Introduction to Computational Cognitive Modeling

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UC Berkeley
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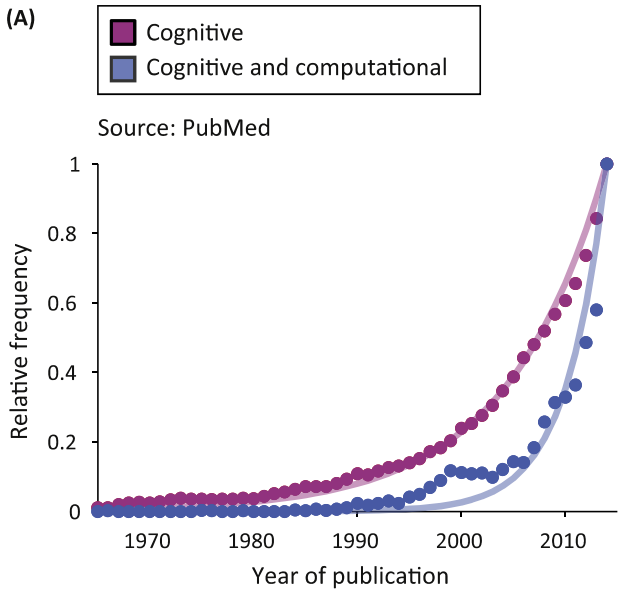
Slide credits to Anne Collins

Computational modeling is useful

- Precise, testable quantitative predictions
- Descriptive, but also generative/mechanistic explanations
  → Cognitive scientists and cognitive neuroscientists
- Relate neural function to mechanisms giving rise to behavior
  →Cognitive and behavioral neuroscientists
- Summarize individual differences into interpretable variables
  → Development, computational psychiatry

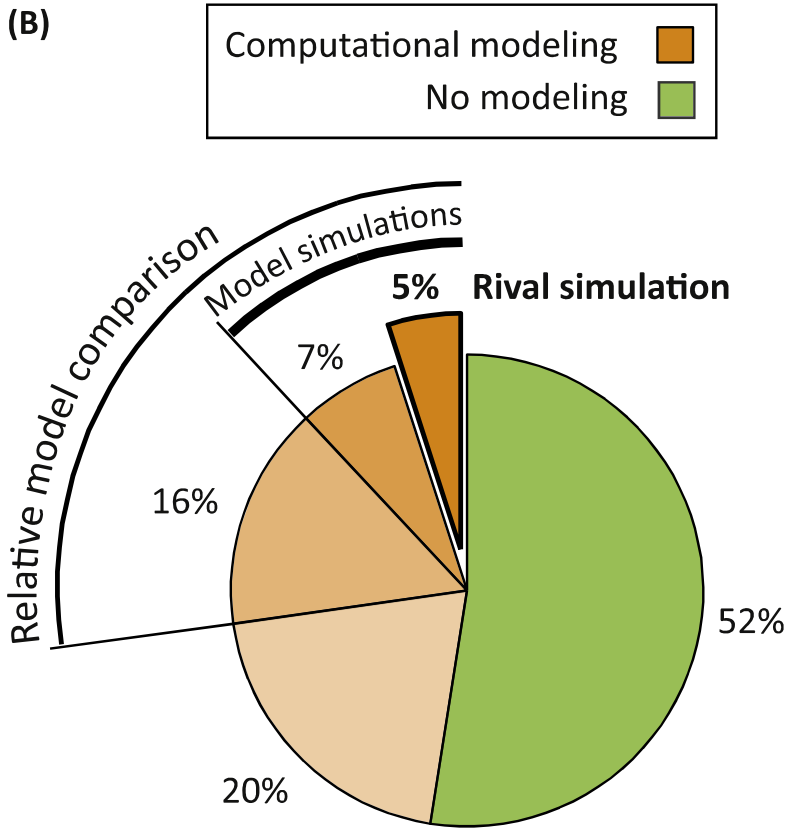


Palminteri et al, 2017

Computational modeling can be dangerous

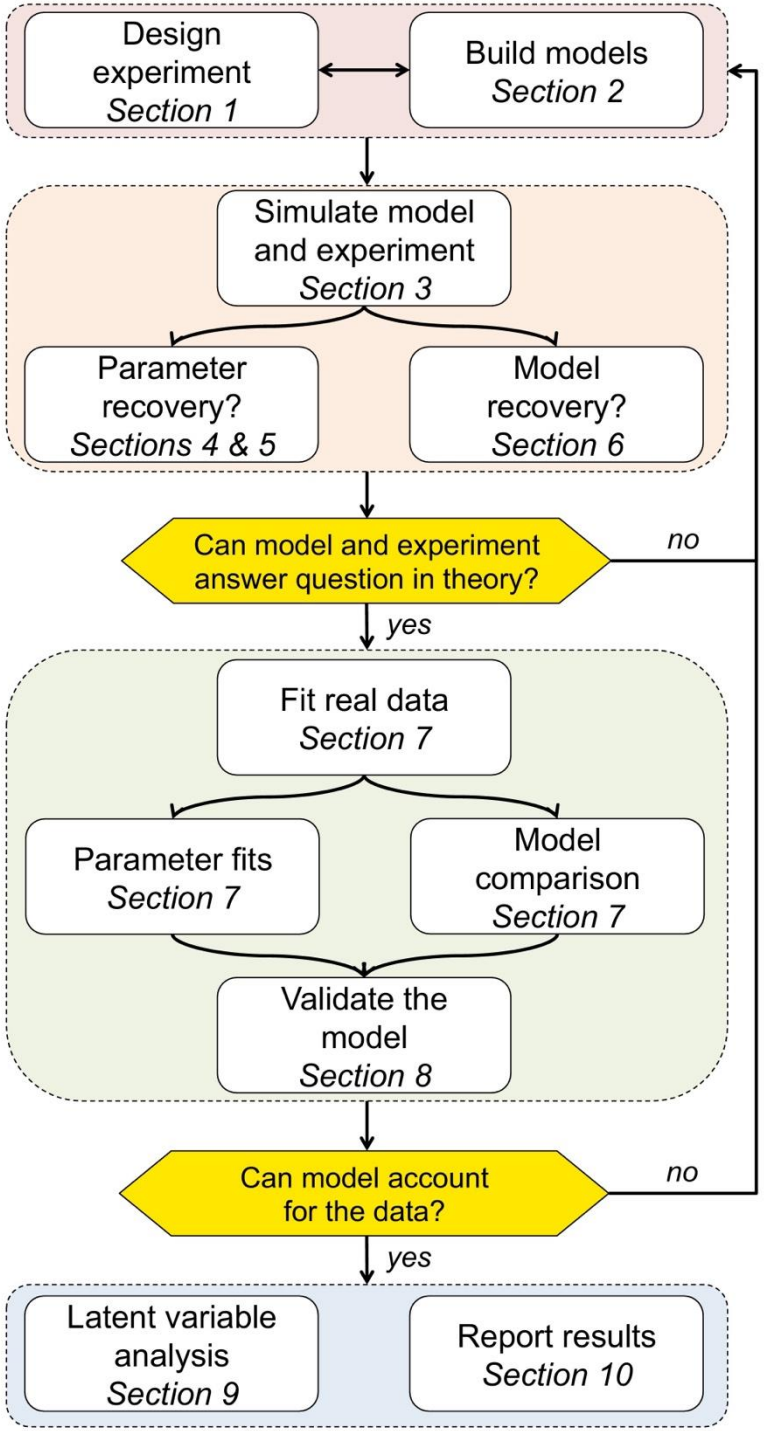
- It's important to understand the basics very well and all the potential pitfalls (the goal of this talk!).

- More bad than good examples in the literature. Be careful!



Palminteri et al, 2017

Life cycle of a modeling project



Wilson et al, 2019

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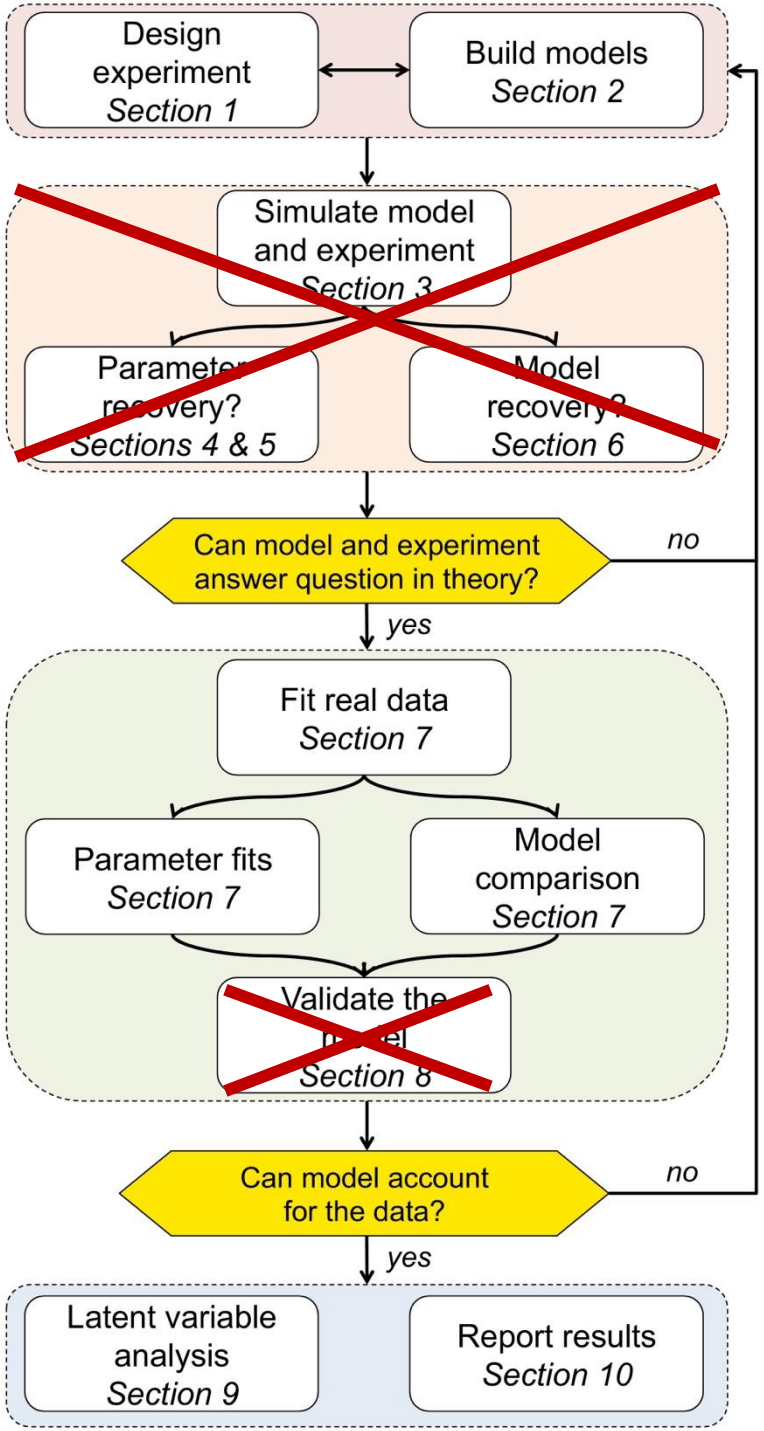


Wilson et al, 2019

Steps

1. Data analysis
2. Model simulation
   - Role of model parameters
   - Setting up models representing competing hypotheses
3. Parameter estimation (model fitting)
4. Model comparison
5. Model validation
6. Improving models

Data analysis and model simulation

- First step: data analysis. Know your data set!
  - What questions are you trying to ask?
  - What questions can you answer in a model-independent way?
  - What questions is your protocol not designed to answer?
  - How do participants behave?

RL example

Two uncertainty levels

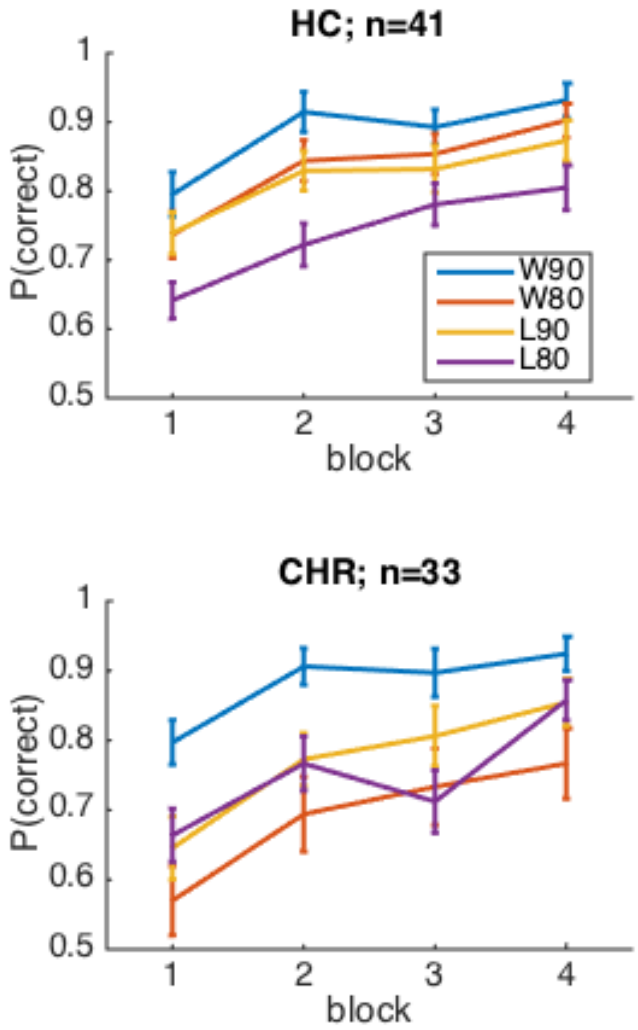
	90%	80%
Win: $0.05 vs. 0	AB	CD
Lose 0 vs. -$0.05	EF	GH

- All conditions interleaved
- 4 blocks of 4*10 = 40 trials

- 41 youths at risk for schizophrenia
- 33 matched controls

Waltz et al 2012

Preliminary behavioral results, modeling targets



- ***Question:*** Do we learn differently from seeking gains vs. avoiding losses? Do youths at risk for schizophrenia learn differently from matched controls?
- Behavior:
  - Learning from ***losses*** is slower than learning from ***gains***
  - Effect of ***uncertainty*** on learning is different in the gain and loss domains for High Risk individuals
  - → two modeling targets

Collins & Strauss

2. model simulation

- A: model building
  - Develop a model that represents your main hypothesis
  - Develop competing models

$$Q_{t+1} \leftarrow Q_t + \alpha \, RPE$$
$$Choice \sim \exp(\beta \, Q)$$

- B: model simulation
  - Simulate your models **in the exact experimental environment**
  - Compare qualitative predictions of different models
  - Know the influence of all model parameters on model behavior

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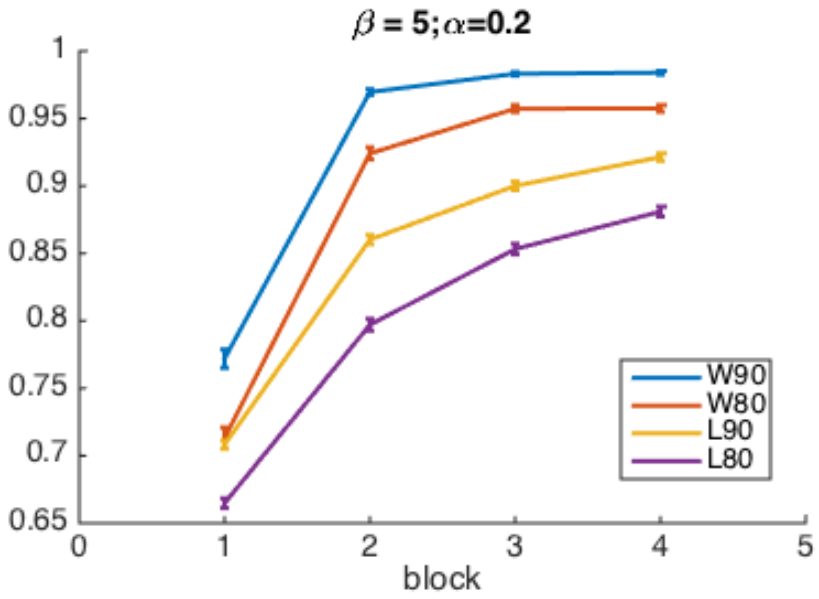

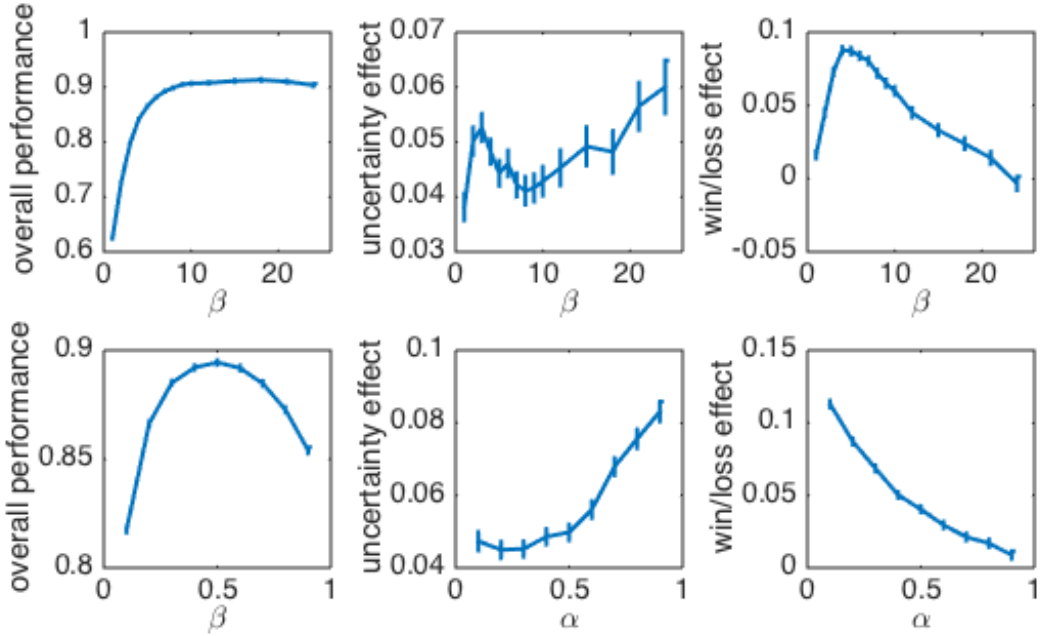

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3. Relate model to data – model fitting

- Bayes Rule!

$$P(\vartheta|D,M) \propto P(D|\theta,M)P(\theta|M)$$

Posterior probability of the parameters

Likelihood of the data

Prior on model parameters

- What we want to know:
  - How likely is it that the data was generated with parameters (α^*, β^*)?
- What we can compute:
  - How likely is the data given model assumptions and parameters (α^*, β^*)?

The theory –a simple trick

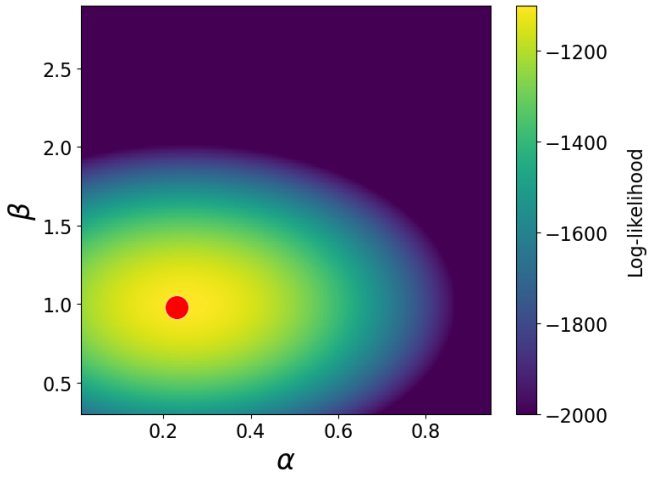
- Likelihood is a tiny number: product of many numbers<1

$$LLH = \log(LH) = log\left(\prod P(a_t|H_{t-1})\right) = \sum log\left(P(a_t|H_{t-1})\right)$$

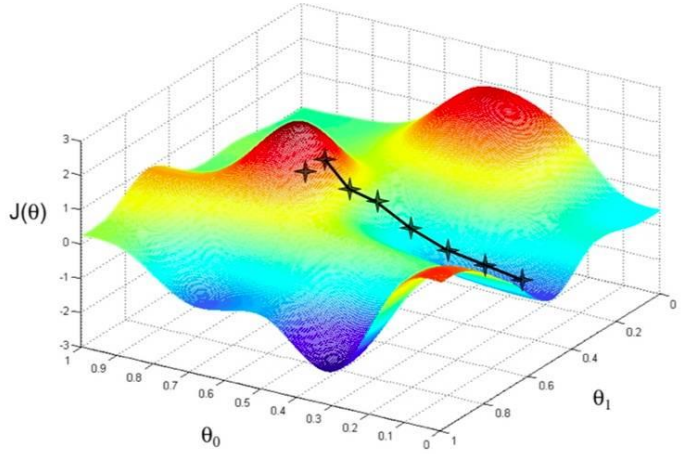
Example!

```
>> probabilities = rand(1,1000);
>> prod(probabilities)

ans =

     0

>> sum(log(probabilities))

ans =

 -965.7124
```

Grid Search



Gradient Descent

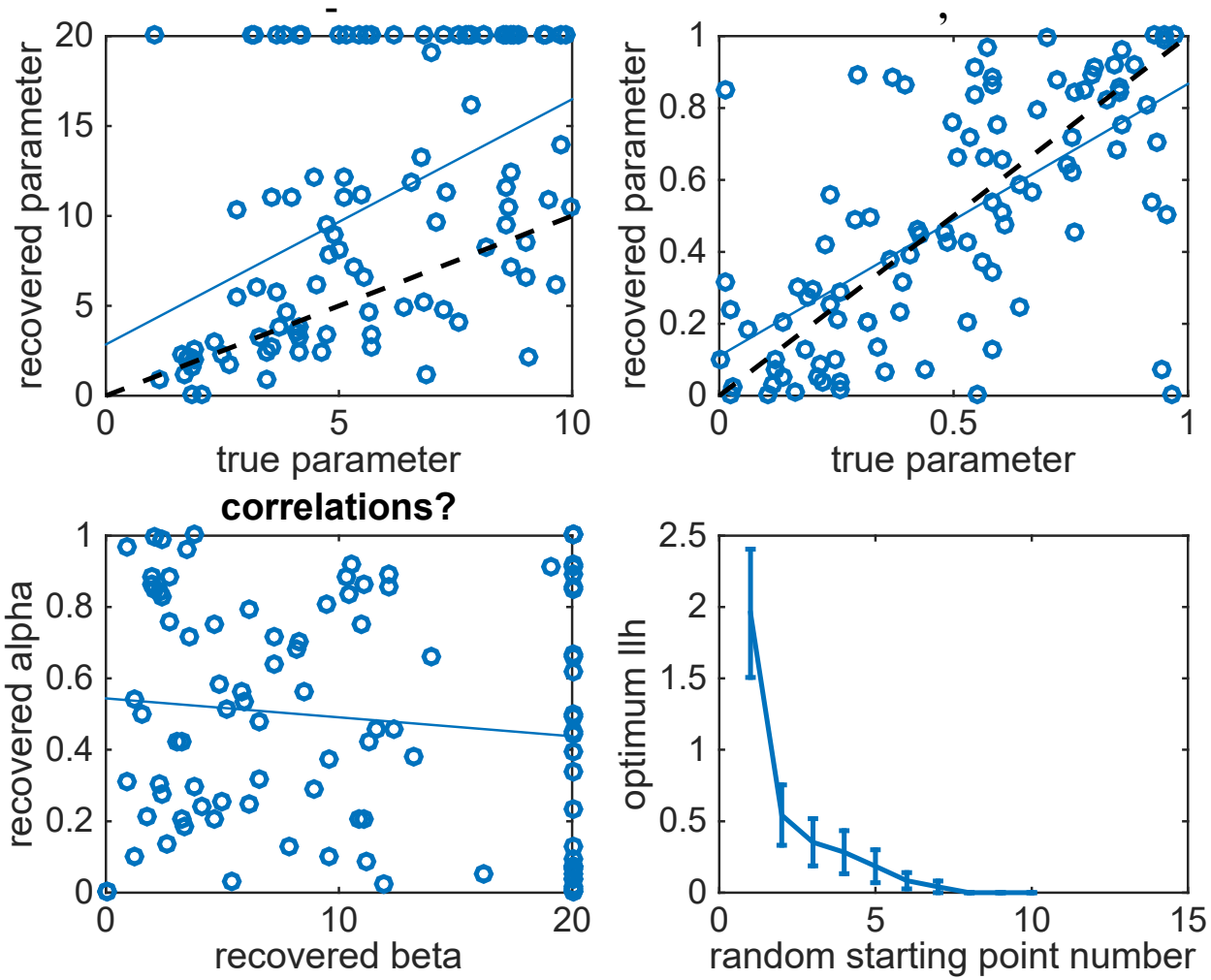


Parameter recovery: Generate and recover!

Validate this procedure!

1. Simulate the model with a reasonable range of parameters to create ***"fake" (synthetic) data***
2. Fit the "fake data"
3. Compare the recovered parameters with the true parameters

n=1 block
10 starting points



Tips and tricks: Parameter fitting

- More data always leads to better parameter recovery
- The generate and recover procedure, on ***your*** experimental protocol, shows you whether you can recover parameters satisfactorily
- Carefully choose constraints on parameters.
- Beware of local minima (always run fitting multiple times with random initial conditions)
- **Once you are satisfied that you can recover parameters for a model, you can fit your real data!**

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4. Model comparison: The question

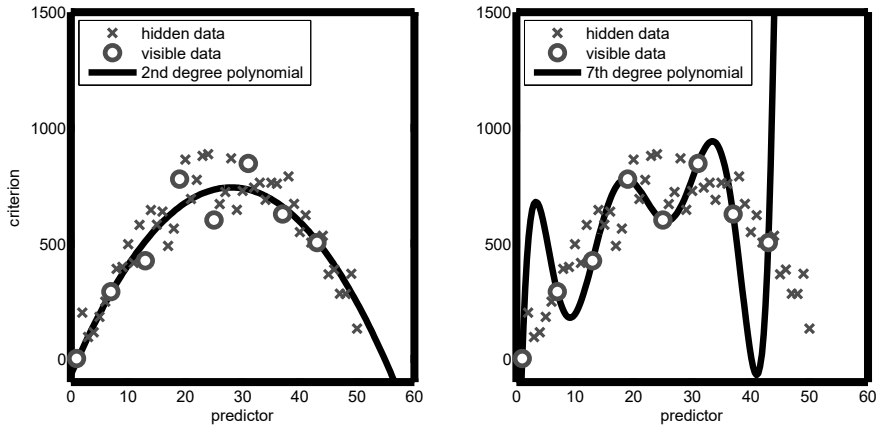
- Which of two (or n) models fits the data best?

- A better question:
  - Which of the models generalizes better?
  - Which of the models will let me predict the participant's behavior best?

Bias-variance tradeoff / Occam's razor

- More is not always better!
  - Capture signal in the data, not noise
- Best solution: **out-of-sample fit measure**

  → how well your fit model predicts new data (generalization)

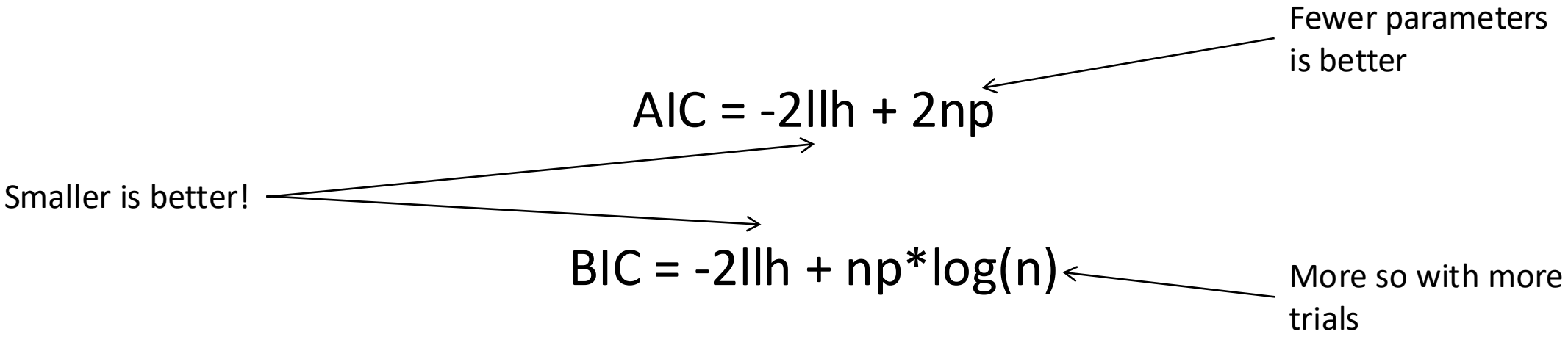


Measure fit out of sample. Why we rarely do it.

- Not enough data
- Not possible to separate data into independent data sets
  - for example, if trying to model a single learning block.

Approximate criteria for model comparison

- Principle:
  - measure model fit by likelihood, but penalize for model complexity.
- Various Information Criteria come from different mathematical theories, with different interpretations and guarantees
  - Bayesian Information Criterion (BIC)
  - Akaike Information Criterion (AIC)



Model comparison – validating the procedure

- Which model comparison method should I use?
  - I.e. are my models ***identifiable***? With my comparison method and the experimental protocol, can I distinguish between the models?
- Test it in the best-case scenario (where the true model is known: synthetic dataset). Create confusion matrices:
  - Generate data with models M1 and M2
  - Fit the generated data with model M1 and M2
  - Verify that data generated with Mi is best fit by model Mi

	M1's AIC better	M2's AIC is better
Data generated by M1	95%	5%
Data generated by M2	0	100%

What other factors could influence model identifiability?

- Model domain: range of parameters over which the model is simulated.
  - ***Case study:*** if range of beta is very low, choice will be mostly noisy, so other parameters will have little influence on the likelihood. This will influence model identifiability.
  - Many other such situations…

- In practice: what range of parameters should I pick to do my model recovery analyses?
  - **Before you have fit to real data: pick a range of parameters where the model behavior mimick expected experimental range.**
  - After you have fit to real data: use real fit parameters. This allows you to draw conclusions for your actual sample, but this will be less generalizable.

Tips and tricks: Model comparison

- Confusion matrices are computationally intensive.
  - Start small!
    - Small number of simulations/participants per model
    - Small number of starting points for fitting
    - Small number of trials (if possible)
- Model + parameter recovery
  - When doing model recovery, you're also doing parameter recovery (you're fitting M1 data with M1, M2 data with M2, etc…)
  - But in practice, to minimize computation cost, you can combine the two steps.
  - Downside: doing parameter recovery is faster (n instead of n^2), and you might not use all models in model recovery analysis – so it sometimes still makes sense to do the two steps separately.

What **can** you conclude so far?
What can you **not** conclude so far?

Yes

- My procedure identifies Mx as most likely from {M1, …, Mn} to generate the data
- Best fit parameters for Mx are the most likely ones.

No

- Mx is a good model of my cognitive process of interest
- Mx is the best model out of {M1, …, Mn} to model my cognitive process.

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5. Model validation (after fitting your behavior data)
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Quantitative measures of model fit is not enough

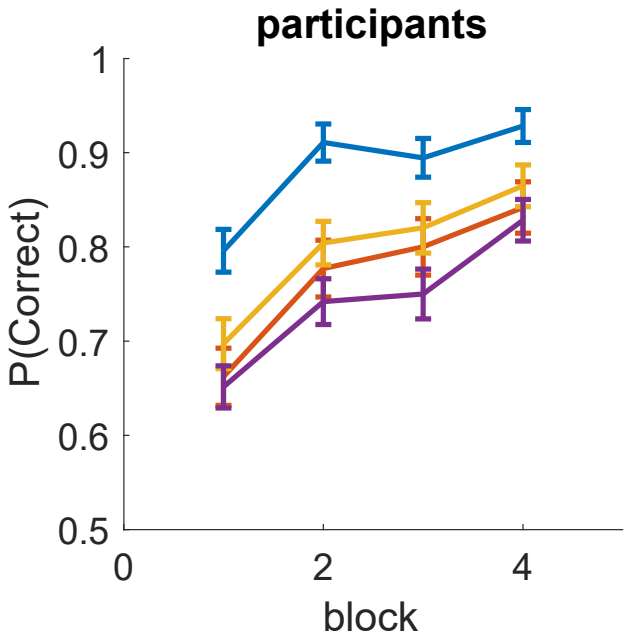
Qualitative questions:

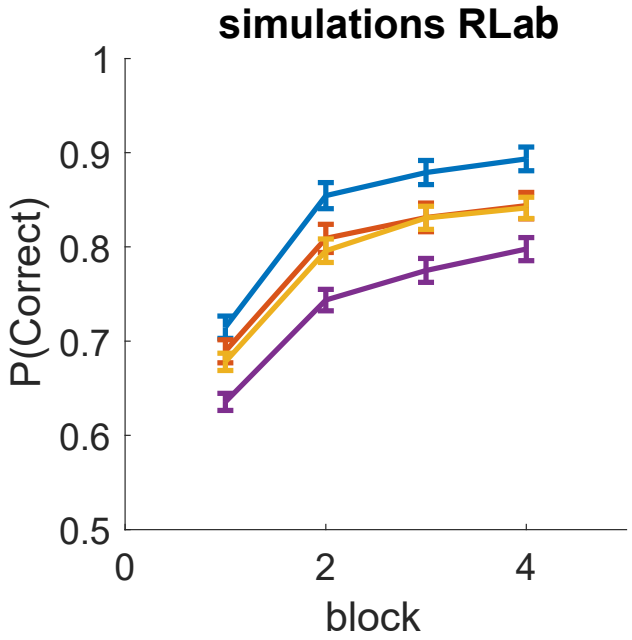
- Can this model produce the behavior patterns I'm expecting from this cognitive process, this experiment, this participant sample?
- Does the behavior of the model produce match participants' behavior?

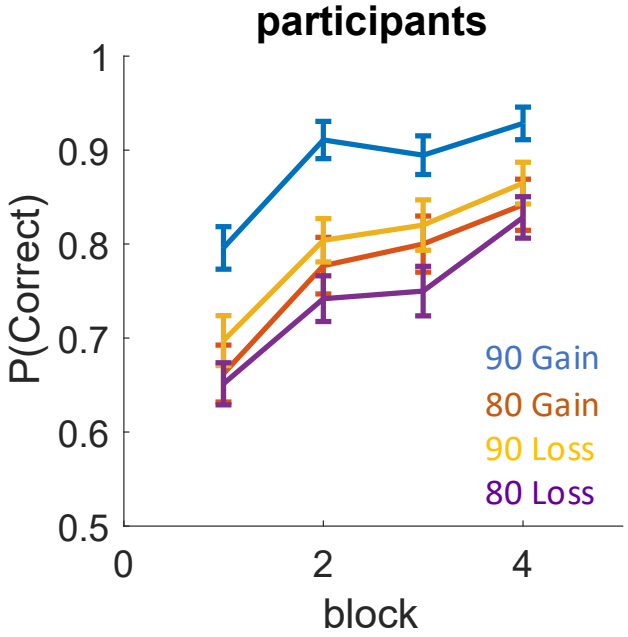
Validate your model!

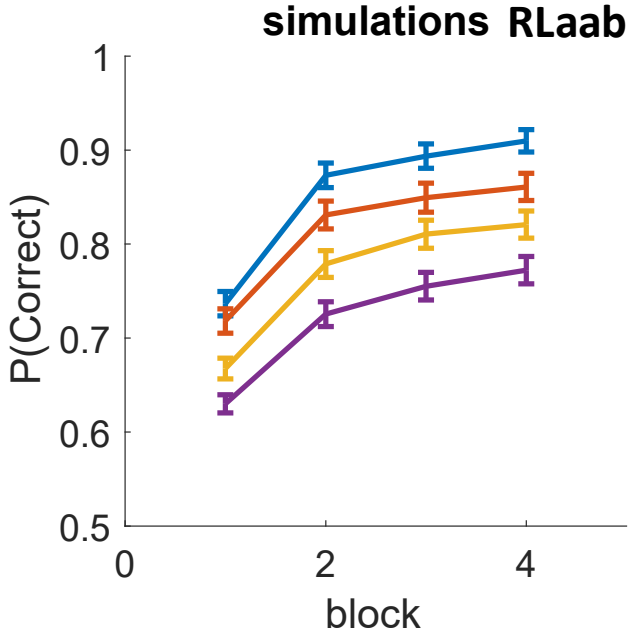
How do I validate my model? (also called *posterior predictive check*)

- Simulate the model on the **exact** experiment, with fit parameters
  - For each participant, with each participant's best fit parameters
  - Multiple times per participant, to average out randomness in choices
- Analyze the behavior of each simulation as if it was a participant
  - Create all the summary measurements you identified as important when you explored participants' behavior
  - Average measures across simulations for each participant, treat this as the validated participant's measure
- Analyze the behavior across participants, and compare to real data







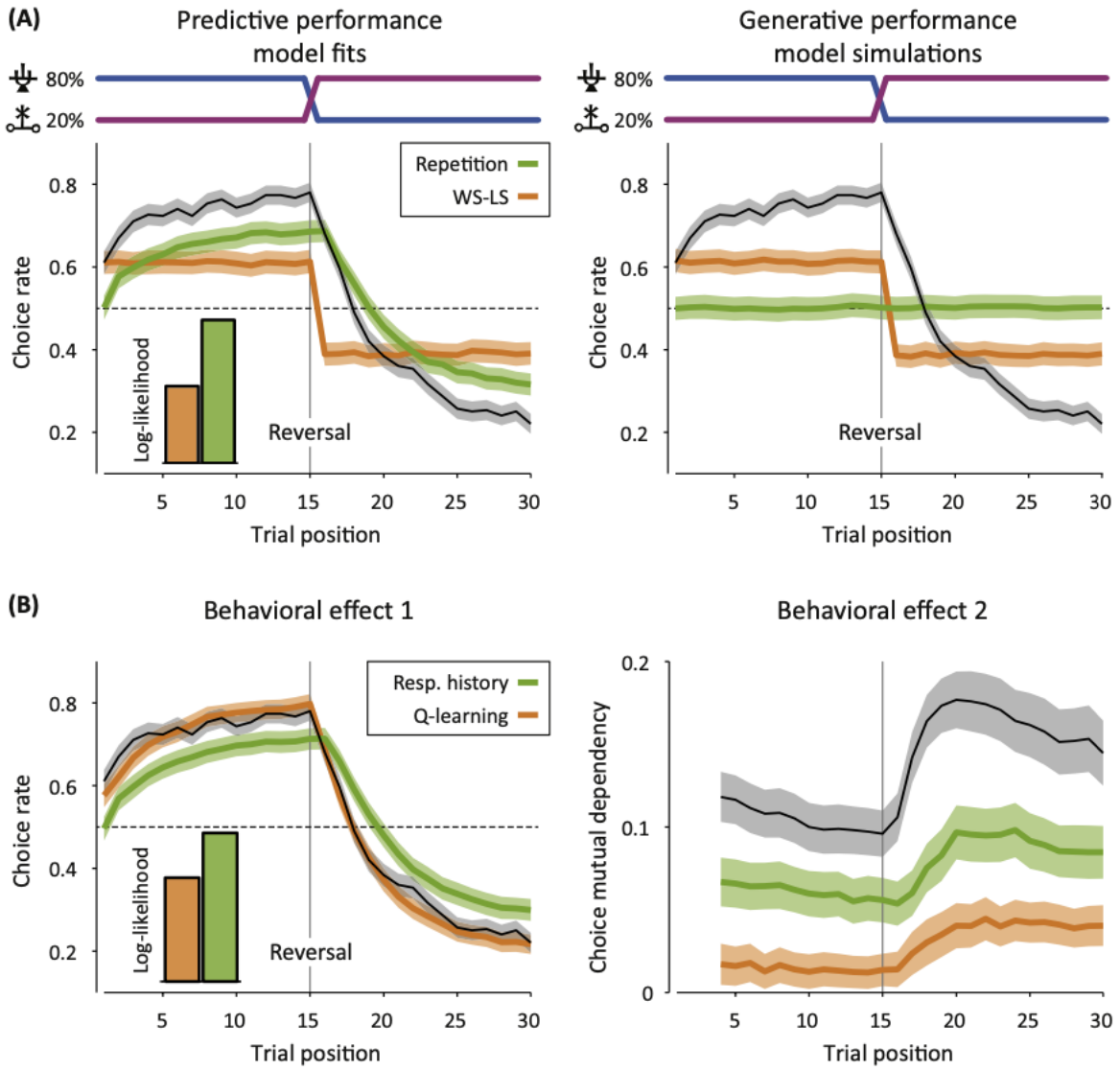


Model validation

- 100 simulations per participant, not looking at group effects yet.
- Good:
  - both capture Learning, Gain/Loss effects
- Not good:
  - underperformance
  - not capturing uncertainty *valence effects
  - Rlaab predicts 80%gain>90% loss learning. Wrong!

Model Predictions and Simulations Are Not Necessarily Related.

- Generating data is different from predicting data (A)
- Quantitative measures don't tell the whole story (A,B)



Palminteri et al, 2017

Simulation for validation, falsification, and model improvement

- Model fitting procedures don't ensure that the model can generate the observed data (*"predictive performance"*).

- Simulations **validate** this and can **falsify** other models.

- When they falsify a model, they indicate where the model can be **improved**.

Questions?

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REVIEW ARTICLE

Ten simple rules for the computational modeling of behavioral data

Robert C Wilson[1,2†*], Anne GE Collins[3,4†*]

Trends in Cognitive Sciences

CellPress

Opinion

The Importance of Falsification in Computational Cognitive Modeling

Stefano Palminteri,[1,2,*,‡] Valentin Wyart,[1,2,*,‡] and Etienne Koechlin[1,2,*]