Computational Cognitive Science

Lecture 18: Recap, Q&A

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Reading

Wilson, Robert C., and Collins, Anne GE. (2019). "Ten simple rules for the computational modeling of behavioral data" (link)

Computational modelling in cognitive science

Today:

- Run through the process of developing and using computational models in cognitive science
- Point out connections to past lectures
- Introducing some opportunities for further study. (*)

Steps

0. What is our scientific question or hypothesis?
1. Techinical design
   - Experiment
   - Model(s)
   - Analysis
2. Simulation-based checks and updates
3. Run experiments
4. Conduct analyses
5. Follow-ups and extensions
6. Sharing results

0. What is our scientific question or hypothesis?

Examples:

- "Perceptual decision-making is based on a process of sequential evidence accumulation" (Lecture 1)
- "We categorize new things by comparing them to {exemplars,prototypes} from our experience" (Lecture 1)
- "Anxious individuals have difficulty learning the causal statistics of aversive environments"
  - Browning et al. 2015

1. Design experiment/model/analysis

Your experiments, models, and analyses are interconnected — design decisions in one have implications for the others.

E.g.,

- Many parameters of interest $\Rightarrow$ many data points.
- Individual differences analysis $\Rightarrow$ many data points per participant.
- Intractable likelihoods $\Rightarrow$ no Bayes factors (probably).

1A. Design experiment(s)*

- Good experiments are hard to design — part of why BOED is a powerful tool.
- We have discussed ways to evaluate an experimental design (e.g., Lecture 17).
  - But not so much the art itself.
  - Sometimes a simple elaboration on an earlier design.
  - Sometimes inspired by watching/reflecting on everyday behavior.
- Have both the model and the analyses in mind; avoid temptation to design complex "fishing expedition" studies.

1B. Design computational model(s)

Desiderata:

- Simplicity is good (Lecture 7) but don't overdo it
  - "nuisance parameters" like left/right bias can help detect interesting patterns
- Makes precise predictions (Lecture 2)
- Interpretable
- Tractable: Make sure you can fit/compare your models on the computers you have

1B. Design computational model(s)

There are many kinds of models.

Recall Marr's taxonomy (Lecture 1)

1. Computational-level
   - Often frames cognition as Bayesian inference/decision theory
   - but not necessarily probabilistic in the F&L sense
   - "Rational", "Ideal-observer" models

1B. Design computational model(s)

2. Process-level
   - Often constrained/inspired by computational-level models.
   - e.g., approximations of computational-level models
   - e.g., Rescorla-Wagner
   - e.g., Random-walk
   - e.g., Nosofsky's categorization model
   - . . . most models

1B. Design computational model(s)

3. Implementation-level
   - Often constrained/inspired by process-level models.
   - "Pure" implementation-level models are rare in higher-level cognition

1B. Design computational model(s)

New models $+$ baseline/alternative models.

Alternatives are most often

1. "Lesioned" versions of the main model (often nested within main model; Lecture 7)
2. Competing proposals from the scientific literature.
3. A random-guessing baseline.

These should capture salient competing hypotheses.

1C. Plan data analysis

Decide how models will be compared and evaluated **before** collecting data.

1C. Plan model comparison/parameter estimation

- Parameter estimation (Lectures 3-5)
- Model selection (Lectures 7-8)
- Individual differences analyses (Lecture 6)

Always connect analyses to psychological questions/claims.

1C. Plan model-free analyses*

Many hypotheses/theories entail simple and distinctive predictions, e.g.,

- "$x > y$"
- "corr(x,y) > 0"

You should plan to run and report direct tests of these predictions.

- Can help convince skeptical and less technically-sophisticated audiences
- Computationally inexpensive
- Models can fit badly for many reasons; model-free analyses can suffice to make a point

2. Simulate data

Almost all cognitive models are **simulator** models; we can run them through a hypothetical experiment and what the data will look like.

1. Sanity-check our models. Do the data look implausible?
2. Run our planned analyses, using sample sizes from our planned experiment(s).

(Lecture 8)

2. Simulate data

Fake-data simulation + analysis can answer many questions:

- Can we come to meaningful conclusions, regardless of which model is actually true*?
- How often do we pick the true model or make a correct inference about θ? (power)
- How often do we come to a spurious conclusion?
- Addresses identifiability in theory and practice.

:) $\rightarrow$ Collect data[1].

:($\rightarrow$ Redesign our models or experiments.

[1] but consider pre-registering first!

3. Run experiment*

Implementing and running experiments is an important topic in its own right.

- Often learned "on the job", e.g., honours or MSc project.
- Tools are numerous and change often.
- Not a focus of our course.

4A. Execute analysis plan

This should be straightforward after Steps 1C and 2!

Do not be disheartened by:

- High individual variability, e.g., in what model explains a participant's behavior.
- No model "winning" decisively.
- Unexpected patterns in data.

Aspire to have something useful and true to say, not to explain everything that might be happening.

4B. Validate winning model(s)*

Not discussed in the course, but increasingly recognized as important.

The best model of those considered may not be a **good** model.

One way to address this concern: Posterior predictive checks: Sample from posterior of fitted model; compare to data.

5. Follow-ups and (post-hoc) model extensions*

Sometimes it is clear where a model went wrong, and a simple change can fix it.

Running additional analyses using modified models is fine — but be honest about it and report both sets of analyses.

6. Disseminating/sharing your results*

Report everything that was in your plan (somewhere).

Additional analyses are fine, but should be noted as such.

- Results of fake-data simulation: Confusion matrices and parameter recovery plots.
- Overall model fits, e.g., BIC/crossVal scores, Bayes factors,
- Fits/posterior estimates for parameters.
- Number of individuals best fit by each model.
- Model-free inferential stats.

Q&A