Developing an interdisciplinary research experience for undergraduates in computational mathematics

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Department of Psychological Sciences

PERS Symposium 2022

(shameless plug...available early April 2022)

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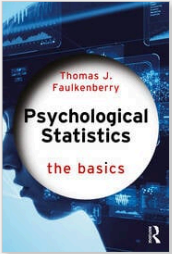

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Psychological Statistics

The Basics

By Thomas J. Faulkenberry

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CMAT: Computational Mathematics at Tarleton

Since 2019, we have hosted a summer REU (Research Experiences for Undergraduates) program in computational mathematics.

Primary funding has been through the MAA NREUP (National Research Experiences for Undergraduates Program), but this past summer, we were able to expand our capacity thanks to a PERS grant.

Research mentors:

- Dr. Tom Faulkenberry (PI, Psychological Sciences)
- Dr. Scott Cook (Co-PI, Mathematics)
- Dr. Chris Mitchell (Co-PI, Mathematics)

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Project goals:

1. provide students with an intensive summer research experience in the mathematical and computational sciences at Tarleton State University.
2. assist with the successful transition between lower-division and upper-division STEM coursework.
3. increase persistence rates in STEM, thus increasing the number of students who may subsequently enroll in STEM graduate programs.

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Research areas:

- Mathematical psychology (Faulkenberry)
  - modeling cognitive processes by developing better tools to describe response times in cognitive tasks
- Mathematics versus gerrymandering (Cook)
  - developing Markov Chain Monte Carlo methods for comparing political redistricting maps
- Mathematical modeling of disease spread (Mitchell)
  - using ordinary differential equations to understand dynamics of disease spread

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Summer activities designed to help students transition from dependent learners to independent researchers. To do this, we use the classic Polya model of problem solving as a model:

1. Understanding the problem
2. Devising a plan of attack
3. Carrying out the plan
4. Reflecting on the work

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Stage 1: Understanding the problem (weeks 1-2)

- daily workshop focusing on computational tools (e.g., R, Python, Mathematica)
- daily workshop focused on getting up to speed in specific research area
- students begin to build good research habits

Stage 2: Devising a plan of attack (weeks 3-4)

- mentors transition away from direct instruction – begin acting as advisor/colleague
- concludes with seminar style meeting where students present research problem and plan of attack

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Stage 3: Carrying out the plan (weeks 5-6)

- mentors step away – students check in daily, but work is almost entirely theirs
- hardest phase of the summer!

Stage 4: Reflecting on the work (weeks 7-8)

- begin writing up results / learning scientific authoring tools (e.g., LaTeX, RMarkdown)
- final "conference" where students give full presentations on their work

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Project alumni:

- Kierah Caldwell
- Cody Drolet
- Brandon Garcia
- Hakiem Grant
- Claire Jean Baptiste
- Dashon Mitchell
- Vianey Rangel
- Bethany Rothrock
- Kaylee Terrell
- Bella Zapata

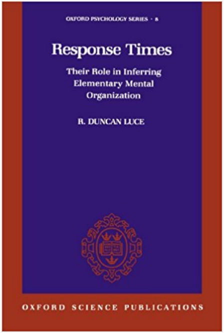
Collaborators:

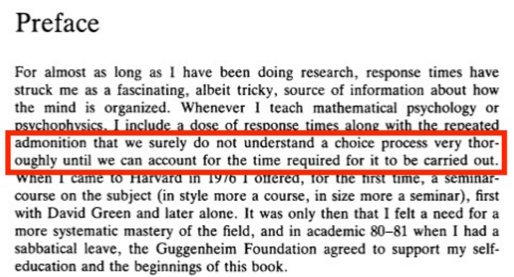
- Kristen Bowman
- Mihaela Codreanu
- Dr. Christopher Cox
- Jaryd Domine
- Aurod Ousinegad
- Nicholas Petela
- Bryanna Scheuler

Some results from my Summer 2021 mathematical psychology group

Response times

Response times are a classic measure of cognitive processing





Preface

For almost as long as I have been doing research, response times have struck me as a fascinating, albeit tricky, source of information about how the mind is organized. Whenever I teach mathematical psychology or psychophysics, I include a dose of response times along with the repeated admonition that we surely do not understand a choice process very thoroughly until we can account for the time required for it to be carried out. When I came to Harvard in 1976 I offered, for the first time, a seminar-course on the subject (in style more a course, in size more a seminar), first with David Green and later alone. It was only then that I felt a need for a more systematic mastery of the field, and in academic 80–81 when I had a sabbatical leave, the Guggenheim Foundation agreed to support my self-education and the beginnings of this book.

Response times

In cognition, RTs inform our understanding of latent processes involved in various decision-making tasks.

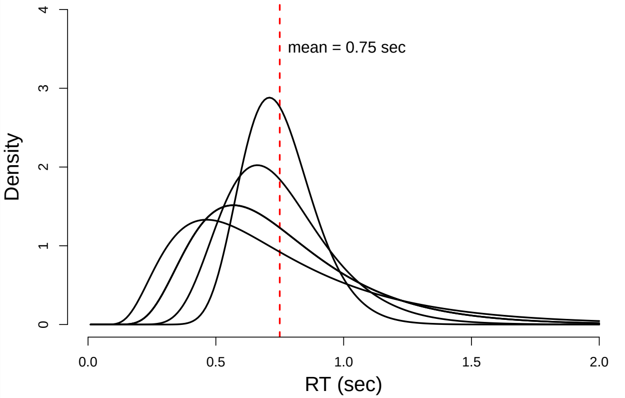
Classical technique:

1. have people do a bunch of trials – measure RT on each trial
2. find mean RT for each experimental condition / person
3. test for differences in means (e.g., ANOVA)

This method is lossy. . . it collapses each person's RT distribution to a single number

RT distributions

The mean does not uniquely identify the distribution – same mean, different behavioral signatures



RT distributions

Need a way to capture the distribution of response times.

Some highlights from this summer:

- Decomposing the flanker effect with an ex-Gaussian model (Mihaela Codreanu)
- Decomposing the unit-decade compatibility effect with the drift diffusion model (Bella Zapata)
- Using parameter recovery methods to assess the validity of classical maximum likelihood estimation as a technique for fitting shifted Wald models (Bryanna Scheuler)

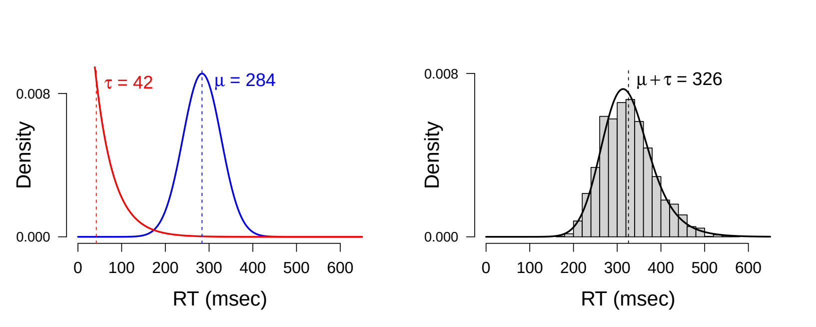
ex-Gaussian decomposition

The ex-Gaussian model decomposes a positively-skewed distribution of response times into two components:

- a normal (Gaussian) component with mean μ
    - duration of sensory/motor processes (Hohle, 1965)
    - stimulus driven automatic (nonanalytic) processes (Balota & Spieler, 1999)
- a exponential "tail" component with mean τ.
    - duration of decisional phase of RT (Hohle, 1965)
    - central attention demanding (analytic) processes (Balota & Spieler, 1999)

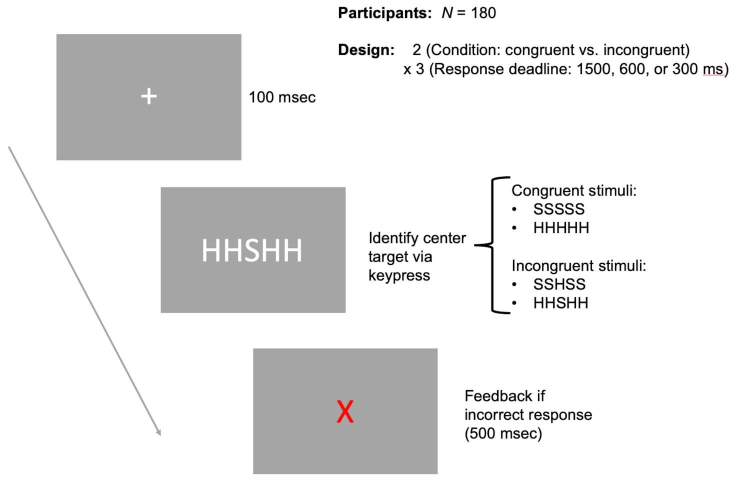
ex-Gaussian decomposition

These two components are then combined (via the mathematical operation of convolution) into a single ex-Gaussian distribution with mean $\mu + \tau$.



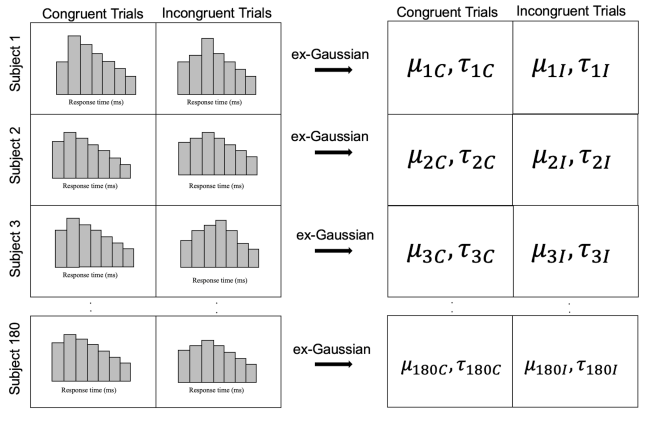
Mihaela’s project

Flanker task:



Mihaela's project

Mihaela collapsed 43,200 trials into 180×2 design cells, then used classical maximum likelihood estimation to extract estimates of μ and τ:



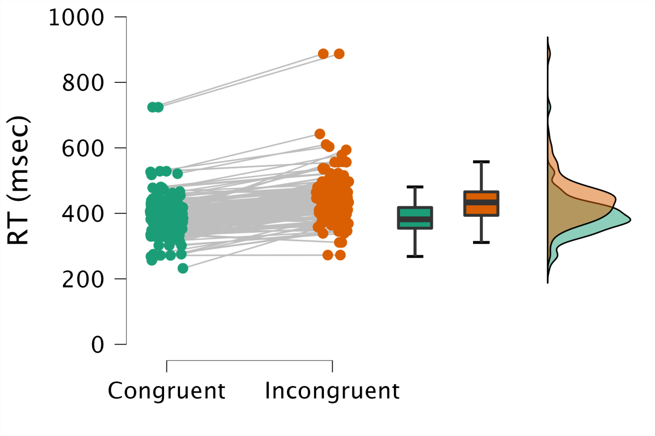
Mihaela's project

Where's the effect?

- In the normal component mean μ?
  - if so, flanker effect is nonanalytic (i.e., automatic / cannot be controlled)
- In the tail component mean τ?
  - if so, flanker effect is analytic (i.e., can be controlled)

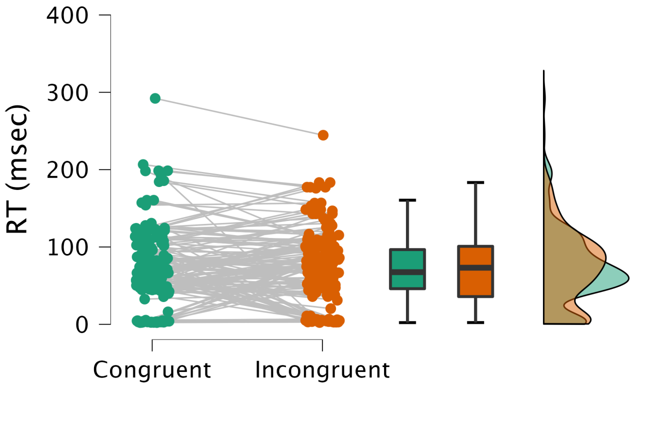
Mihaela's project

Here's what she found; there's a reliable, consistent increase in μ on incongruent trials:



Mihaela's project

..but not in τ:



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Thanks to PERS, we were able to expand the reach of our REU program and impact a lot more students. The students you've seen in today's poster sessions have not only done good science, but more importantly, they've each gained real, concrete scientific skills that they will take with them throughout their careers.

Thank you!