Universität Basel

# Principles of modeling

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# Agenda: What today teaches or repeats

## Conceptual modeling steps

- Do I really need a process model?
- (Cognitive) measurement vs. computational vs. process models

## Testability/Precision/Complexity

- What’s a response surface?
- Tension between flexibility and testability
- Computational complexity

## Inferential Fallacies

- What0s reverse inference

## Important Other Criteria

- Inclusiveness
- Referencing
- The toothbrush problem

# Cognitive Process Modeling Steps

# An Informal Cooking Recipe

## Cognitive Process Model Development Steps

a. Decide what to model
b. Specify in what stages the model transforms data
c. Ensure model makes precise, testable predictions
d. Check for fallacies, e.g. reverse inference
e. Check of model's processes not implausible?

(Jarecki, Tan, Jenny, 2020)

# a. What to model

# What's the Goal and Content of my Model?

## Modeling goals

- Implement processes (at a given level of abstraction)? (> *cognitive process model*)
- Describe responses (in a particular domain)? (> *cognitive formal model*)
- Measurement of cognitive constructs? (> *cognitive measurement model*)
- Statistical test? (> *statistical model*)

## Explain and/or predict?

- Explanation of phenomena?
- Prediction of new phenomena?

**Important, note:** there is no hierarchy as long as you are clear on what you do.

# What's the Goal of Modeling?

## Implement Cognitive Processes

- Theory contains statements about how the mind transforms information
- *Computation Assumption:* We assume that the mind does something *like* computing something (it's a metaphor)
- *Multi-realizability:* A theoretical statement can be realized in many different ways

# b. Specify stages

# Specify stages

Write down what your model does to the input – this is what this school is mostly about

## c. Ensure precise, testable predictions

# Response Scope of a Model

## Response Scope as data patterns

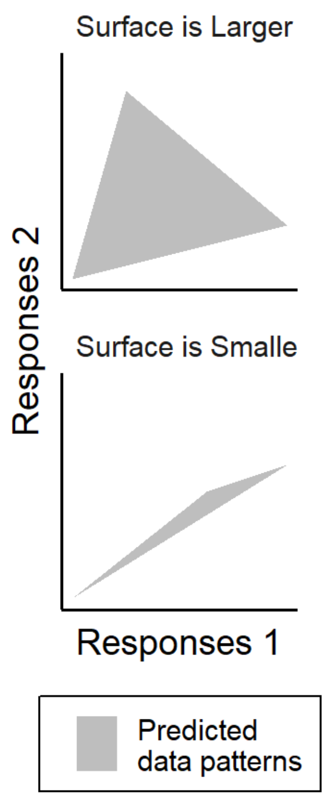
- **How much a model can handle** (Farrell & Lewandowsky, 2018)
- How many different data patterns a model can predict

## (Other meanings of scope)

- Purpose of the model and guides interpreting model variables (Hodges, 2013)
- Which model variables represent which properties of the cognitive system and sets the level of abstraction (Jarecki, Tan, Jenny, 2020)

# Response Surface of a Model

A model's **response surface**, meaning the amount of the total data space occupied by the model




Response Surface tends to be larger in models

- with many free parameters which can adapt the model to different patterns in the data
- with a more complex functional form, e.g. an cosine curve compared to a linear curve

# Response Surface - Example

## Three models

that predict a response $y$ given a variable $t$ with 1 free model parameter $\theta$:

a. Linear model $y=1-\theta t$

b. Power model $y=t^\theta$

c. Blackhole model $y=(1.102^{-\theta} \sin(5\theta+\pi t/12) + 1)/2$

*Haw large is their response surface, meaning how many response patterns can the models – with the values of the free parameter – produce?*

Say, we have two responses for inputs $t_1, t_2$. Get the models' response surfaces by computing response predictions $y_2, y_2$ given inputs $t_1, t_2$ for each value that parameter $\theta$ is allowed to take. If we then plot the possible response combinations $y_1$, $y_2$ against each other, we see the model's response patterns.

(Pitt, Myung, Zhang, 2002)

# Response Surface - Example

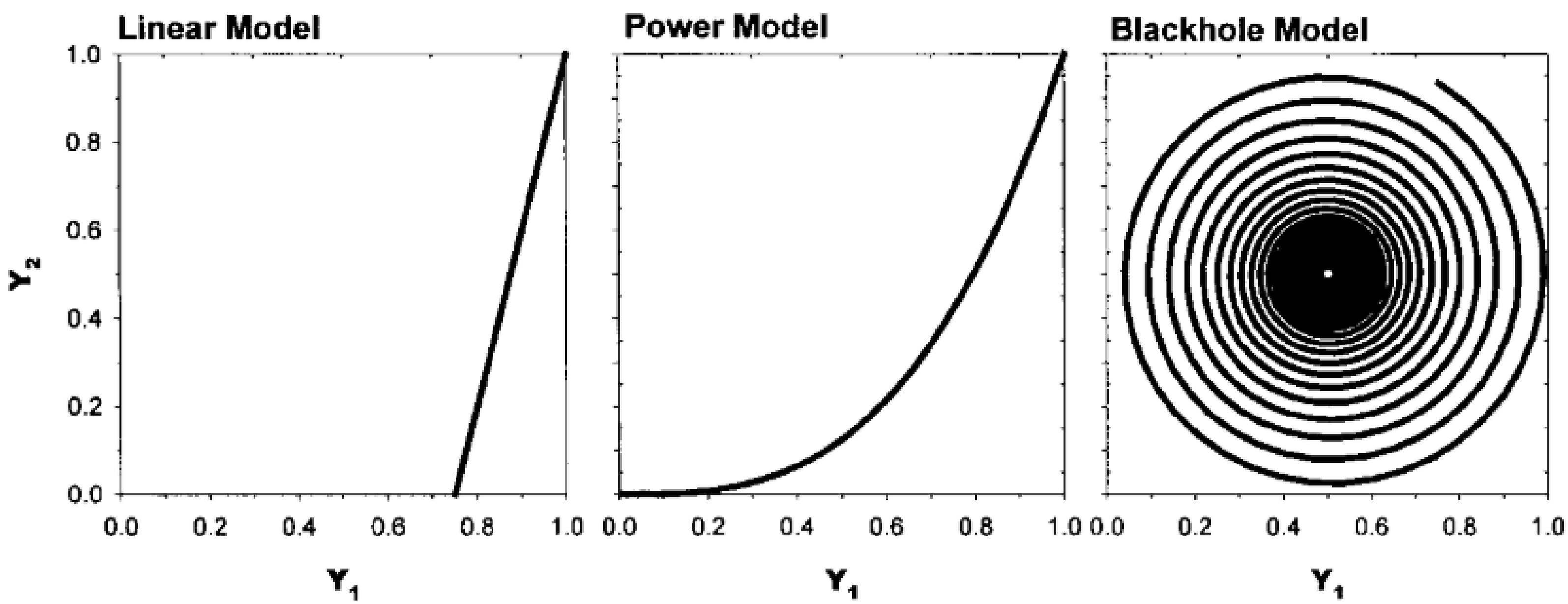



*Figure 4.* Response curves of three one-parameter models that have the same number of parameters but differ in functional form, each obtained for $t_1 = 2$ and $t_2 = 8$.

This is called response surface analysis (RSA).

(Pitt, Myung, Zhang, 2002)

# Response Surface

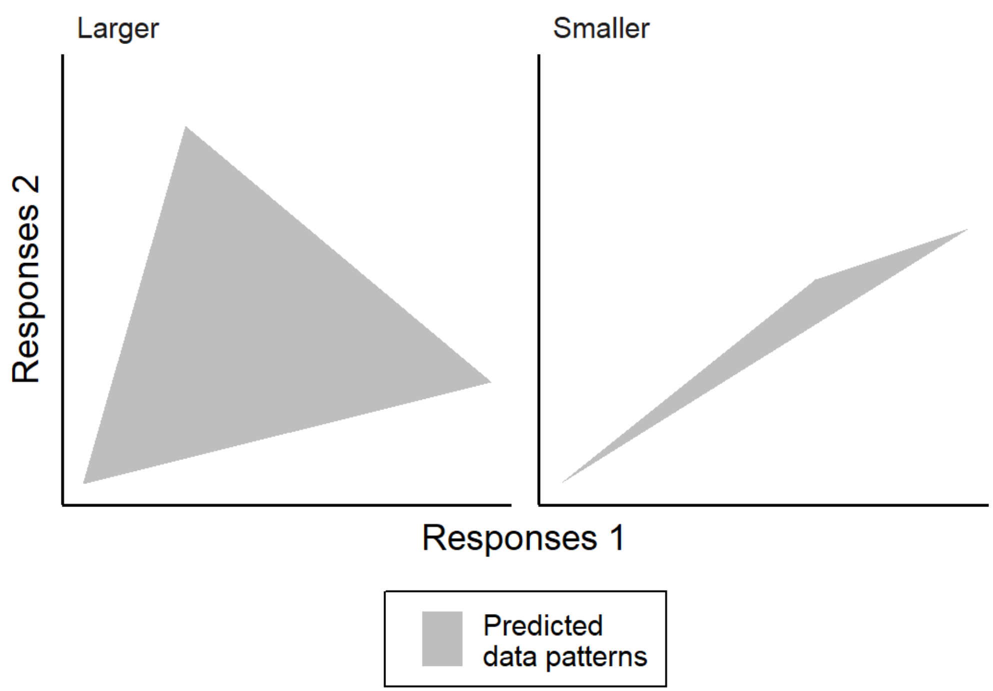
The response surface is a measure for how many data patterns our model can handle.

If you want to know more, check out

- The Bible :)
- Pitt, M. A., Myung, I. J., & Zhang, S. (2002). Toward a method of selecting among computational models of cognition. *Psychological Review, 109(3)*, 472–491. https://doi.org/10.1037/0033-295X.109.3.472
- Roberts, S., & Pashler, H. (2000). How persuasive is a good fit? A comment on theory testing. *Psychological Review, 107(2)*, 358–367. https://doi.org/10.1037/0033-295X.107.2.358

# Response Surface - But Wait?

How large do we want the response surface of our models to be?



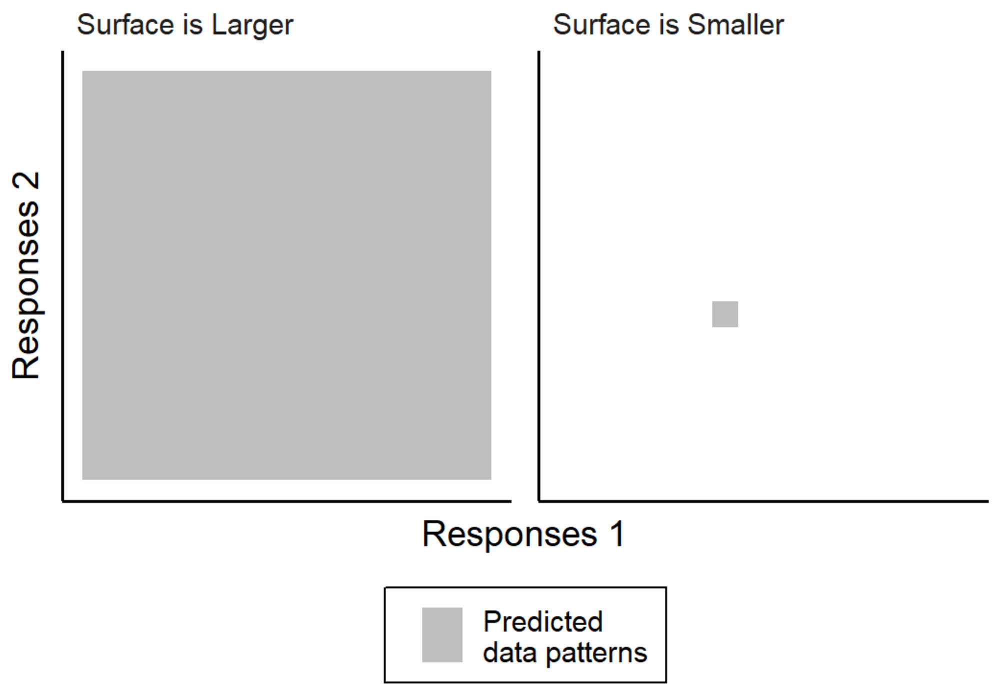
# Falsifiability

# Falsifiability

- Is there anything a model can’t handle?

- The potential of samples of data to speak against a model’s prediction

# vs. Flexibility



# Response Surface - Three Important Aspects

## When designing and testing models, consider

a. **Model's flexibility**: how large is the response surface compared to the possible data space?

b. (Expected) **data variability**: how firmly can the observed data rule out what the model cannot fit?

c. **Other outcomes**: Might the model have been able to produce any plausible result?

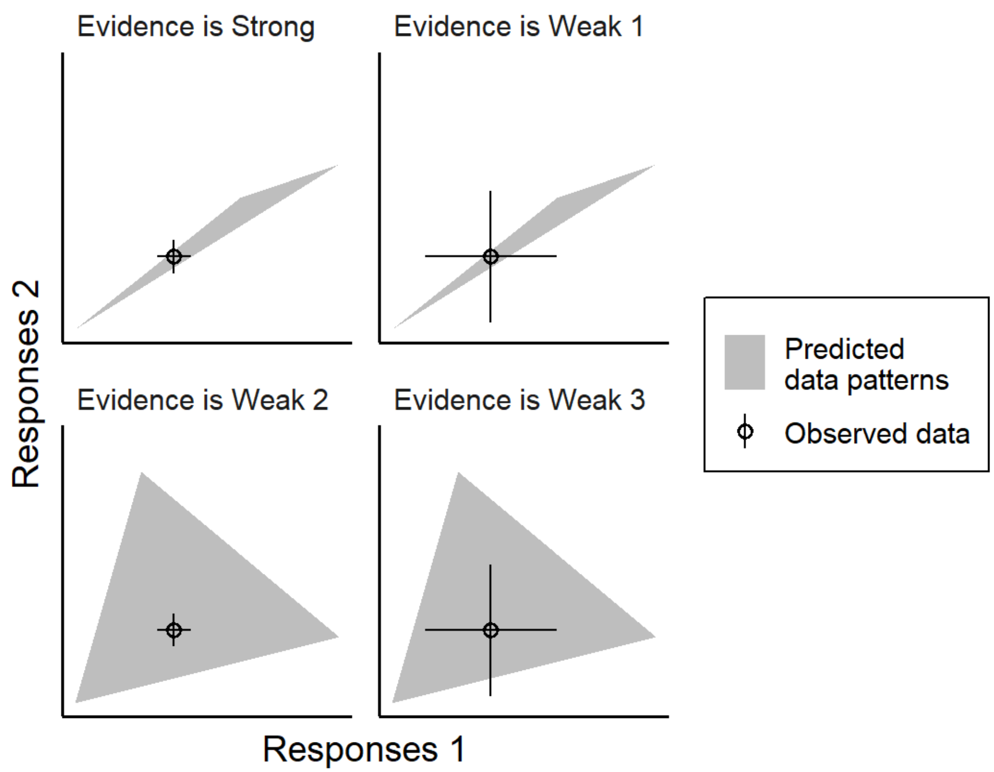
The nice thing is that modeling actually allows us to quantify model flexibility (theoretical cognitive psychology).

## We want falsifiable, precise models

| Data / Model | Model very flexible | Model precise |
|---|---|---|
| Data very variable | any result goes | maybe unrealistic |
| Data stable | not informative | **falsifiable** |

(Roberts & Pashler, 2000)

# Response Surface - Potential Evidence




(Farrell & Lewandowsky, 2018; Roberts & Pashler, 2002)

# Fit, Generalizability

# Fit versus Generalizability

## Model Fit

- How good a model handles old things
- AKA: *goodness of fit, GOF*
- Precision with which a model fits a particular sample of observed data (Myung & Pitt, 2005)
- Quantifiable by e.g., mean distance of predictions vs. observations; or probability of data sample given model predictions

## Model Generalizability

- How good a model handles new things
- AKA: *predictive GOF, predictive fit*
- model's ability to fit all data samples generated by the same cognitive process, not just the currently observed sample (i.e. the model's expected GOF with respect to new data samples) (Myung & Pitt, 2005)
- Quantifiable by e.g. GOF of model predictions for new experimental data; or GOF for old data but leaving out some data

# d. A Modeling Fallacy: Reverse Inference

# Reverse Inference

If a model's predictions …

- **match** a data sample well
- **fail to match** a data sample well

… can we infer support for the process implemented within the model?

Computational Cognitive Models, Cognitive Process Models, Cognitive Measurement Models

# Reverse Inference

## Cognitive Process Models

- Intermediate Stages/Computations have psychological interpretations and predictive power
- Estimated parameters are either fixed (e.g. population distribution for salience) a function of inputs (e.g., attention depends on salience)
- E.g., can be fixed and tested

## Cognitive Measurement Models

- Estimated parameters have psychological interpretations
- Inter-individual differences
- E.g., prospect theory model's parameters can be interpreted as risk aversion/risk seekingness measures

(Jarecki, Tan, Jenny, 2020)

# e. Not too Implausible?

# Worthwhile to check if the model's processes don't assume things that you (the scientific community) know to be false

- E.g., Cognitive constraints
- E.g., Limits on human cognitive capacities
- E.g., Machine-learning neuronal networks often use infinite learning and perfect retrieval

Van Rooij, I. (2008). The tractable cognition thesis. Cognitive Science, 32(6), 939–984. https://doi.org/10.1080/03640210801897856

# Limits on Human Cognitive Capacities

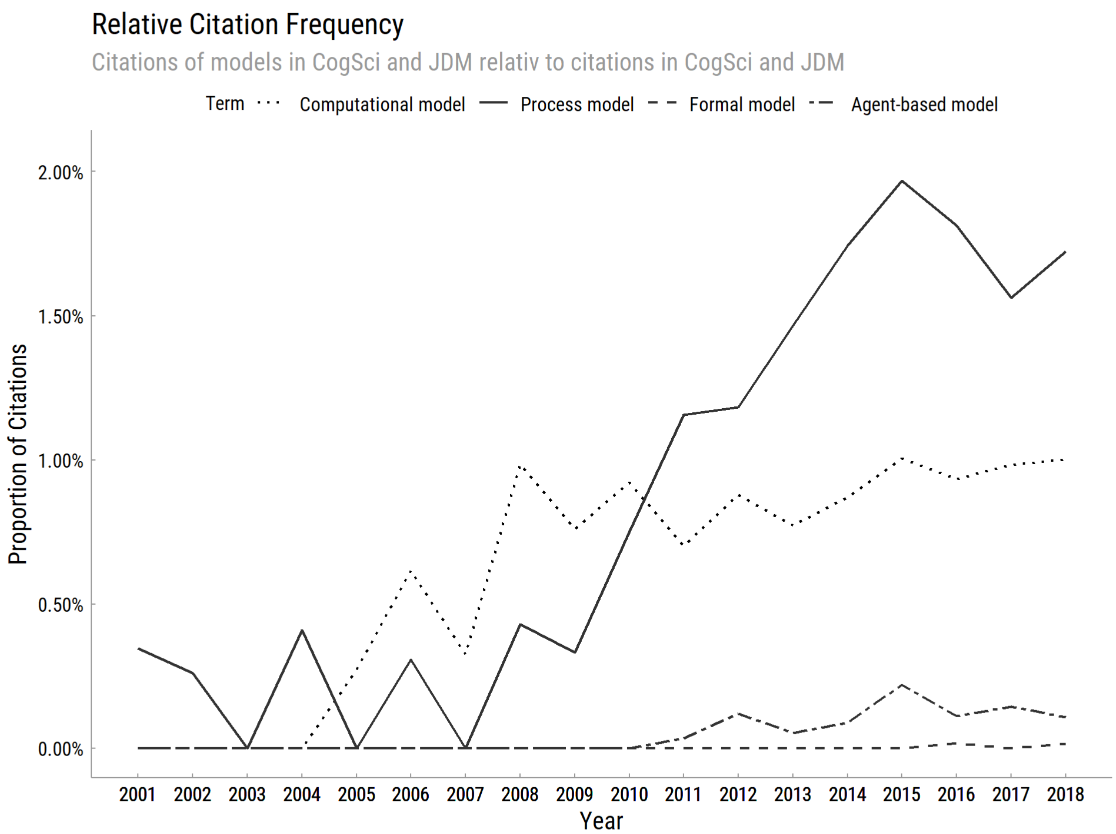
## Computational Complexity

- how much processing power the model assumes
- demands on computational resources as a function of the size of the input (Van Rooij, 2008; introduction to the topic: Papadimitriou & Steiglitz; 1988)
    - time: *how long does it take to compute the input/output mapping*
    - space: *how much computational memory does it take to compute the input/output mapping*
- Computational measures
- Data-based measures - talk to senior researchers

# Important Other Criteria

- Inclusiveness
- Theory interoperability
- Referencing other’s work

# The Toothbrush Problem



# The Toothbrush Problem

## Proliferation of Models

- In 2016: **100+ cognitive models** only in the field of judgment and decision making
- There is not a lot of consensus as to which models are process models
- *Although almost all (51 of 62) agreed that process models are important, they disagreed about which models constituted process models with an inter-rater agreement of Fleiss–Cuzick's κ = .27, far below the .60* (Jarecki, Tan, Jenny, 2020)

## Toothbrush problem

Models are like toothbrushes: Everybody has their own toothbrush and I won't use yours

# Referencing Other's Work as Criterion

For instance:

- GCM Model that Steve introduced was developed in the 1980ies
- Some theorists in other fields pick the mechanism up in 99% similar in the mid-1990ies without referencing the work

*I am error-tolerant*, a real overlooking can happen, but if ever anybody alerts me (you) to that the ideas in my model existed prior, *cite and embrace* rather than trying to justify that my model is actually new