The scientific process as cumulative

15 January 2020

Modern Research Methods

Molly Lewis

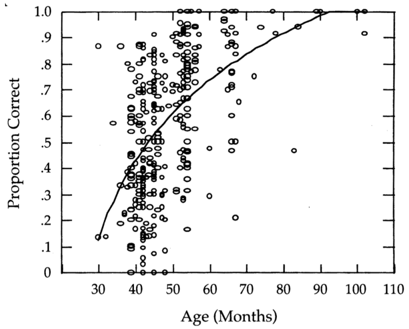
Course Website: https://cumulativescience.netlify.com/

Business

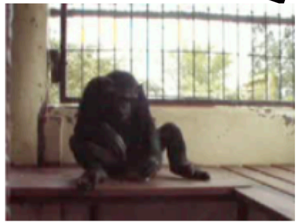
- Survey
  - https://tinyurl.com/MRM-survey
- Jaeah's office location: Psych. lounge
- Qs about syllabus? https://cumulativescience.netlify.com/

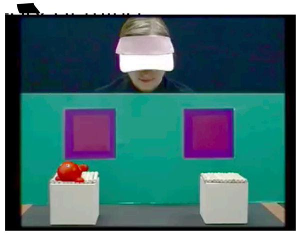
Last Time: Cumulative Science

The Scientific Process



THEORY 1



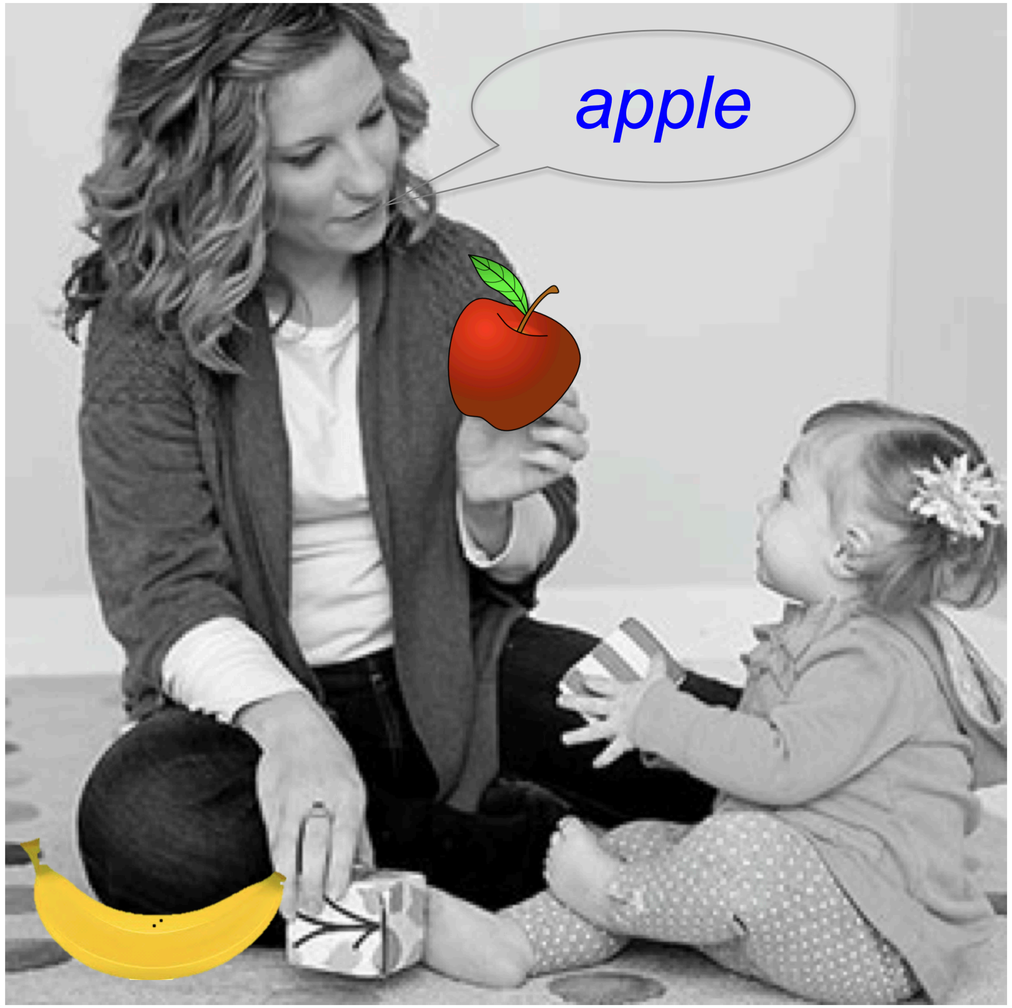


THEORY 2

Today: An introduction to cumulative science tools

How do kids learn the meaning of new words?

Graduate Student, Molly



There are infinite possibilities when a child hears a new word, how do they figure out the right one?

But, it gets even harder…

“dax”

Proposal in the literature

How do kids learn the meaning of new words?

Psychological Review
2007, Vol. 114, No. 2, 245–272

0033-295X/07/$12.00 DOI: 10.1037/0033-295X.114.2.245

Word Learning as Bayesian Inference

Fei Xu
University of British Columbia

Joshua B. Tenenbaum
Massachusetts Institute of Technology

The authors present a Bayesian framework for understanding how adults and children learn the meanings of words. The theory explains how learners can generalize meaningfully from just one or a few positive examples of a novel word's referents, by making rational inductive inferences that integrate prior knowledge about plausible word meanings with the statistical structure of the observed examples. The theory addresses shortcomings of the two best known approaches to modeling word learning, based on deductive hypothesis elimination and associative learning. Three experiments with adults and children test the Bayesian account's predictions in the context of learning words for object categories at multiple levels of a taxonomic hierarchy. Results provide strong support for the Bayesian account over competing accounts, in terms of both quantitative model fits and the ability to explain important qualitative phenomena. Several extensions of the basic theory are discussed, illustrating the broader potential for Bayesian models of word learning.

Keywords: word learning, Bayesian inference, concepts, computational modeling

Let's try it out

P("dax" means dog) =
P("dax" means dalmation) =

"dax"

P("dax" means dalmation) =
P("dax" means dog) =

If I'm picking examples from the dalmation category, I'm more likely to pick three dalmations

If I'm picking examples from the dog category, it would be <u>really</u> unlikely to pick three dalmations

It would be a "suspicious coincidence"!

Xu and Tenenbaum (2007)

The Size Principle

dax

dalmatian? (Subordinate)

dog? (Basic)

animal? (Superordinate)

In general, more exemplars make the more specific category more likely.

dax

dax

dax

dalmatian (Subordinate)

dog (Basic)

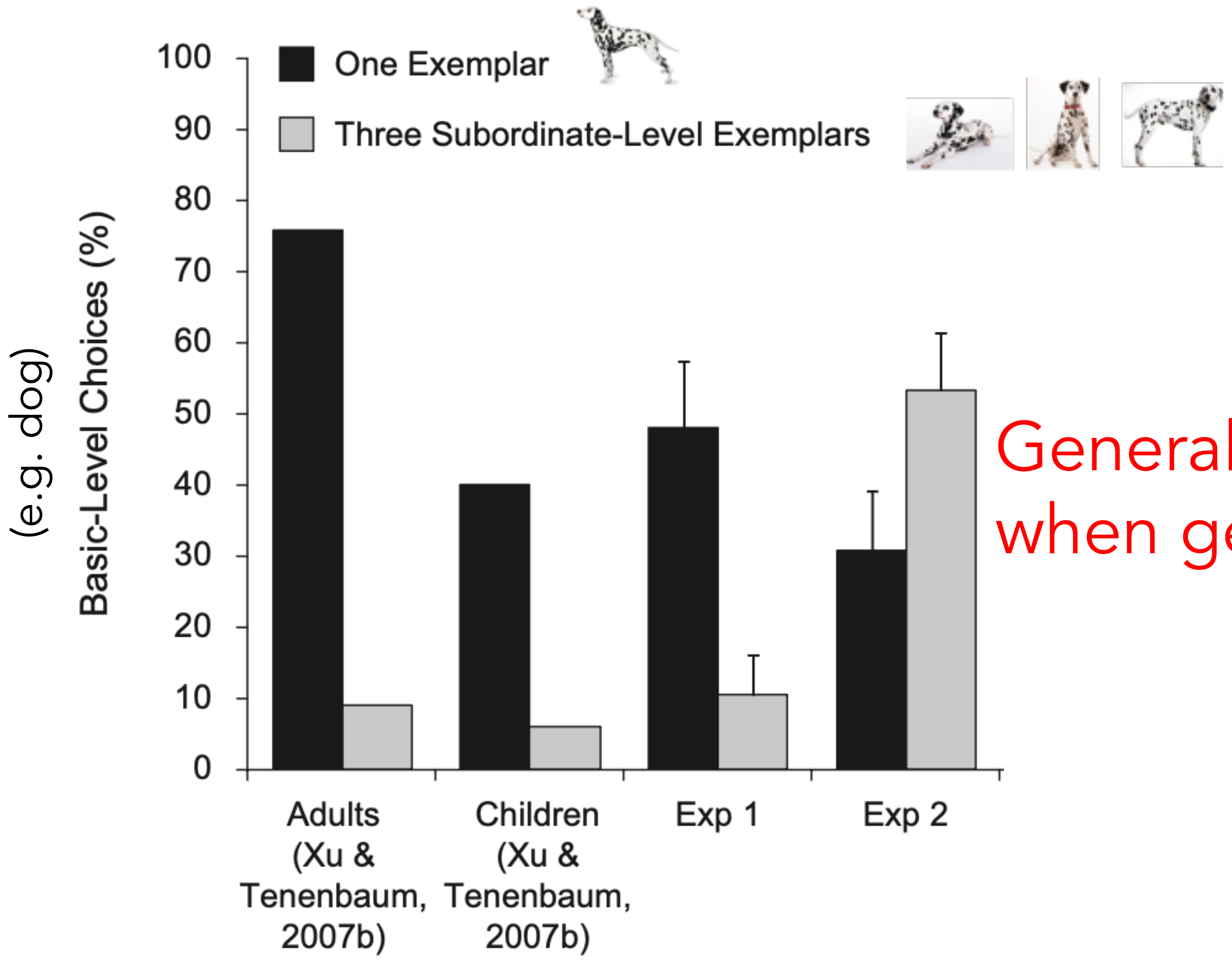
animal (Superordinate)

Xu and Tenenbaum (2007)

Testing the suspicious coincidence effect

Each participant saw some "1 example" trials, and some "3 example" trials

Children and adults make this inference



Generalize word <u>more</u> narrowly when get more examples!

Xu and Tenenbaum (2007)

A theory of how children could learn the meaning of new words at **multiple levels of abstraction**.

“dax”

NUMBER of examples of word meaning provides information

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Word learning as **Bayesian inference**.
F Xu, JB Tenenbaum - Psychological review, 2007 - psycnet.apa.org
The authors present a Bayesian framework for understanding how adults and children learn the meanings of words. The theory explains how learners can generalize meaningfully from just one or a few positive examples of a novel word's referents, by making rational inductive …
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2011

Research Article

aps ASSOCIATION FOR PSYCHOLOGICAL SCIENCE

Psychological Science
22(8) 1049–1057

DOI: 10.1177/0956797611413934
http://pss.sagepub.com
SAGE

Learning Words in Space and Time: Probing the Mechanisms Behind the Suspicious-Coincidence Effect

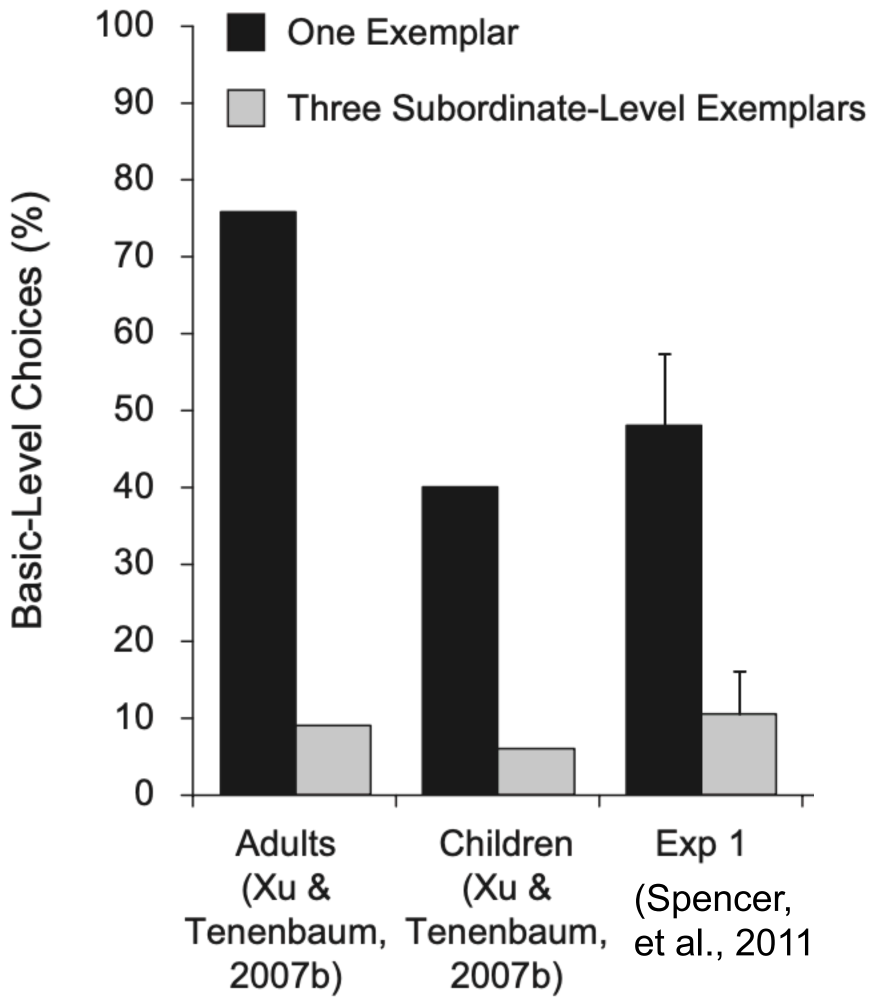
John P. Spencer[1], Sammy Perone[1], Linda B. Smith[2], and Larissa K. Samuelson[1]
[1]Department of Psychology and Delta Center, University of Iowa, and [2]Department of Psychological and Brain Sciences, Indiana University

Your theory is wrong…

"The striking finding that led Xu and Tenenbaum (2007b) to this conclusion—broader generalization from a single instance than from three (nearly identical) instances—**is also consistent with mechanistic accounts** couched in terms of memories and representations for learning events. […] In the case of the suspicious-coincidence effect, two such task factors may be particularly critical: The fact that the exemplars **are simultaneously visible** in the task space and that they are nearly identical instances in **close spatial proximity.** " – Spencer, et al. (2011)

Your theory predicts that it's just NUMBER of examples but other things might matter too.

Sequential presentation of exemplars



...makes the effect reverse??

Resolving a conflict in the literature

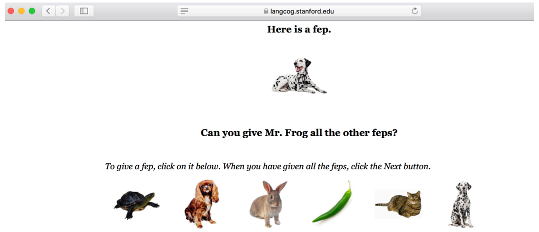
?? I want to understand this discrepancy, and build on it

2018

Did a <u>replication</u> of both studies.

REPLICATE = Repeat a study with the same population, hypothesis, experimental design, and analysis plan and get same result (Patil, et al. 2016)

Replicating previous results



- Stimuli and code from original experiments weren't available so I had to implement using Javascript and HTML (https://tinyurl.com/ry3tvyz)
- Analyzed data in a programming language called R
- Before I ran my study, I pre-registered experimental code/analysis plan (https://osf.io/wgvcw) - why?
- Conducted a replication of these studies online using a large sample (*N* = 600) of participants

Reproducibility

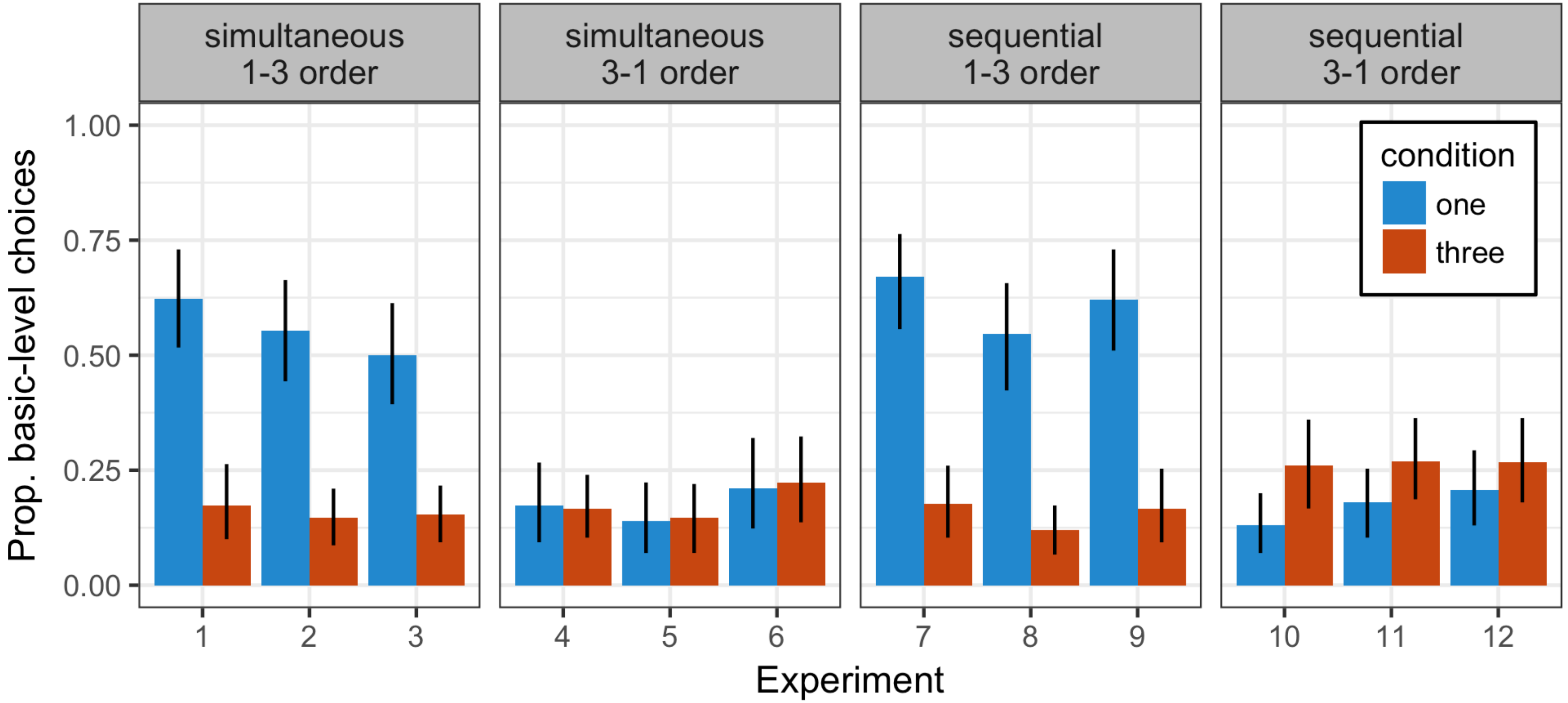
REPRODUCE = Repeat procedure (e.g. experimental code, analysis code) and get same result

- All my code is available online so that other researchers can **reproduce** my experiment and analysis
- Website called Github (https://github.com/)
- https://github.com/mllewis/XTMEM

What did I find?

Replication of
Xu and Tenenbaum (2007)

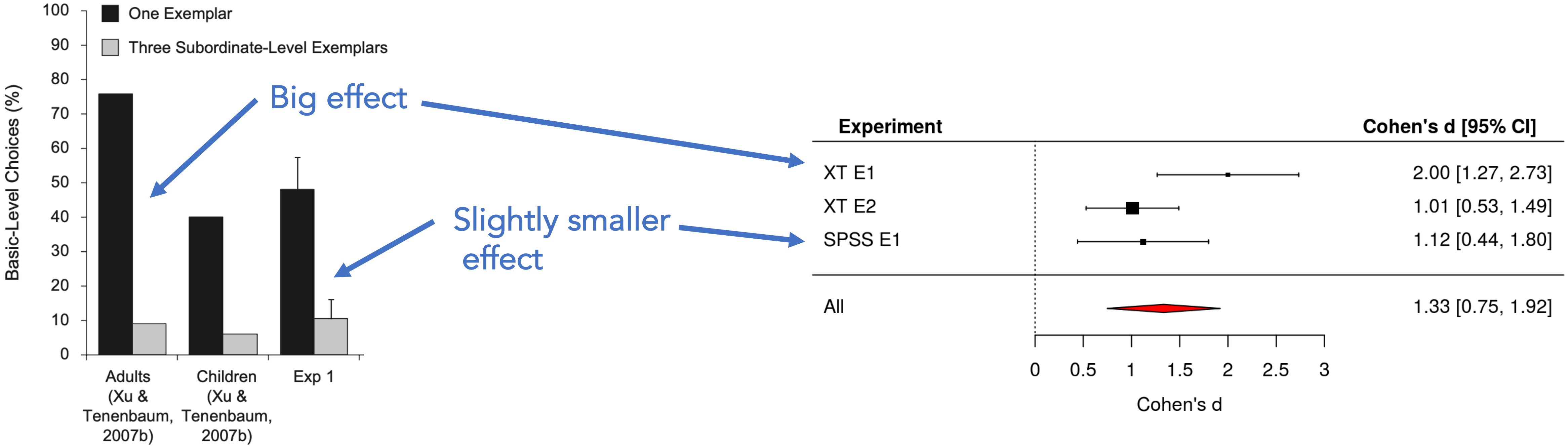
Replication of
Spencer et al. (2011)

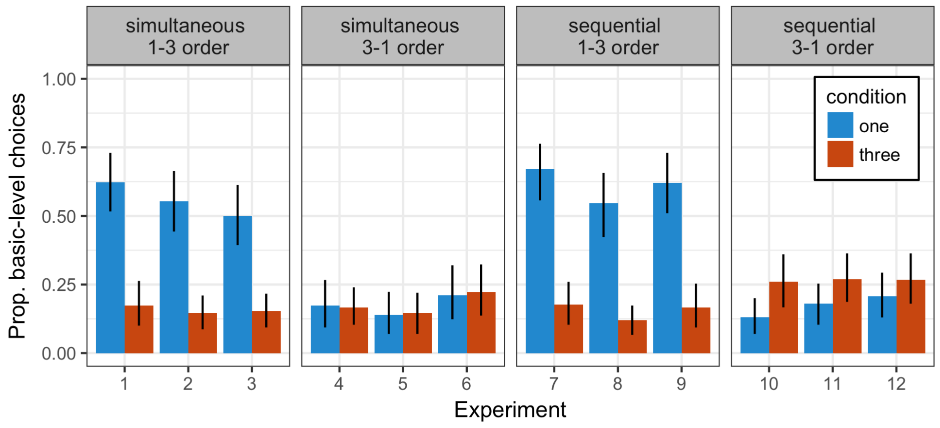


(Lewis & Frank, *Psych. Science*, 2018)

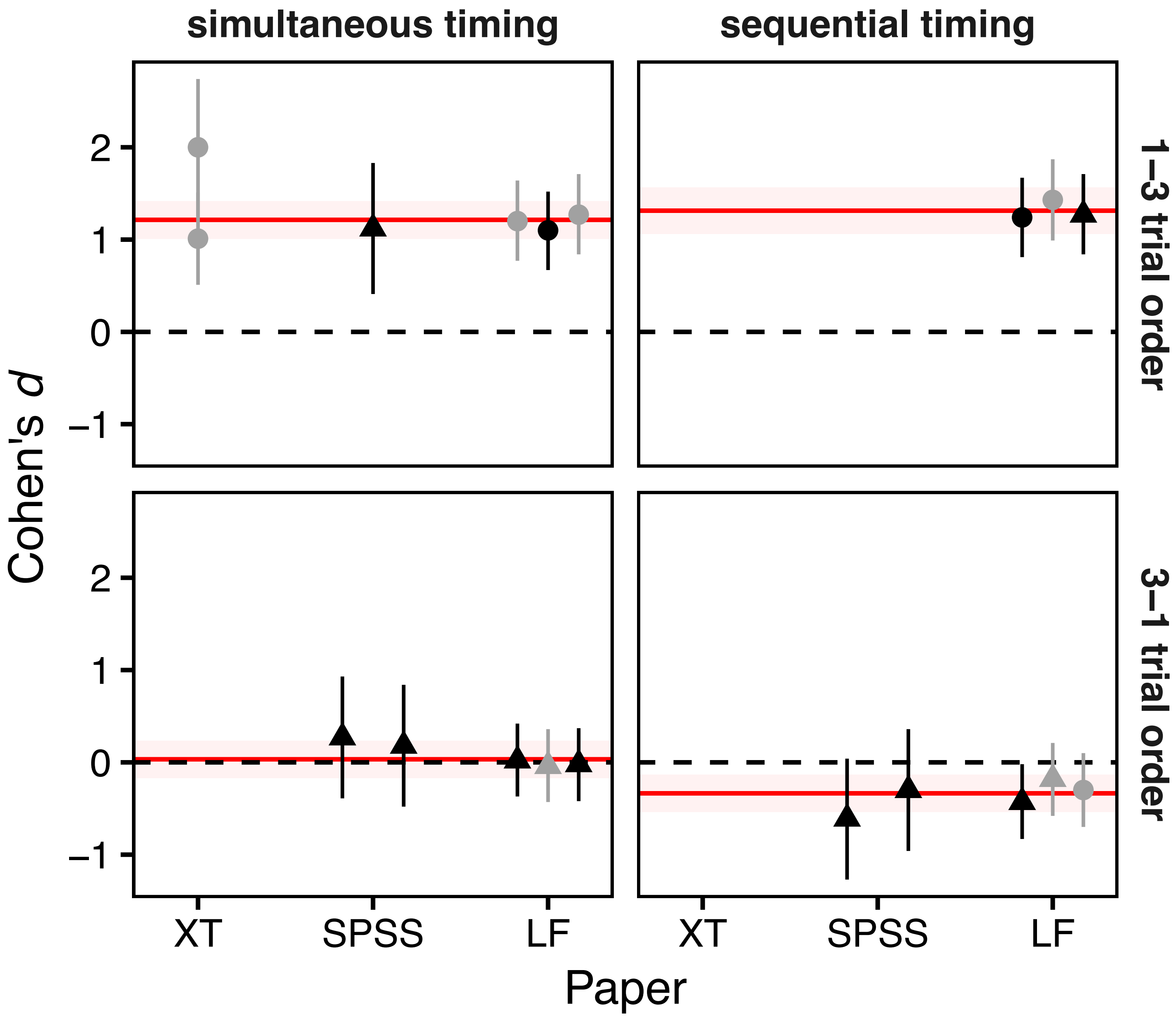
Trial order matters!

- Only see the suspicious coincidence effect in the 1-3 ordering
- How can we test this idea?
- Meta-analysis – technique for quantifying size of an effect across studies.





simultaneous 1-3 order
simultaneous 3-1 order
sequential 1-3 order
sequential 3-1 order
condition
one
three
Prop. basic-level choices
1.00
0.75
0.50
0.25
0.00
1 2 3 4 5 6 7 8 9 10 11 12
Experiment



simultaneous timing
sequential timing
1–3 trial order
3–1 trial order
Cohen's d
2
1
0
−1
XT SPSS LF
Paper

Peer Review Process

Running head: THE SUSPICIOUS COINCIDENCE EFFECT REVISITED 1

Still suspicious: The suspicious coincidence effect revisited

Molly L. Lewis[1,2] & Michael C. Frank[3]

[1] Computation Institute, University of Chicago

[2] Department of Psychology, University of Wisconsin, Madison

[3] Department of Psychology, Stanford University

Submit to a journal

Editor

Expert

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Preregistered Direct Replication

Still Suspicious: The Suspicious-Coincidence Effect Revisited

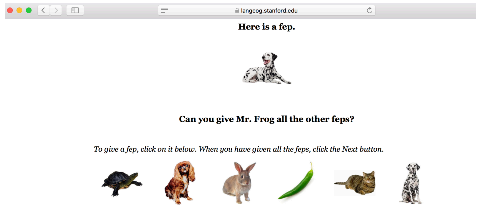
Molly L. Lewis[1,2] and Michael C. Frank[3]
[1]Computation Institute, University of Chicago; [2]Department of Psychology, University of Wisconsin–Madison; and [3]Department of Psychology, Stanford University

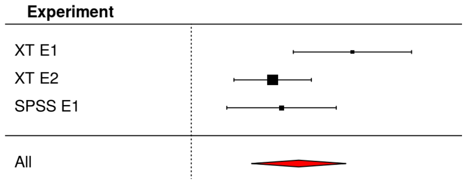
Psychological Science
2018, Vol. 29(12) 2039–2047

DOI: 10.1177/0956797618794931
www.psychologicalscience.org/PS
SAGE

Tools I used in this project

- Online experiments
- Data analysis in R
- Preregistration
- Reproducible workflows (e.g. Github)
- Meta-analysis





- In this class, you will learn about all of these tools
- You will not master any of them, but my goal is to introduce them to you so you can have the ability to learn more

Next Time: Introduction to R (Lab)

- Bring your computer if you prefer to use it
- Porter 332P
- Reading:

Chapter 3 Introduction to R

This chapter is the first of several distributed throughout the book that will introduce you to increasingly sophisticated things that you can do using the R programming language.

The name “R” is a play on the names of the two authors of the software package (Ross Ihaka and Robert Gentleman) as well as an homage to an older statistical software package called “S”. R has become one of the most popular programming languages for statistical analysis and “data science”. Unlike general-purpose programming languages such as Python or Java, R is purpose-built for statistics. That doesn’t mean that you can’t do more general things with it, but the place where it really shines is in data analysis and statistics.

R for cats and cat lovers

An intro to R for new programmers

This is an introduction to R. I promise this will be fun. Since you have never used a programming language before, or any language for that matter, you won’t be tainted by other programming languages with different ways of doing things. This is good - we can teach you the R way of doing things.