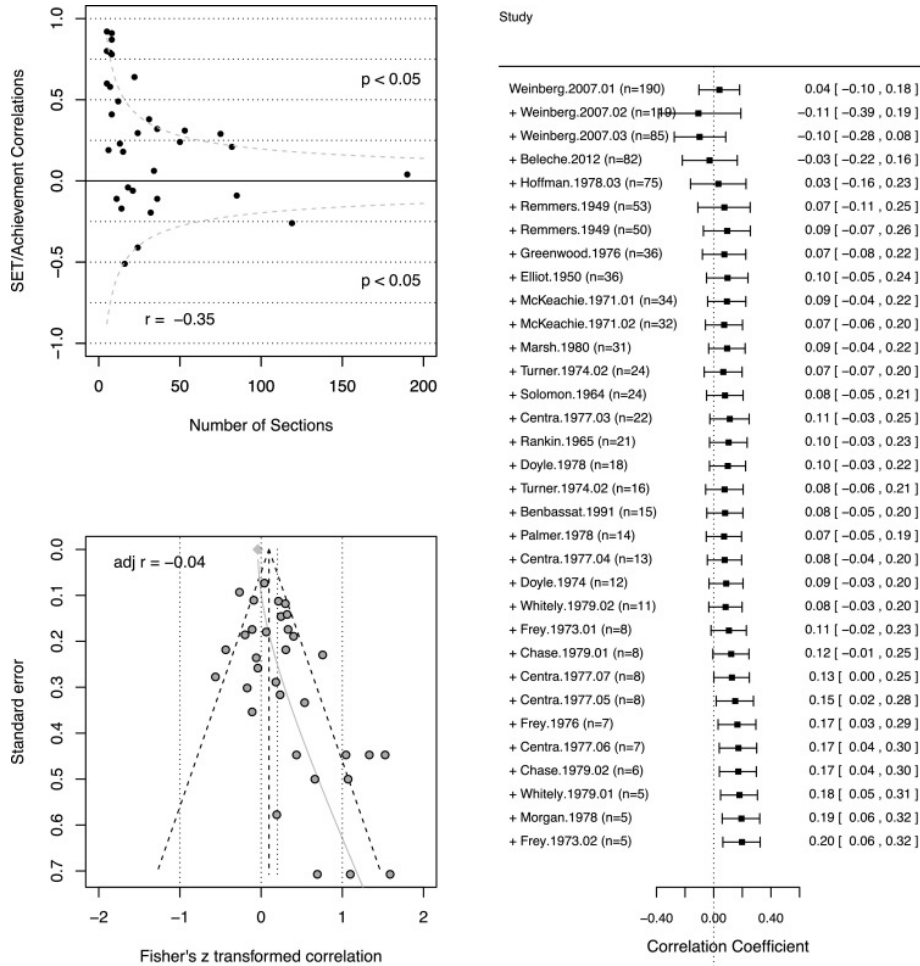
(Charlton 2007)

## **“Teaching Excellence” Framework**

- student satisfaction using the teaching on course, assessment and feedback and academic support scales from the National Student Survey;
- retention using [Higher Education Statistics Agency] UK Performance Indicators;
- proportion in employment in further study using 6 month [Destination of Leavers from Higher Education Survey].

UK government Higher education: success as a knowledge economy - white paper

## Student Evaluations do not measure teaching effectiveness



(Uttl, White, and Gonzalez 2017)

## Summary of meta analysis

The reported correlations between [Student Evaluations of Teaching] ratings and learning are completely consistent with randomly generating correlations from the population correlation with  $\rho = 0$  and applying publication selection bias.

(Uttl, White, and Gonzalez 2017)

## What do student ratings measure?

- the grade the student expects to get;
- the subject being taught;
- whether the instructor is white and male
- biscuits

## Expected grade

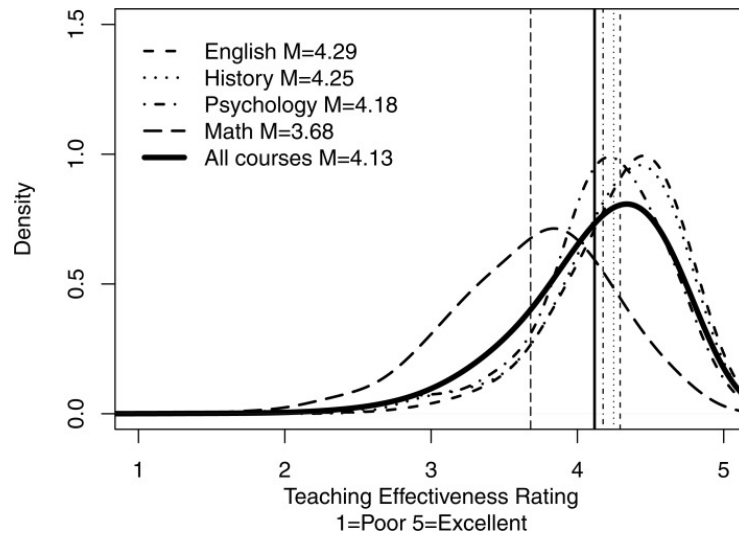
**Table 7.** Average correlation between SET and interim grades

|                        | $\bar{\rho}$ | $p$  |
|------------------------|--------------|------|
| Overall                | 0.16         | 0.00 |
| History                | 0.32         | 0.00 |
| Political institutions | −0.02        | 0.61 |
| Macroeconomics         | 0.15         | 0.01 |
| Microeconomics         | 0.13         | 0.03 |
| Political science      | 0.17         | 0.02 |
| Sociology              | 0.24         | 0.00 |

$p$ -values are one-sided.

(Boring, Ottoboni, and Stark 2016)

## Subject being taught



14872 class summary evaluations from New York University  
(Uttl and Smibert 2017)

## Whether the instructor is male

**Table 8.** Mean ratings and reported instructor gender (male minus female).

|              | Difference in means | Nonparametric $p$ -value | MacNell et al. $p$ -value |
|--------------|---------------------|--------------------------|---------------------------|
| Overall      | 0.47                | 0.12                     | 0.128                     |
| Professional | 0.61                | 0.07                     | 0.124                     |
| Respectful   | 0.61                | 0.06                     | 0.124                     |
| Caring       | 0.52                | 0.10                     | 0.071                     |
| Enthusiastic | 0.57                | 0.06                     | 0.112                     |
| Communicate  | 0.57                | 0.07                     | NA                        |
| Helpful      | 0.46                | 0.17                     | 0.049                     |
| Feedback     | 0.47                | 0.16                     | 0.054                     |
| Prompt       | 0.80                | 0.01                     | 0.191                     |
| Consistent   | 0.46                | 0.21                     | 0.045                     |
| Fair         | 0.76                | 0.01                     | 0.188                     |
| Responsive   | 0.22                | 0.48                     | 0.013                     |
| Praise       | 0.67                | 0.01                     | 0.153                     |
| Knowledge    | 0.35                | 0.29                     | 0.038                     |
| Clear        | 0.41                | 0.29                     | NA                        |

$p$ -values are two-sided.

(Boring, Ottoboni, and Stark 2016)

## Biscuits

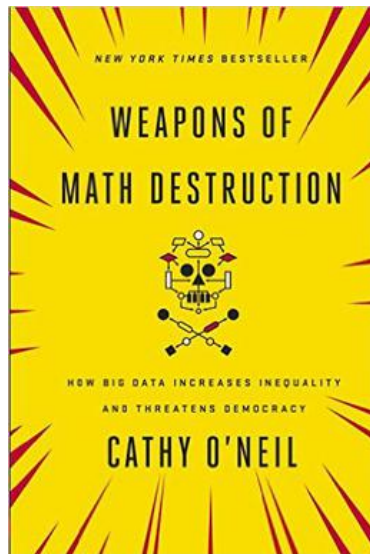
The cookie group evaluated teachers significantly better than the control group (113.4  $pm$  4.9 versus 109.2  $pm$  7.3;  $p = 0.001$ , effect size 0.68). Course material was considered better (10.1  $pm$  2.3 versus 8.4  $pm$  2.8;  $p = 0.001$ , effect size 0.66) and summation scores evaluating the course overall were significantly higher (224.5  $pm$  12.5 versus 217.2  $pm$  16.1;  $p = 0.008$ , effect size 0.51) in the cookie group.

(Hessler et al. 2018)

## For discussion

- Given the data here, why did the government want to use student ratings to evaluate teaching?
- Imagine I propose an alternative rating of teaching excellence, which is a random number between 1 and 10. Make arguments for preferring a metric based on student evaluations.
- If you could decide how to evaluate teaching, what do you propose?

## Algorithms and public policy



(O'Neil 2016)

## Garbage in, Gospel out

From Garbage in, garbage out

## Risk scores for re-offending



Full analysis at <https://github.com/propublica/compas-analysis>

## COMPAS

“Correctional Offender Management Profiling for Alternative Sanctions”

Proprietary algorithm

Marketed by Northpointe

## Risk score officer questions

8. How many prior misdemeanor assault offense arrests (not sex, or domestic violence) as an adult?  
☐ 0 ☐ 1 ☐ 2 ☐ 3+
9. How many prior family violence offense arrests as an adult?  
☐ 0 ☐ 1 ☐ 2 ☐ 3+
10. How many prior sex offense arrests (with force) as an adult?  
☐ 0 ☐ 1 ☐ 2 ☐ 3+
11. How many prior weapons offense arrests as an adult?  
☐ 0 ☐ 1 ☐ 2 ☐ 3+
12. How many prior drug trafficking/sales offense arrests?  
☐ 0 ☐ 1 ☐ 2 ☐ 3+

COMPAS questionnaire

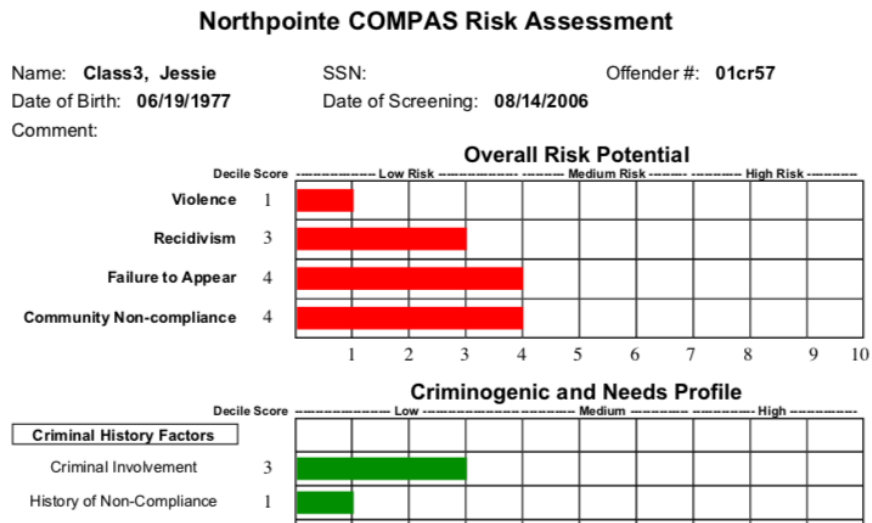


## Risk score offender questions

24. In the last 12 months before this incarceration, how often did you have contact with your family (may be in person, phone, mail)?
- ☐ No family ☐ Never ☐ Less than once/month ☐ Once per week ☐ Daily
25. In the last 12 months before this incarceration, how often did you move?
- ☐ Never ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5+
26. Did you have a regular living situation prior to your current incarceration (an address where you routinely stayed and could be reached)?
- ☐ No ☐ Yes
27. How long had you been living at your last address prior to this incarceration?
- ☐ 0-5 mo. ☐ 6-11 mo. ☐ 1-3 yrs. ☐ 4-5 yrs. ☐ 6+ yrs.
28. Was there a telephone at this residence (a cell phone is an appropriate alternative)?
- ☐ No ☐ Yes

COMPAS questionnaire

## Risk score results



COMPAS results

## Background - a crash course on machine learning

See <https://www.inferentialthinking.com/chapters/17/Classification>

### Prediction errors by race

|                | Black Defendants |      |                | White Defendants |      |
|----------------|------------------|------|----------------|------------------|------|
|                | Low              | High |                | Low              | High |
| Survived       | 990              | 805  | Survived       | 1139             | 349  |
| Recidivated    | 532              | 1369 | Recidivated    | 461              | 505  |
| FP rate: 44.85 |                  |      | FP rate: 23.45 |                  |      |
| FN rate: 27.99 |                  |      | FN rate: 47.72 |                  |      |
| PPV: 0.63      |                  |      | PPV: 0.59      |                  |      |
| NPV: 0.65      |                  |      | NPV: 0.71      |                  |      |
| LR+: 1.61      |                  |      | LR+: 2.23      |                  |      |
| LR-: 0.51      |                  |      | LR-: 0.62      |                  |      |

Analysis description

### Assessing risk scores

Although these measures were crafted with the best of intentions, I am concerned that they inadvertently undermine our efforts to ensure individualized and equal justice.

Eric Holder, US Attorney General, 2014 (quoted in Propublica).

### For discussion

- Given the importance of the risk scores, and their potential for bias, why was there so little study of their performance?
- What would be your recommendation for the use of the Northpointe system studied here?
- What recommendations would you make, to a state that was considering using a system like this? What resources would you provide to help them?

### Is this the end?

Yes, it's the end of the workshop.

All material for these slides at <https://github.com/matthew-brett/lans-workshop>

## References

- Boring, Anne, Kellie Ottoboni, and Philip Stark. 2016. “Student Evaluations of Teaching (Mostly) Do Not Measure Teaching Effectiveness.” *ScienceOpen Research*.
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