Advances in Intervention Studies (and other things)

CCN-Prosem / December 6th, 2023

C. Shawn Green & Freya Joëssel

Why random assignment can be problematic

Basic Design and Logic

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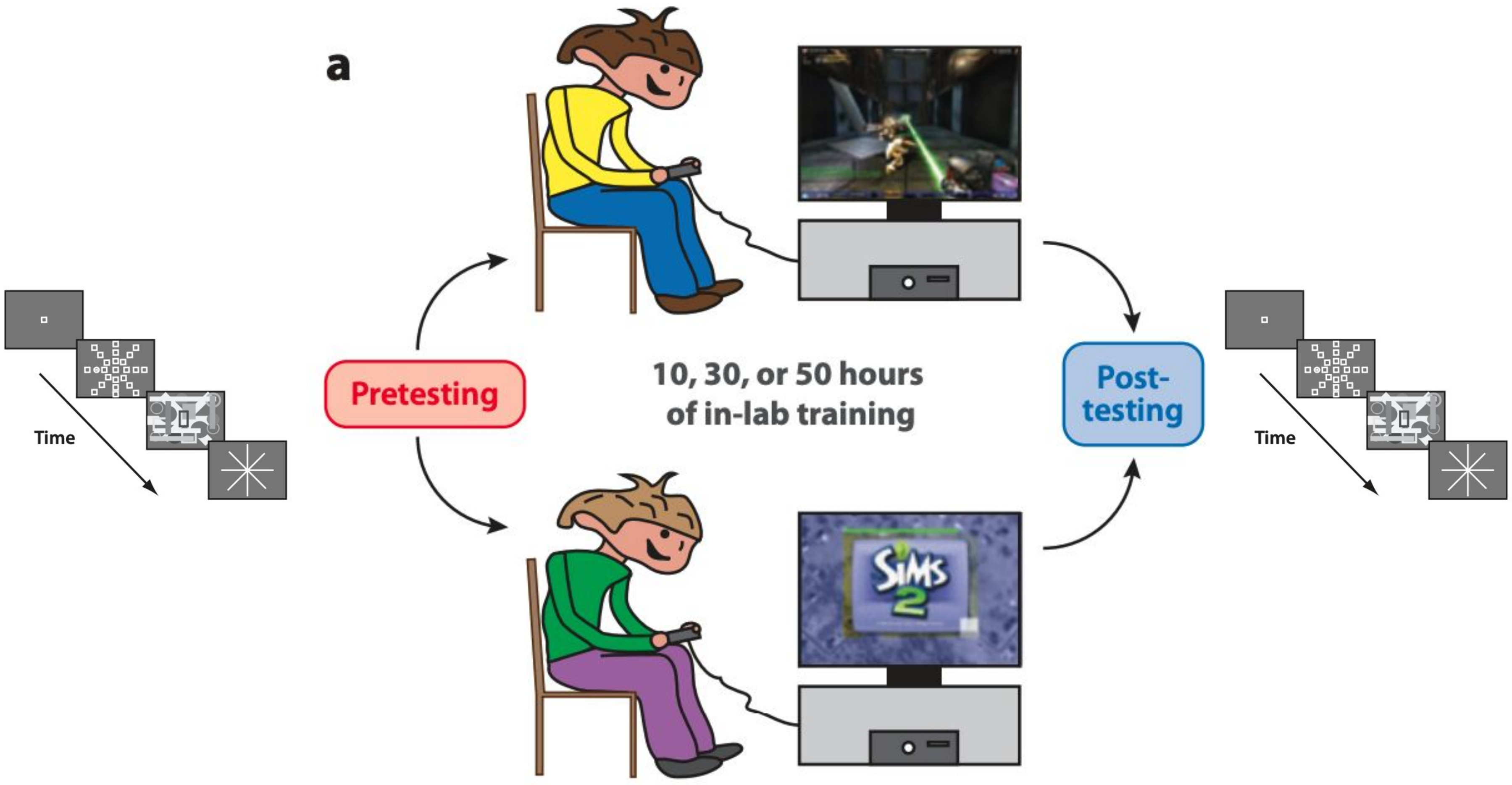
Basic Intervention Design and Logic



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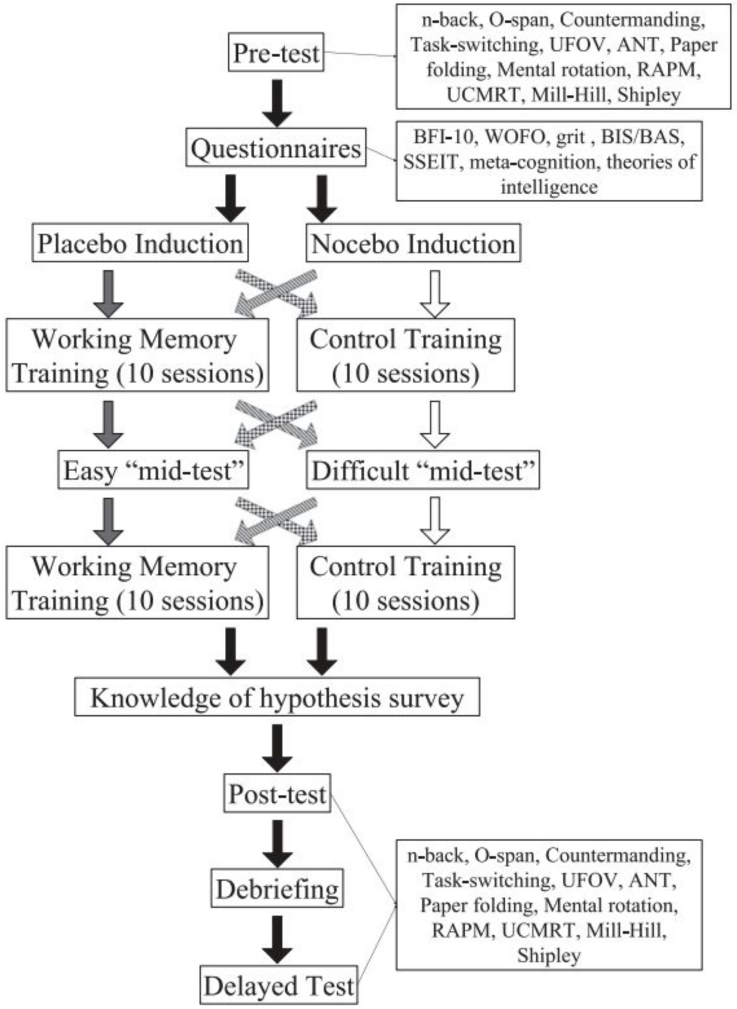

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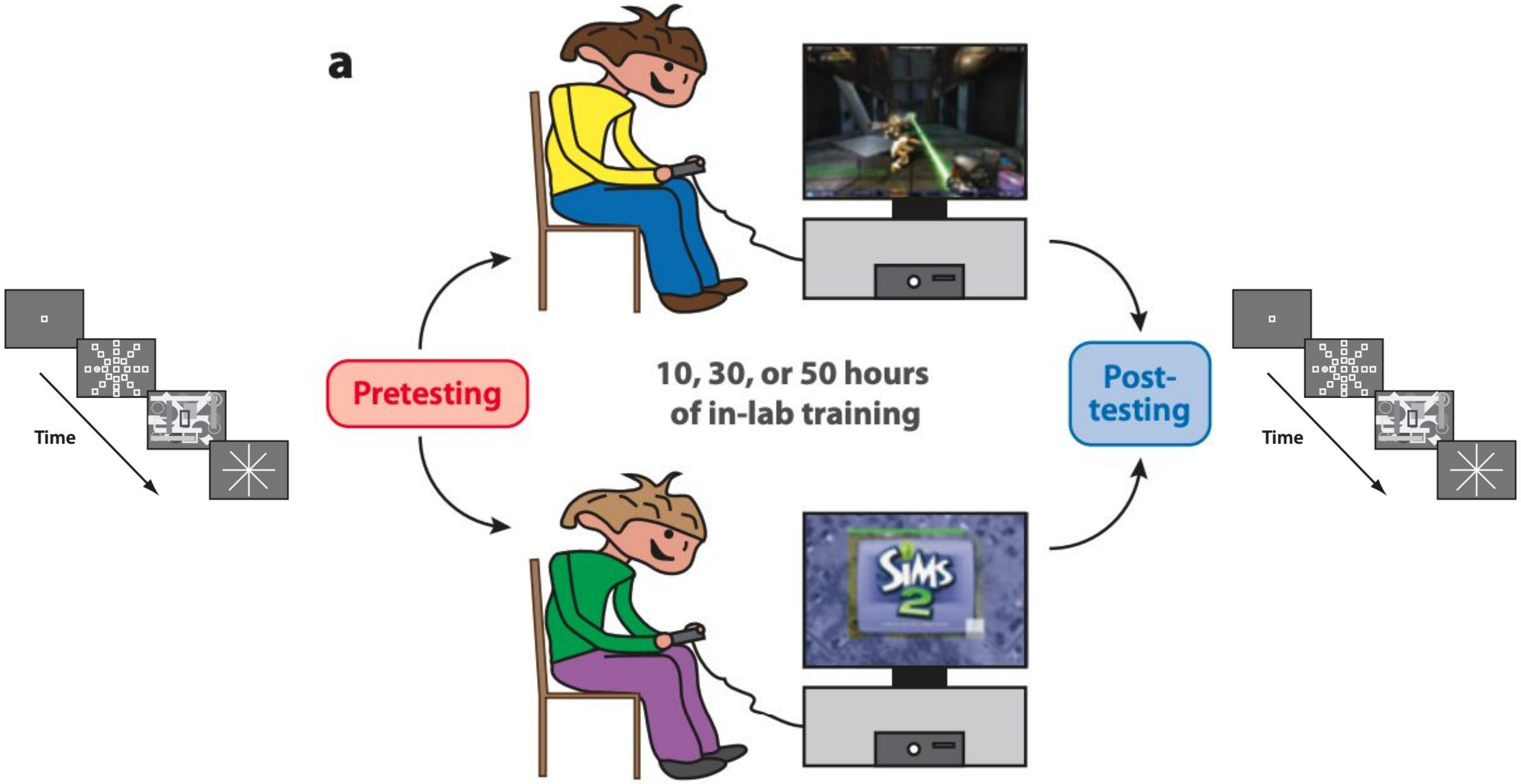

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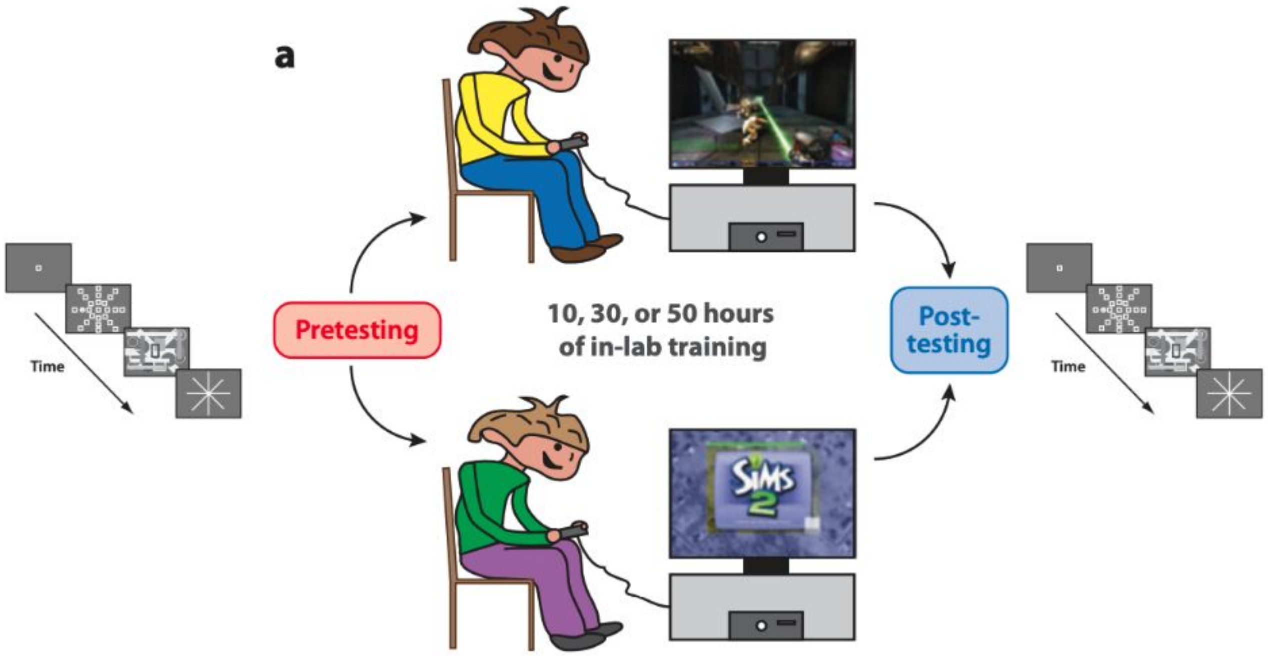
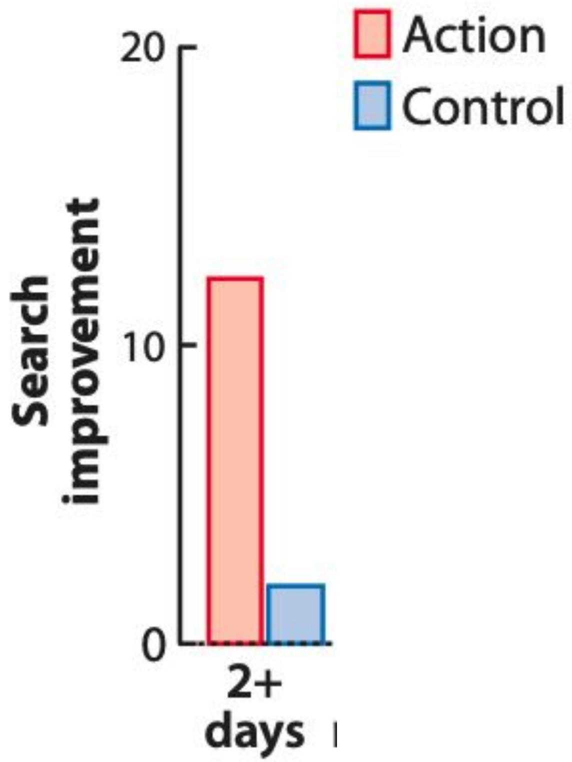
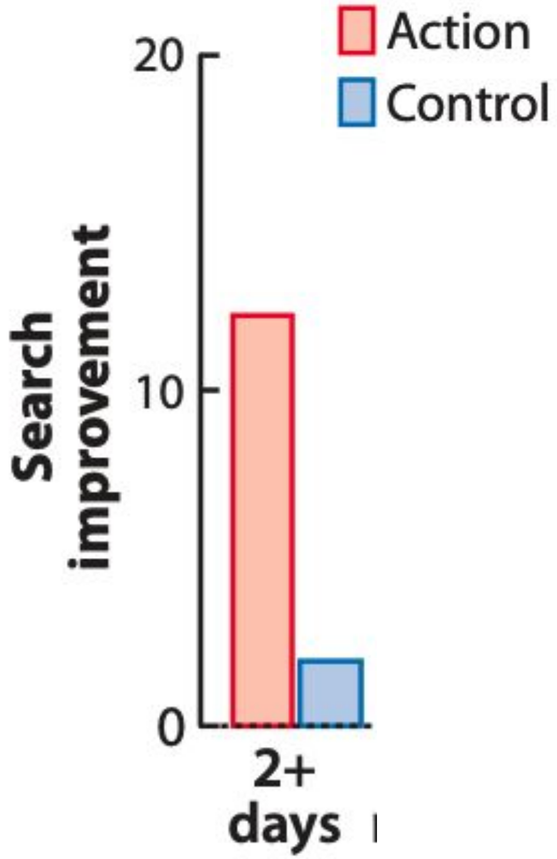
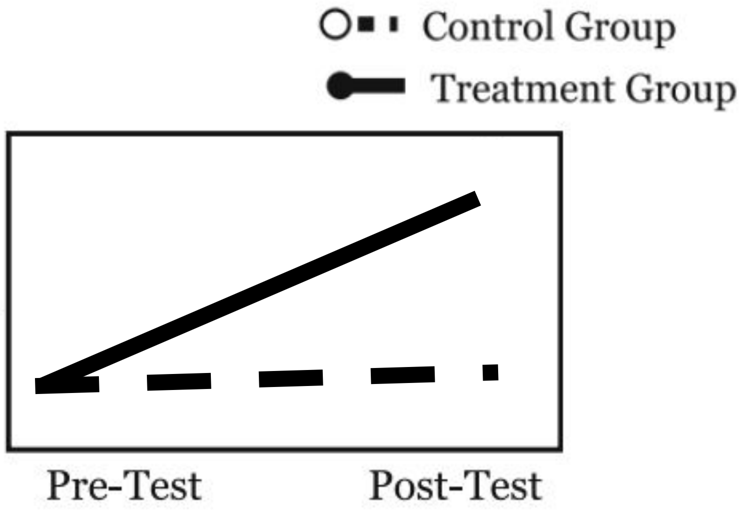




Why random assignment can be problematic

Problem





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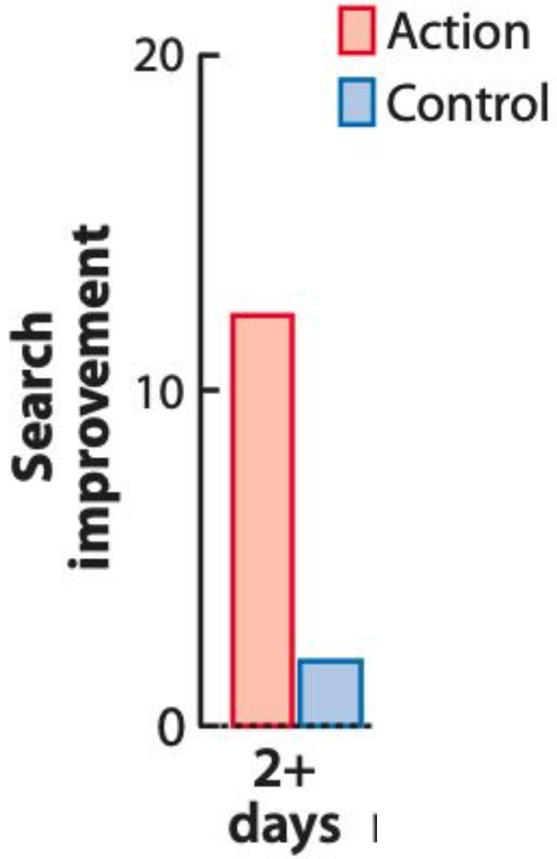

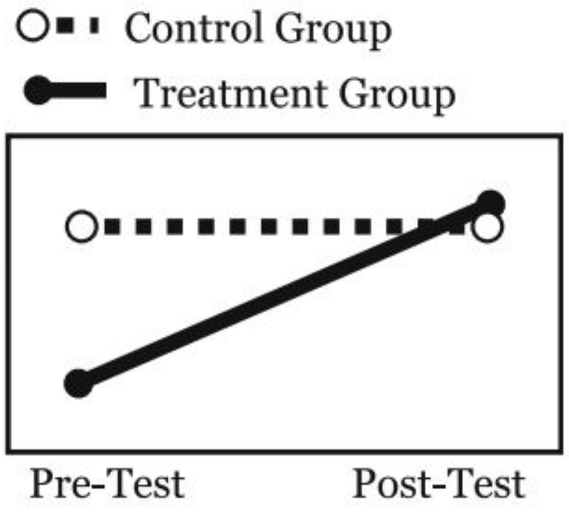

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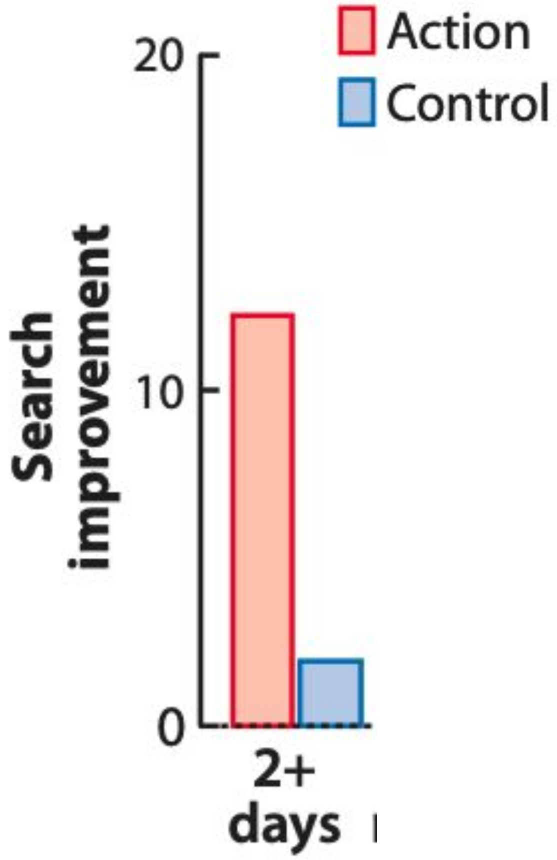

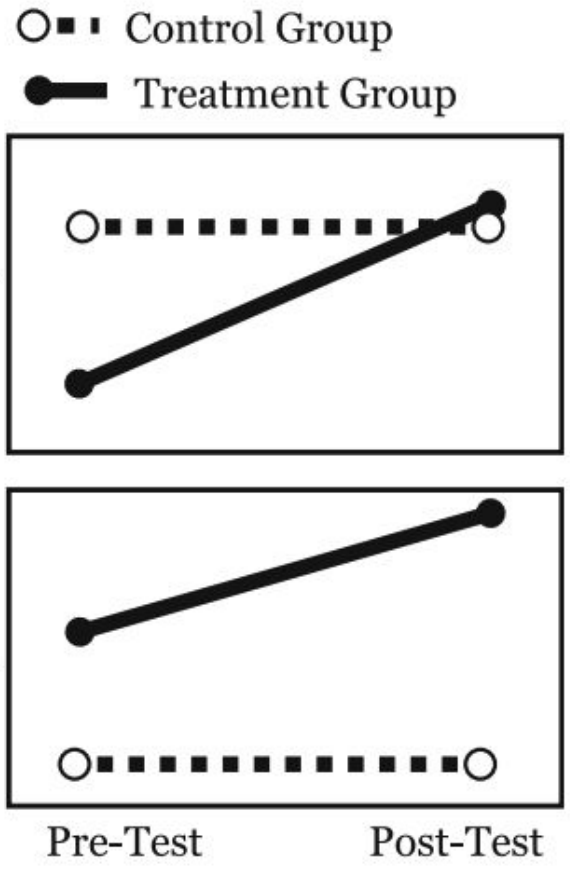

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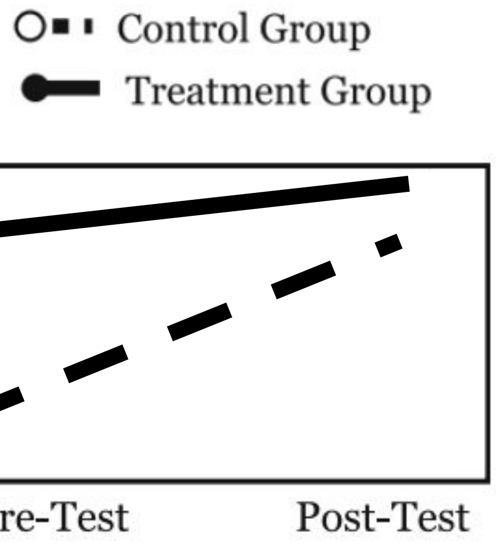

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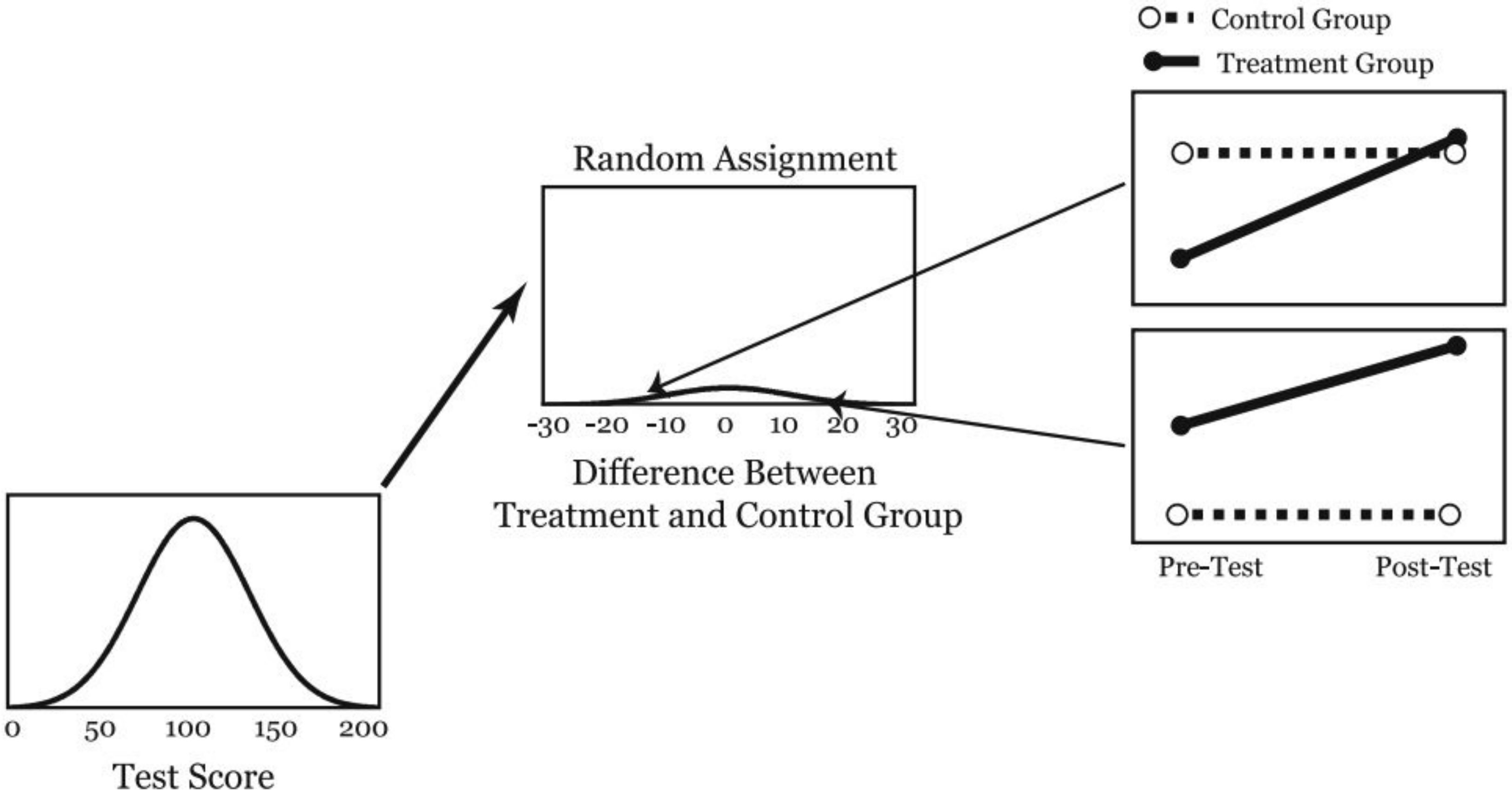

<u>Core Problem:</u>
Random Assignment Can (Often Does) Result in Group Differences at Pre-Test…

Solution: Non-Random Assignment

Allows to randomize on variables where stratification is not obvious (e.g. performance on a task at pre-test, or on a questionnaire)

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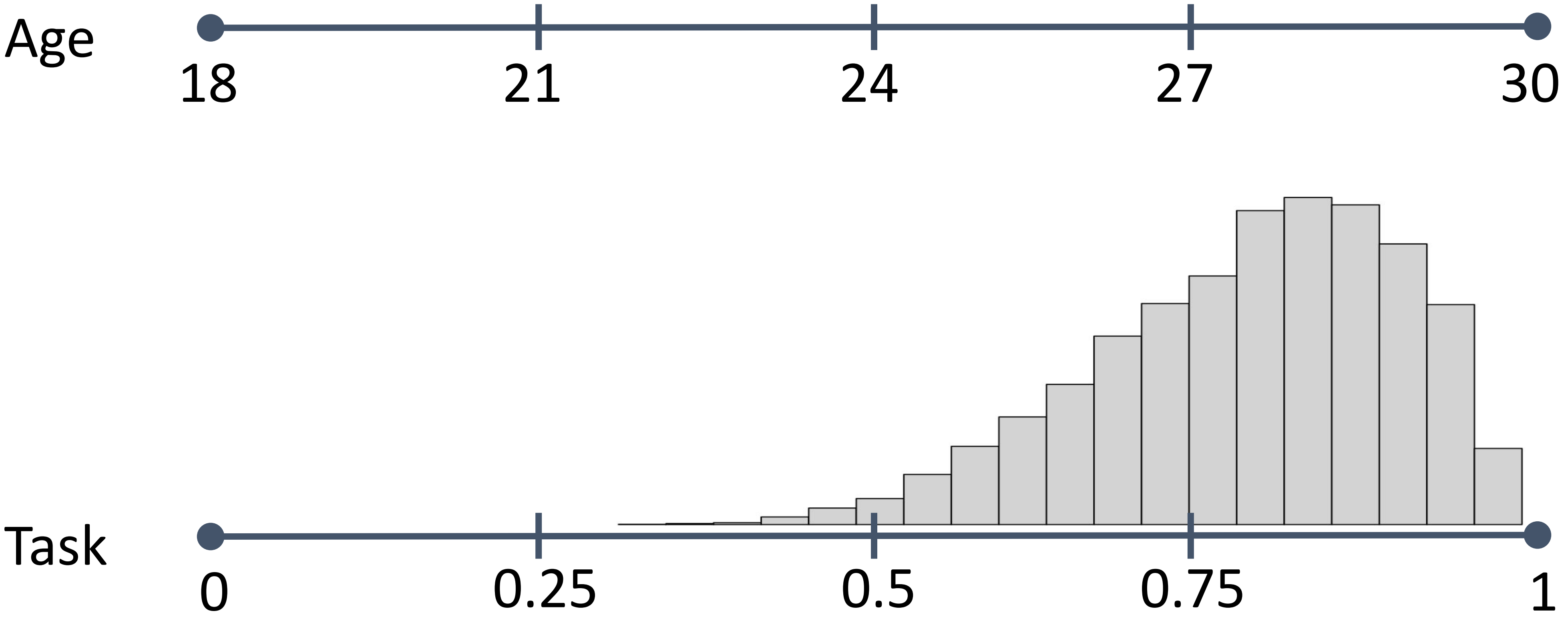

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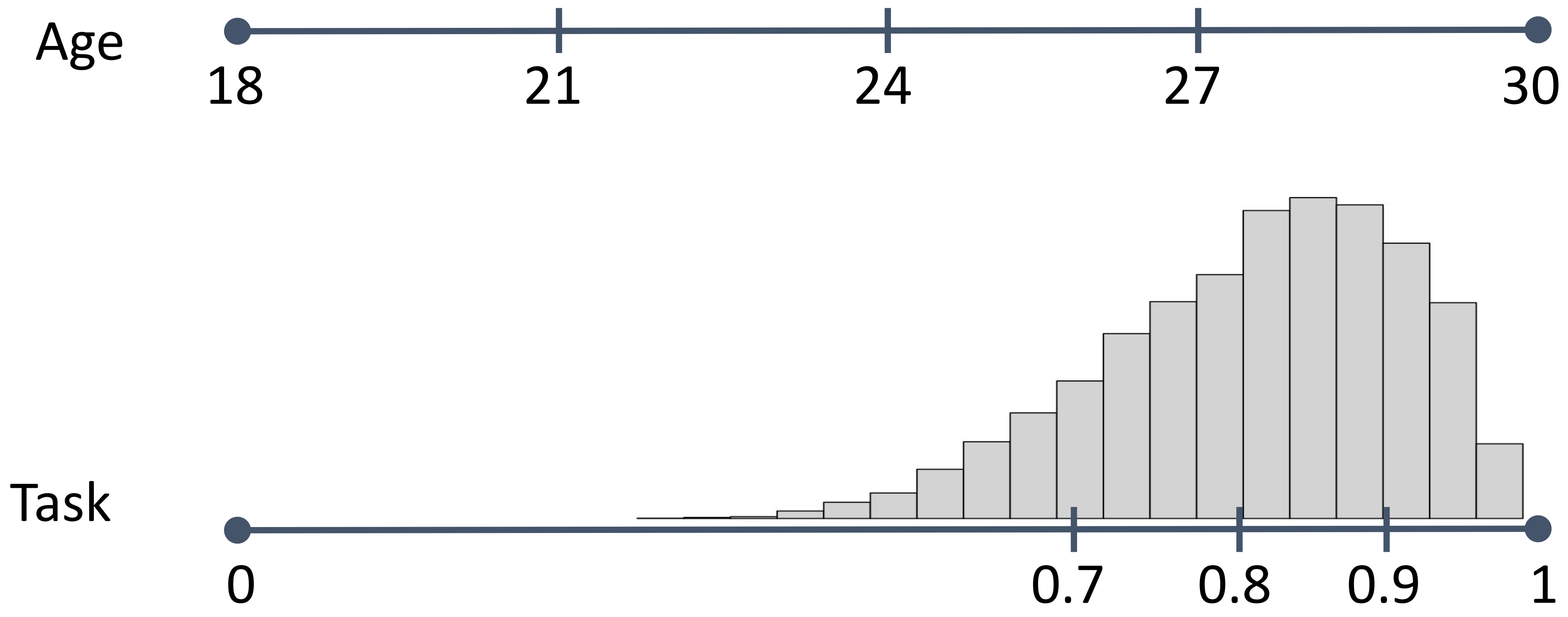

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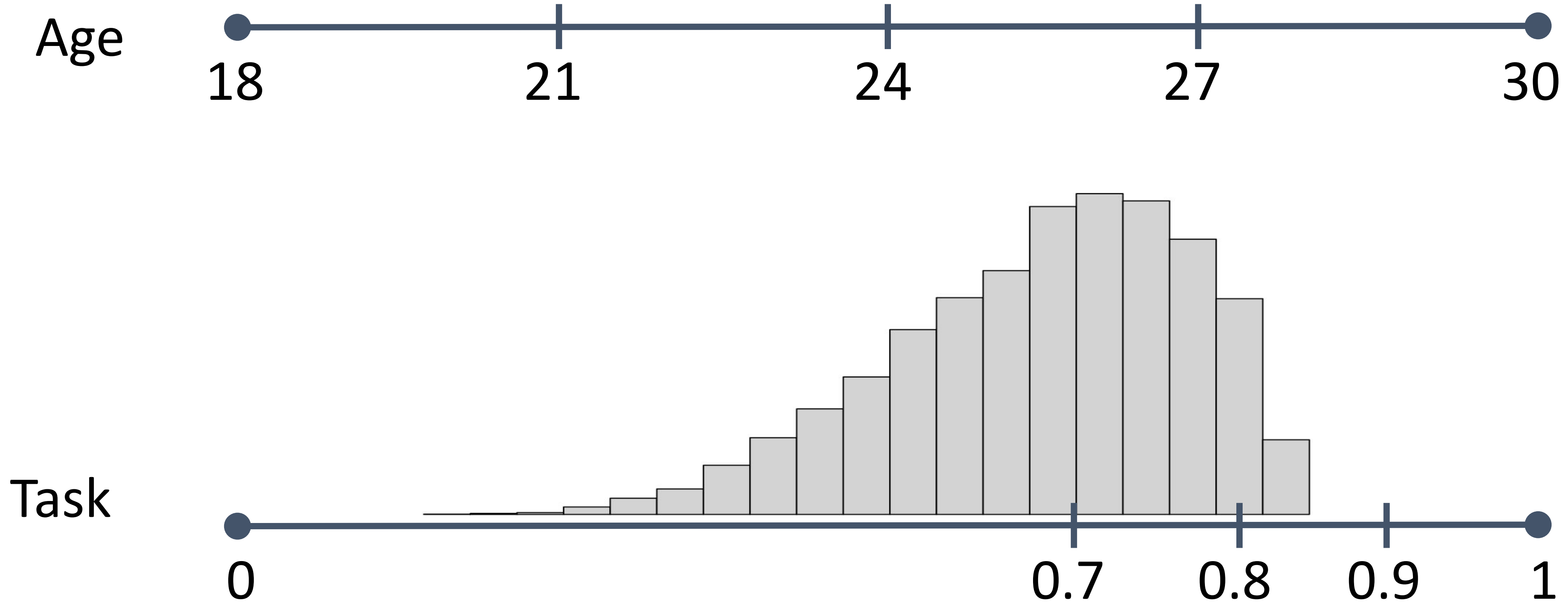
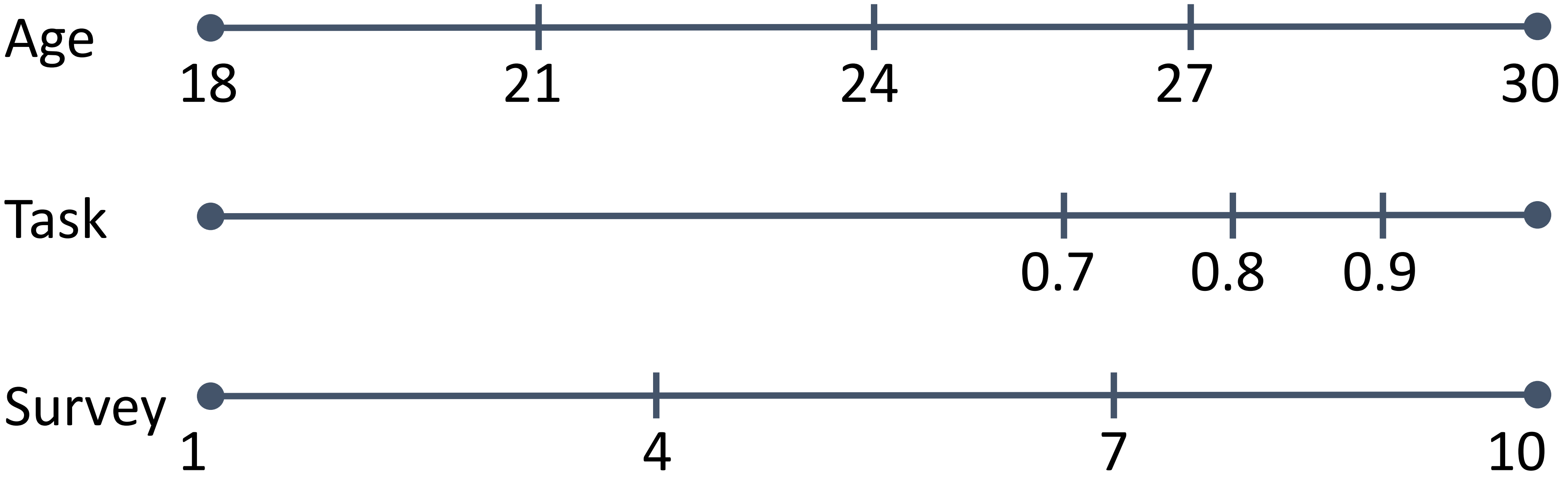


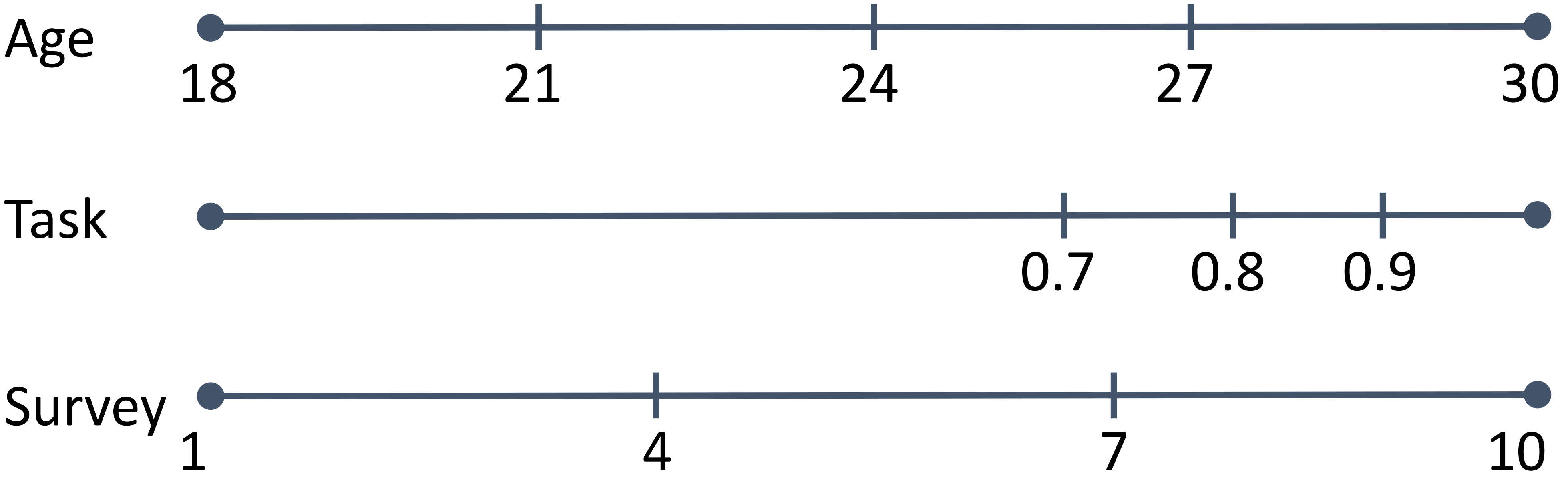
Solution: Non-Random Assignment

Can easy take multiple variables into account, whereas stratification can lead to a number of cells that is just not manageable



Solution: Non-Random Assignment

Can easy take multiple variables into account, whereas stratification can lead to a number of cells that is just not manageable



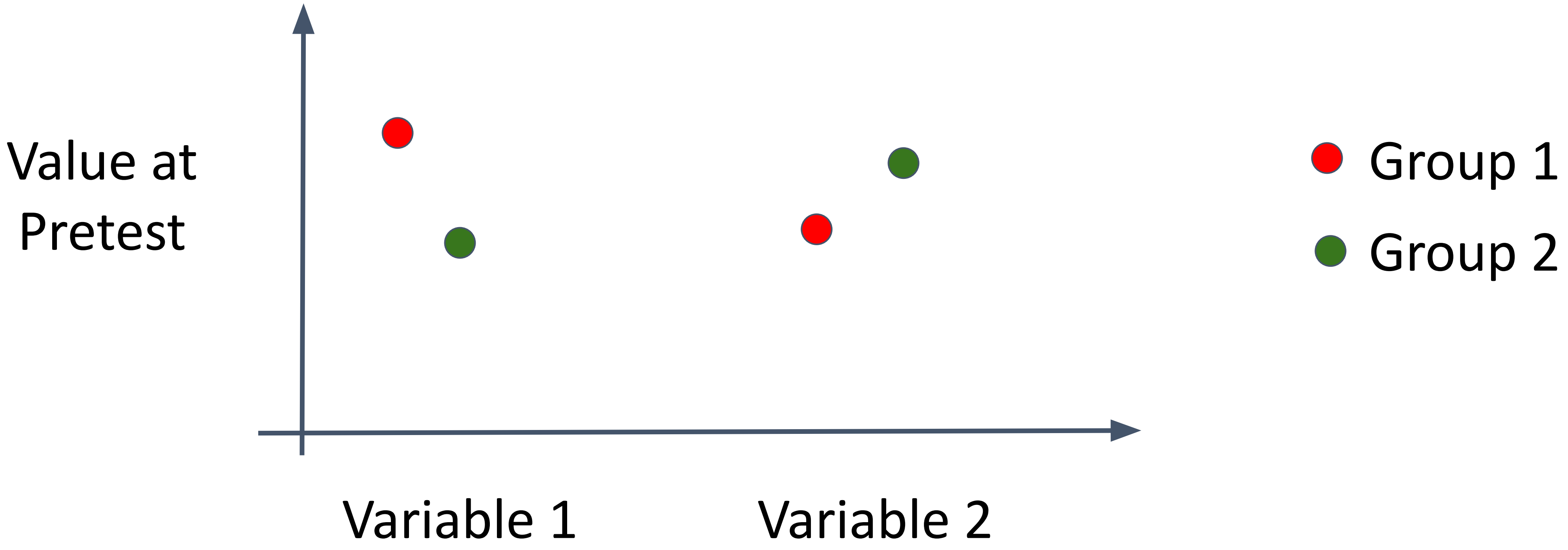
-> 4 x 4 x 3 = 48 cells

Solution: Non-Random Assignment

Able to randomize on the fly

Solution: Non-Random Assignment

Variance Minimization (Sella et al. 2021)



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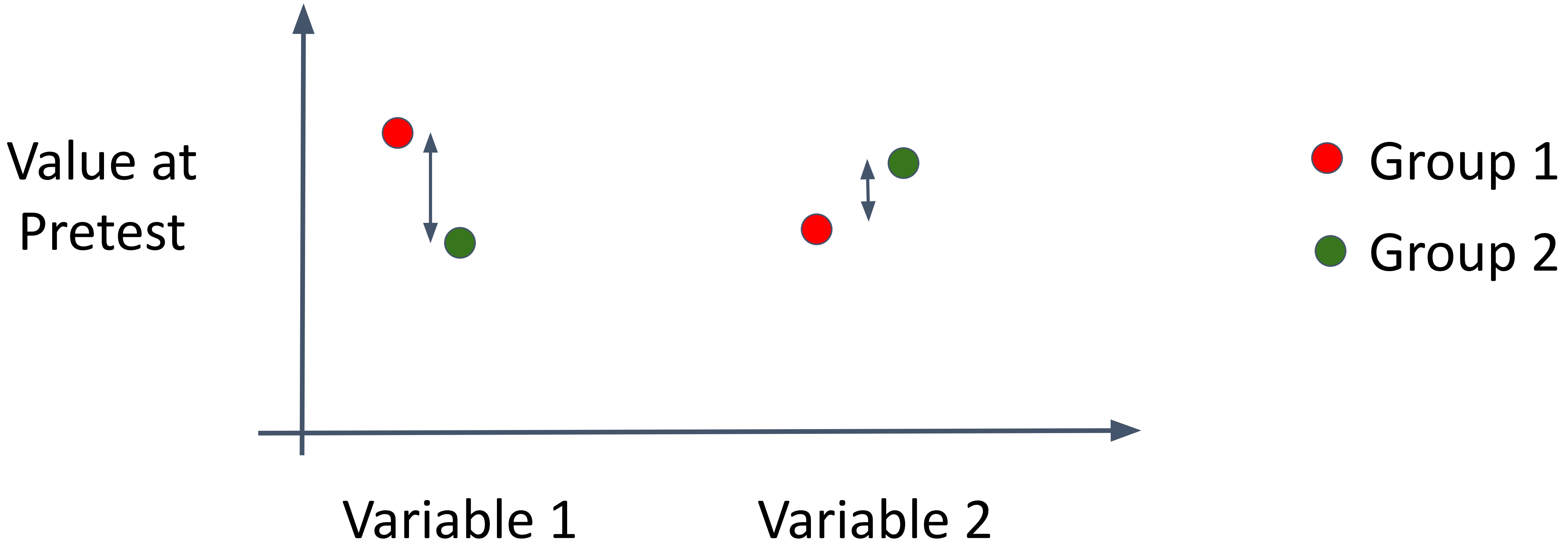

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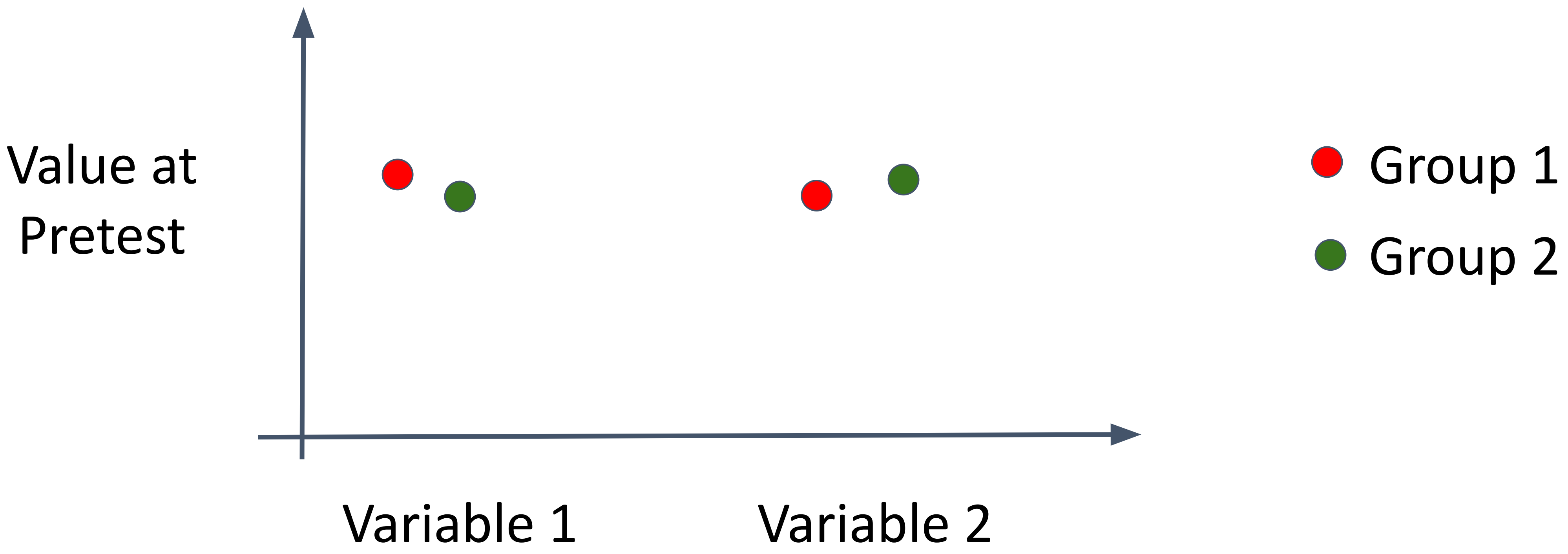
Variance Minimization (Sella et al. 2021)



Variance Minimization Algorithm

Incoming Participant :
(19, 0.75)

	Age	Task Performance
Group 1		
Group 2		
Group 3		

Variance Minimization Algorithm

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(19, 0.75)

	Age	Task Performance
Group 1		
Group 2		
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Variance Minimization Algorithm

Incoming Participant :
(19, 0.75)

	Age	Task Performance
Group 1	19	0.75
Group 2		
Group 3		

Variance Minimization Algorithm

Incoming Participant :
(23, 0.55)

	Age	Task Performance
Group 1	19	0.75
Group 2	23	0.55
Group 3		

Variance Minimization Algorithm

Incoming Participant :
(18, 0.68)

	Age	Task Performance
Group 1	19	0.75
Group 2	23	0.55
Group 3	18	0.68

Variance Minimization Algorithm

Incoming Participant :
(19, 0.71)

?

	Age	Task Performance
Group 1	19, 19	0.75, 0.71
Group 2	23	0.55
Group 3	18	0.68
Group-wise Mean		
Sum of Squares		

Variance Minimization Algorithm

Incoming Participant :
(19, 0.71)

?

	Age	Task Performance
Group 1	-0.34, <u>-0.34</u>	0.90, <u>0.43</u>
Group 2	1.47	-1.42
Group 3	-0.79	0.087
Group-wise Mean		
Sum of Squares		

Variance Minimization Algorithm

Incoming Participant :
(19, 0.71)

?

	Age	Task Performance
Group 1	-0.34, <u>-0.34</u>	0.90, <u>0.43</u>
Group 2	1.47	-1.42
Group 3	-0.79	0.087
Group-wise Mean	0.11	-0.22
Sum of Squares	0.95	0.77

SS(1) = 1.72

Variance Minimization Algorithm

Incoming Participant :
(19, 0.71)

?

	Age	Task Performance
Group 1	-0.34	0.90
Group 2	1.47, -0.34	-1.42, 0.43
Group 3	-0.79	0.087
Group-wise Mean	-0.18	0.16
Sum of Squares	0.32	0.32

SS(1) = 1.72
SS(2) = 0.64

Variance Minimization Algorithm

Incoming Participant :
(19, 0.71)

?

	Age	Task Performance
Group 1	-0.34	0.90
Group 2	1.47	-1.42
Group 3	-0.79, <u>-0.34</u>	0.087, <u>0.43</u>
Group-wise Mean	0.19	0.09
Sum of Squares	0.82	0.94

SS(1) = 1.72
SS(2) = 0.64
SS(3) = 1.74

Variance Minimization Algorithm

Incoming Participant :
(19, 0.71)

?

	Age	Task Performance
Group 1	-0.34	0.90
Group 2	1.47, <u>-0.34</u>	-1.42, <u>0.43</u>
Group 3	-0.79	0.087
Group-wise Mean	0.19	0.09
Sum of Squares	0.82	0.94

~~SS(1) = 1.72~~
SS(2) = 0.64
~~SS(3) = 1.74~~

Variance Minimization Algorithm

Incoming Participant :
(19, 0.71)

	Age	Task Performance
Group 1	19	0.75
Group 2	23, 19	0.55, 0.71
Group 3	18	0.68

~~SS(1) = 1.72~~
SS(2) = 0.64
~~SS(3) = 1.74~~

Variance Minimization Algorithm

Incoming Participant :
(25, 0.62)

?

	Age	Task Performance
Group 1	19	0.75
Group 2	23, 19	0.55, 0.71
Group 3	18	0.68

Variance Minimization Algorithm

Incoming Participant :
(25, 0.62)

?

	Age	Task Performance
Group 1	19, 25	0.75, 0.62
Group 2	23, 19	0.55, 0.71
Group 3	18	0.68

Variance Minimization Algorithm

Incoming Participant :
(25, 0.62)

?

	Age	Task Performance
Group 1	-0.59, <u>1.38</u>	1.12, -<u>0.53</u>
Group 2	0.73, -0.59	-1.43, 0.61
Group 3	-0.92	0.23
Group-wise Mean		
Sum of Squares		

Variance Minimization Algorithm

Incoming Participant :
(25, 0.62)

?

	Age	Task Performance
Group 1	-0.59, <u>1.38</u>	1.12, -<u>0.53</u>
Group 2	0.73, -0.59	-1.43, 0.61
Group 3	-0.92	0.23
Group-wise Mean	-0.15	0.038
Sum of Squares	0.31	0.10

SS(1) = 0.41

Variance Minimization Algorithm

Incoming Participant :
(25, 0.62)

?

	Age	Task Performance
Group 1	-0.59	1.12
Group 2	0.73, -0.59	-1.43, 0.61
Group 3	-0.92, 1.38	0.23, -0.53
Group-wise Mean	-0.099	0.19
Sum of Squares	0.13	0.44

SS(1) = 0.41
SS(3) = 0.57

Variance Minimization Algorithm

Incoming Participant :
(25, 0.62)

?

	Age	Task Performance
Group 1	-0.59, <u>1.38</u>	1.12, -<u>0.53</u>
Group 2	0.73, -0.59	-1.43, 0.61
Group 3	-0.92	0.23
Group-wise Mean	-0.099	0.19
Sum of Squares	0.13	0.44

SS(1) = 0.41
~~SS(3) = 0.57~~

Variance Minimization Algorithm

Incoming Participant :

(25, 0.62)

	Age	Task Performance
Group 1	19, 25	0.75, 0.62
Group 2	23, 19	0.55, 0.71
Group 3	18	0.68

SS(1) = 0.41

~~SS(3) = 0.57~~

Variance Minimization Algorithm

Incoming Participant :
(22, 0.9)

	Age	Task Performance
Group 1	19, 25	0.75, 0.62
Group 2	23, 19	0.55, 0.71
Group 3	18, 22	0.68, 0.9

Example 1

Matching on 2 variables : age & performance on a task at pretest

Age

Performance on a task at pretest

G1 G2 G3 G4 G5

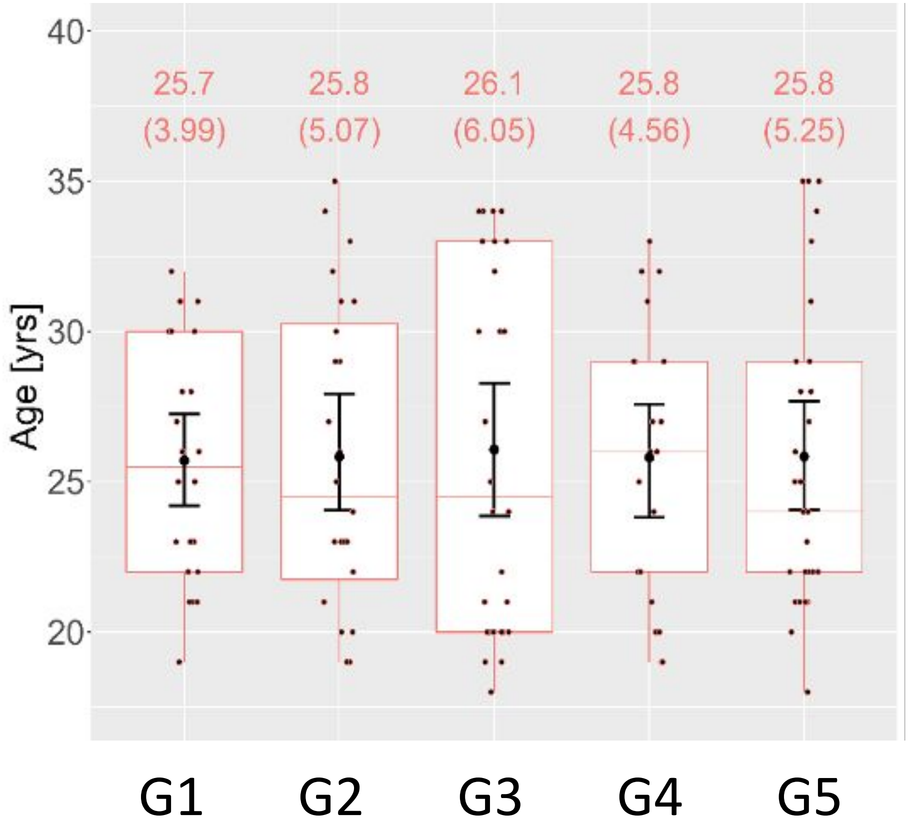
Group 1 Group 2 Group 3 Group 4 Group 5

Joessel F. (2022), *Development of a Video Game to Investigate the AVG Features Promoting Attentional Control*.. https://archive-ouverte.unige.ch/unige:164866

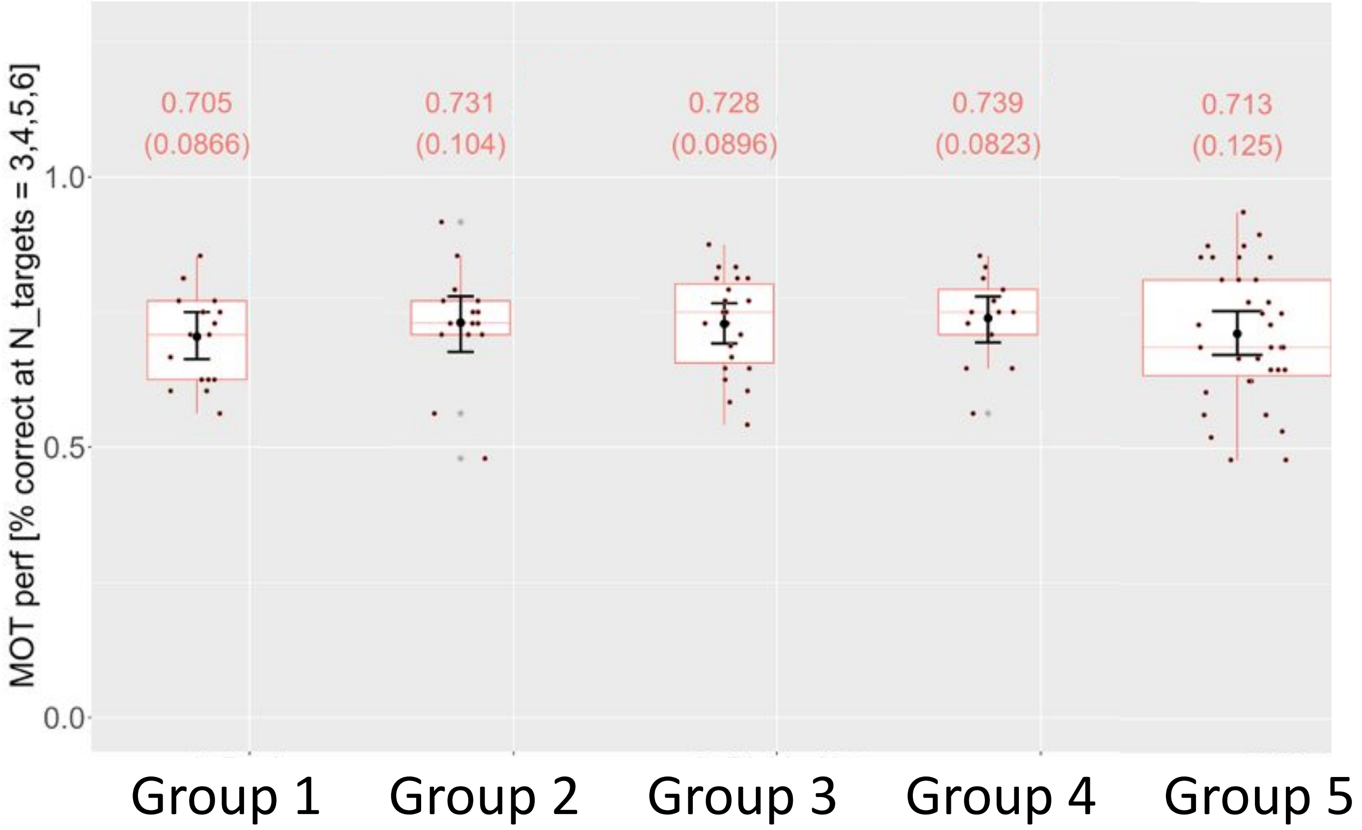
Example 1

Matching on 2 variables : age & performance on a task at pretest

Age



Performance on a task at pretest



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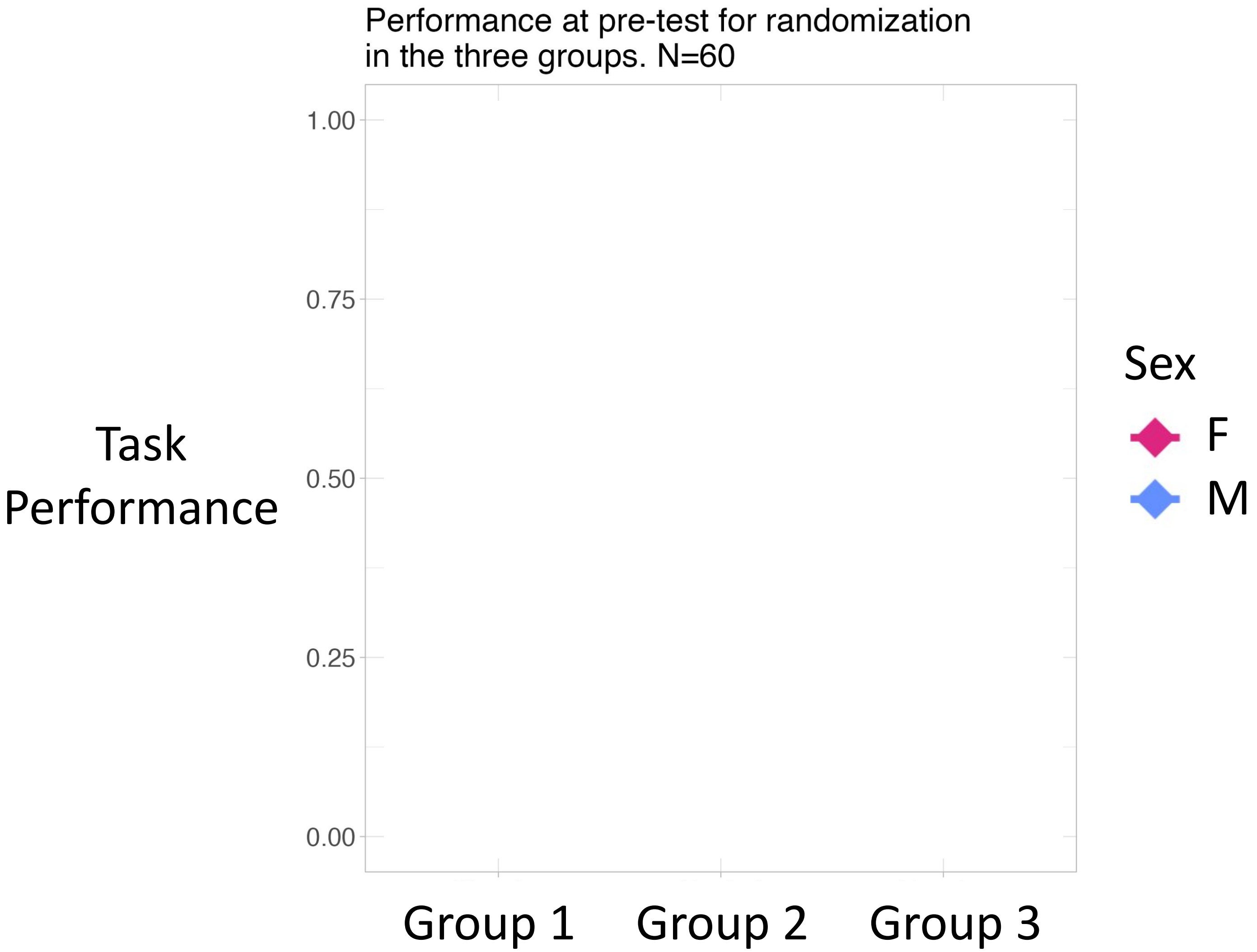
Example 2

Matching on 1 variable : performance on a task at pretest



Example 2

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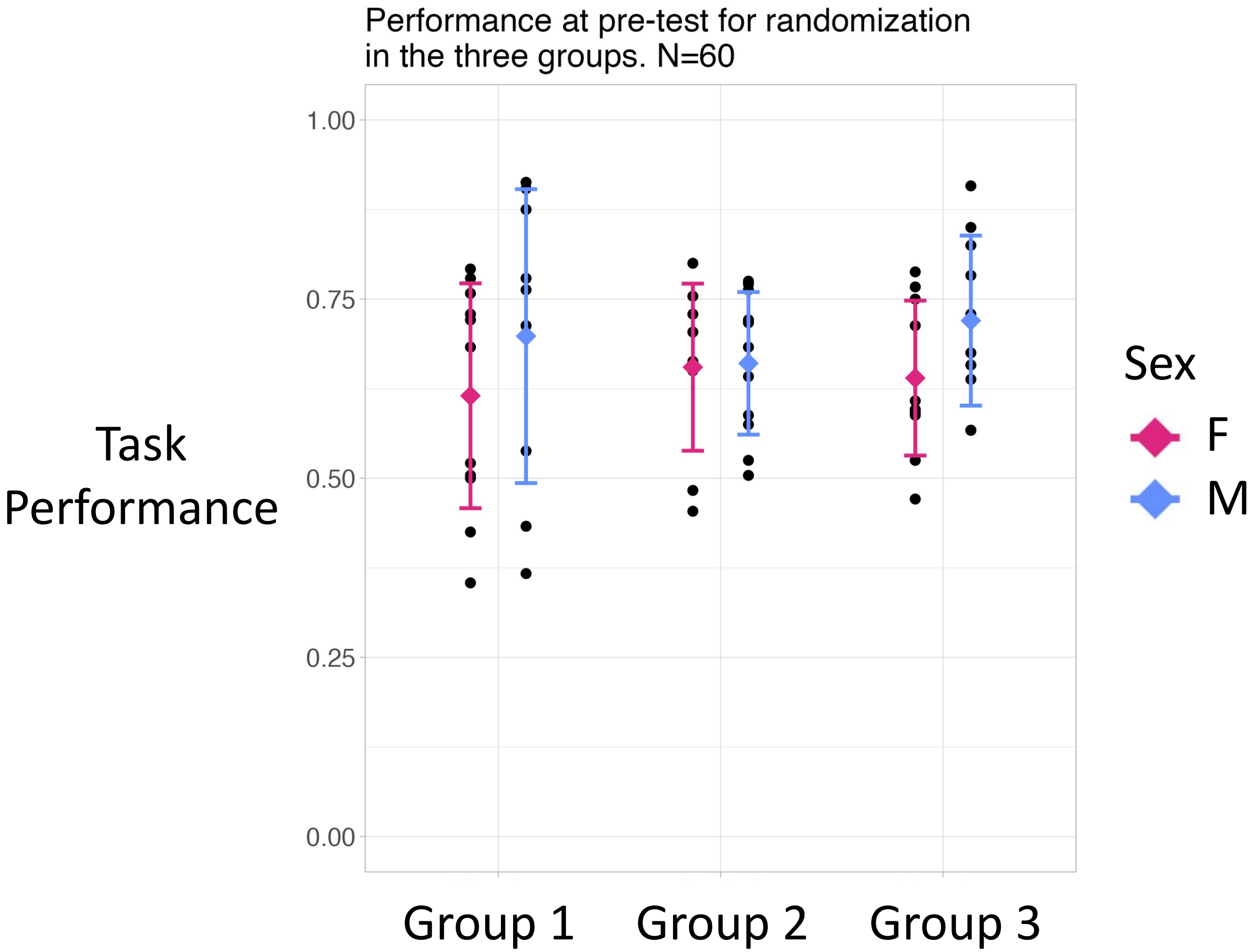
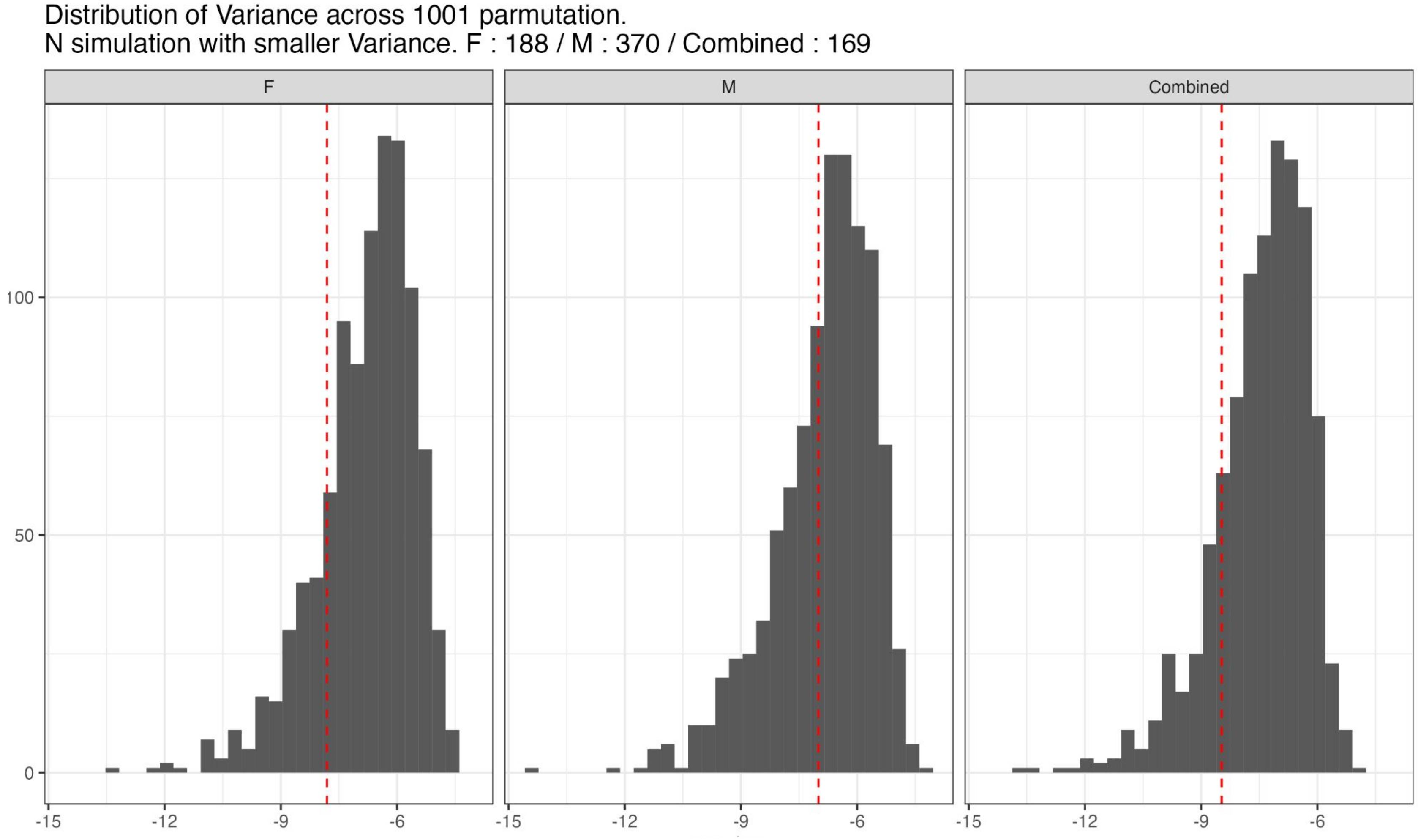


But how good is it, really?



Log(Variance)

Limitations

The algorithm forces the groups to have the same number of participants $\longrightarrow$ The means thus will not be identical

Outliers may mess with the variance minimization $\longrightarrow$ Remove the outliers as soon as possible during the recruitment process

I am excited, where can I find this tool?

Sella, F., Gal, R., & Roi, C. K. (2021). When randomisation is not good enough: Matching groups in intervention studies. Psychonomic Bulletin & Review, 9. https://doi.org/10.3758/s13423-021-01970-5

bit.ly/sella-2021

Instructions and scripts in the following languages are available on OSF :

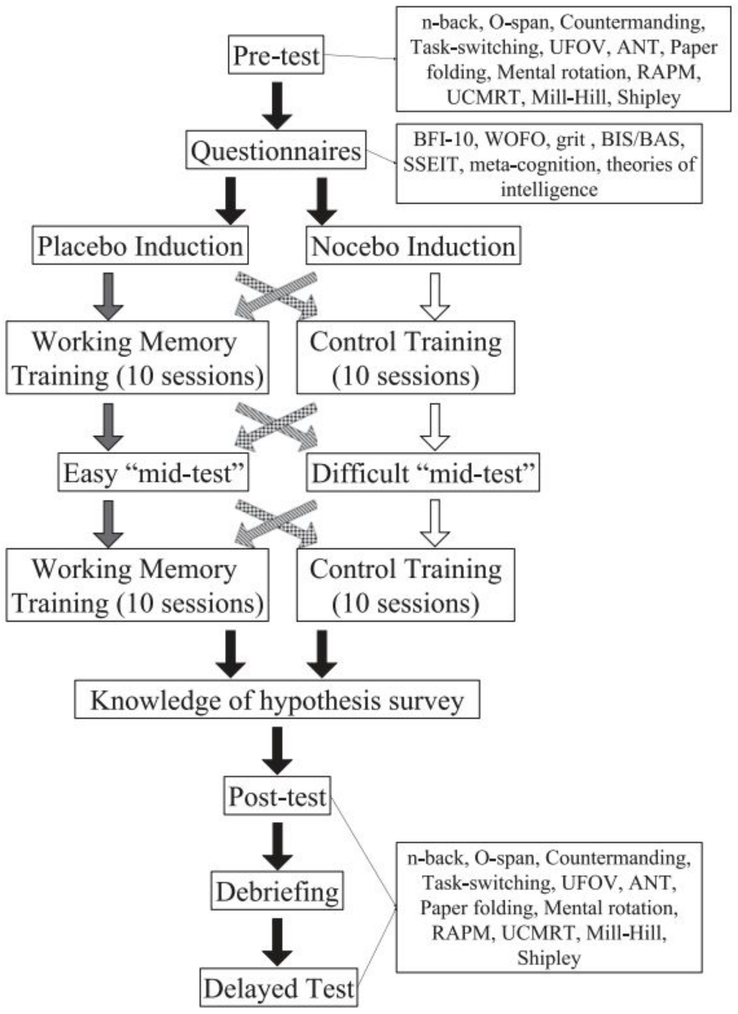
- R
- Python
- Matlab
- Excel

bit.ly/sella-2021-scripts

The Issue with Power Analyses

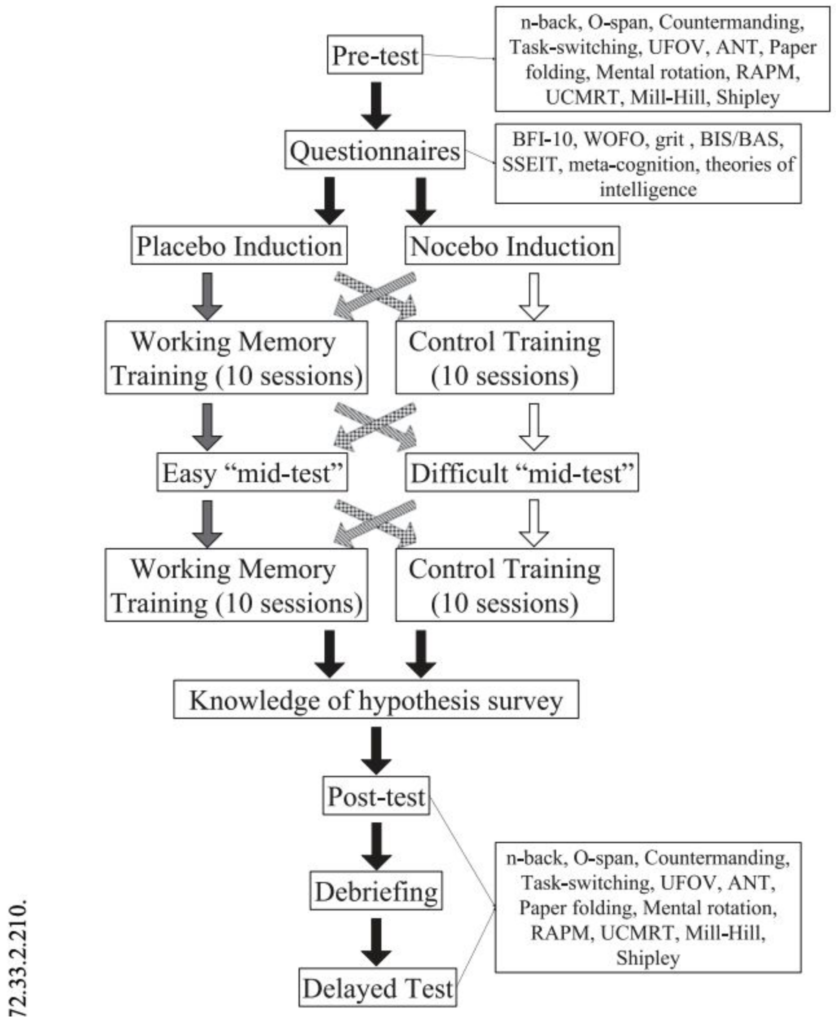
The Issue with Power Analyses

- Perfectly sensible for replications or clinical trials
- Require knowing things that we might not know in basic science studies
- As such, we…make stuff up…



The Issue with Power Analyses

- This results in many studies that have "null results" that were "properly powered" - but in practice, the nulls aren't that informative…



Core Problem:

Power analyses don’t *really* take care of the problems we’d like to take care of… (i.e., we want to ensure informative results whether positive or negative)

Sequential Bayes Factor Design

I.e. when should I stop recruiting participants?

Schönbrodt, F. D., & Wagenmakers, E.-J. (2018). Bayes factor design analysis: Planning for compelling evidence. Psychonomic Bulletin & Review, 25(1), 128–142. https://doi.org/10.3758/s13423-017-1230-y

Sequential Bayes Factor Design

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BF_{10}

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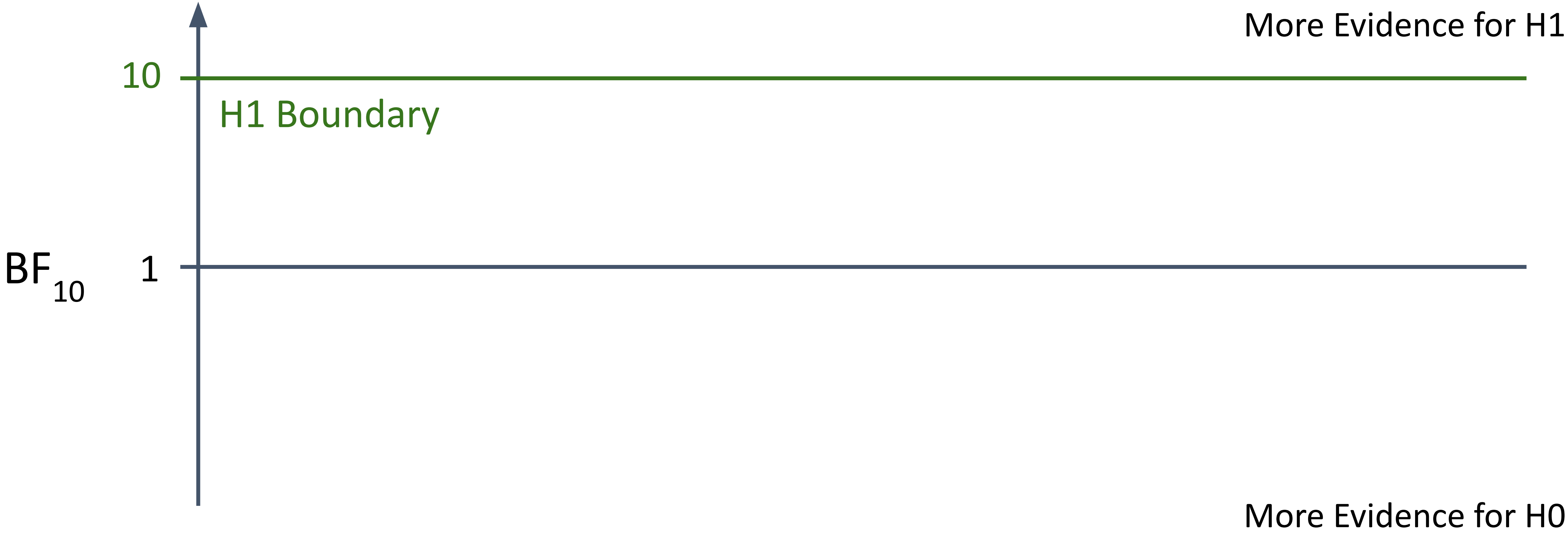

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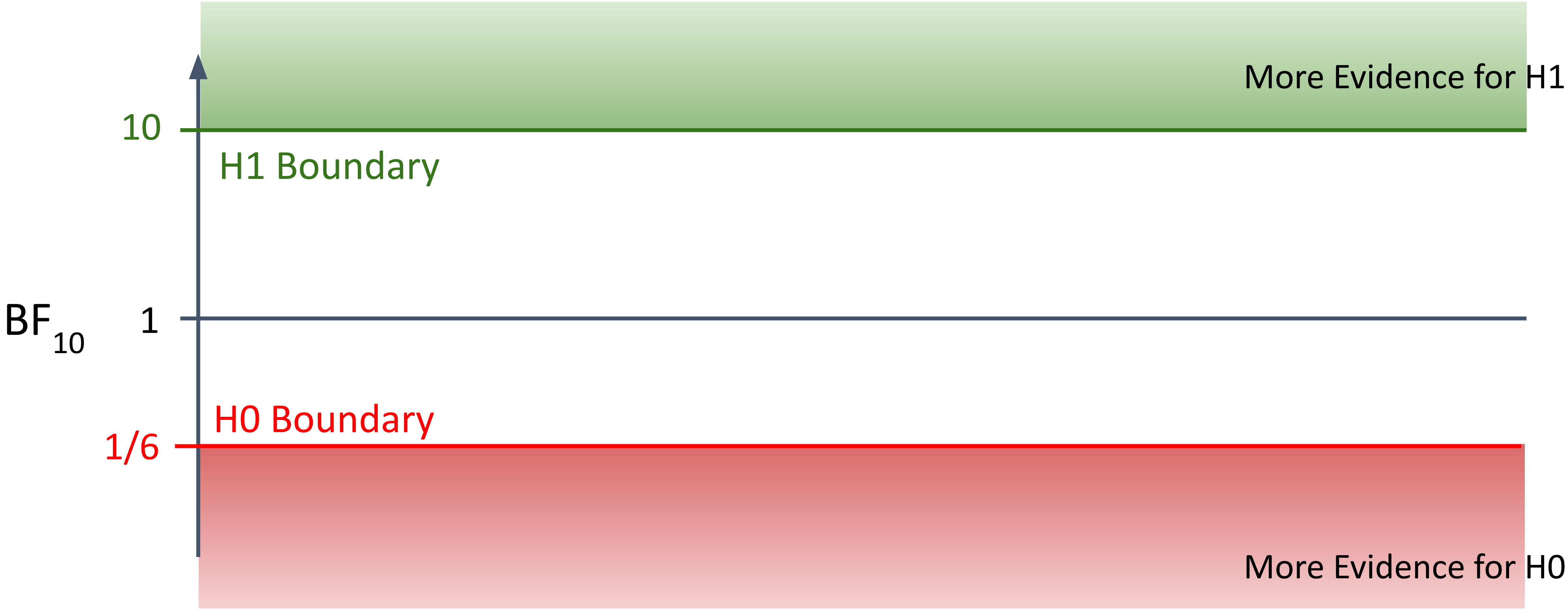

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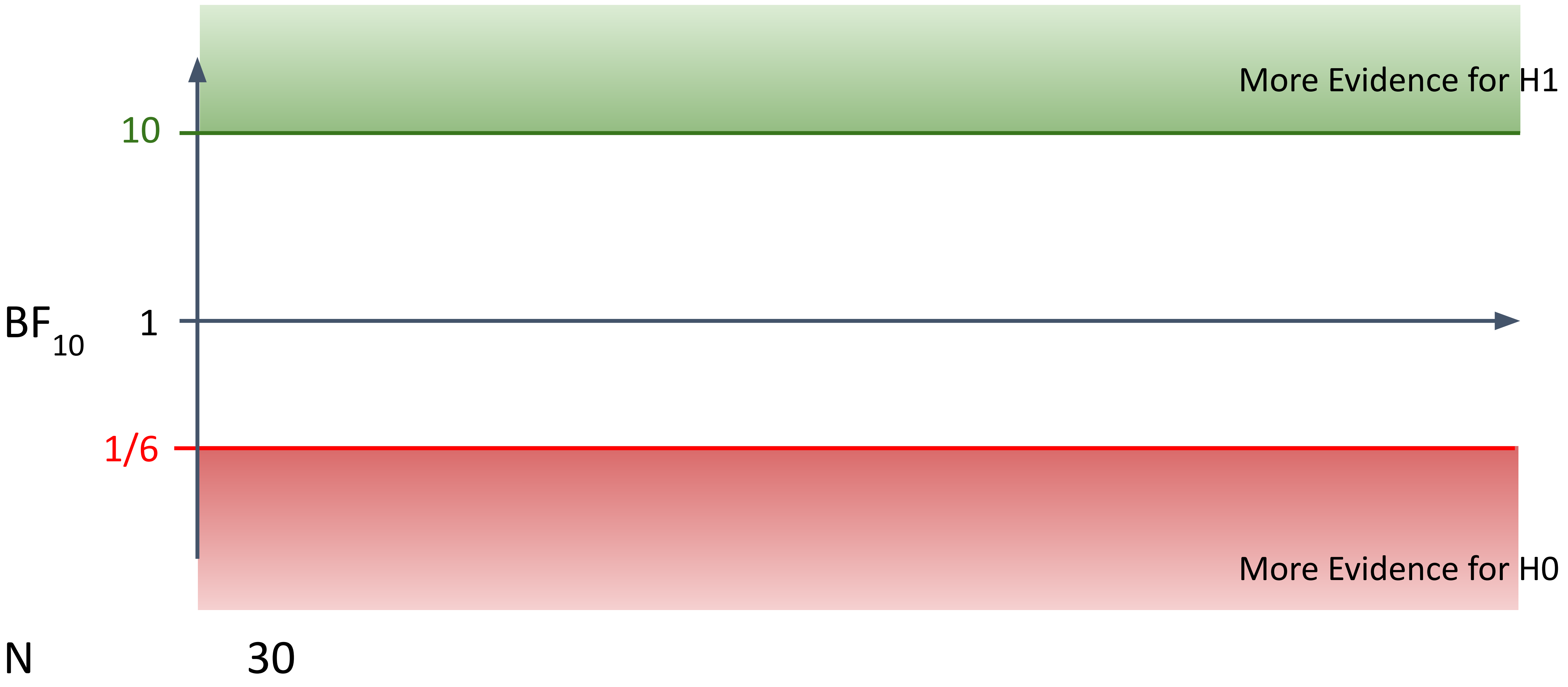

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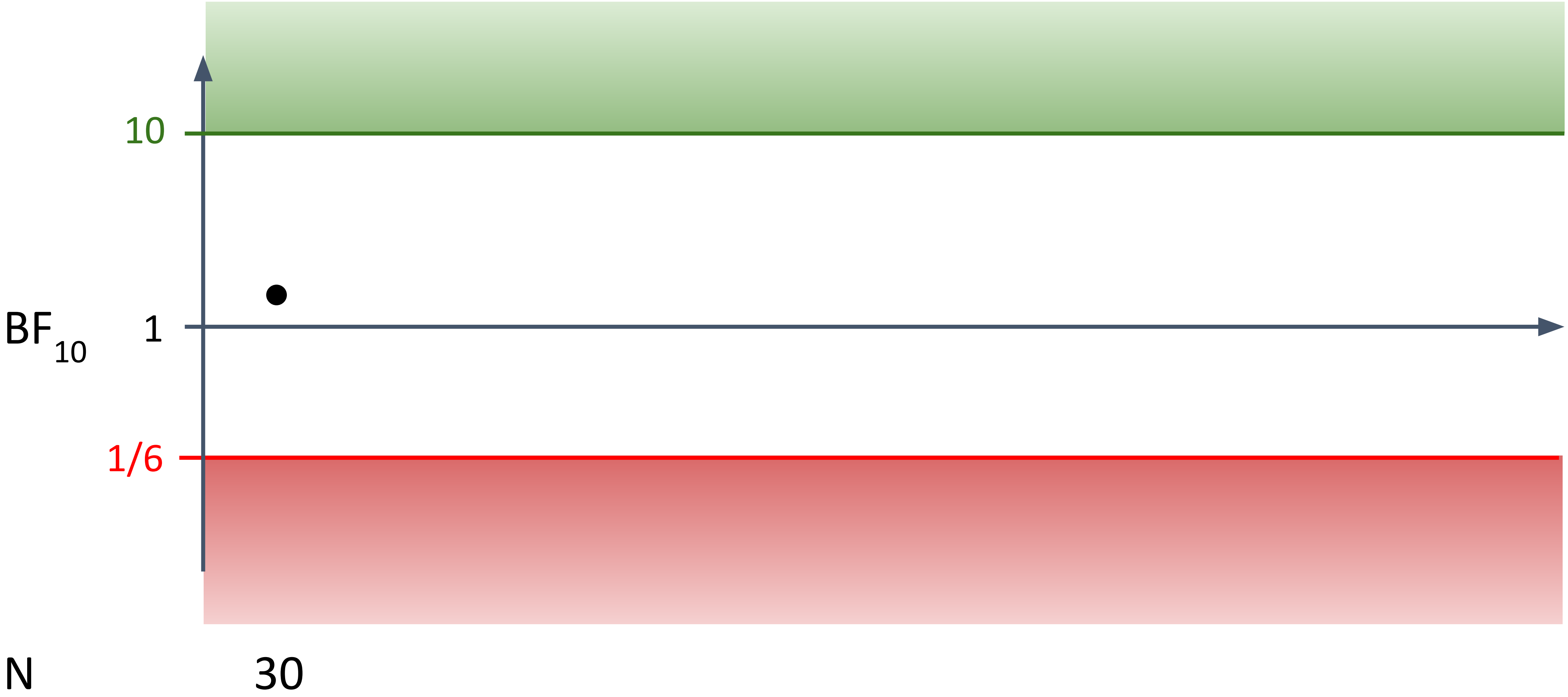

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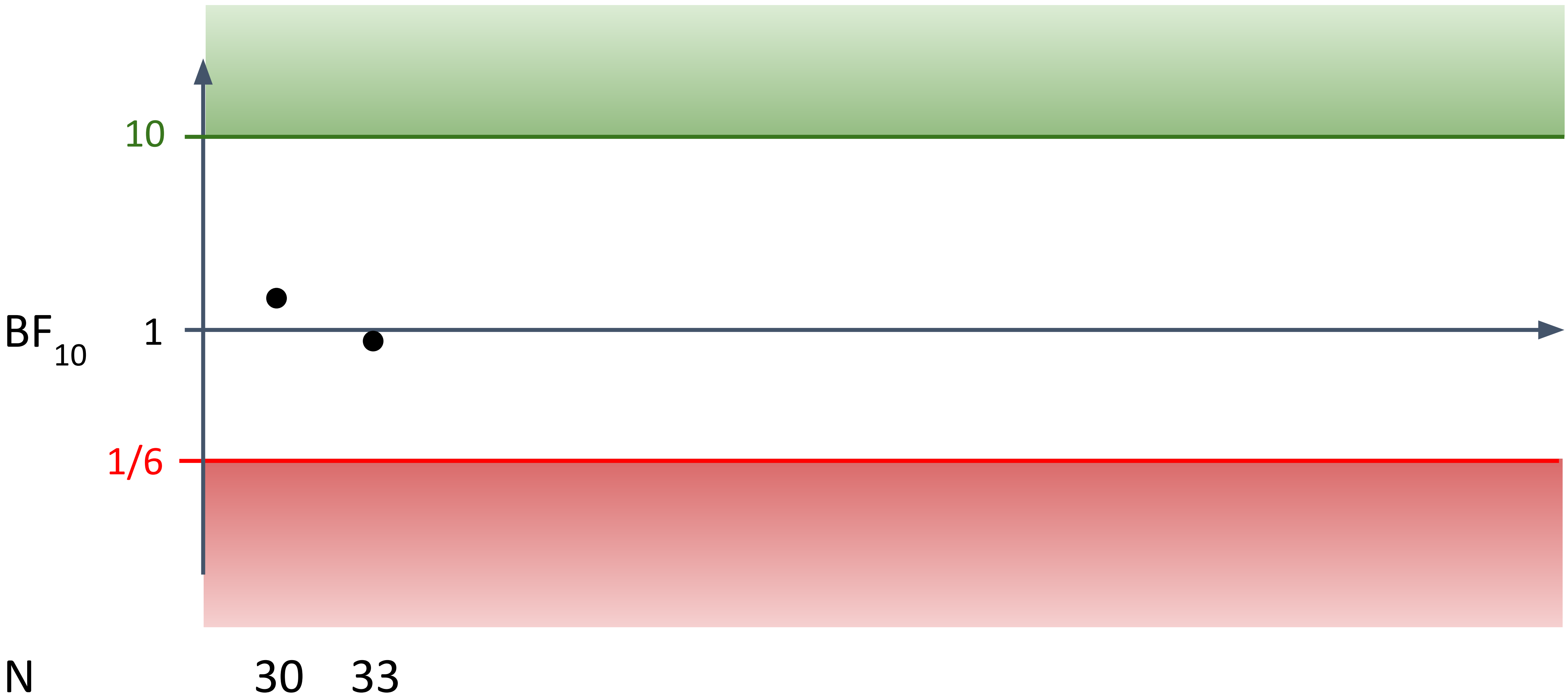

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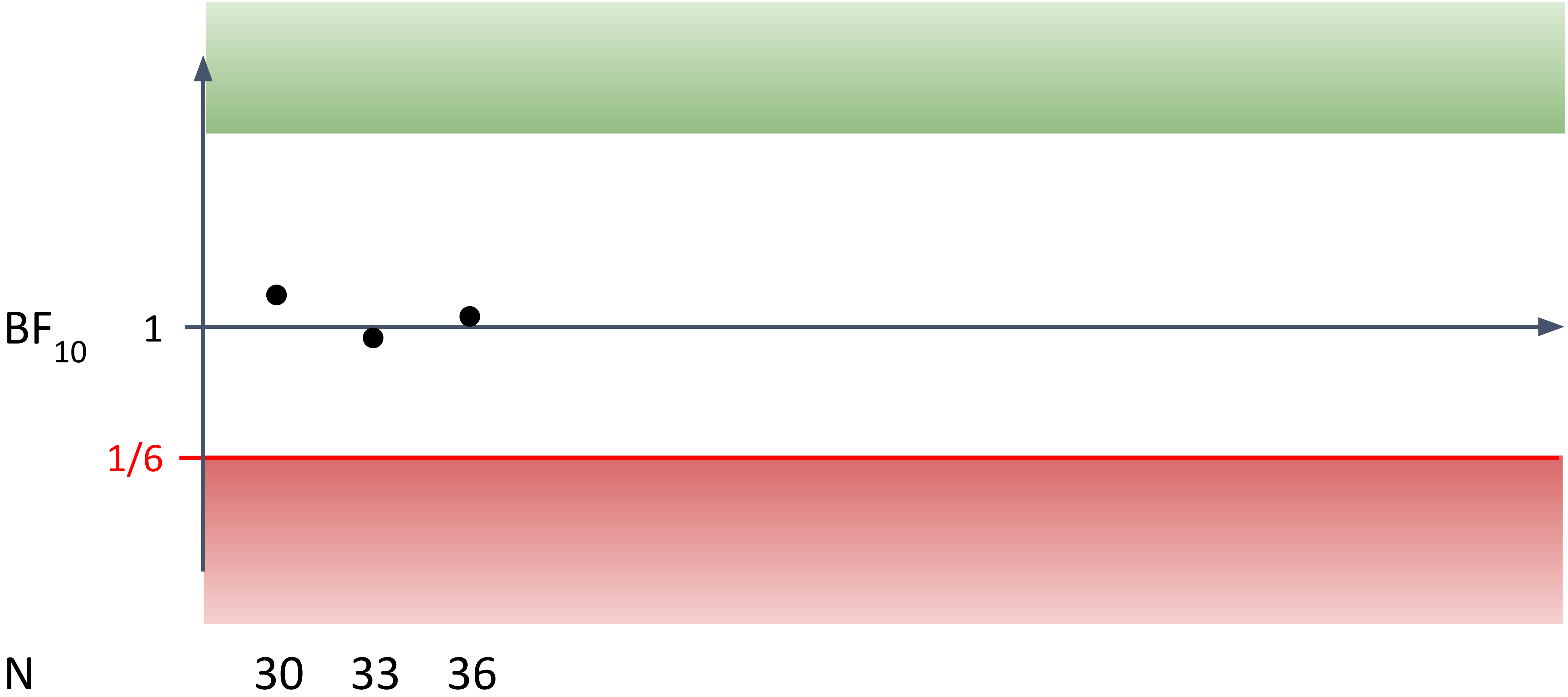

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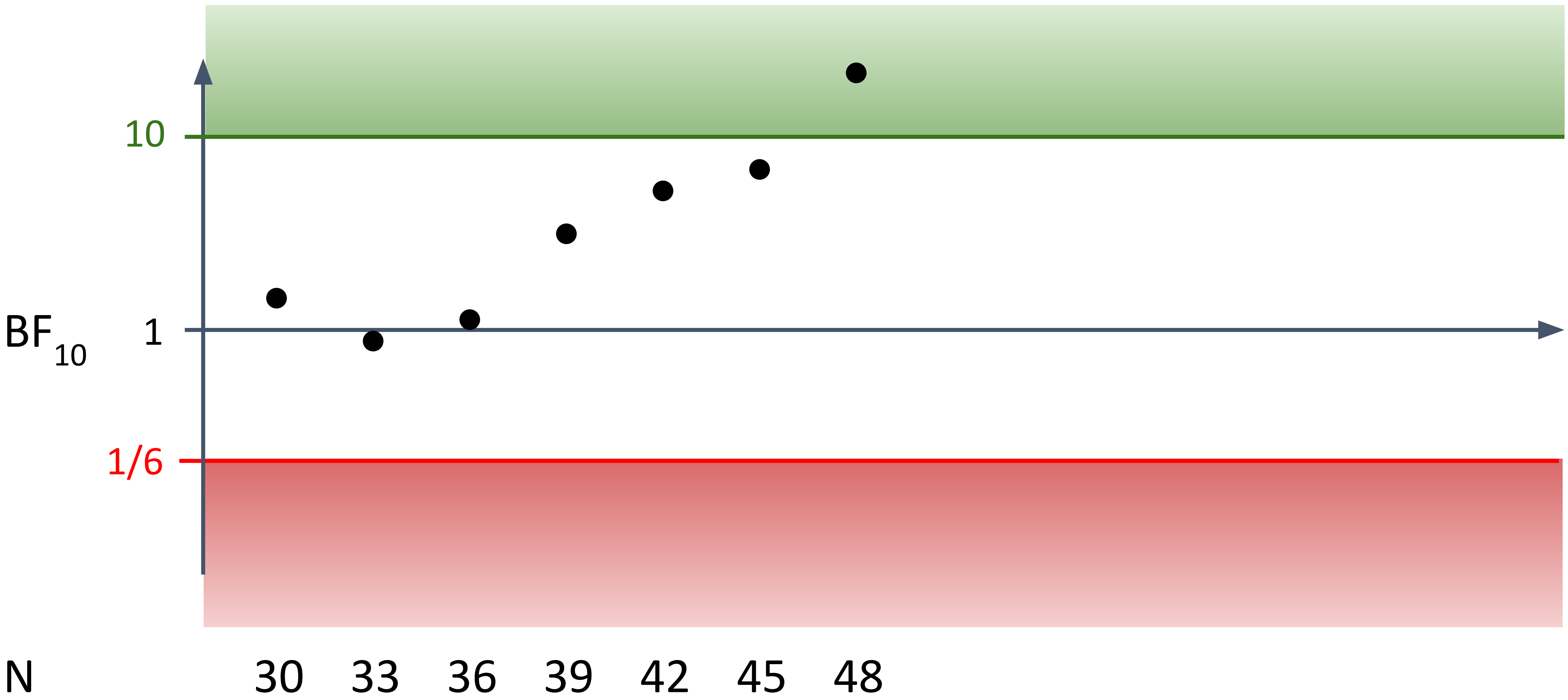
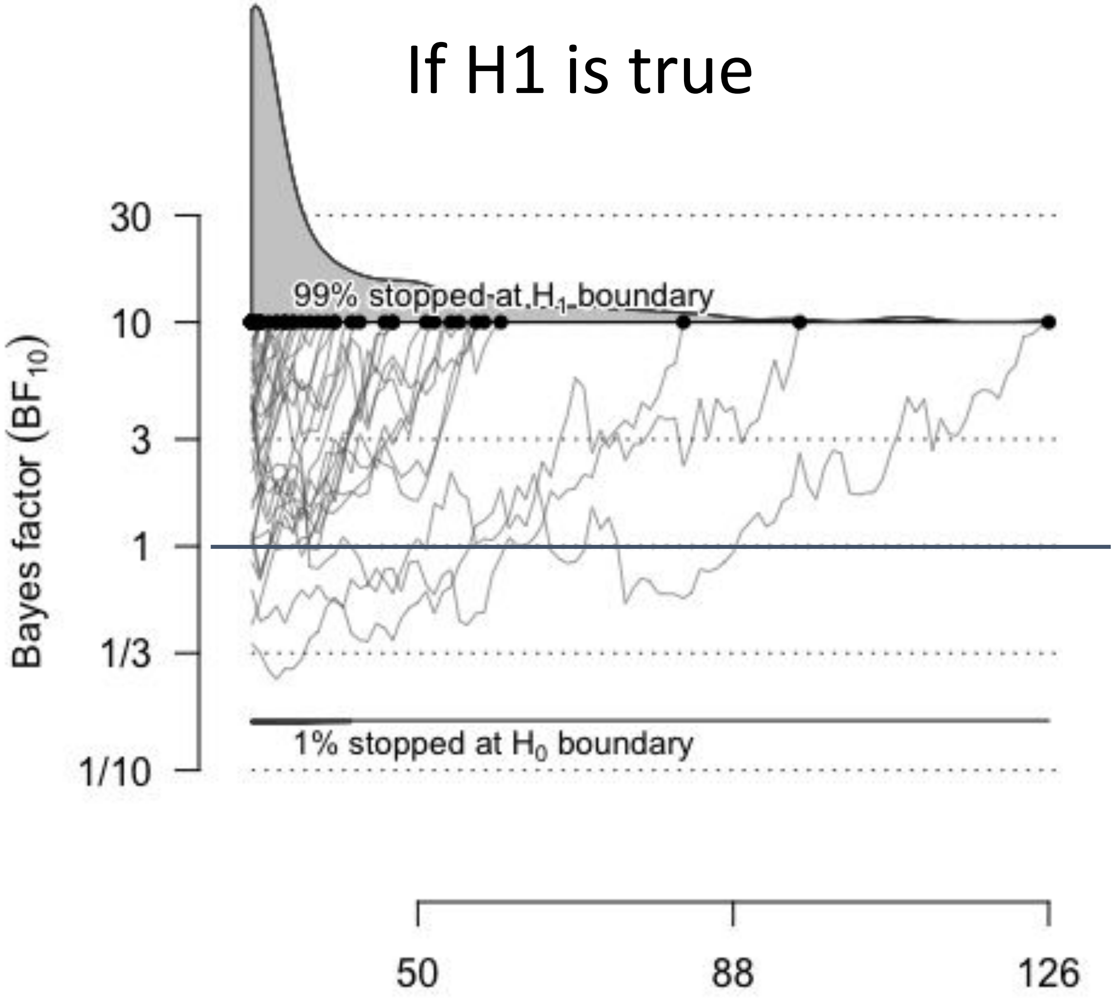


Sequential Bayes Factor Design

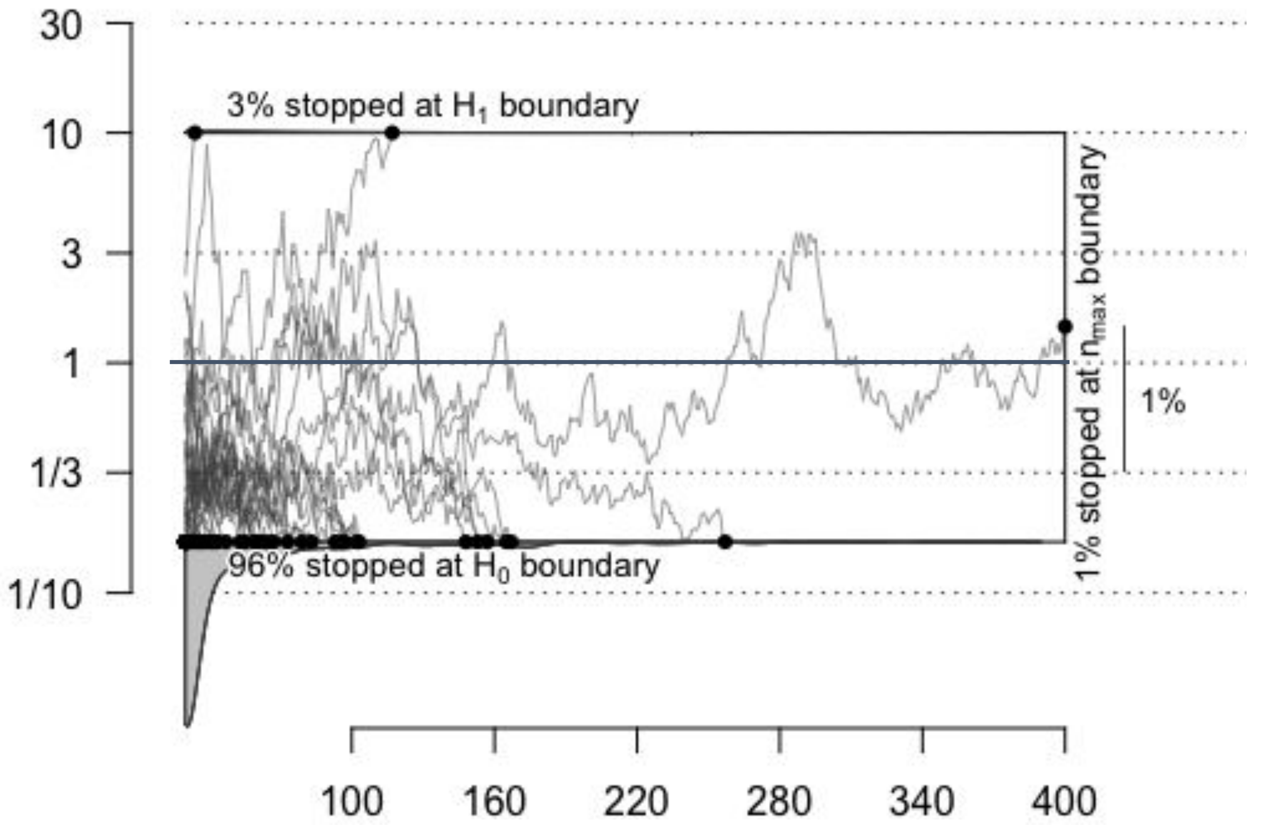
I.e. when should I stop recruiting participants?

If H1 is true



Sample Size

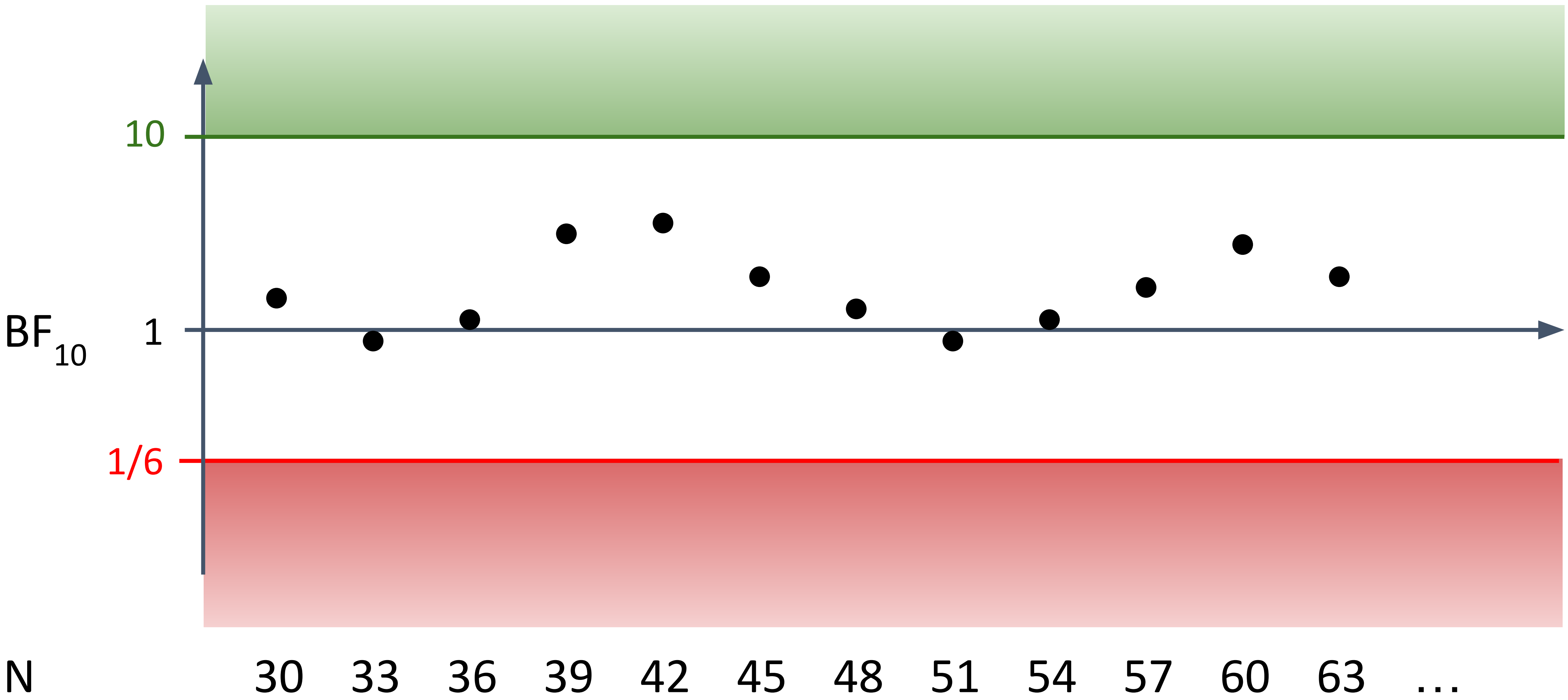
If H0 is true



Sample Size

Sequential Bayes Factor Design With Max N

I.e. Can I stop recruiting now? Pleeeease…



Sequential Bayes Factor Design With Max N

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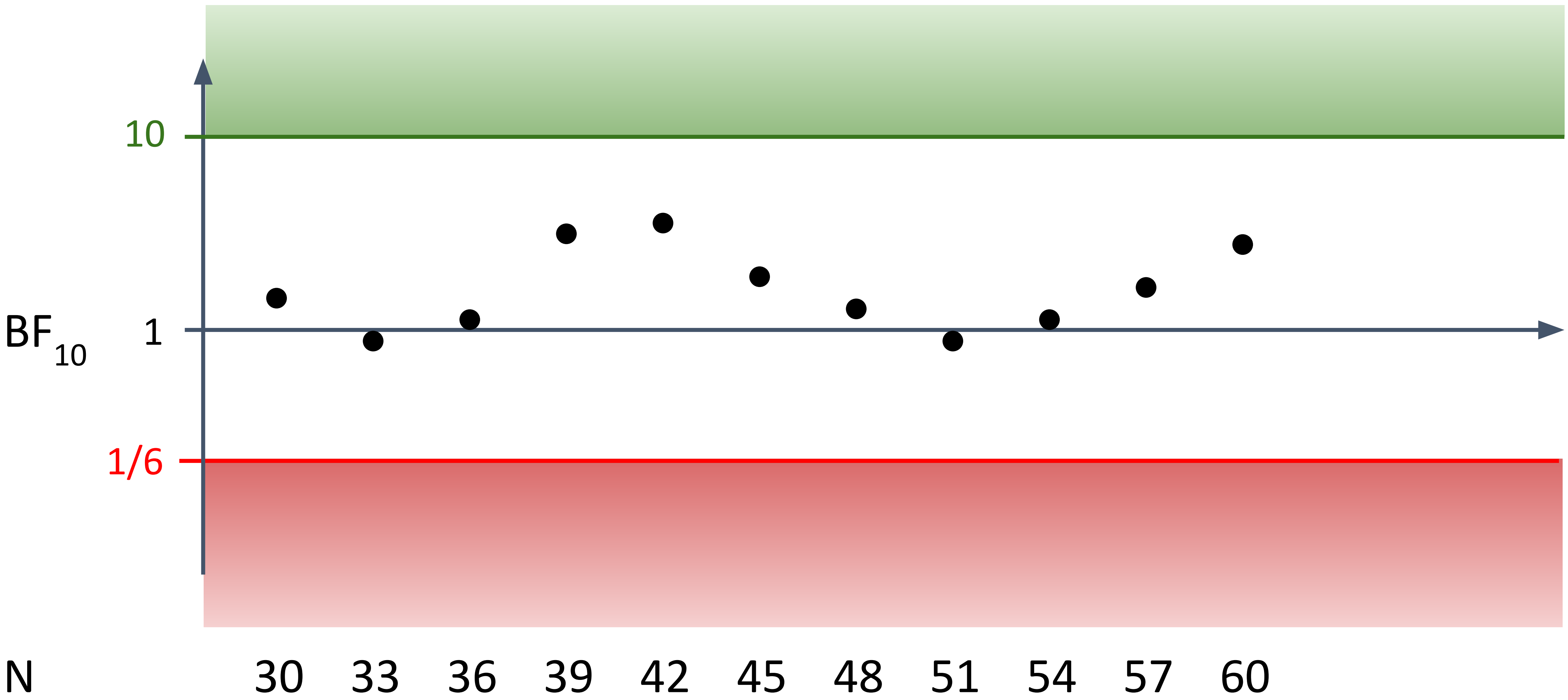

Sequential Bayes Factor Design With Max N

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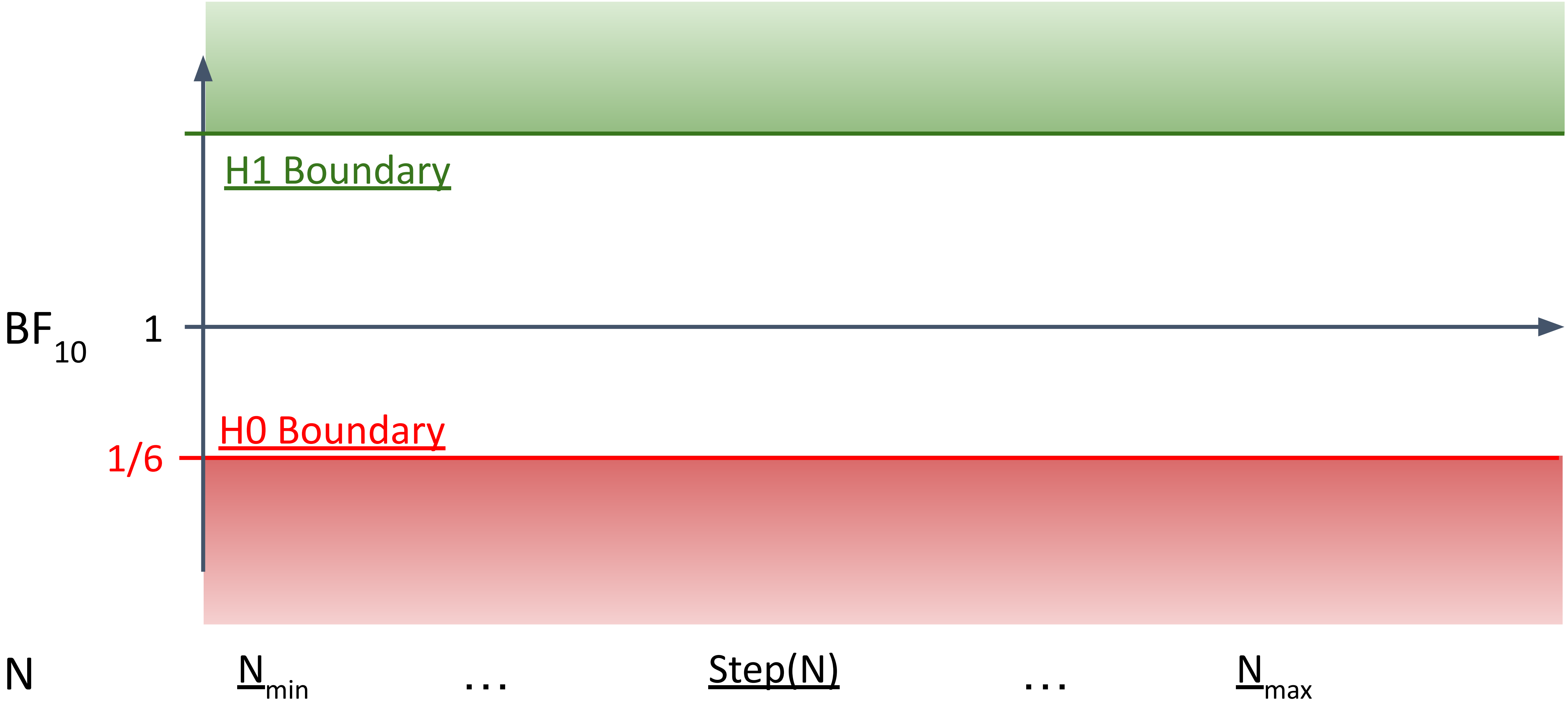

Finding the right parameters

What are the probabilities to hit the H1 and H0 boundaries before reaching the maximum sample size?

From BFDA package https://github.com/nicebread/BFDA

Finding the right parameters

```
sim.H1 <- BFDA.sim(expected.ES=ES, type="t.paired", alternative="greater",
```

```
sim.H0 <- BFDA.sim(expected.ES=0, type="t.paired", alternative="greater",
```

From BFDA package https://github.com/nicebread/BFDA

Finding the right parameters

```
sim.H1 <- BFDA.sim(expected.ES=ES, type="t.paired", alternative="greater",
                n.min=30, n.max=60, stepsize = 1, boundary=c(1/6, 10),
```

```
sim.H0 <- BFDA.sim(expected.ES=0, type="t.paired", alternative="greater",
                n.min=30, n.max=60, stepsize = 1, boundary=c(1/6, 10),
```

From BFDA package https://github.com/nicebread/BFDA

Finding the right parameters

```
sim.H1 <- BFDA.sim(expected.ES=ES, type="t.paired", alternative="greater",
                n.min=30, n.max=60, stepsize = 1, boundary=c(1/6, 10),
                prior=list("Cauchy",list(prior.location=0, prior.scale=sqrt(2)/2)),


sim.H0 <- BFDA.sim(expected.ES=0, type="t.paired", alternative="greater",
                n.min=30, n.max=60, stepsize = 1, boundary=c(1/6, 10),
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                prior=list("Cauchy",list(prior.location=0, prior.scale=sqrt(2)/2)),
                B=10000, design = "sequential")

sim.H0 <- BFDA.sim(expected.ES=0, type="t.paired", alternative="greater",
                n.min=30, n.max=60, stepsize = 1, boundary=c(1/6, 10),
                prior=list("Cauchy",list(prior.location=0, prior.scale=sqrt(2)/2)),
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                n.min=30, n.max=60, stepsize = 1, boundary=c(1/6, 10),
                prior=list("Cauchy",list(prior.location=0, prior.scale=sqrt(2)/2)),
                B=10000, design = "sequential")

sim.H0 <- BFDA.sim(expected.ES=0, type="t.paired", alternative="greater",
                n.min=30, n.max=60, stepsize = 1, boundary=c(1/6, 10),
                prior=list("Cauchy",list(prior.location=0, prior.scale=sqrt(2)/2)),
                B=10000, design = "sequential")

BFDA.analyze(sim.H1, design="sequential", n.min=30, n.max=60, boundary=c(1/6, 10))
BFDA.analyze(sim.H0, design="sequential", n.min=30, n.max=60, boundary=c(1/6, 10))
```

From BFDA package https://github.com/nicebread/BFDA

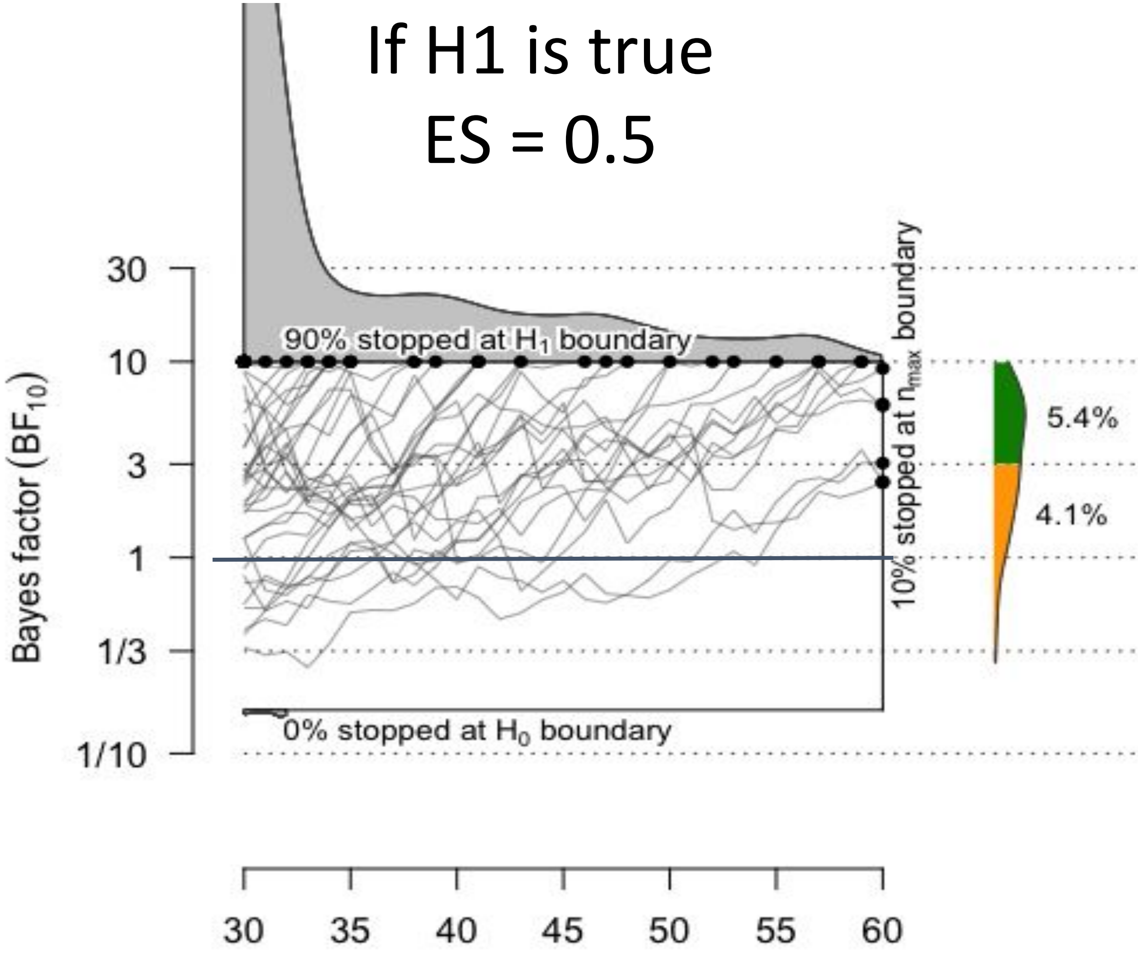
Finding the right parameters

```
sim.H1 <- BFDA.sim(expected.ES=ES, type="t.paired", alternative="greater",
                   n.min=30, n.max=60, stepsize = 1, boundary=c(1/6, 10),
                   prior=list("Cauchy",list(prior.location=0, prior.scale=sqrt(2)/2)),
                   B=10000, design = "sequential")

sim.H0 <- BFDA.sim(expected.ES=0, type="t.paired", alternative="greater",
                   n.min=30, n.max=60, stepsize = 1, boundary=c(1/6, 10),
                   prior=list("Cauchy",list(prior.location=0, prior.scale=sqrt(2)/2)),
                   B=10000, design = "sequential")

BFDA.analyze(sim.H1, design="sequential", n.min=30, n.max=60, boundary=c(1/6, 10))
BFDA.analyze(sim.H0, design="sequential", n.min=30, n.max=60, boundary=c(1/6, 10))


plot(sim.H1, n.min=N_min, n.max=N_max, boundary=boundaries_test)
plot(sim.H0, n.min=N_min, n.max=N_max, boundary=boundaries_test)
```

From BFDA package https://github.com/nicebread/BFDA

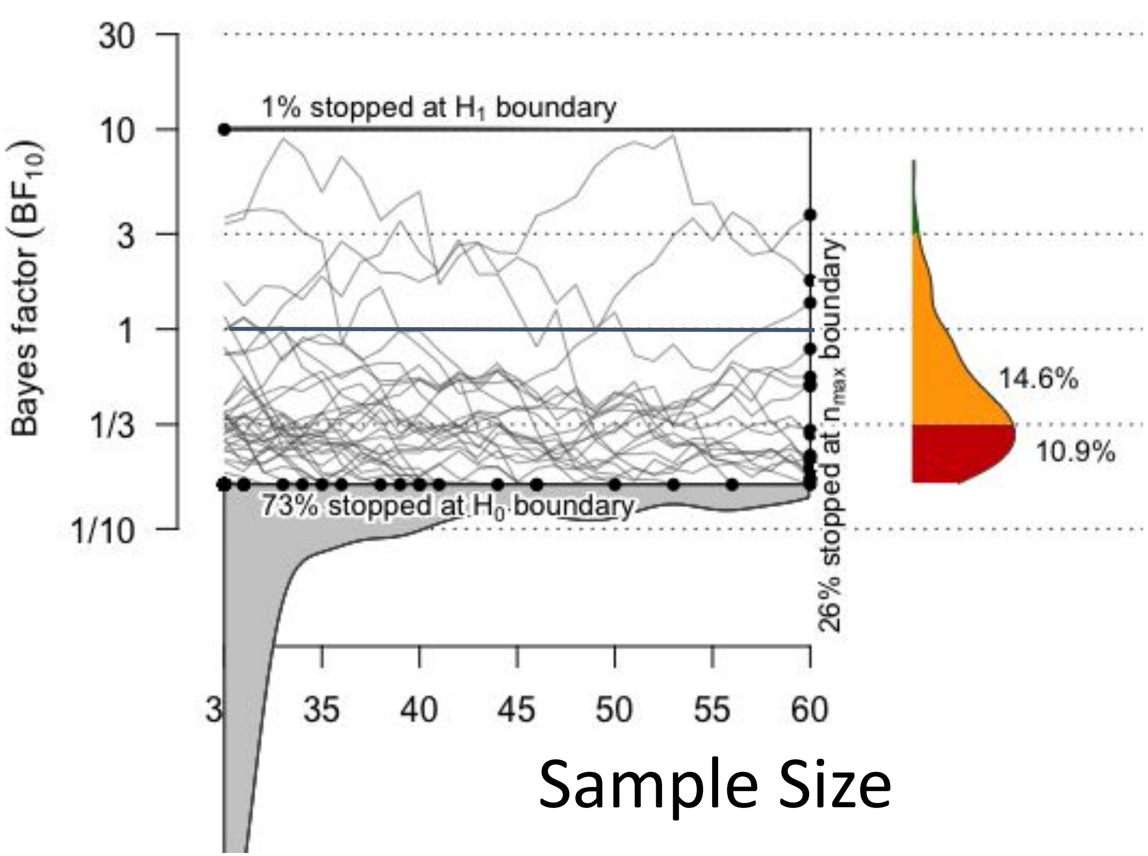
Finding the right parameters

If H1 is true
ES = 0.5



Sample Size

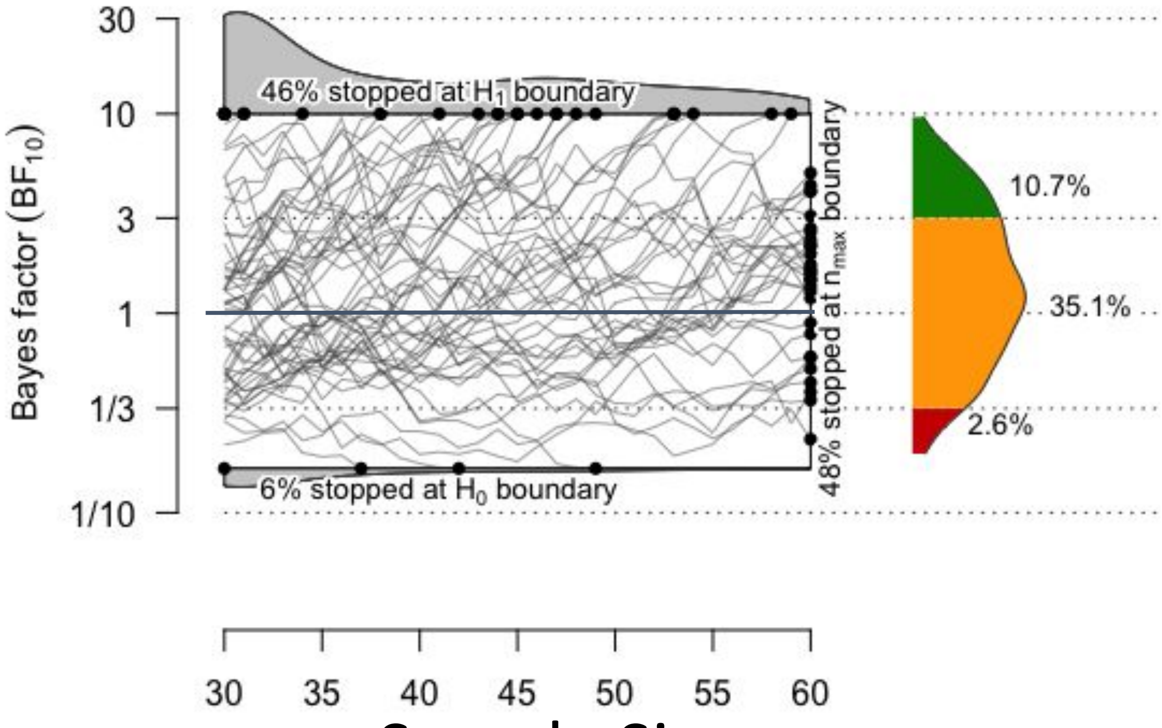
If H0 is true



Sample Size

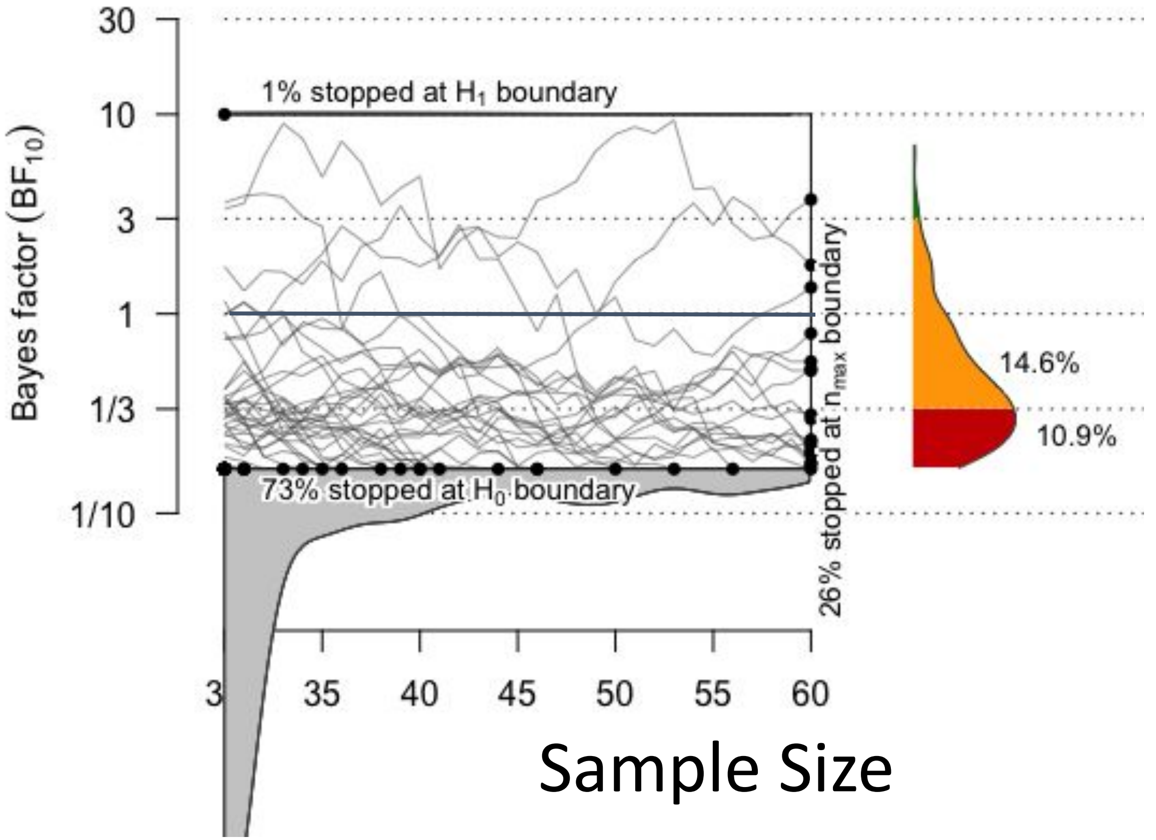
Finding the right parameters

If H1 is true
ES = 0.3



Sample Size

If H0 is true



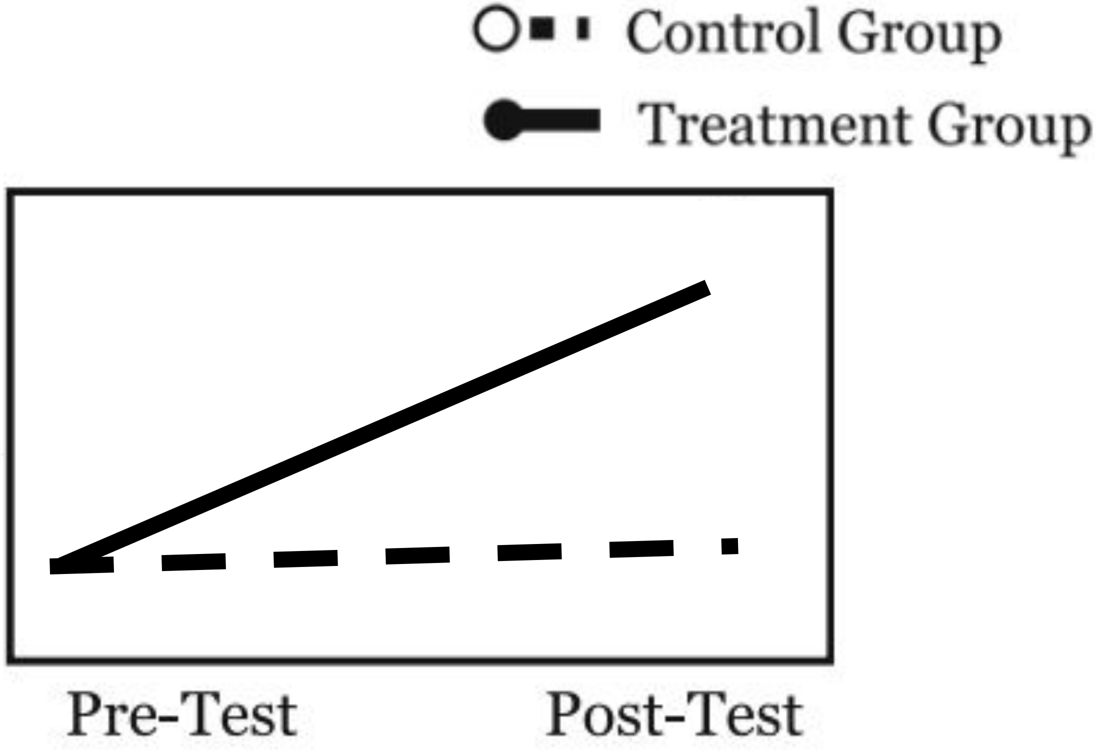
Sample Size

We can also provide a distribution of Effect sizes instead of a point estimate

For example, here a normal distribution with mean 0.5 and standard deviation 0.1, but it could be any array of Effect Sizes (even discrete values).

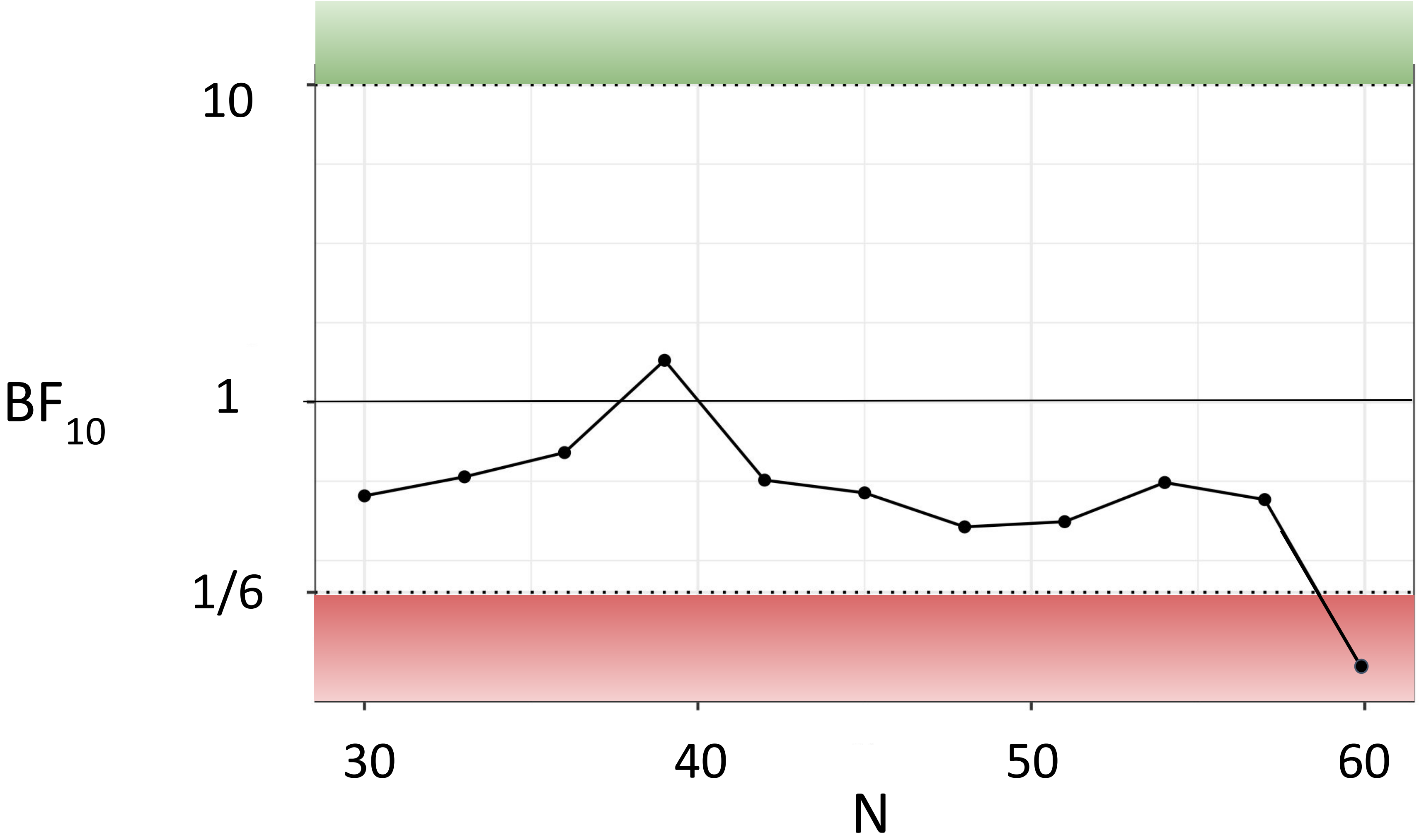
```
sim.H1 <- BFDA.sim(expected.ES=rnorm(100000, 0.5, 0.1), type="t.paired", alternative="greater",
                n.min=30, n.max=60, stepsize = 1, boundary=c(1/6, 10),
                prior=list("Cauchy",list(prior.location=0, prior.scale=sqrt(2)/2)),
                B=10000, design = "sequential")

sim.H0 <- BFDA.sim(expected.ES=0, type="t.paired", alternative="greater",
                n.min=30, n.max=60, stepsize = 1, boundary=c(1/6, 10),
                prior=list("Cauchy",list(prior.location=0, prior.scale=sqrt(2)/2)),
                B=10000, design = "sequential")

BFDA.analyze(sim.H1, design="sequential", n.min=30, n.max=60, boundary=c(1/6, 10))
BFDA.analyze(sim.H0, design="sequential", n.min=30, n.max=60, boundary=c(1/6, 10))


plot(sim.H1, n.min=N_min, n.max=N_max, boundary=boundaries_test)
plot(sim.H0, n.min=N_min, n.max=N_max, boundary=boundaries_test)
```

Example (fresh out of the oven)



How much evidence is there for an interaction?
And follow-up, is it in the hypothesized direction?

Example (fresh out of the oven)



I am excited, where can I find this tool?

Schönbrodt, F. D., & Wagenmakers, E.-J. (2018). Bayes factor design analysis: Planning for compelling evidence. Psychonomic Bulletin & Review, 25(1), 128–142. https://doi.org/10.3758/s13423-017-1230-y

bitly

https://bit.ly/schonbrodt-2018

Instructions and scripts (in R) are available on gitlab, here :

https://github.com/nicebread/BFDA

bitly

https://bit.ly/bfda-gitlab

The Issue with Aggregation-Based Analyses

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1) The techniques that we frequently use in psychology to analyze behavior on tasks (at least implicitly) assume that people ARE NOT changing during those tasks (i.e., that behavior is stationary).

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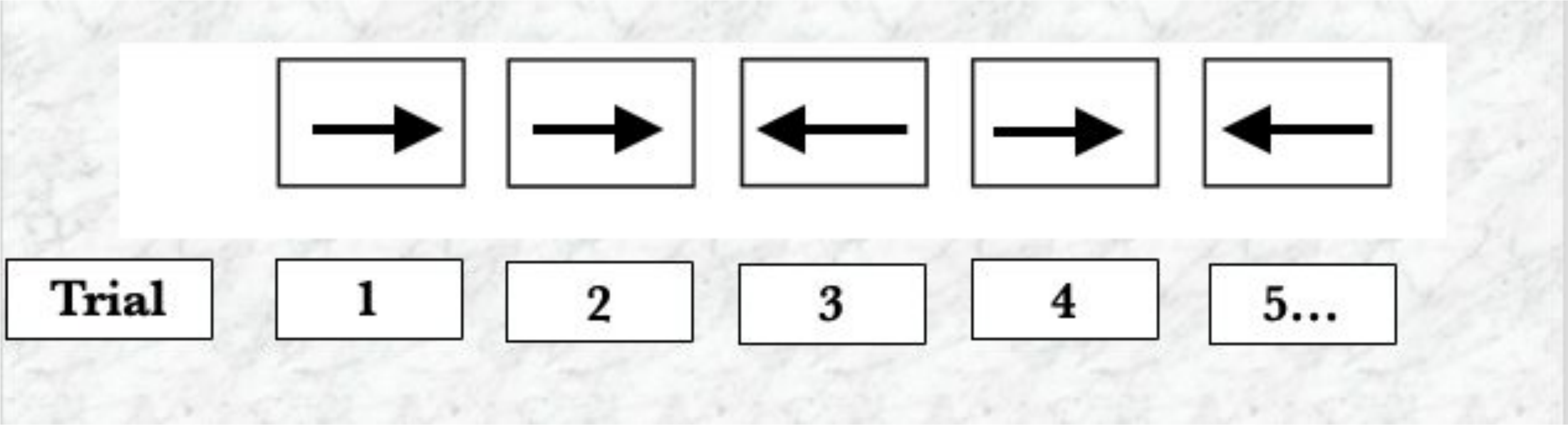
1) The techniques that we frequently use in psychology to analyze behavior on tasks (at least implicitly) assume that people ARE NOT changing during those tasks (i.e., that behavior is stationary).

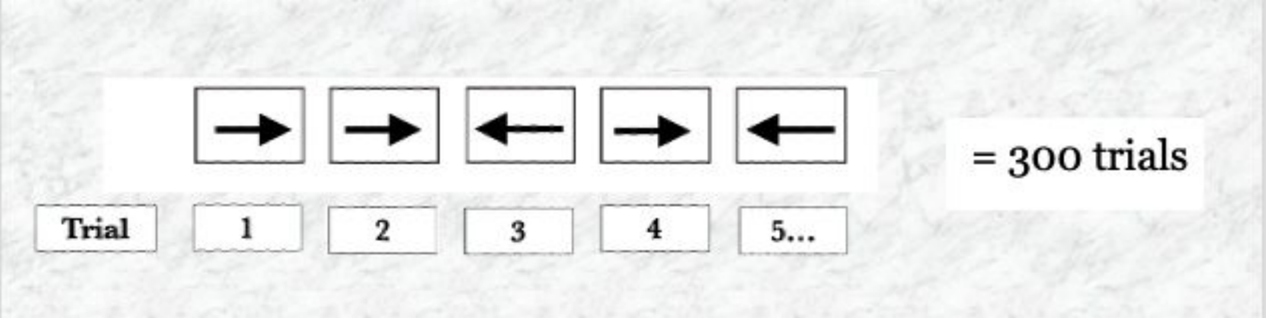
2) That assumption is (almost always) wrong.

3) Making a stationarity assumption weakens our understanding of actual behavior and thus can make the inferences we draw incomplete/wrong.

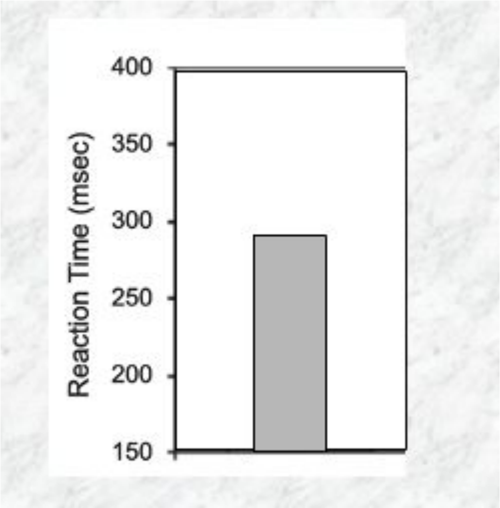
Example Simple RT Task



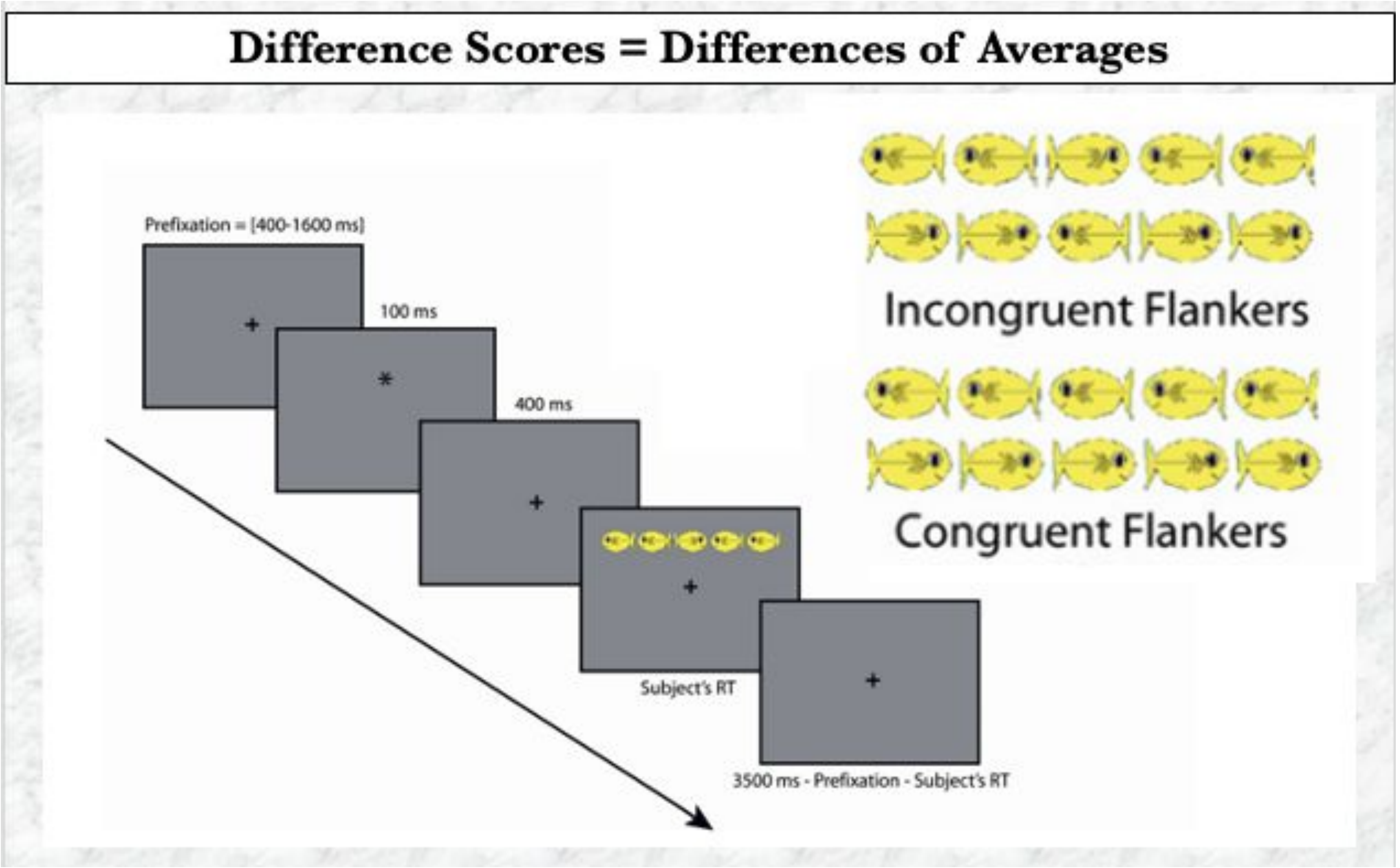
DVs: Average RT & Average %Corr



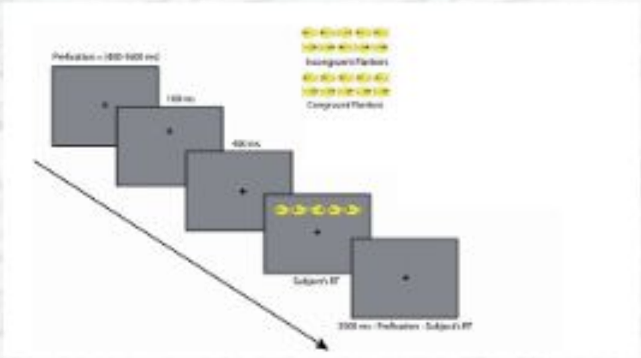
Trial	1	2	3	4	5...
RT	296	275	253	255	261
Corr	1	1	1	0	1



Subtracted Measures

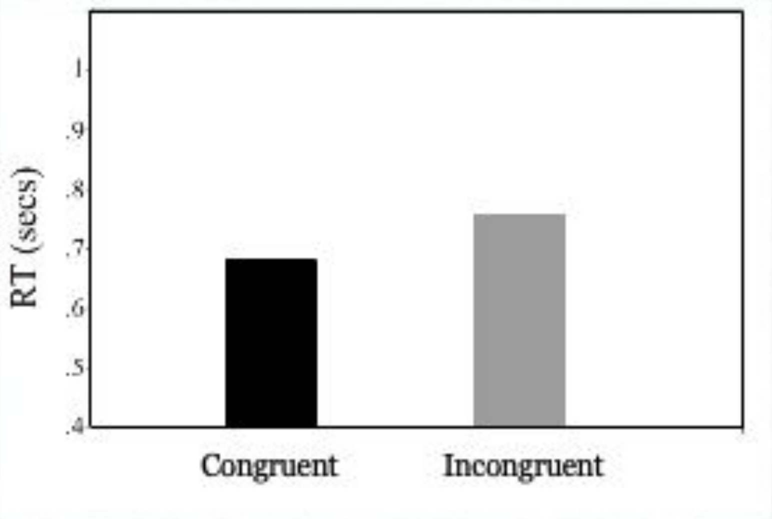


Subtracted Measures



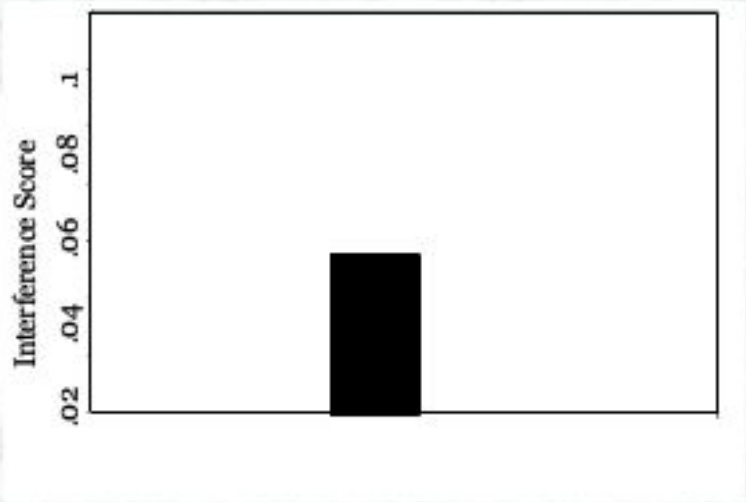
2 levels of congruence
(congruent/incongruent)
x
84 trials for each level
=
168 trials

Subtracted Measures



For each individual, take the average reaction time across all 84 trials of the same level of congruence

Subtracted Measures



Subtract the average RT for congruent trials from the average RT for incongruent trials

What Assumptions Are We Making?

A) The trials are independently and identically distributed (*iid*)

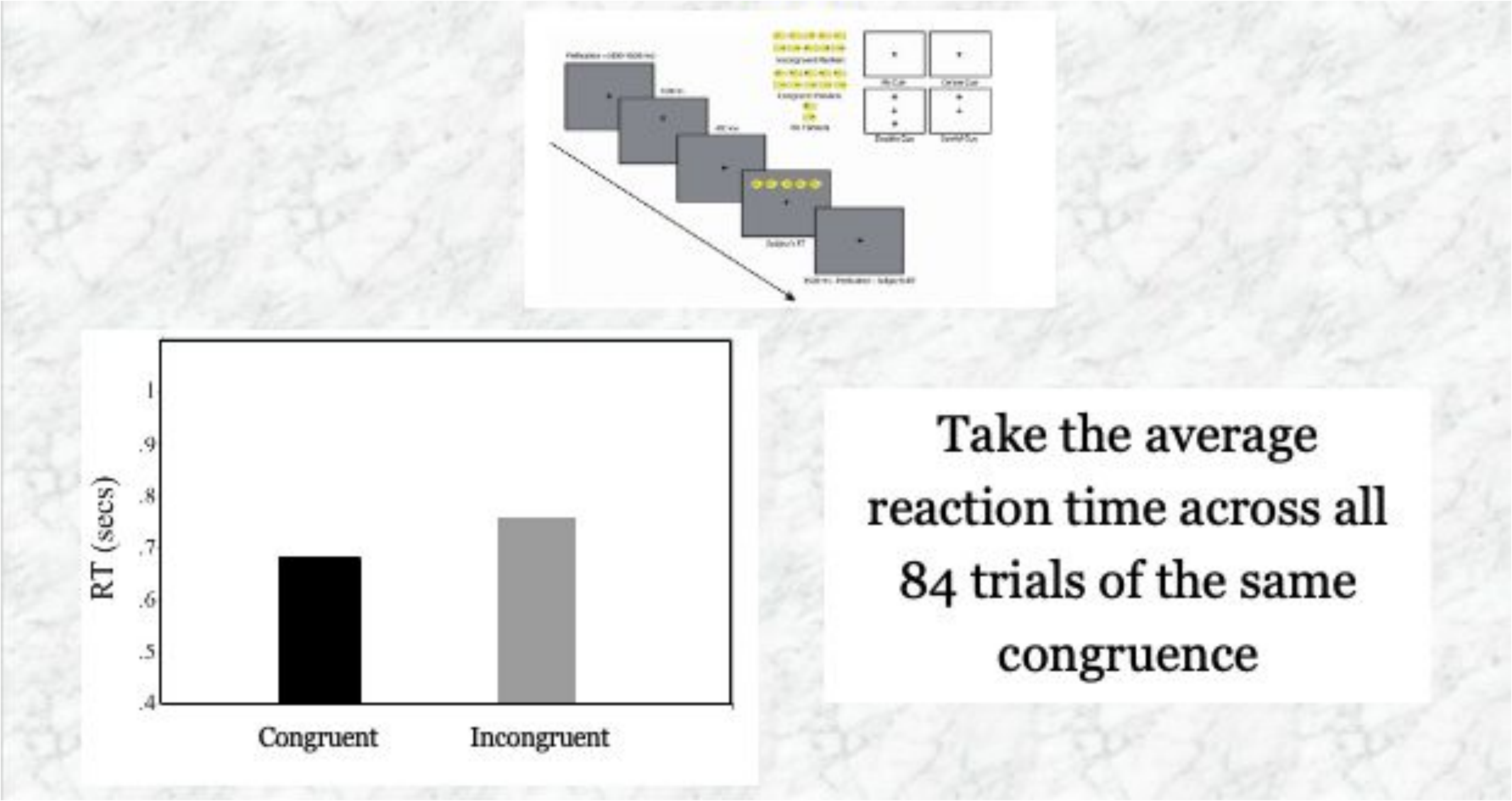
What Assumptions Are We Making?

A) The trials are independently and identically distributed (*iid*)

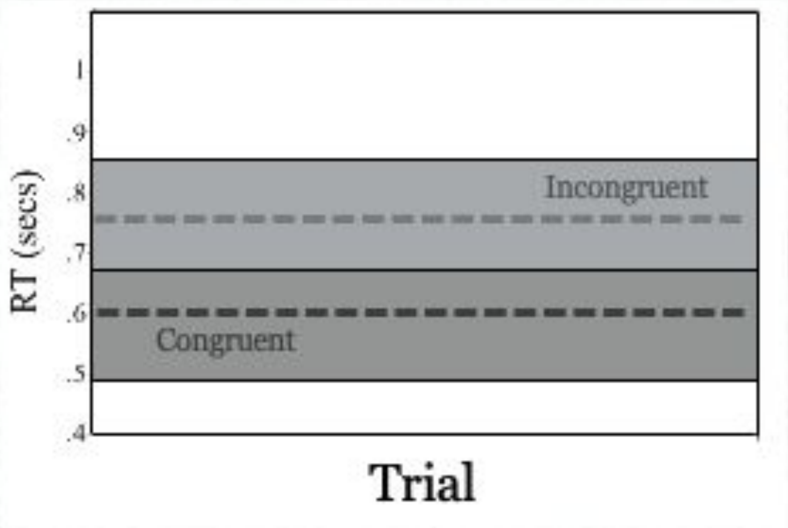
or

B) The trials are not iid, but any violations (e.g., temporal dynamics) are irrelevant to what we're trying to measure

What If Those Assumptions Are Wrong

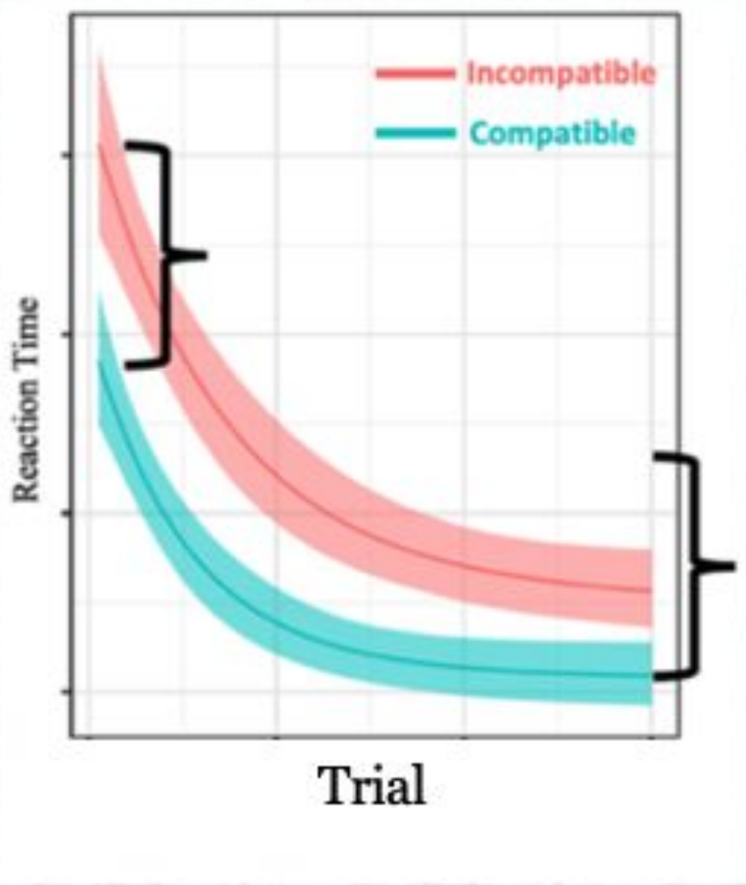


What If Those Assumptions Are Wrong



We're assuming that participants not getting better/worse or faster/slower through time
(i.e., behavior on all trials drawn from a constant process with those means)

What If Those Assumptions Are Wrong



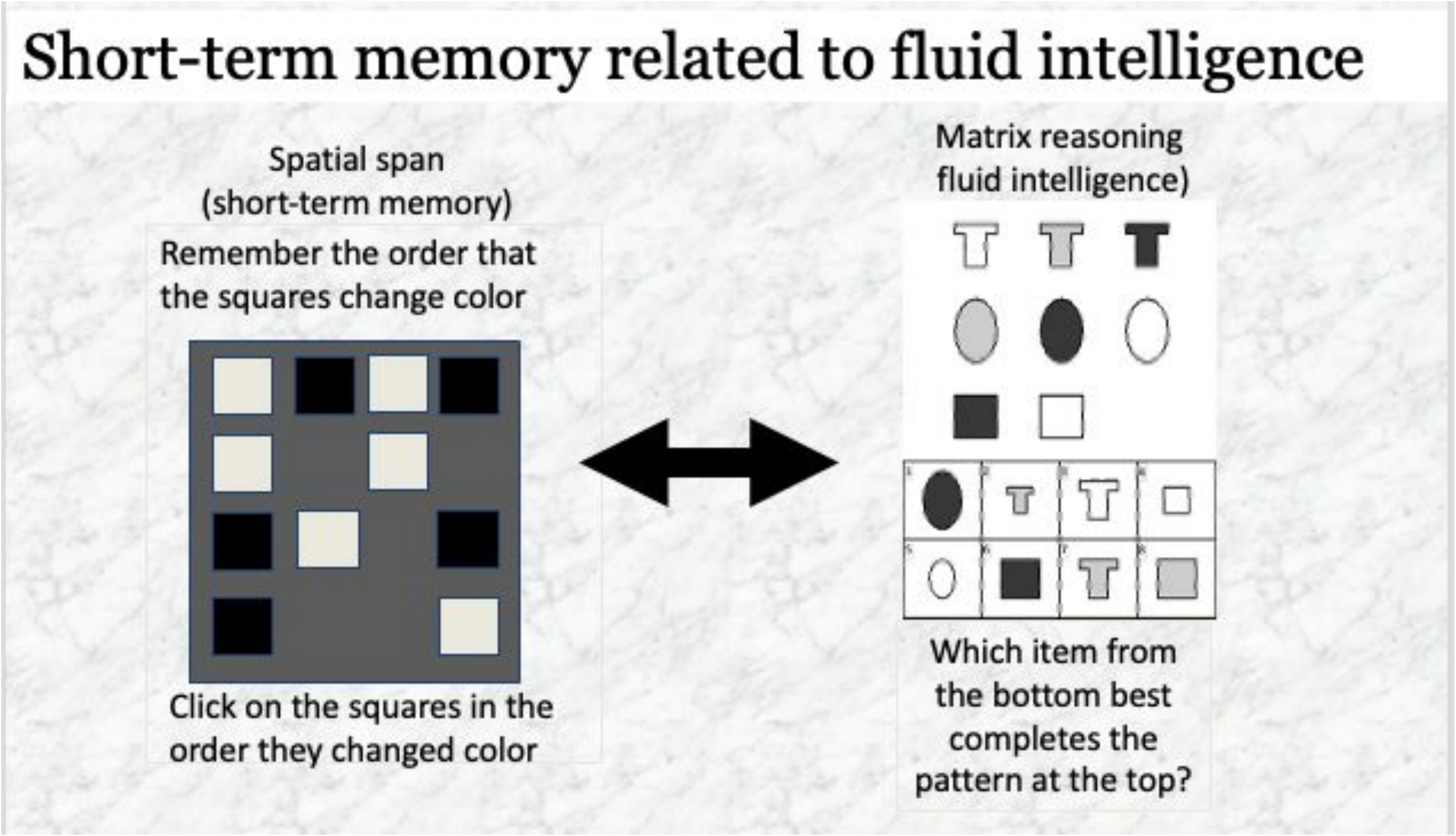
If that assumption is wrong (it is)...

and the data actually looks like this through time?

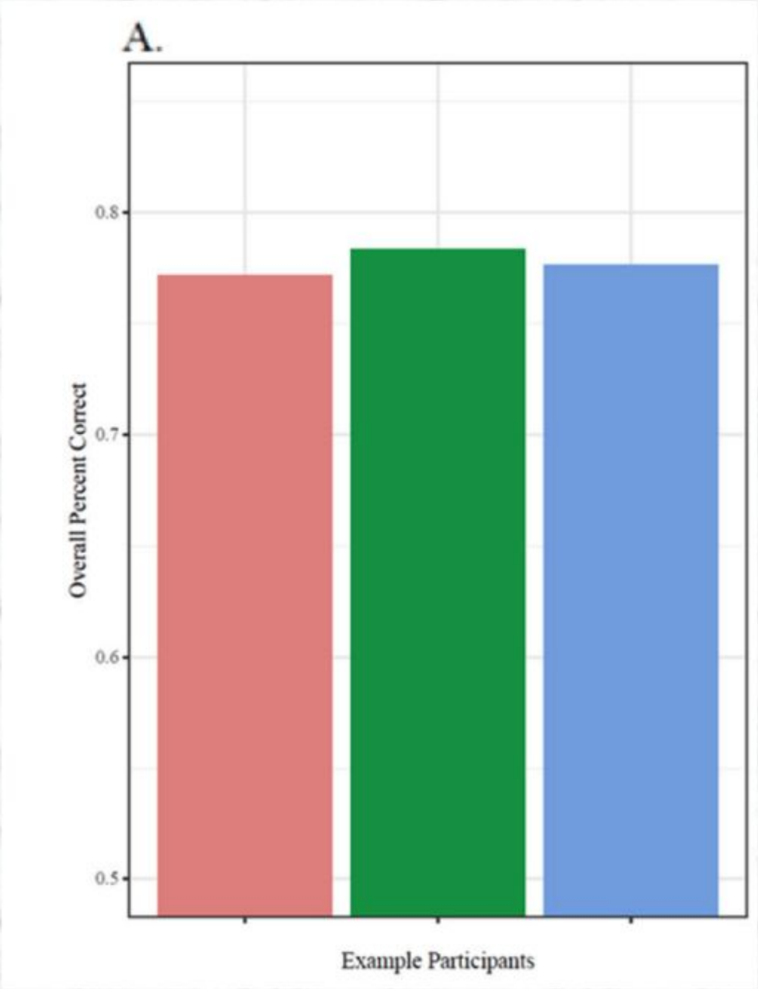
It's unclear what that the average-based metric even means?

Why Should We Care That Our Assumptions Are Wrong?

Understanding Individual Differences



Understanding Individual Differences



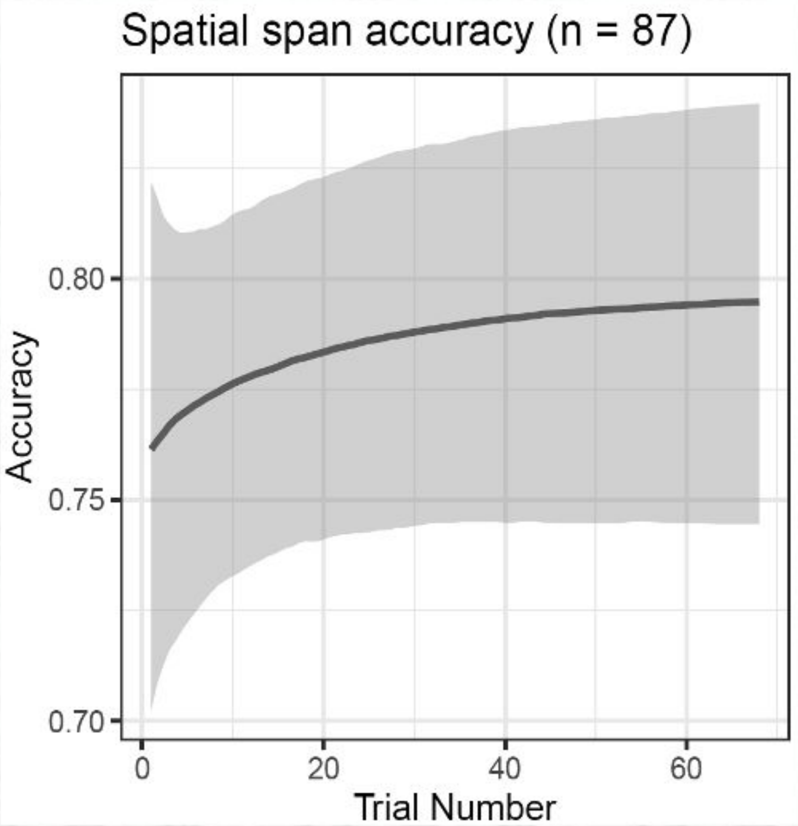
Typical STM analyses – average accuracy

Key assumption: That this DV provides an informative window into individual differences

In particular, people with the same score should be "the same"….

Understanding Individual Differences

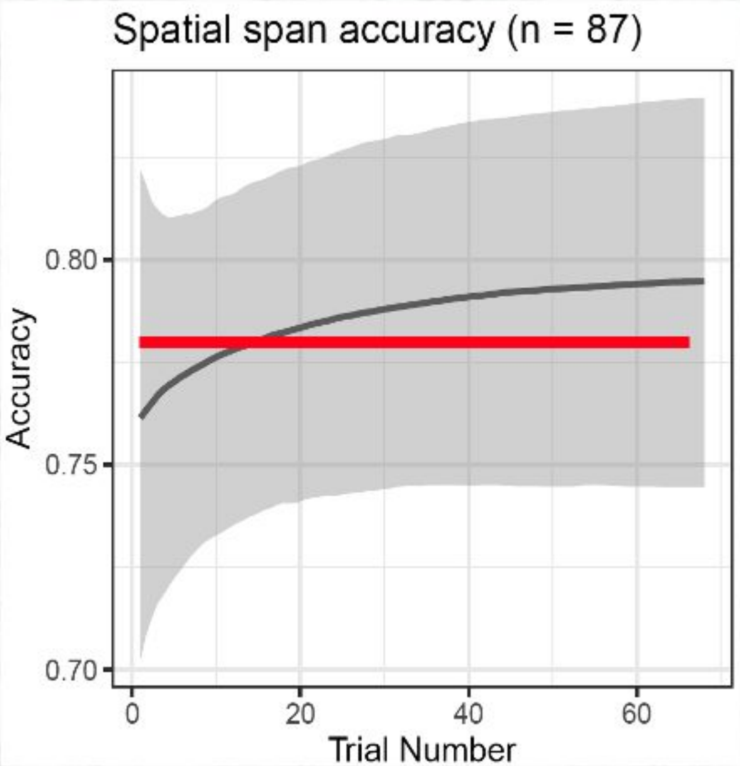
But performance is NOT stationary on the short-term memory task.



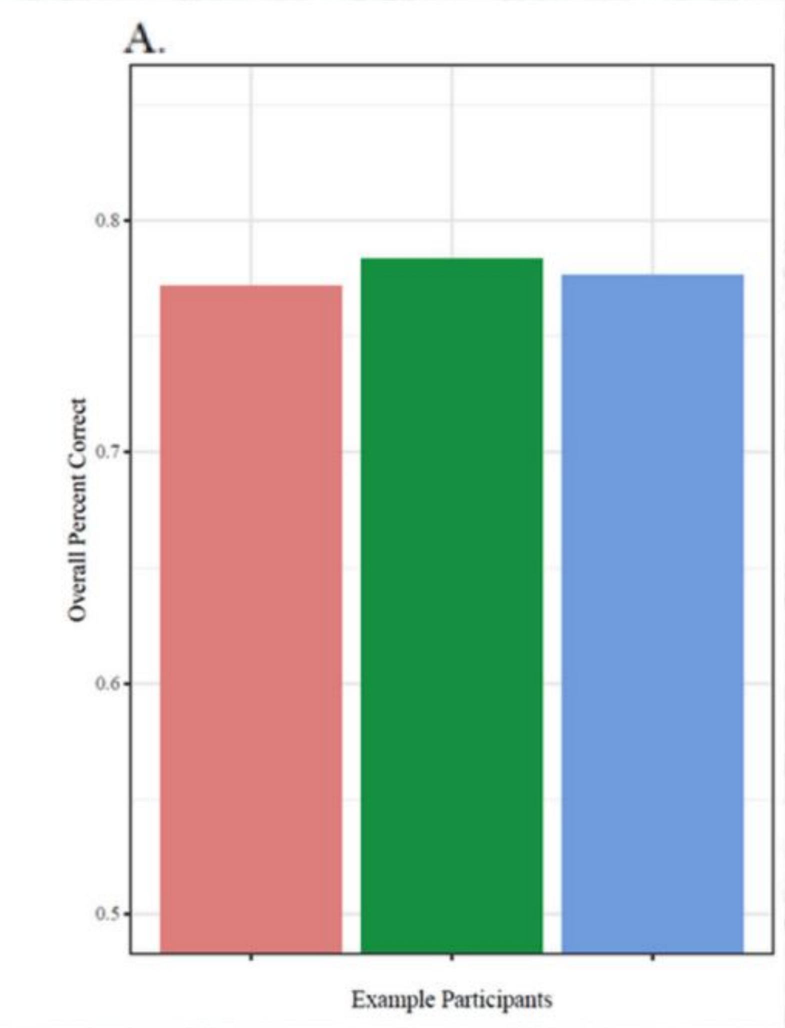
Indeed, not only do people improve at this task through time, we can identify reliable individual differences in their initial ability, rate of change, and estimated final performance.

Understanding Individual Differences

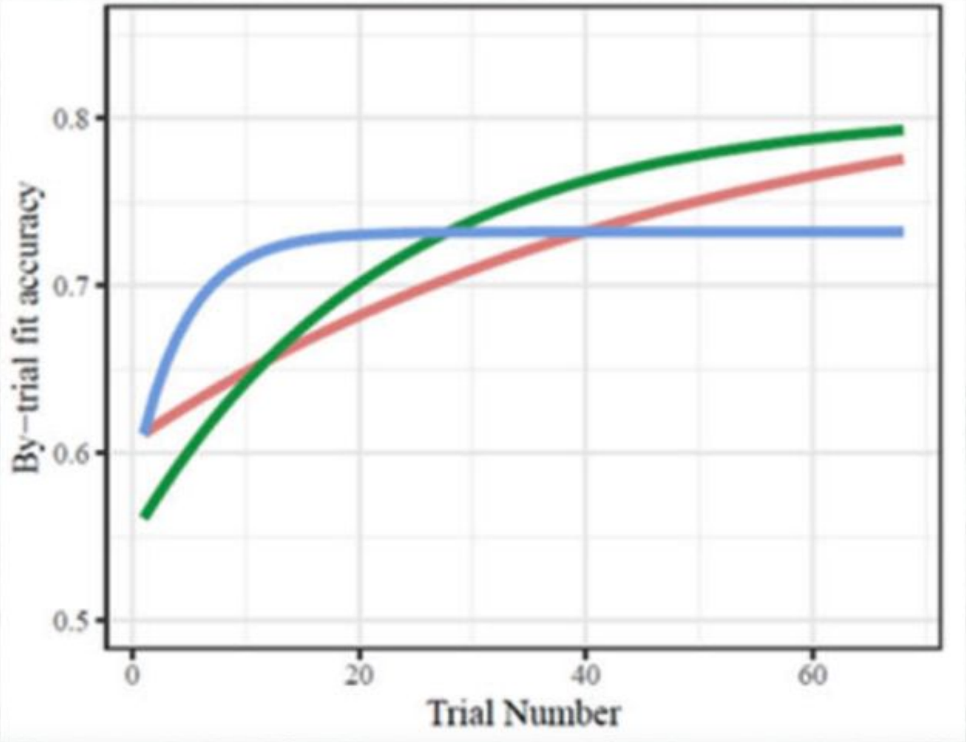
Problem #1: Not really clear what "average" performance on this task means; it's not a good description of the behavior



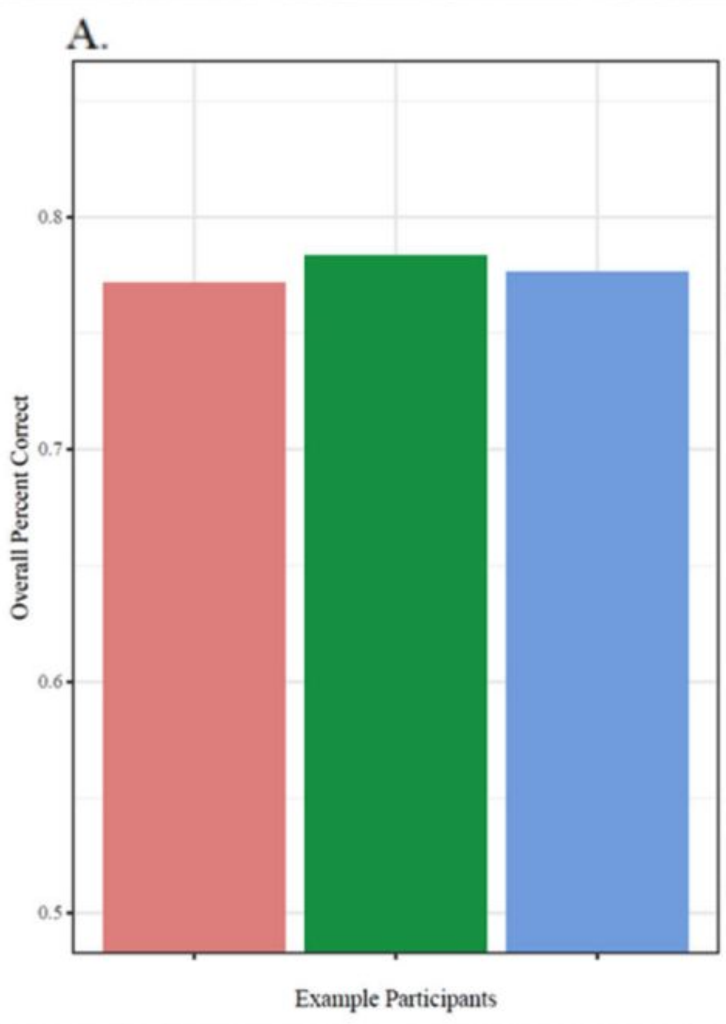
Understanding Individual Differences



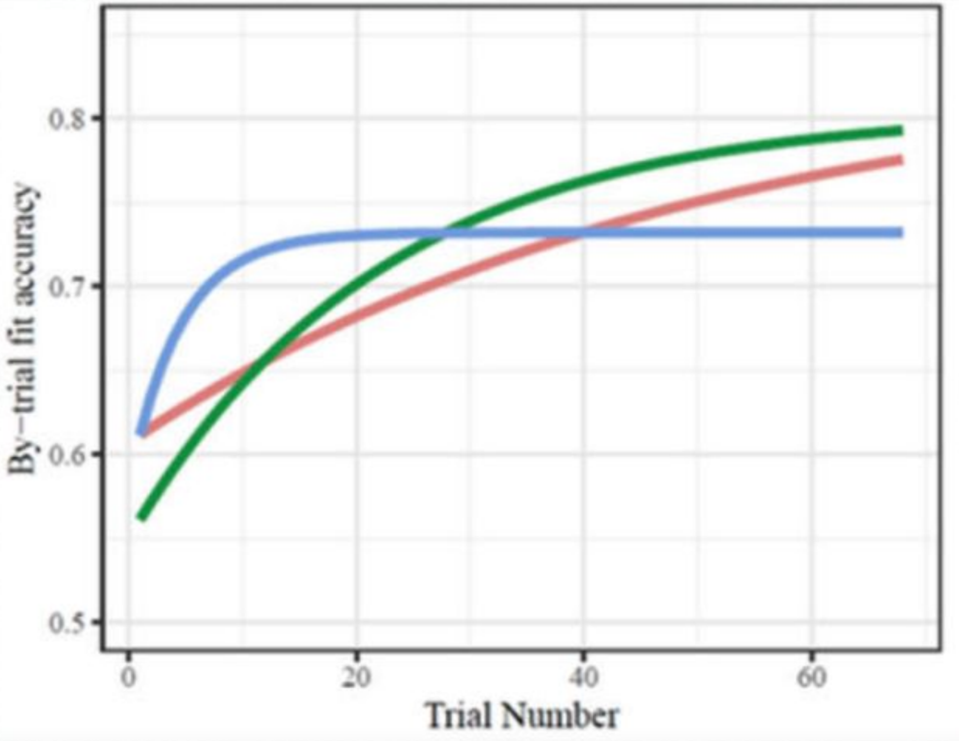
Problem #2: Worse, taking an average can make people who are different look "the same"



Understanding Individual Differences



Problem #3: Theories are no longer specific enough to predict links with true behavior…

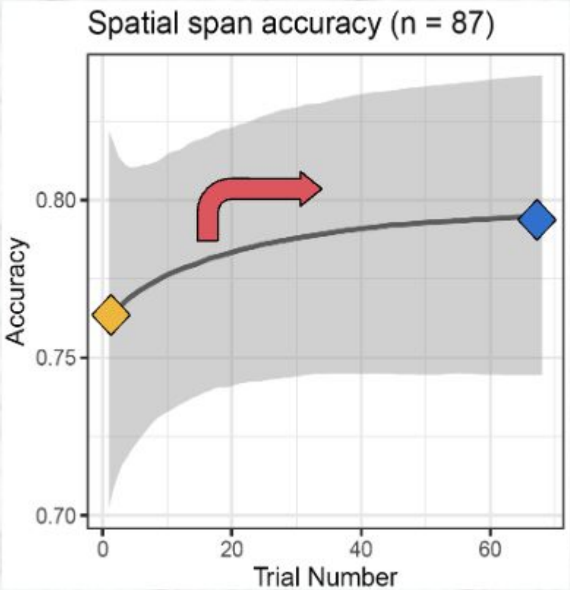


Understanding Individual Differences

Fluid intelligence as "the ability to immediately be successful on novel tasks" -- Starting STM accuracy

Fluid intelligence as "the ability to learn novel tasks" -- Rate of change in STM accuracy

Fluid intelligence as "sharing stable process(es) with short term memory" -- Asymptotic STM accuracy



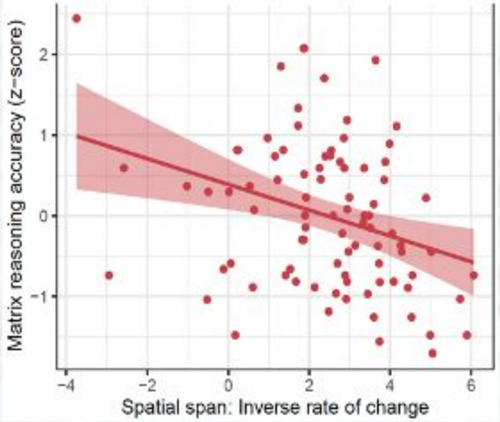
Understanding Individual Differences

~~Fluid intelligence as "the ability to immediately be successful on novel tasks" -- Starting STM accuracy~~

$BF_{log2} = -0.78$

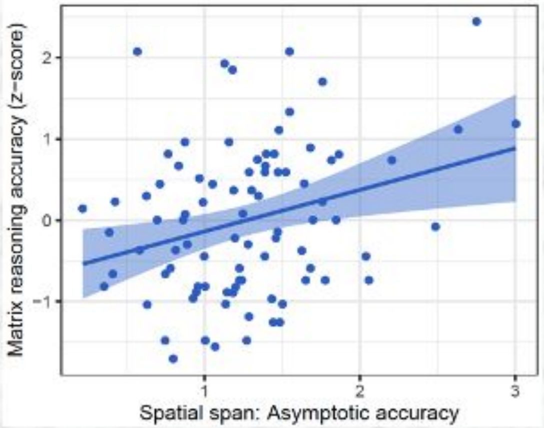
Fluid intelligence as "the ability to learn novel tasks" -- Rate of change in STM accuracy

Robust Pearson $r(85) = -0.30$, $BF_{log2} = 2.36$



Fluid intelligence as "sharing stable process(es) with short term memory" -- Asymptotic STM accuracy

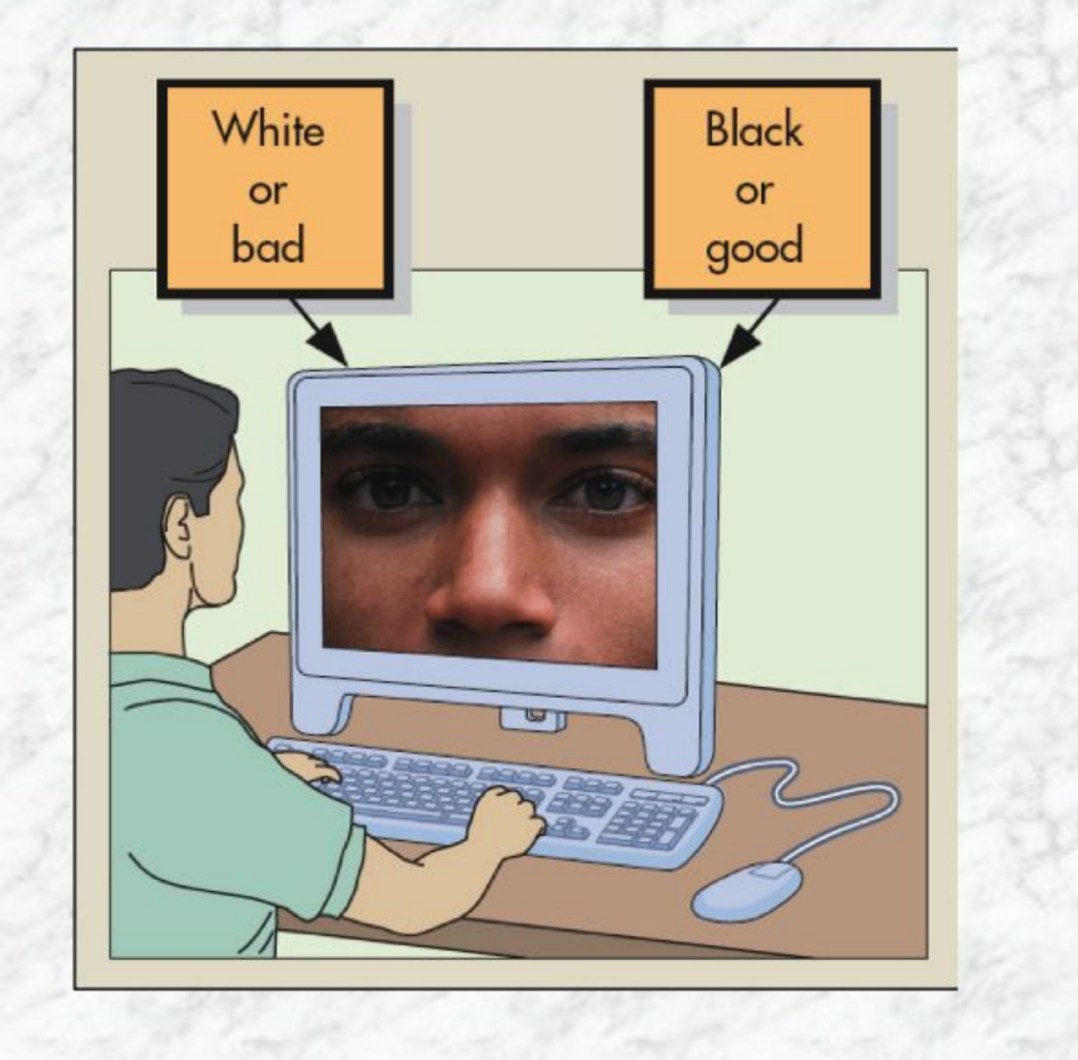
Robust Pearson $r(85) = 0.33$, $BF_{log2} = 3.72$



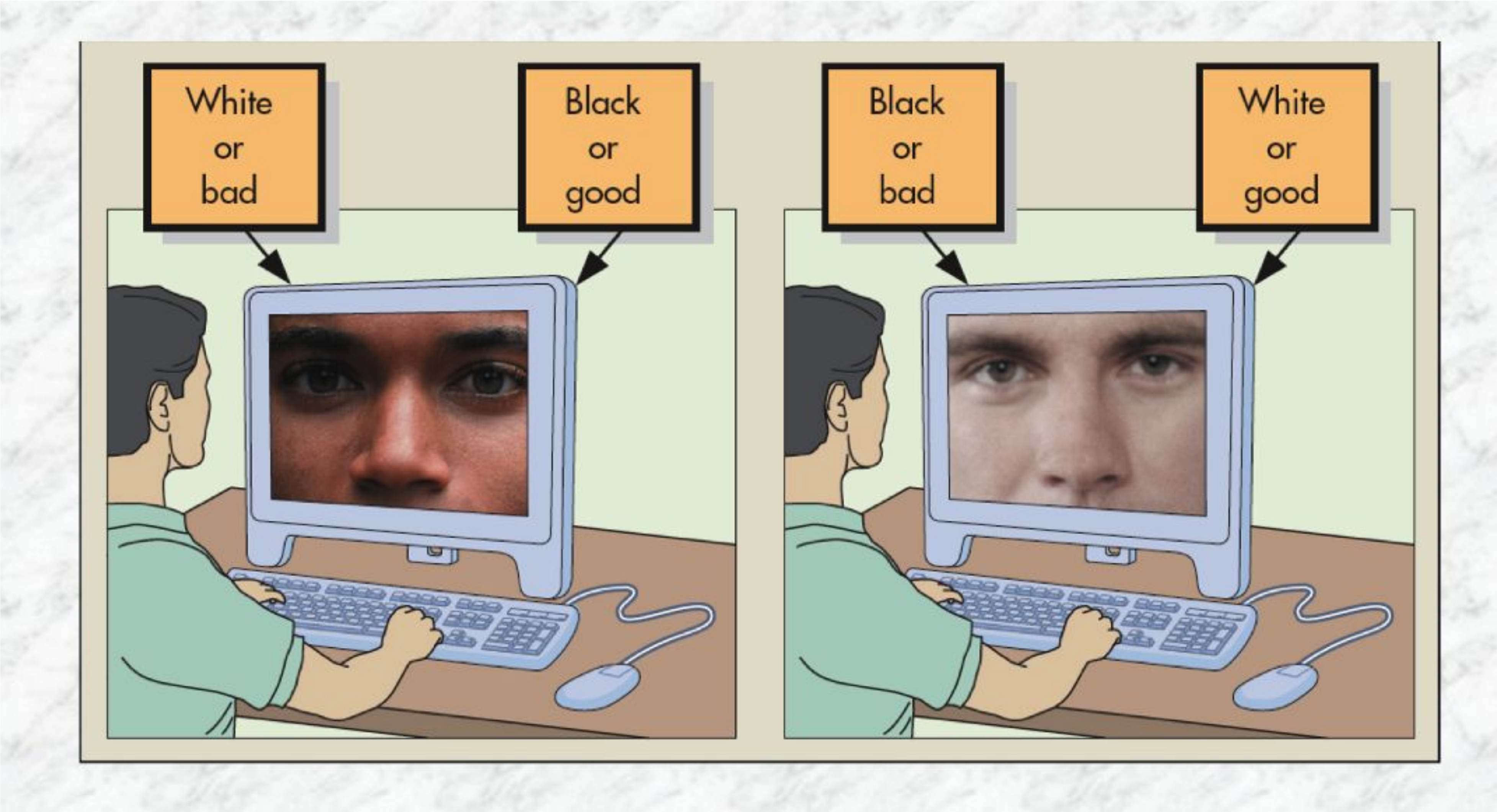
Critically, rate of change and asymptote are not collinear. Appear to be capturing *reasonably* independent variation in intelligence score.

Next Example: The IAT Task

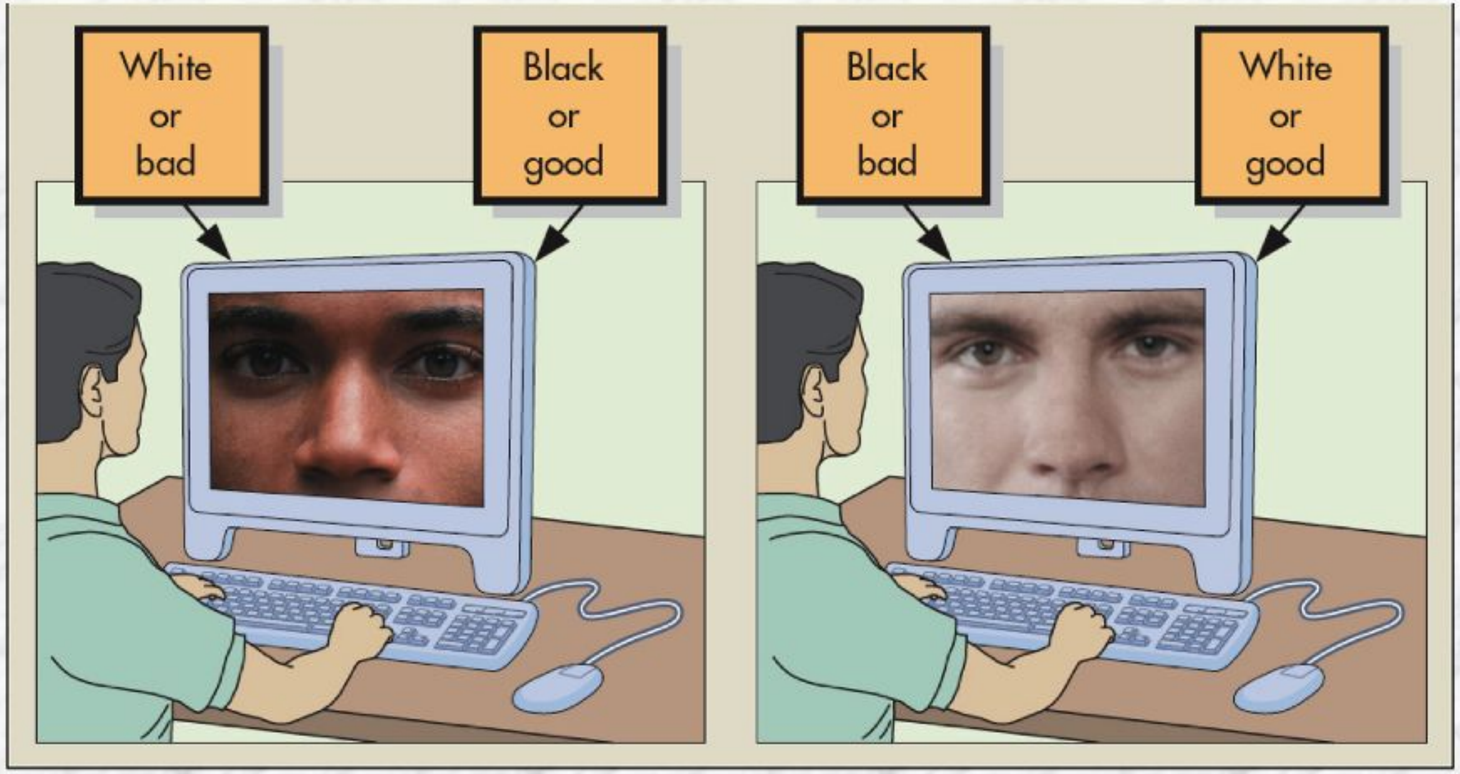
IAT Task



IAT Task



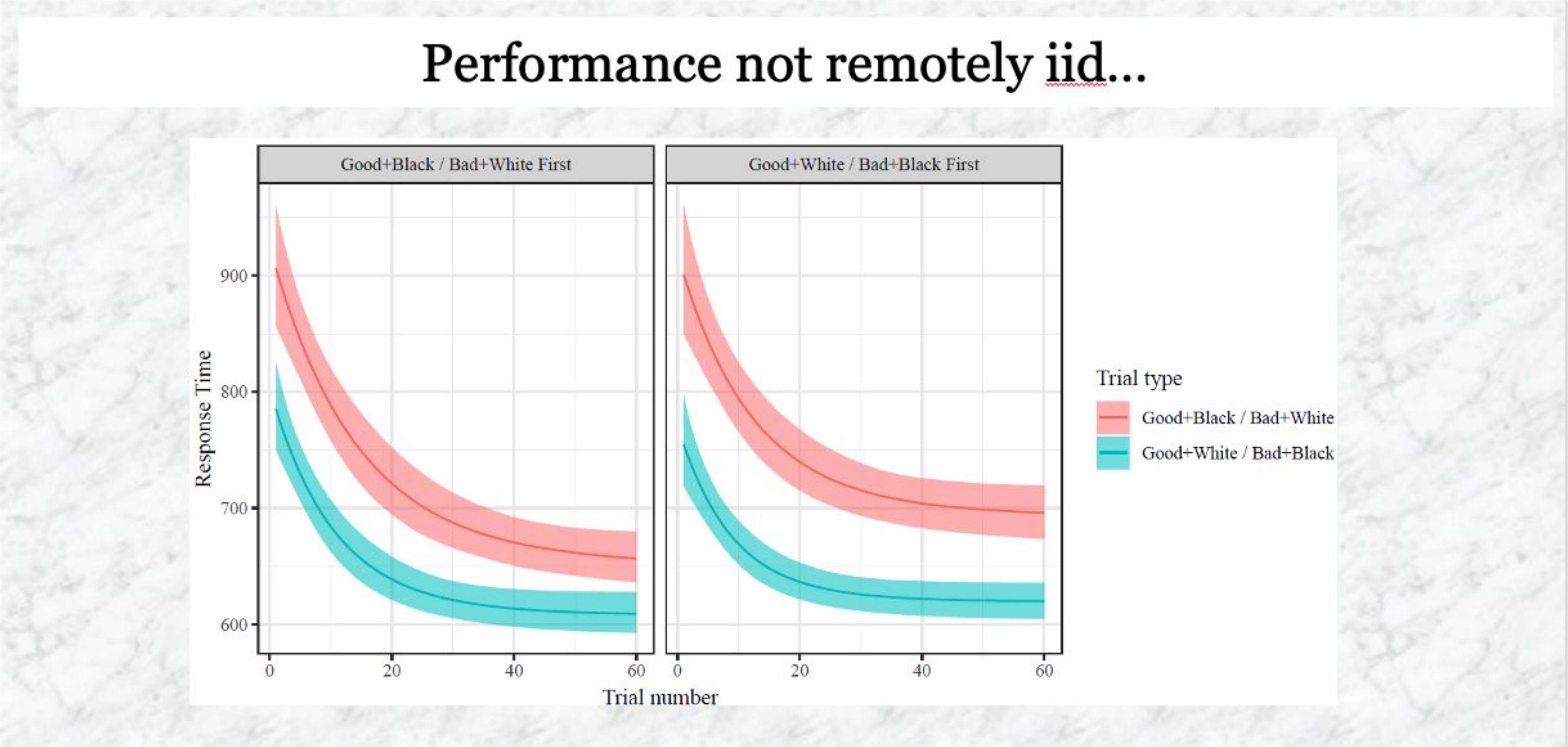
IAT Task



Measure of Implicit Bias =

Average RT in first block type – Average RT in second block type

IAT Task

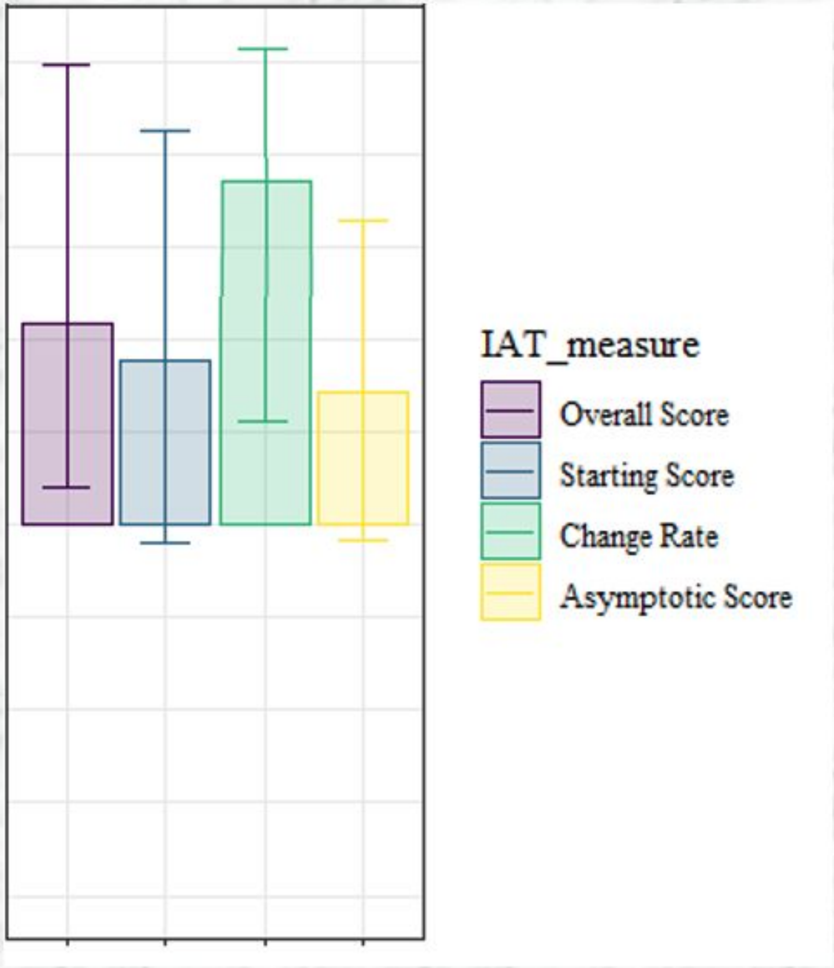

Performance not remotely iid…
Good+Black / Bad+White First
Good+White / Bad+Black First
Response Time
900
800
700
600
0
20
40
60
Trial number
Trial type
Good+Black / Bad+White
Good+White / Bad+Black

IAT Task

Lots of controversy as to whether this implicit bias score predicts any real-world behavior (like seating distance)

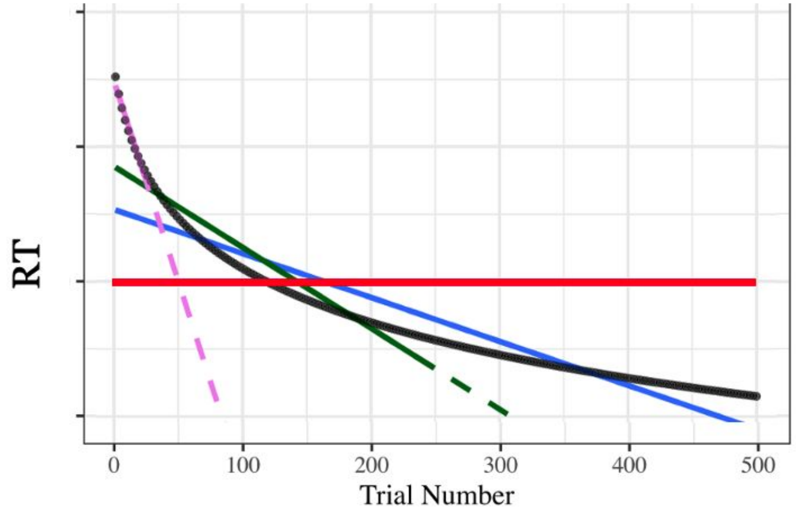
IAT Task

Rate of change best predictor of seating distance...



Why Use Time-Continuous Rather Than Aggregate Approaches?

- Benefits:
  - It's typically just a better description of the data



Journal of Vision (2017) 17(11):3, 1–16

Trial-dependent psychometric functions accounting for perceptual learning in 2-AFC discrimination tasks

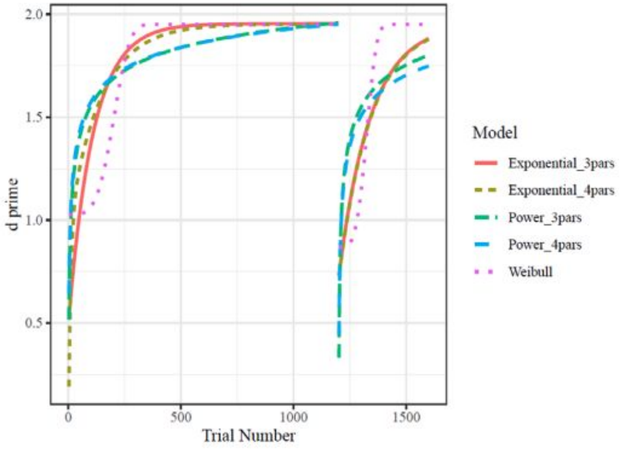
Florian Kattner — Department of Psychology, University of Wisconsin-Madison, Madison, WI, USA; Institute of Psychology, Technische Universität Darmstadt, Darmstadt, Germany

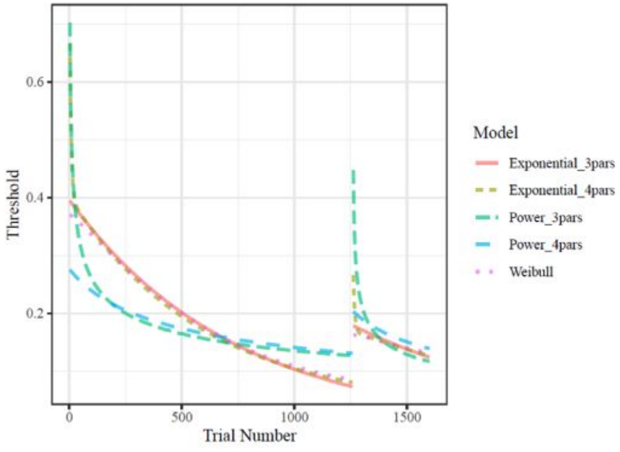
Aaron Cochrane — Department of Psychology, University of Wisconsin-Madison, Madison, WI, USA

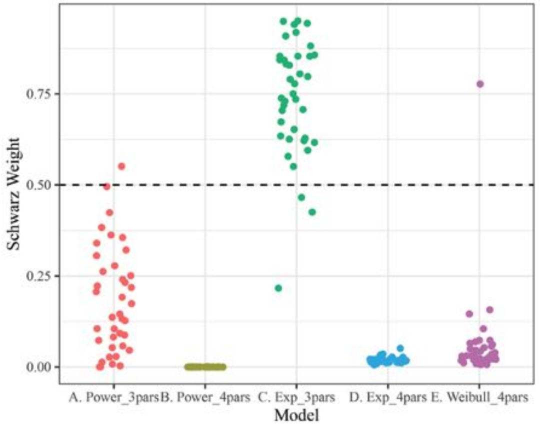
C. Shawn Green — Department of Psychology, University of Wisconsin-Madison, Madison, WI, USA

Why Use Time-Continuous Rather Than Aggregate Approaches?

- **Benefits:**
  - **Allows considerations of functional forms**







Journal of Vision (2021) 21(13):5, 1–16 1

Assessing the functions underlying learning using by-trial and by-participant models: Evidence from two visual perceptual learning paradigms

Aaron Cochrane Faculty of Psychology and Education Sciences, University of Geneva, Geneva, Switzerland

C. Shawn Green Department of Psychology, University of Wisconsin–Madison, Madison, WI, USA

Why Use Time-Continuous Rather Than Aggregate Approaches?

- Benefits:
  - Forces theories to be in the space of human behavior
    - Not just that learning “will” (or “won’t”) generalize – what form does it take?
      - Immediate (transfer)
      - Faster learning (learning to learn)

Current Biology
Report

Perceptual Learning Generalization from Sequential Perceptual Training as a Change in Learning Rate

Florian Kattner,[1,3] Aaron Cochrane,[2,3] Christopher R. Cox,[2] Thomas E. Gorman,[2] and C. Shawn Green[2,4,*]
[1]Institute of Psychology, Technische Universität Darmstadt, Alexanderstr. 10, 64283 Darmstadt, Germany
[2]Department of Psychology, University of Wisconsin–Madison, 1202 West Johnson Street, Madison, WI 53706-1611, USA
[3]Co-first author
[4]Lead Contact
*Correspondence: cshawn.green@wisc.edu
http://dx.doi.org/10.1016/j.cub.2017.01.046

PNAS
CrossMark

Action video game play facilitates the development of better perceptual templates

Vikranth R. Bejjanki[a,b,1], Ruyuan Zhang[a,1], Renjie Li[a], Alexandre Pouget[a,c], C. Shawn Green[d], Zhong-Lin Lu[e], and Daphne Bavelier[a,f,2]
[a]Department of Brain and Cognitive Sciences and Center for Visual Science, University of Rochester, Rochester, NY 14627; [b]Princeton Neuroscience Institute, Princeton University, Princeton, NJ 08544; [c]Department of Basic Neurosciences, University Medical Center, University of Geneva, Geneva CH-1205, Switzerland; [d]Department of Psychology, University of Wisconsin–Madison, Madison, WI 53706; [e]Center for Brain and Cognitive Sciences and Department of Psychology, The Ohio State University, Columbus, OH 43210; and [f]Faculté de Psychologie et des Sciences de l'Education, University of Geneva, Geneva CH-1205, Switzerland

communications biology
ARTICLE
https://doi.org/10.1038/s42003-021-02652-7 OPEN

Action video game play facilitates “learning to learn”

Ru-Yuan Zhang[1,2,3,13], Adrien Chopin[4,5,6,13], Kengo Shibata[4,5], Zhong-Lin Lu[7,8,9], Susanne M. Jaeggi[10], Martin Buschkuehl[11], C. Shawn Green[12] & Daphne Bavelier[4,5]

Why Use Time-Continuous Rather Than Aggregate Approaches?

- Benefits:
  - Forces theories to be in the space of human behavior
    - Not just that working memory task performance is related to fluid intelligence task performance on average
      - Ability to learn new tasks
      - Asymptotic capabilities

npj | Science of Learning

www.nature.com/npjscilearn

BRIEF COMMUNICATION OPEN

Check for updates

Trajectories of performance change indicate multiple dissociable links between working memory and fluid intelligence

Aaron Cochrane[1] and C. Shawn Green[2]

Attention, Perception, & Psychophysics (2021) 83:2241–2255

https://doi.org/10.3758/s13414-021-02268-3

Individual difference predictors of learning and generalization in perceptual learning

Gillian Dale[1] · Aaron Cochrane[2] · C. Shawn Green[2]

Why Use Time-Continuous Rather Than Aggregate Approaches?

- Benefits:
  - Forces theories to be in the space of human behavior
    - Not just "more bias" versus "less bias"
      - How bias changes with experience…

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Article | Open access | Published: 27 September 2023

Robust within-session modulations of IAT scores may reveal novel dynamics of rapid change

Aaron Cochrane, William T. L. Cox & C. Shawn Green

Scientific Reports **13**, Article number: 16247 (2023) | Cite this article

161 Accesses | **1** Altmetric | Metrics

The Issue with Aggregation-Based Analyses

- Benefits:
  - More practical benefits…
    - "Practice trials" unnecessary…

The Issue with Aggregation-Based Analyses

Learning is just one of many factors that make behavioral data non-iid

- Fatigue
- Mind-wandering
- Post-error slowing
- Beliefs about temporal dependence

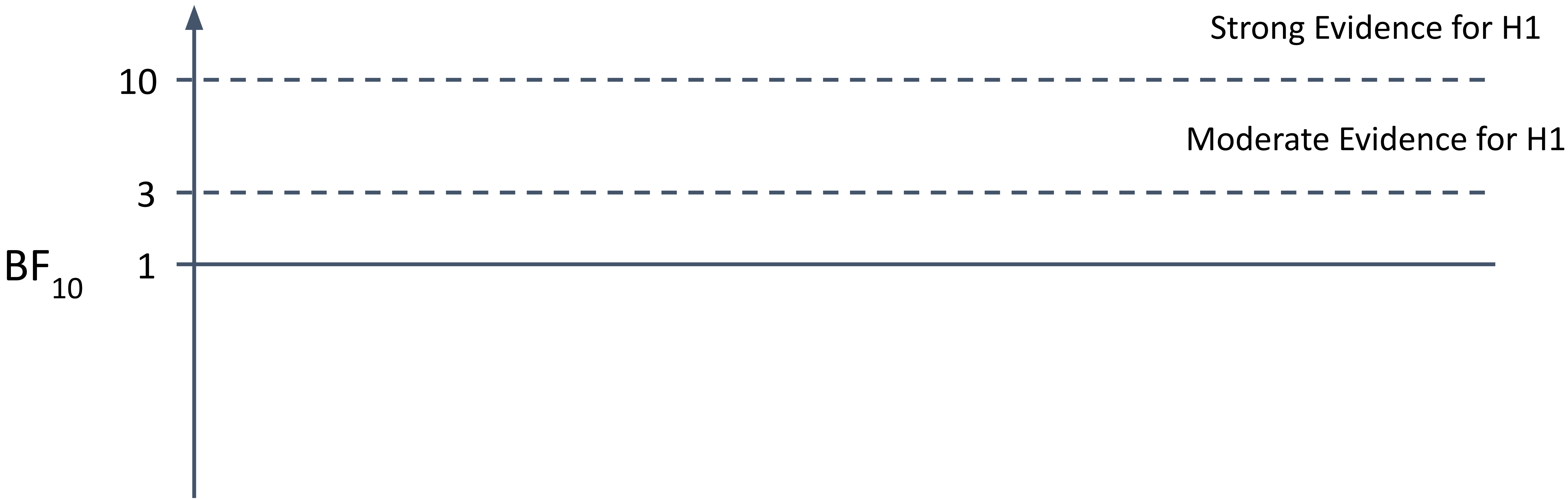
BONUS SLIDES

Enter at your own risks

```
sim.H1 <- BFDA.sim(expected.ES=expected.ES=rnorm(100000, 0.5, 0.1), type="t.paired",
alternative="greater",
                n.min=30, n.max=60, stepsize = 1, boundary=c(1/6, 10),
                prior=list("Cauchy",list(prior.location=0, prior.scale=sqrt(2)/2)),
                B=10000, design = "sequential")

sim.H0 <- BFDA.sim(expected.ES=0, type="t.paired", alternative="greater",
                n.min=30, n.max=60, stepsize = 1, boundary=c(1/6, 10),
                prior=list("Cauchy",list(prior.location=0, prior.scale=sqrt(2)/2)),
                B=10000, design = "sequential")

BFDA.analyze(sim.H1, design="sequential", n.min=30, n.max=60, boundary=c(1/6, 10))
BFDA.analyze(sim.H0, design="sequential", n.min=30, n.max=60, boundary=c(1/6, 10))


plot(sim.H1, n.min=N_min, n.max=N_max, boundary=boundaries_test)
plot(sim.H0, n.min=N_min, n.max=N_max, boundary=boundaries_test)
```

Sequential Bayes Factor Design

I.e. when should I stop recruiting participants?



Schönbrodt, F. D., & Wagenmakers, E.-J. (2018). Bayes factor design analysis: Planning for compelling evidence. Psychonomic Bulletin & Review, 25(1), 128–142. https://doi.org/10.3758/s13423-017-1230-y

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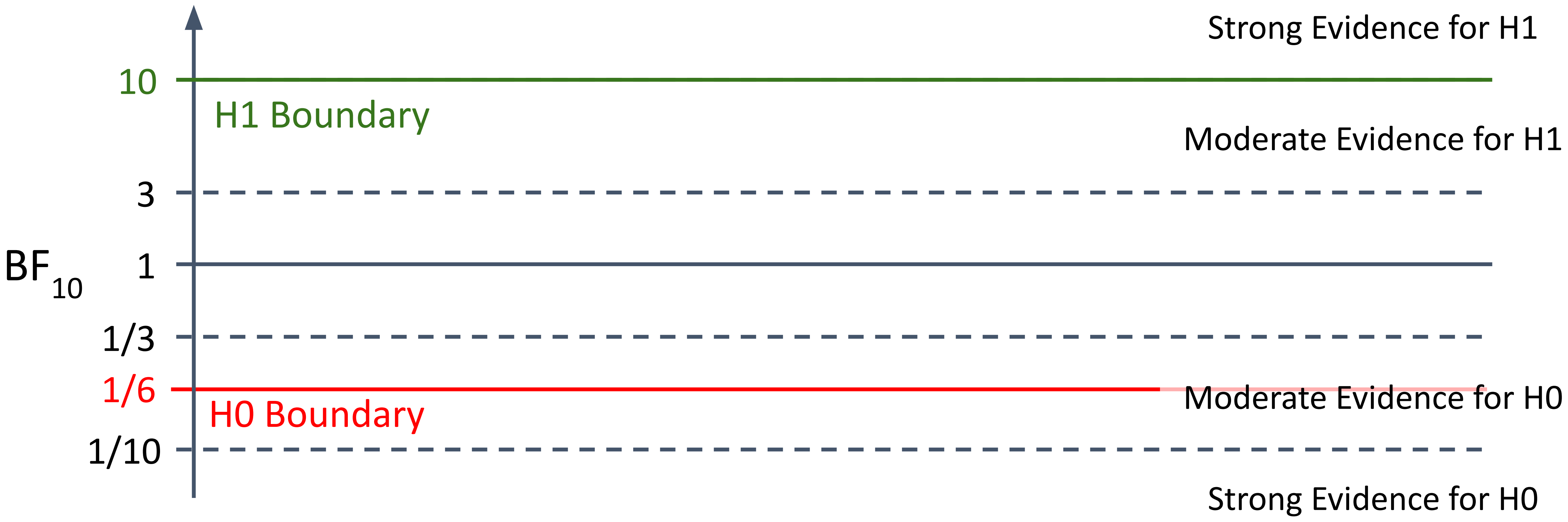

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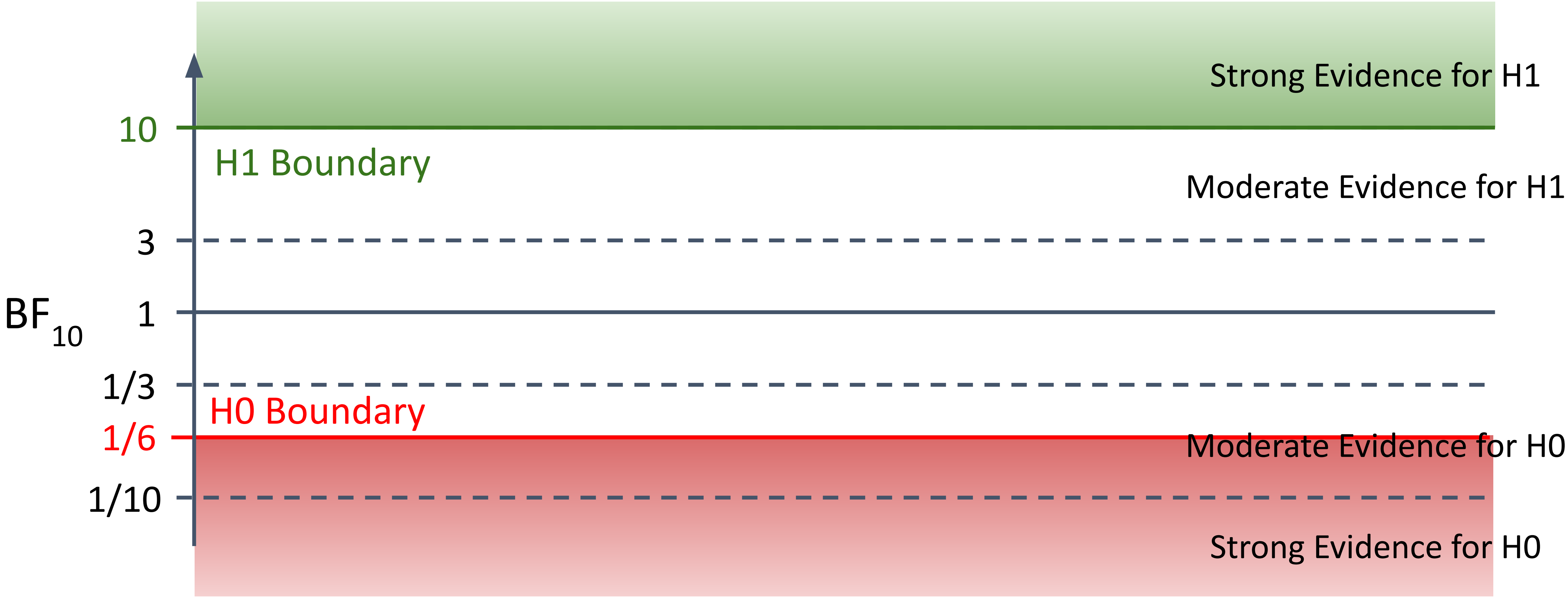

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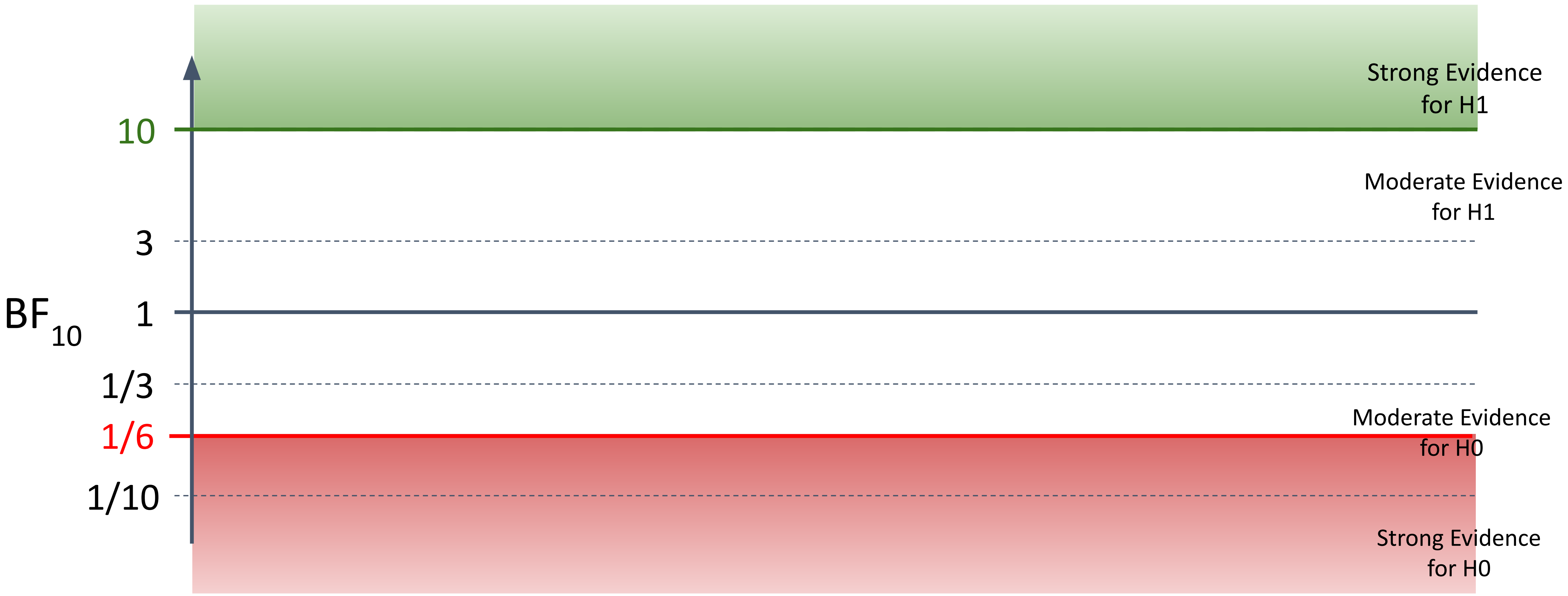

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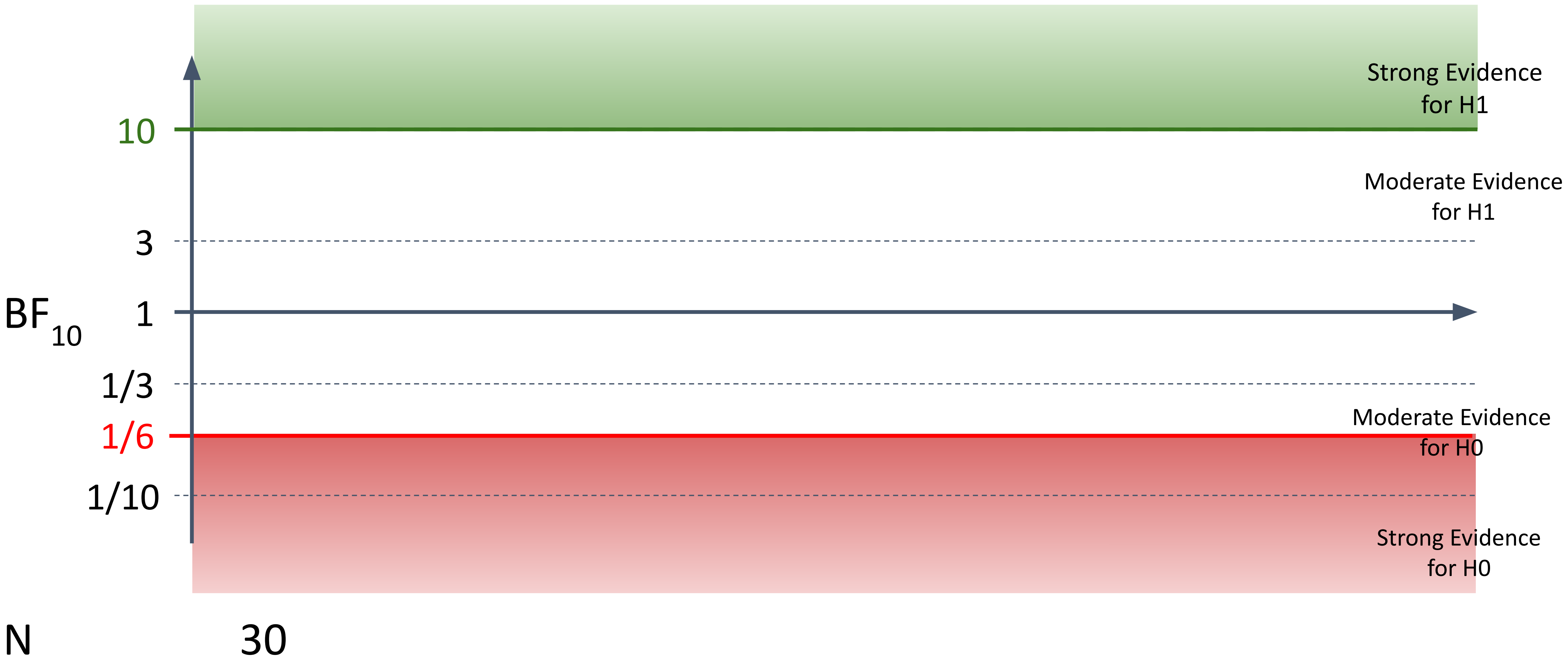

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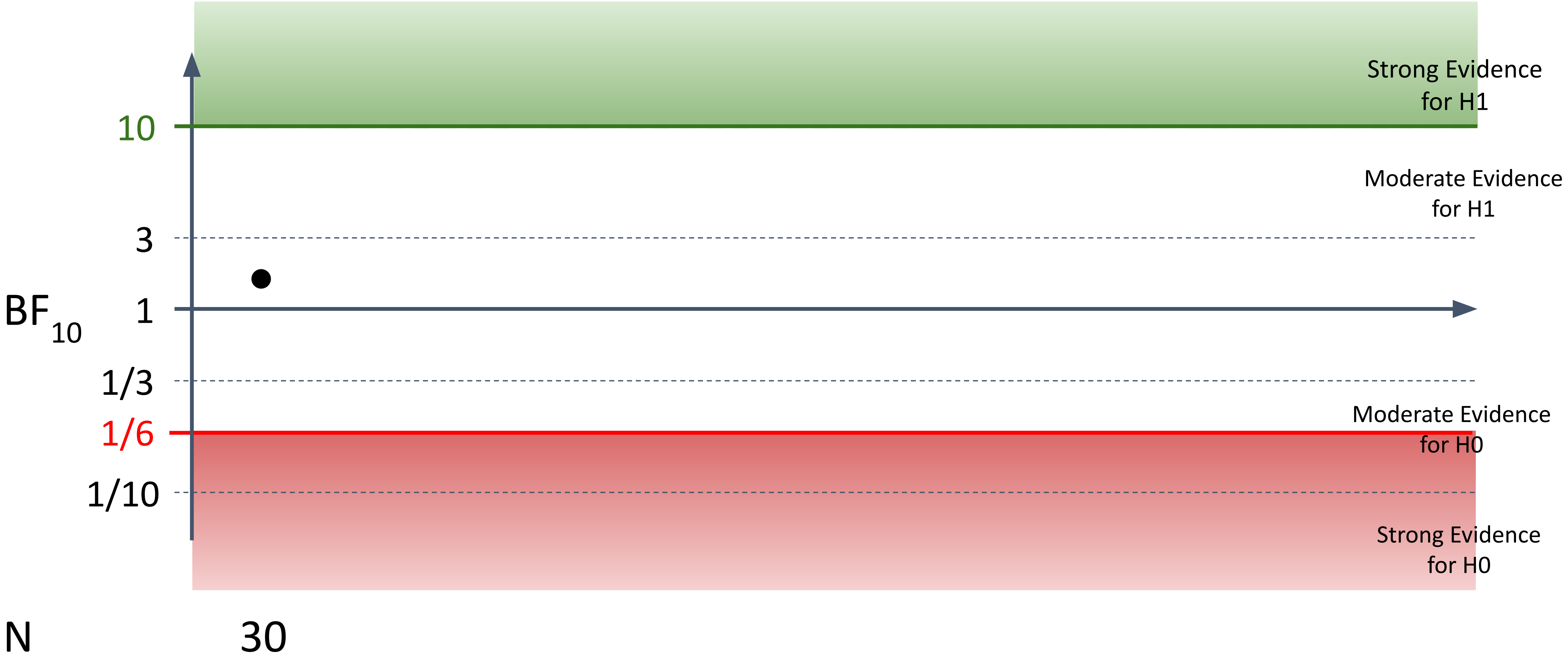

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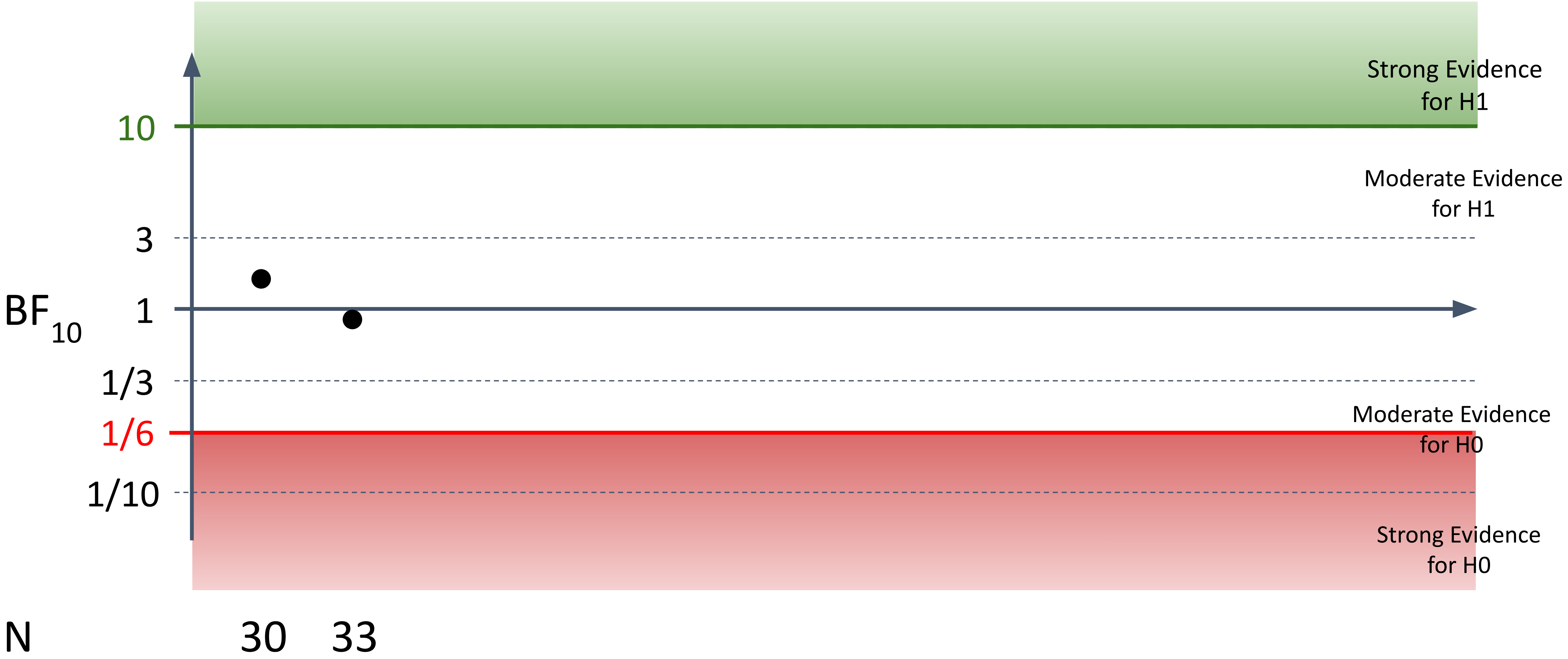

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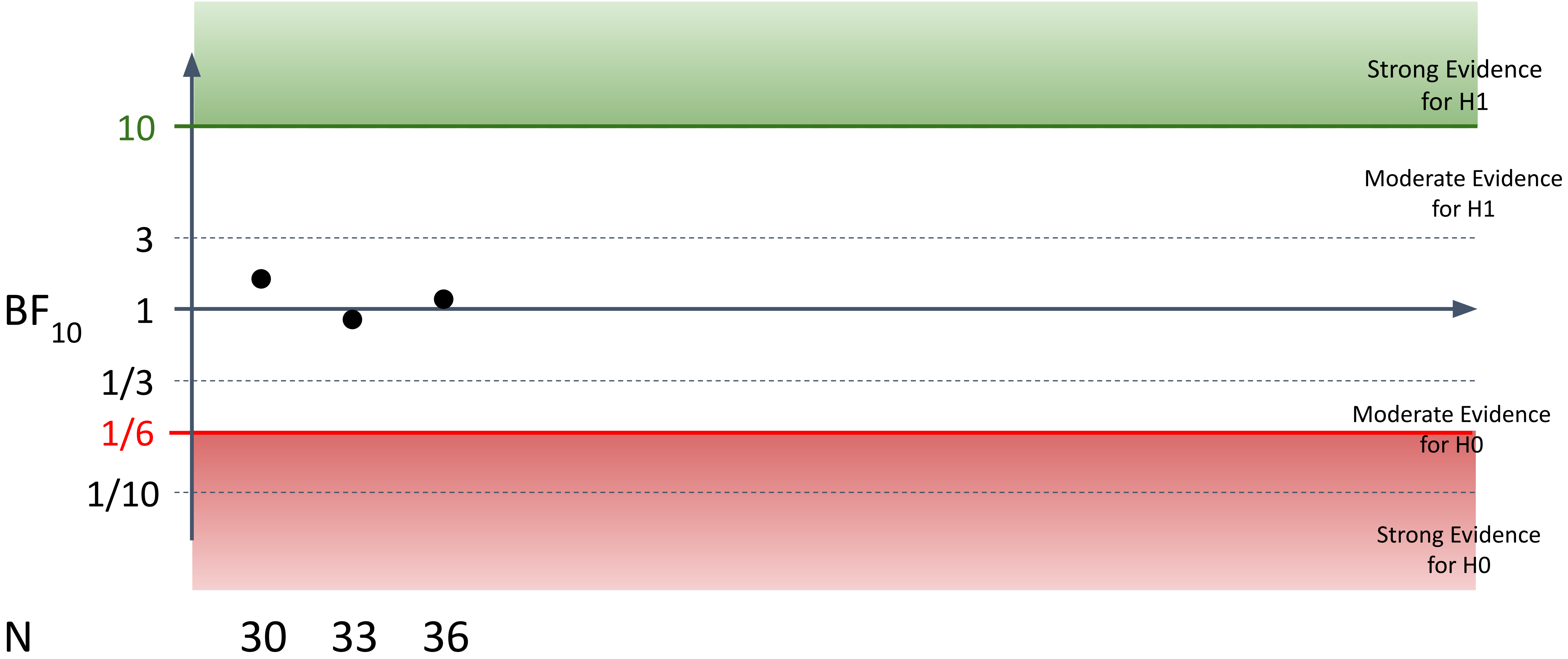

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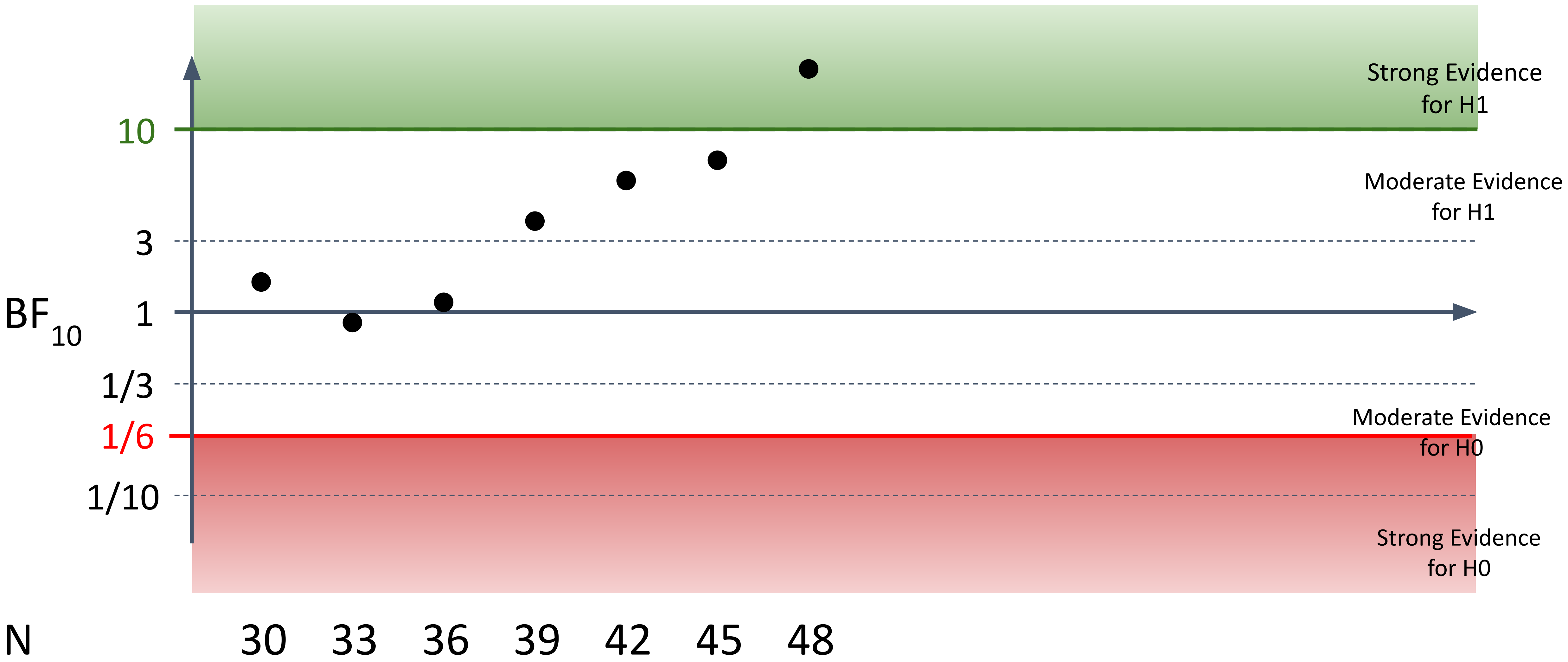
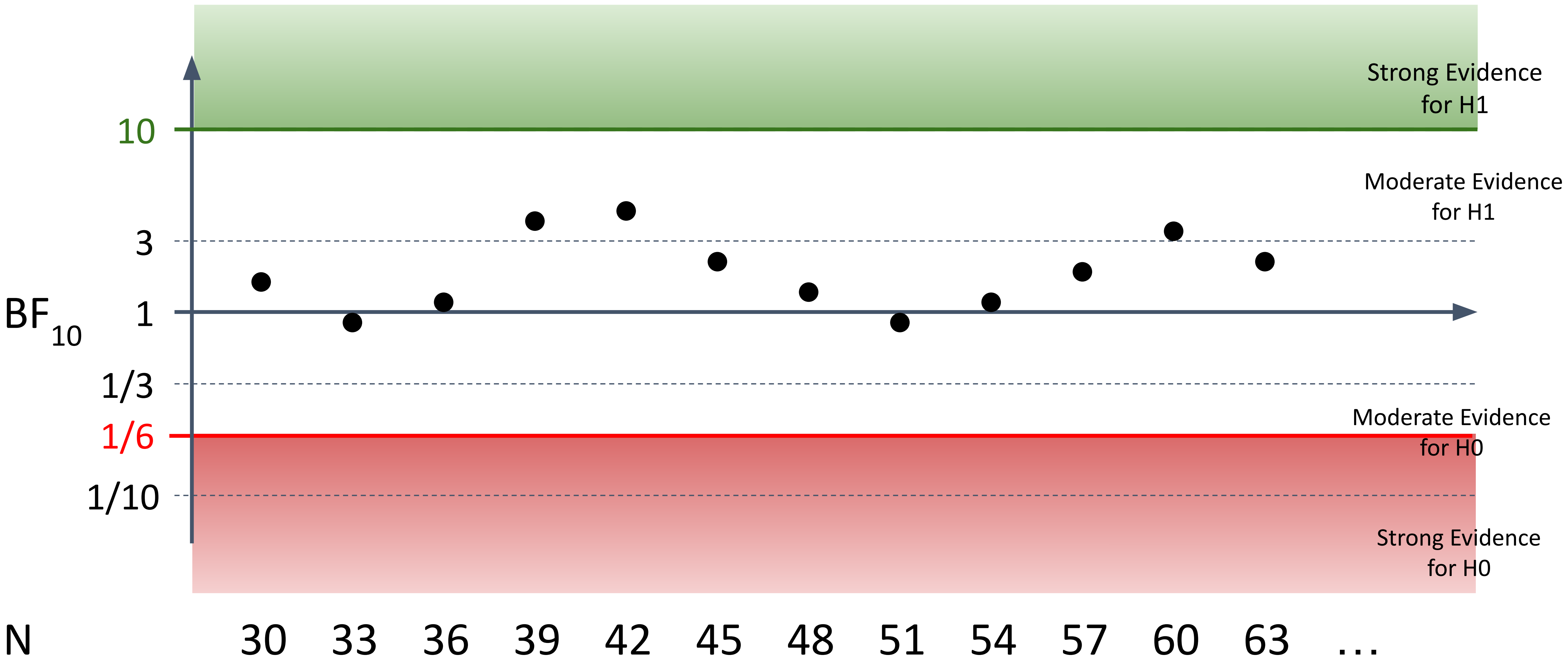


Sequential Bayes Factor Design With Max N

I.e. Can I stop recruiting now? Pleeeease…



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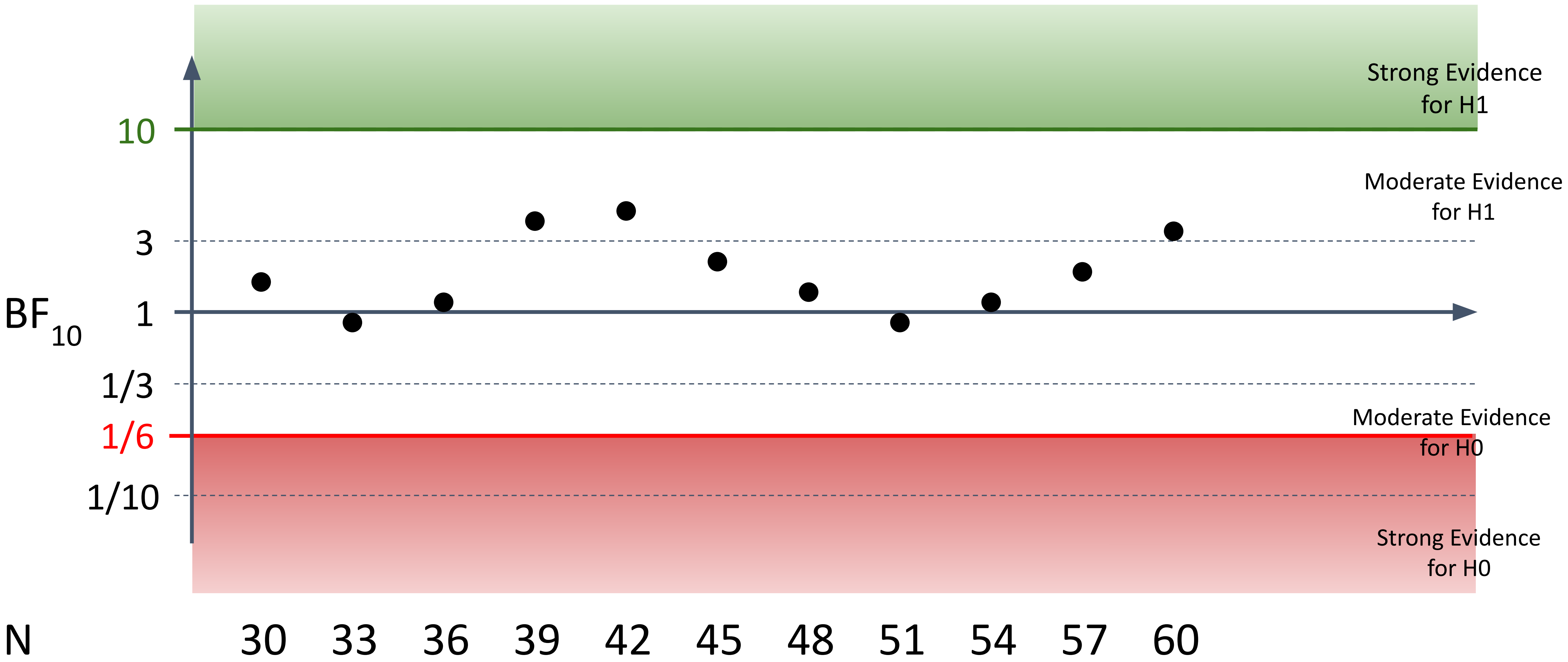

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