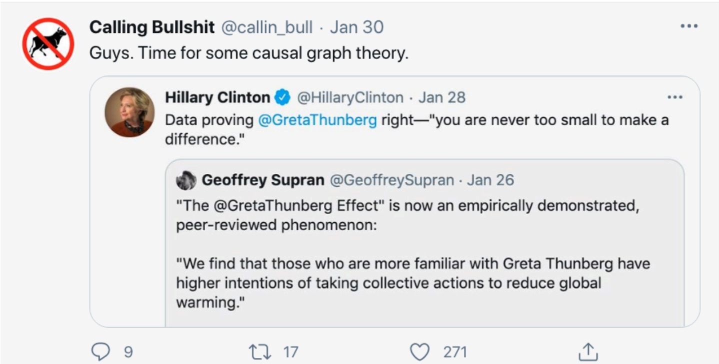
Mathematical Statistics II

STA2212H S LEC9101

Week 4

February 3 2021

Start recording!



Received: 5 December 2020 | Accepted: 18 December 2020
DOI: 10.1111/jasp.12737

ORIGINAL ARTICLE

Journal of Applied Social Psychology WILEY

The Greta Thunberg Effect: Familiarity with Greta Thunberg predicts intentions to engage in climate activism in the United States

Anandita Sabherwal[1] | Matthew T. Ballew[2] | Sander van der Linden[1] | Abel Gustafson[3] | Matthew H. Goldberg[4] | Edward W. Maibach[5] | John E. Kotcher[5] | Janet K. Swim[6] | Seth A. Rosenthal[4] | Anthony Leiserowitz[4]

Calling Bullshit @callin_bull · Jan 30

Guys. Time for some causal graph theory.

> **Hillary Clinton** @HillaryClinton · Jan 28
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> > **Geoffrey Supran** @GeoffreySupran · Jan 26
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> > "We find that those who are more familiar with Greta Thunberg have higher intentions of taking collective actions to reduce global warming."

9 17 271

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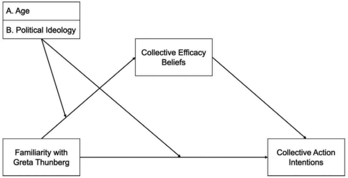

FIGURE 1 Conceptual model for hypotheses. Model tests the effect of familiarity with Greta Thunberg on intentions to take collective action through collective efficacy beliefs, as a simple mediation (Hypothesis 1), moderated by age (A; Hypotheses 2a and 2b), and moderated by political ideology (B; Hypotheses 3a and 3b), respectively

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Recap

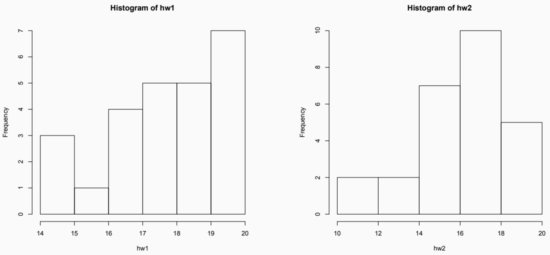
Are you recording?

- Choosing test statistics – optimality, likelihood, convenience
- Simple and composite hypotheses $\theta = \theta_0; \quad \theta \in \Theta_0$
- Generalized likelihood ratio tests $W(\theta_0) = 2\{\ell(\hat{\theta}) - \ell(\tilde{\theta}_0)\}$
- Wald tests $(\hat{\theta} - \theta_0)/\widehat{se}$
- significance tests p-value: $\Pr(T > t^{obs}; H_0)$

Today

Start Recording

1. Homework 2
2. confidence intervals
3. goodness-of-fit tests
4. multiple testing



- February 8 3.00 – 4.00 Paul McNicholas
- "Selected Problems in Classification" Link

Data Science and Applied Research Series

Confidence intervals

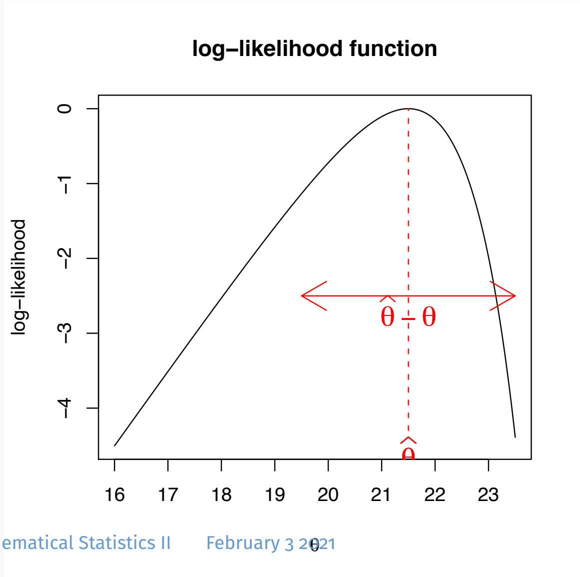

```
Coefficients:
             Estimate Std. Error z value Pr(>|z|)    
(Intercept) -34.103704   6.530014  -5.223 1.76e-07 ***
zn           -0.079918   0.033731  -2.369  0.01782 *  
indus        -0.059389   0.043722  -1.358  0.17436    
chas          0.785327   0.728930   1.077  0.28132    
nox          48.523782   7.396497   6.560 5.37e-11 ***
rm           -0.425596   0.701104  -0.607  0.54383    
age           0.022172   0.012221   1.814  0.06963 .  
dis           0.691400   0.218308   3.167  0.00154 ** 
rad           0.656465   0.152452   4.306 1.66e-05 ***
tax          -0.006412   0.002689  -2.385  0.01709 *  
ptratio       0.368716   0.122136   3.019  0.00254 ** 
black        -0.013524   0.006536  -2.069  0.03853 *  
lstat         0.043862   0.048981   0.895  0.37052    
medv          0.167130   0.066940   2.497  0.01254 *  
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

logistic regression

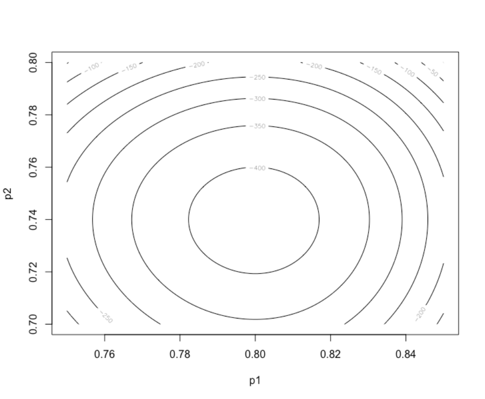
```
> summary(lm1)
Call:
lm(formula = log(cost) ~ date + log(t1) + log(t2) + log(cap) +
    pr + ne + ct + bw + log(cum.n) + pt, data = nuclear)
Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -14.24198    4.22880  -3.368  0.00291 **
date          0.20922    0.06526   3.206  0.00425 **
log(t1)       0.09187    0.24396   0.377  0.71025
log(t2)       0.28553    0.27289   1.046  0.30731
log(cap)      0.69373    0.13605   5.099 4.75e-05 ***
pr           -0.09237    0.07730  -1.195  0.24542
ne            0.25807    0.07693   3.355  0.00300 **
ct            0.12040    0.06632   1.815  0.08376 .
bw            0.03303    0.10112   0.327  0.74715
log(cum.n)   -0.08020    0.04596  -1.745  0.09562 .
pt           -0.22429    0.12246  -1.832  0.08125 .
---
Residual standard error: 0.1645 on 21 degrees of freedom
```

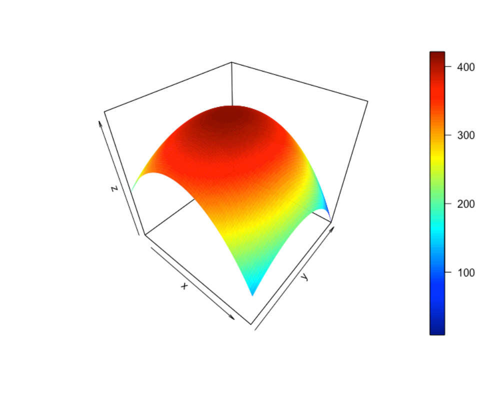
```
log(cap)      0.69373    0.13605   5.099 4.75e-05 ***
pr           -0.09237    0.07730  -1.195  0.24542
ne            0.25807    0.07693   3.355  0.00300 **
ct            0.12040    0.06632   1.815  0.08376 .
bw            0.03303    0.10112   0.327  0.74715
log(cum.n)   -0.08020    0.04596  -1.745  0.09562 .
pt           -0.22429    0.12246  -1.832  0.08125 .
---
Residual standard error: 0.1645 on 21 degrees of freedom
Multiple R-squared:  0.8717,Adjusted R-squared:  0.8106
F-statistic: 14.27 on 10 and 21 DF,  p-value: 3.081e-07
```

Example: Likelihood confidence intervals


log−likelihood function
log−likelihood
0
−1
−2
−3
−4
16
17
18
19
20
21
22
23
$\hat\theta - \theta$
$\hat\theta$
θ

... likelihood confidence intervals





Confidence and power

Confidence and power

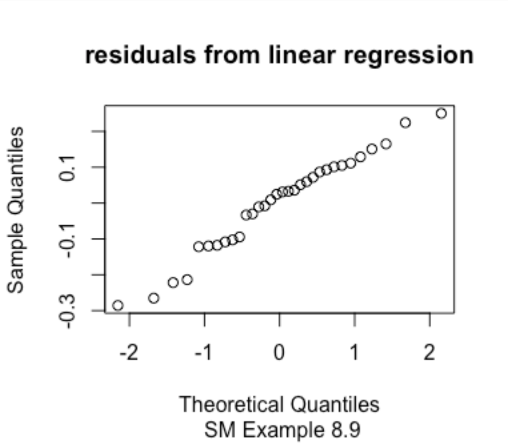
- interpretation of confidence interval or confidence bound

random endpoint(s)

- size of test $\leftrightarrow$ confidence level
- power of test $\leftrightarrow$ width of confidence interval

Pure significance tests

- data $x_1, \dots x_n$ independent, identically distributed
- test statistic $t = t(\boldsymbol{x})$, observed value t^{obs}
- $$p^{obs} = \Pr(T \geq t^{obs}; H_0)$$
- Example: sign test


residuals from linear regression
Sample Quantiles
0.1
-0.1
-0.3
-2
-1
0
1
2
Theoretical Quantiles
SM Example 8.9

Goodness-of-fit tests

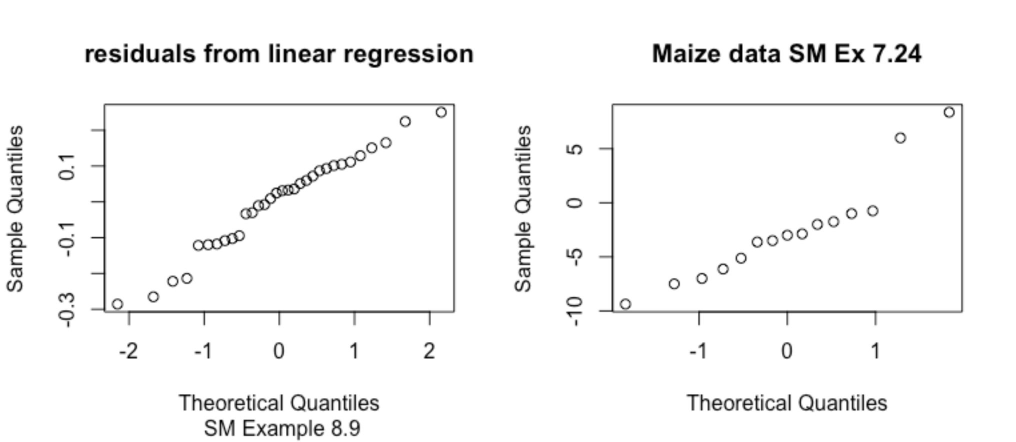
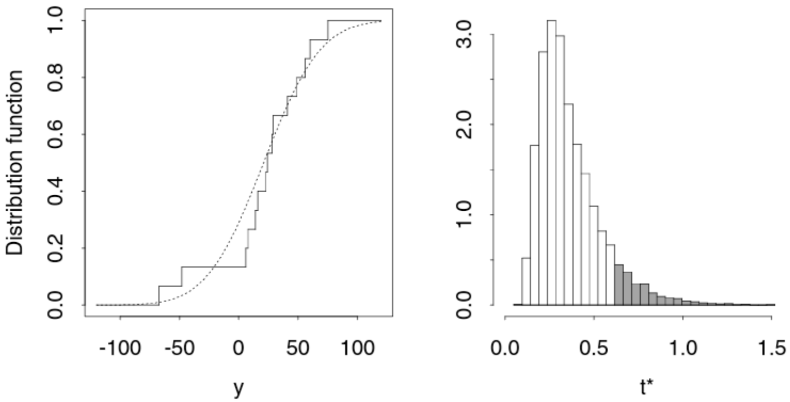


Figure 7.5 Analysis of maize data. Left: empirical distribution function for height differences, with fitted normal distribution (dots). Right: null density of Anderson–Darling statistic T for normal samples of size $n = 15$ with location and scale estimated. The shaded part of the histogram shows values of T^* in excess of the observed value t_{obs}.



SM Example 7.24 testing $N(\mu, \sigma^2)$ distribution

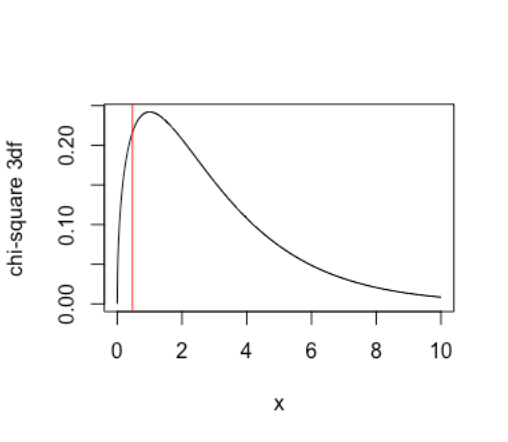
SM Example 7.23; 6.14 testing $U(0, 1)$ distribution

Goodness-of-fit tests

Goodness-of-fit tests

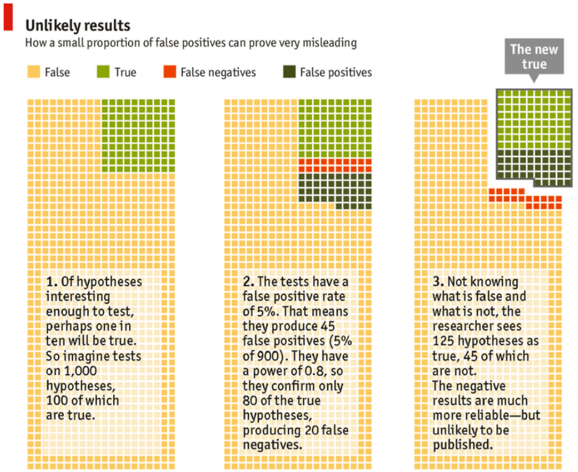
- $X_1, \ldots, X_n \quad i.i.d. \quad F(\cdot); \quad H_0 : F = F_0$ cumulative d.f.
- $\widehat{F}_n(t) = \frac{1}{n}\sum_{i=1}^{n} 1\{X_i \leq t\}$
- test statistic:
    1. $\sup_t |\widehat{F}_n(t) - F_0(t)|$
    2. $\int \{\widehat{F}_n(t) - F_0(t)\}^2 dt$
    3. $\displaystyle\int \frac{\{\widehat{F}_n(t) - F_0(t)\}^2}{\widehat{F}_n(t)\{1 - \widehat{F}_n(t)\}} dt$
    4. χ^2 tests AoS 10.4
- SM Example 7.24 testing $N(\mu, \sigma^2)$ distribution
- SM Example 7.23; 6.14 testing $U(0, 1)$ distribution

AoS Example 10.18



Pause

Multiple testing



Source: *The Economist*

Bonferroni correction

AoS Thm 10.24; EH §15.1

False Discovery Rates

Benjamini-Hochberg

Benjamini-Hochberg