

## Working with data in your research and paper

Ioannis Konstantinidis
Sr. Researcher, Dept. of Computer Science ikonstantinidis@uh.edu

Nutrition Facts Serving Size

On two occasions I have been asked,-"Pray, Mr. Babbage, if you put into the machine wrong figures, will the right answers come out?" ... I am not able rightly to apprehend the kind of confusion of ideas that could provoke such a question.

Charles Babbage (1791-1871) Passages from the Life of a Philosopher, ch. 5 "Difference Engine No. 1" (1864)

## Does

- the statistical summary say what you think it says?
- the statistical summary give the full picture?
- the statistical test ask the right question?
- the statistical test say what you think it says?


## STATISTICAL SUMMARIES

## Congratulations!

Your dataset summaries look right

But does your dataset contain "wrong figures"?

## Does

$>$ the statistical summary say what you think it says?

- the statistical summary give the full picture?
- the statistical test ask the right question?
- the statistical test sav what you think it savs?


## If your weight is average, then

A. You are as likely to run into someone that weighs more than you as you are to run into someone that weighs less than you
B. If everyone else's weight changed to match yours exactly, elevator capacity signs could stay the same; but if everyone's weight changed to be double your weight, then elevator capacities would need to be cut in half
C. None of the above

If your weight is average, then
A. Median

VS.
B. Mean

## Text-based summary (by threshold)

## Centrality

What value splits the observations in half?
(half the values are above, the other half are below)
MEDIAN

The median describes RELATIVE POSITION for a SINGLE individual within an ENSEMBLE of peers

## Text-based summary (by threshold)



## Text-based summary (in aggregate)

## Centrality

How does the sum total of all values compare ${ }^{1}$ ?
MEAN

The mean compares CUMULATIVE VALUES for a POOLED ENSEMBLE of peers to a STANDARDIZED MEASURE (sum/\#)
${ }^{1}$ to the number of observations

## Text-based summary (in aggregate)

Centrality
How does the sum total of all values compare ${ }^{1}$ ?
MEAN

> Simple to compute, even on paper - no need to reorder the column of observations

The mean compares CUMULATIVE VALUES for a POOLED ENSEMBLE of peers to a STANDARDIZED MEASURE (sum/\#)

## MEAN as a stand-in for MEDIAN

If the histogram is symmetric,
i.e., for each value above the median,
there is a value at equal distance below the median
and vice versa
then all these differences will cancel each other out when we compute the sum total of all the values,
so the MEAN will be equal to the MEDIAN

## Cautions

If the histogram is not symmetric (we call that skew) then the MEDIAN and MEAN might be very different from each other

## Cautions

If the histogram is not symmetric (we call that skew) then the MEDIAN and MEAN might be very different from each other

Why does this matter?

## MEAN is the flip-side of the MEDIAN

The mean is the POV of the house
Q: How much profit did the house realize (per gambler)?
A: The mean is equal to the profit per gambler
Note: This is not saying how many people profited/lost

## MEAN is the flip-side of the MEDIAN

The mean is the POV of the house
Q: How much profit did the house realize (per gambler)?
A: The mean is equal to the profit per gambler
Note: This is not saying how many people profited/lost

The median is the POV of the gambler
Q: How many gamblers in a group realized a profit?
A: If median $>0$, then more than half profited; If median $<0$, then less than half did
Note: This is not saying how much the profit/loss would be per gambler

## If your weight is average, then

A. You are as likely to run into someone that weighs more than you as you are to run into someone that weighs less than you
B. If everyone else's weight changed to match yours exactly, elevator capacity signs could stay the same; but if everyone's weight changed to be double your weight, then elevator capacities would need to be cut in half
C. Clothes fitted in your size are the most popular size option
D. All of the above
E. None of the above

## Text-based summaries: three ways

| Centrality | Dispersion |
| :---: | :---: |
| What value is the most popular? <br> MODE | How many values are very popular? <br> Modality |
| What value splits the observations in half? (half the values are above, the other half are below) <br> MEDIAN | What band of values splits the observations in half? (half the values are inside, the other half are outside) <br> IQR |
| How does the sum total of all values compare ${ }^{1}$ ? <br> MEAN | How does the sum total of all deviations ${ }^{2}$ compare ${ }^{1}$ ? $\text { Variance }=(\text { standard deviation })^{2}$ |

[^0]${ }^{2}$ squared distances from the mean, i.e., (value-MEAN) ${ }^{2}$

## Does

$\checkmark$ the statistical summary say what you think it says?
$>$ the statistical summary give the full picture?

- the statistical test ask the right question?
- the statistical test say what you think it says?



## The Datasaurus

## STATISTICAL TESTS: meaningful differences



Congratulations! Your experiment found a difference in performance

## STATISTICAL TESTS: $\underline{\text { meaningful differences }}$



Congratulations! Your experiment found a difference in performance

But should you be measuring this difference to begin with?

## Does

$\checkmark$ the statistical summary say what you think it says?
$\checkmark$ the statistical summary give the full picture?
$>$ the statistical test ask the right question?

- the statistical test say what you think it says?


## SAT scores over time

| GPA | SAT (1992) | SAT (2002) |
| :---: | :---: | :---: |
| A+ | 619 | 607 |
| A | 575 | 565 |
| A- | 546 | 538 |
| B | 486 | 479 |
| C | 434 | 424 |
| All grades | $\mathbf{5 0 1}$ | 516 |

Rinott, Yosef and Michael Tam, 2003, "Monotone Regrouping, Regression, and Simpson's Paradox", The American Statistician, 57(2): 139-141. doi:10.1198/0003130031397

## SAT scores over time

| GPA | SAT (1992) | SAT (2002) | \% change |
| :---: | :---: | :---: | :---: |
| A+ | 619 | 607 | $-2 \%$ |
| A | 575 | 565 | $-2 \%$ |
| A- | 546 | 538 | $-1 \%$ |
| B | 486 | 479 | $-1 \%$ |
| C | 434 | 424 | $-2 \%$ |
| All grades | $\mathbf{5 0 1}$ | $\mathbf{5 1 6}$ |  |

Rinott, Yosef and Michael Tam, 2003, "Monotone Regrouping, Regression, and Simpson's Paradox", The American Statistician, 57(2): 139-141. doi:10.1198/0003130031397

## SAT scores over time

| GPA | SAT (1992) | SAT (2002) | \% change |
| :---: | :---: | :---: | :---: |
| A+ | 619 | 607 |  |
| A | 575 | 565 |  |
| A- | 546 | 538 |  |
| B | 486 | 479 |  |
| C | 434 | 424 |  |
| All grades | $\mathbf{5 0 1}$ | $\mathbf{5 1 6}$ | $\mathbf{3 \%}$ |

Among ALL students, an average INCREASE of 3\%
Rinott, Yosef and Michael Tam, 2003, "Monotone Regrouping, Regression, and Simpson's Paradox", The American Statistician, 57(2): 139-141. doi:10.1198/0003130031397

## SAT scores over time

| GPA | SAT (1992) | SAT (2002) | \% change |
| :---: | :---: | :---: | :---: |
| A+ | 619 | 607 | $-2 \%$ |
| A | 575 | 565 | $-2 \%$ |
| A- | 546 | 538 | $-1 \%$ |
| B | 486 | 479 | $-1 \%$ |
| C | 434 | 424 | $-2 \%$ |
| All grades | $\mathbf{5 0 1}$ | $\mathbf{5 1 6}$ | $\mathbf{3 \%}$ |

Rinott, Yosef and Michael Tam, 2003, "Monotone Regrouping, Regression, and Simpson's Paradox", The American Statistician, 57(2): 139-141. doi:10.1198/0003130031397

Suppose grading curves change over time ("grade inflation"), so ALL students get slightly better grades.

- Now the high scorers in one letter grade will be classified among the low scorers in the next higher letter grade,
$>$ This would lower the SAT average per group.
- At the same time, the overall SAT average could rise from 501 to 516.
A conclusion from the stratified data that "students scores are falling" would be mistaken

Far better an approximate answer to the right question, which is often vague, than an exact answer to the wrong question, which can always be made precise.

- John Tukey, "The future of data analysis," Annals of Mathematical Statistics 33 (1) (1962)
- https://projecteuclid.org/downloa d/pdf 1/euclid.aoms/1177704711


## STATISTICAL TESTS: meaningful differences



Congratulations! Your experiment found a difference in performance

But is this difference real or random?

## Does

$\checkmark$ the statistical summary say what you think it says?
$\checkmark$ the statistical summary give the full picture?
$\checkmark$ the statistical test ask the right question?
$>$ the statistical test say what you think it says?

## R. Fisher

- Thinks like a detective
- Tries to identify suspects
- Wants to doubt everyone


## Fisher thinks like a detective

Null hypothesis $\left(\mathrm{H}_{0}\right)$ is the default position (claims innocence):

- This person's actions are NOT incriminating
- The difference in population means is ZERO


## Fisher thinks like a detective

Null hypothesis $\left(\mathrm{H}_{0}\right)$ is the default position (claims innocence):

- This person's actions are NOT incriminating
- The difference in population means is ZERO

There is no specific alternative hypothesis; $\mathrm{H}_{0}$ can be rejected for any reason

- A person may be declared suspect for any incriminating reason (e.g., obstruction)
- There is no minimum level for the difference in population (arbitrary precision)


## Fisher thinks like a detective

Null hypothesis $\left(\mathrm{H}_{0}\right)$ is the default position (claims innocence):

- This person's actions are NOT incriminating
- The difference in population means is ZERO

There is no specific alternative hypothesis; $\mathrm{H}_{0}$ can be rejected for any reason

- A person may be declared suspect for any incriminating reason (e.g., obstruction)
- There is no minimum level for the difference in population (arbitrary precision)

The test computes a $p$-value, which measures this likelihood:

## Prob( evidence \| $\mathrm{H}_{0}$ is true)

i.e., what percentage of innocent people behave this way?

Time for a thought experiment


## $H_{0}$ : Coin is fair, meaning $\operatorname{Prob}(H)=\operatorname{Prob}(T)$

## Experiment: 100 flips

$p$-value is the proportion of experiments that would produce a specific degree of bias (i.e., \# of T), or more

Also known as false alarms


Degree of bias (i.e., \# of T) observed in the actual experiment

## $\mathrm{H}_{0}$ : Coin is fair, meaning $\operatorname{Prob}(\mathrm{H})=\operatorname{Prob}(\mathrm{T})$

## Experiment: 100 flips

$p$-value is the proportion of experiments that would produce a specific degree of bias (i.e., \# of T), or more


Degree of bias (i.e., \# of T) observed in the actual experiment

## $H_{0}$ : Coin is fair, meaning $\operatorname{Prob}(H)=\operatorname{Prob}(T)$

Experiment: 100 flips
$p$-value is the proportion of experiments that would produce a specific degree of bias (i.e., \# of T), or more

Significance is the \# of standard deviations that correspond to that degree of bias (measured in sigma)


Degree of bias (in sigma) observed in the actual experiment

## $\mathrm{H}_{0}$ : Coin is fair, meaning $\operatorname{Prob}(\mathrm{H})=\operatorname{Prob}(\mathrm{T})$

Experiment: 100 flips
$p$-value is the proportion of experiments that would produce a specific degree of bias (i.e., \# of T), or more

Significance is the \# of standard deviations that correspond to that degree of bias (measured in sigma)


Degree of bias (in sigma) observed in the actual experiment

## $H_{0}$ : Coin is fair, meaning $\operatorname{Prob}(H)=\operatorname{Prob}(T)$

$p$-value and significance are an inversely related pair

The higher the significance, the lower the $p$-value that corresponds to it

They both depend on $\mathrm{H}_{0}$ being true


Degree of bias (in sigma) observed in the actual experiment

## Not all detectives think alike

A smaller $p$-value is always more significant (more cause for doubt, or less risk) but different people/fields have different risk tolerance

- Opinion Polls are very risk tolerant: $p=0.10$ means l've seen enough; it's well beyond the margin of error level (one sigma)
- Physics does not like risk: $p=0.04$ means I'm not remotely convinced; it's barely past two sigma, not even close to five sigma

Given tolerance // e.g., 0.05 for (95\% ↔ two sigma)
Compute $p$
IF $p$ < tolerance
// either guilty
// or rare (based on sian ficance_level) coincidence, // reject $\mathrm{H}_{0}$ declare suspect

ELSE
seek more evidence OR close case

Compute $p$
Compute significance_Level
// e.g., $p=0.05$ means significance_level = 1.96 sigma Print " $H_{\theta}$ may be rejected at significance level:"
Print significance_Level

The real issue with Fisher's thinking

## The real issue with Fisher's thinking

In this hypothetical example, the $p$-value is the ratio from the green row:

$$
p=\frac{4}{96+4}=0.04
$$

|  | Acting <br> suspiciously? <br> NO | Acting <br> suspiciously? <br> YES |
| :--- | :---: | :--- |
| Guilty? NO | 96 | 4 |

The $p$-value only measures this likelihood:

$$
\text { Prob( evidence | } \mathrm{H}_{0} \text { is true) }
$$

## The real issue with Fisher's thinking

In this hypothetical example, the $p$-value is the ratio from the green row:

$$
p=\frac{4}{96+4}=0.04
$$

But we should be in the business of looking at the red row!


Hypothesis testing should be a binary classifier algorithm

|  | Acting <br> suspiciously? <br> NO | Acting <br> suspiciously? <br> YES |
| :--- | :--- | :--- |
| Guilty? NO | True <br> Negative | False <br> Positive |
| Guilty? YES | False <br> Negative | True <br> Positive |

## J. Neyman and E. Pearson

- Think like lawyers
- Want to distinguish innocence from guilt
- Perform binary classification



## A binary classification algorithm



The $p$-value is the ratio: $\frac{\text { false positive }}{\text { not guilty }}$
AKA

- the probability of False Alarm,
- False Positive Rate (FPR)

We want this percentage to be small (ideally it would be 0\%)

## A binary classification algorithm



But we also need assumptions about the ratio:

$$
\frac{\text { true positive }}{\text { guilty }}
$$

AKA the probability of detection, or

- True positive rate (TPR)
- recall
- sensitivity
- hit rate
- power

We want this percentage to be large (ideally it would be 100\%)

## A binary classification algorithm



## A binary classification algorithm



## A binary classification algorithm



## A binary classification algorithm



## A binary classification algorithm




## A binary classification algorithm



## A binary classification algorithm

An actual classifier can be anywhere in the large box

|  | Acting <br> suspiciously? <br>  | Acting <br> suspiciously? <br> YES |
| :--- | :--- | :--- |
| Guilty? <br> NO | True <br> Negative | False <br> Positive |
| Guilty? <br> YES | False <br> Negative | True <br> Positive |



## A binary classification algorithm

|  | Acting <br> suspiciously? <br>  <br> NO | Acting <br> suspiciously? <br> YES |
| :--- | :--- | :--- |
| Guilty? <br> NO | True | False <br> Positive |
| Guilty? <br> YES | False <br> Negative | True <br> Positive |



## A binary classification algorithm



## Recall: Fisher thinks like a detective

Null hypothesis $\left(\mathrm{H}_{0}\right)$ is the default position (claims innocence):

- This person's actions are NOT incriminating
- There is no minimum level for the difference in population (arbitrary precision)


## Contrast: Neyman and Pearson think like lawyers

Null hypothesis $\left(H_{M}\right)$ is the main/default position (presumed innocent):

- The prosecution has NOT proved guilt beyond reasonable doubt
- The difference in population means (effect size) is NOT above a MINIMUM LEVEL (fixed precision)


## Contrast: Neyman and Pearson think like lawyers

Null hypothesis $\left(H_{M}\right)$ is the main/default position (presumed innocent):

- The prosecution has NOT proved guilt beyond reasonable doubt
- The difference in population means (effect size) is NOT above a MINIMUM LEVEL (fixed precision)
- The specific treatment being tested did NOT produce a detectable effect


## Recall: Fisher thinks like a detective

There is no specific alternative hypothesis; $\mathrm{H}_{0}$ can be rejected for any reason

- A person may be declared suspect for any incriminating reason (e.g., obstruction)
- The difference in population means can be arbitrarily small!


## Contrast: Neyman and Pearson think like lawyers

There is a specific alternative hypothesis $\mathrm{H}_{\mathrm{A}}$ (guilty as charged):

- The prosecution has proved the charges beyond reasonable doubt
- The difference in population means is ABOVE a MINIMUM LEVEL (fixed precision)


## Contrast: Neyman and Pearson think like lawyers

There is a specific alternative hypothesis $\mathrm{H}_{\mathrm{A}}$ (guilty as charged):

- The prosecution has proved the charges beyond reasonable doubt
- The difference in population means is ABOVE a MINIMUM LEVEL (fixed precision)
- The specific treatment being tested INDID produced a detectable effect



## Recall: Fisher thinks like a detective

The $p$-value only measures this likelihood:
Prob( evidence | $\mathrm{H}_{0}$ is true )

## Contrast: Neyman and Pearson think like lawyers

We must compute the unique $p$-value cutoff defined by the trade-off between

Prob( evidence \| $H_{M}$ is true )
and
Prob( evidence \| $\mathrm{H}_{\mathrm{A}}$ is true )
(the precision level)

Decision Time


## Detection error tradeoff (DET)

Causes two different types of possible error

- Mistaken detection: the effect was above the minimum level, but it was not produced by the treatment / wrongful conviction (Type I error)
- Missed detection: the treatment produced an effect, but it was not above the minimum level / guilty yet acquitted (Type II error)


## Detection error tradeoff (DET)

Causes two different types of possible error
And these two errors depend on each other

- Minimum precision $=0$ means that everyone will be convicted
- no missed detections (power=100\%) AND
- maximum mistaken detections
- As the minimum precision threshold increases,
- more guilty people will walk scot-free (less power), but ALSO
- fewer innocent people will be convicted (mistakes)
- If the minimum precision threshold is high enough,
- all guilty people will be acquitted / no power, because no jury trial will result in a conviction (reasonable doubt becomes unreasonably lax)


## Detection error tradeoff (DET)

Any given threshold corresponds to a specific pair of values for

- \% of mistakes ( $p$-value) and
these two rates are not independent, but fall along a curve (sometimes called ROC)



## The power of sample size

More samples (higher N ) lead to better DET/ROC curves

- Higher power for given $p$-value
- Lower $p$-value for given power


The power of sample size

$\frac{\text { true positive }}{\text { positive }}$ is the

- Positive Predictive Value (PPV)
- Precision



## Back to the jury

## Contrast: Neyman and Pearson think like lawyers

## Fix values for

- alpha, the long-term probability of mistaken detection (Type I error):
- wrongful conviction, or
- falsely accepting the alternative/prosecution's argument $\mathrm{H}_{\mathrm{A}}$
- beta, the long-term probability of missed detection (Type II error):
- guilty yet acquitted, or
- falsely accepting the main/defense's argument $H_{M}$
- keep beta > alpha


## Contrast: Neyman and Pearson think like lawyers

With alpha and beta computed,

- Set the fixed threshold for p-value to be alpha
- Use beta to compute the fixed power value that reflects the sample size
(Note that power = 1 - beta)


## Neyman and Pearson think like lawyers

Given alpha < beta
Compute p
Compute power // power is based on amount of evidence (sample size)
IF power < 1 - beta
// not enough evidence was presented either way, so inconclusive warning "TEST LACKS SUFFICIENT POWER TO MAKE RELIABLE DECISIONS"
// but prosecution has the burden of proof
accept $\mathrm{H}_{\mathrm{M}}$
ELSE

```
IF p<alpha
        accept HA // enough incriminating evidence was presented, so find guilty
    ELSE
        accept HM // enough exonerating evidence was presented, so find innocent
```


## For more on this topic:

frontiers
in Psychology

REVIEW article
Front. Psychol, 03 March 2015 I hitps://doi org/10 3389//psyg 2015.00223

## Fisher, Neyman-Pearson or NHST? A

 tutorial for teaching data testing
## Jive Jose Perezgonzalez ${ }^{*}$

Business School, Massey University, Palmerston North. New Zealand

Eur J Epidcmiol (2016) 31:337-350
DOI 10.1007/10654-016-0149-3

## ESSAY

Statistical tests, $P$ values, confidence intervals, and power: a guide to misinterpretations

Sander Greenland ${ }^{1}$ - Stephen J. Senn ${ }^{2}$ - Kenneth J. Rothman ${ }^{3}$ - John B. Carlin ${ }^{4}$.<br>Charles Poole ${ }^{5}$ - Steven N. Goodman ${ }^{6}$ - Douglas G. Altman ${ }^{7}$

## Does

$\checkmark$ the statistical summary say what you think it says?
$\checkmark$ the statistical summary give the full picture?
$\checkmark$ the statistical test ask the right question?
$\checkmark$ the statistical test say what you think it says?

Thats all colks!


[^0]:    ${ }^{1}$ to the number of observations, i.e., sum/\#

