Cognitive Modeling: Final class
Bringing it all together: reflection & the future of modeling

Chris Janssen

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Exam

- Jan 29, 17:00 – 20:00
  Educatorium room Beta
- During dinner time so…
  … bring a snack if you need to. Keep "smell" and noise to a minimum ☺
- Practice exam on Blackboard
- General structure: 4 questions with subquestions
- What to learn:
  – All lectures
  – Core papers associated with lectures, as spelled out in course manual
  – Experience from the lab
  (e.g., useful for exam question 4)
- Aim: To test insight
  (occasional asking for a fact or simple question -- > as you need these to demonstrate insight)

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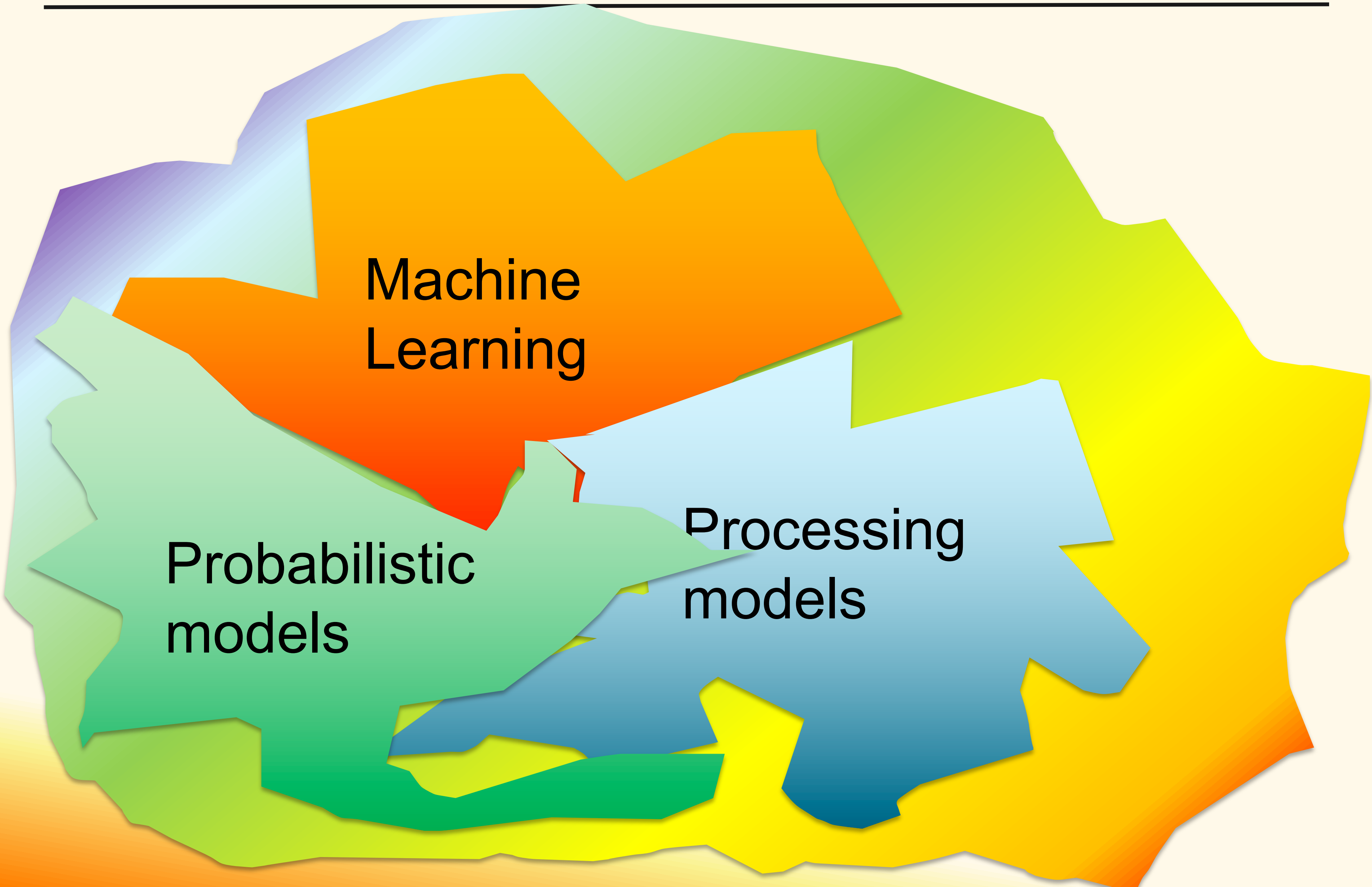
Machine Learning

Probabilistic models

Processing models


Machine Learning
Probabilistic models
Processing models

This week's articles

1. **McClelland (2009)**

   CogSci / theory perspective

2. **Goodfellow, Benglio, Courville (2016)**

   Application/ Software engineering perspective

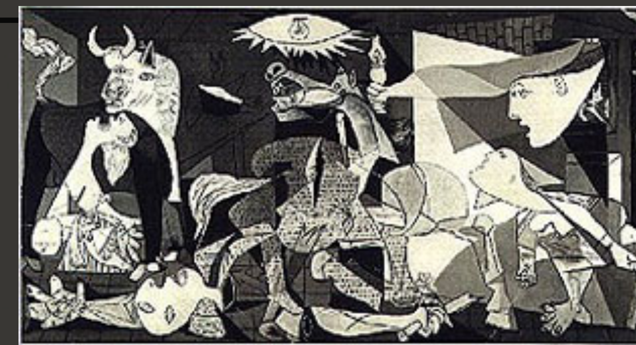
- **Provide additional (valuable!) perspectives to today's class**

  & are part of exam material
  (& good to know anyway…)

Ways to classify models

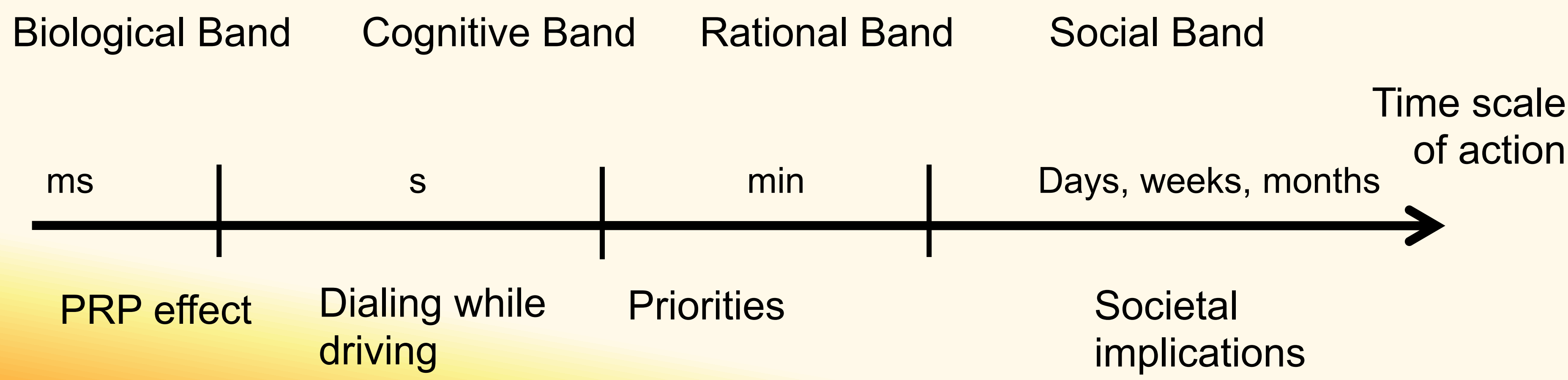
Option 1: Levels of abstraction

- Marr
- Newell



Newell's time scales (of action)

- **NOT:**
  - **How long does the task take in total?**
- **Instead:**
  - **At what level is the task MODELLED?**
  - **What are the *smallest* units of action in the model**



Marr’s levels

- NOT:
  - Was an algorithm used? In the context of computer simulations, algorithms are (almost) always used
- Instead: does the model focus on:
  - Computational problem (why certain behavior?) Typically: optimization accounts (e.g., probabilistic; Bayes; some forms of ML)
  - Algorithmic problem (which steps are achieved?) Typically: process models
  - Implementation problem (How is this implemented in the brain?) Typically: neural models (e.g. ML)

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Option 2: top-down or bottom-up

Theory

- ACT-R model of fan-effect (Proc2)

Driver distraction model

Grey area that mixes top-down and bottom-up

- sHMM model of fan-effect (Proc2)
- Cognitive models of language with applied logic (Prob1)
- Models of numerosity (ML)

Representational Similarity Analysis (ML)

Rational speech act model

Approach is to **model**
Aim is to gain **insight**
(though extent of that aim varies per application)

Data

HMM model of fan-effect (Proc2)
Tech applications of ML (ML1)
Engineering models of language (Prob1)

Option 3: Stand-alone or Cumulative?

- **Stand-alone: for single purpose**
  - **Machine Learning tech examples**
- **Cumulative: builds on preceding theory**
  - **Most cognitive (neuro-) science and linguistics models**
  - **Cognitive architectures**

Driver distraction model;
Representation similarity analysis;
Rational speech act

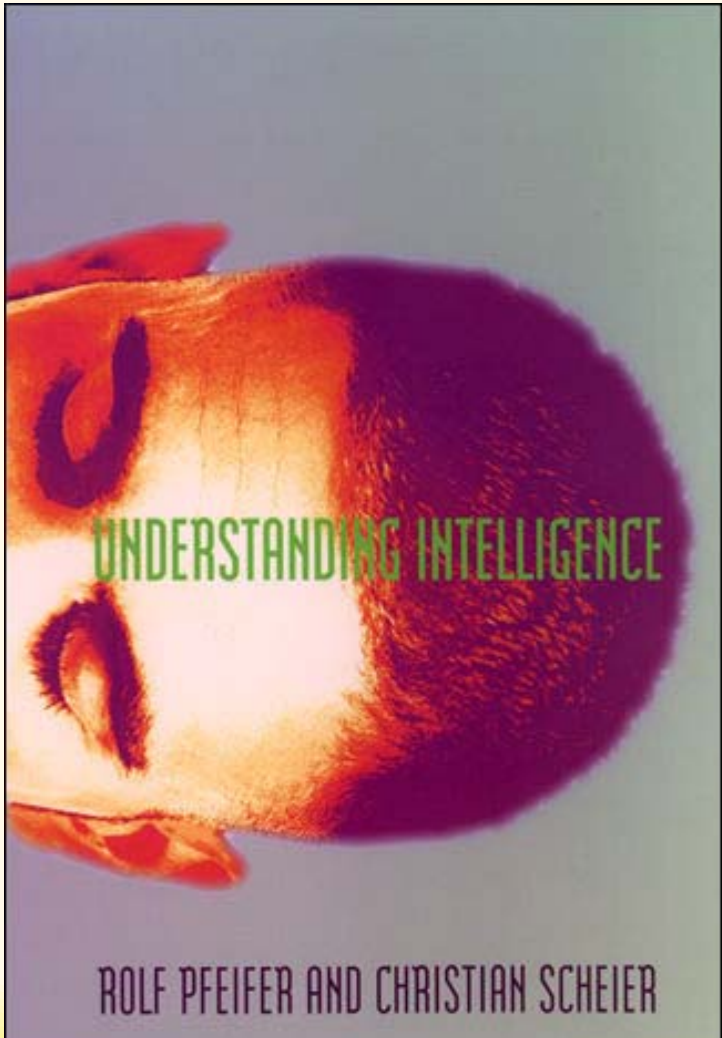
Option 4: Which aspect/feature of cognition / behavior

- All models focus on specific aspects, e.g.
  - Vision
  - Reasoning
  - Action
  - Linguistics
- About what aspect are "core claims" and "core assumptions"?
- Note: even cognitive architectures have specific focuses
  - E.g., ACT-R vs EPIC

Option 5: Embodied? Situated?

- **Embodied:**
  own sensory and action system to interact with environment

- **Situated:**
  acquires all information about environment from own perspective through sensory system



Recall: MAIR


08:42
B-Human
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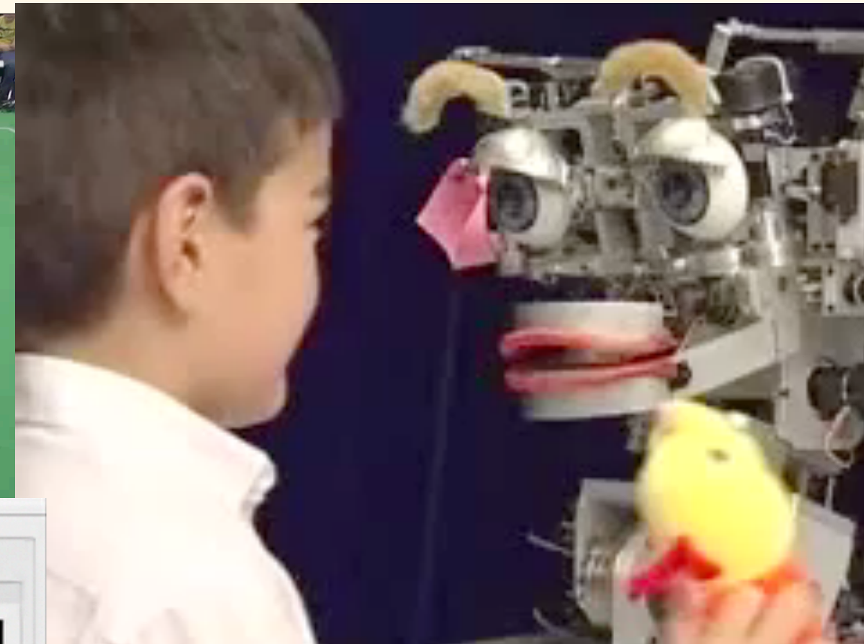

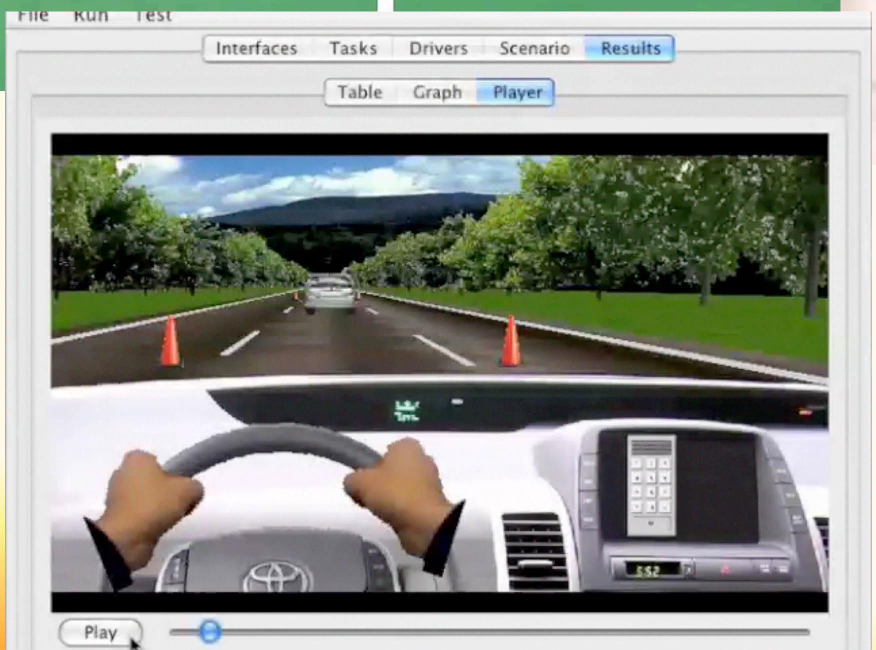
File Run Test
Interfaces Tasks Drivers Scenario Results
Table Graph Player
Play

PHILOSOPHICAL TRANSACTIONS OF THE ROYAL SOCIETY B

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A continuous-time neural model for sequential action

George Kachergis[1,2], Dean Wyatte[3], Randall C. O'Reilly[3], Roy de Kleijn[1,2] and Bernhard Hommel[1,2]

[1]Institute for Psychological Research, and [2]Leiden Institute for Brain and Cognition, 2333 AK Leiden University, Leiden, The Netherlands
[3]Department of Psychology and Neuroscience, University of Colorado Boulder, Boulder, CO 80309, USA

t evolve
o-down

Partially situated & embodied

NOT situated & embodied (despite focus on walking & motion)

Three Machine Learning Techniques for Automatic Determination of Rules to Control Locomotion

Slavica Jonić, *Student Member, IEEE*, Tamara Janković, Vladimir Gajić, and Dejan Popović,* *Member, IEEE*

***Abstract*— Automatic prediction of gait events (e.g., heel contact, flat foot, initiation of the swing, etc.) and corresponding**

a muscular system impose that a command signal precedes the required muscle activity when a real-time control is to be

Option 5: Embodied? Situated?

Embodiment without situated

Option 5: Embodied? Situated?

Situated can be without a PHYSICAL body (i.e., software body)
(and still be classified as “embodied”)

Option 6: Number of agents

- Single-agent vs multi-agent

- Focus in course on single-agent
- Yet, techniques can be applied in multi-agent systems
  - Example: past MSc project student

Option 7: Origin of model (& audience)

- As seen in student presentations, this differs between papers:
  - Biology
  - (cognitive) psychology
  - Mathematics
  - Computer science
  - Engineering
  - Designers
  - Doctors
  - …

Option 8: What is goal/contribution?

- Science / theory vs practice / application
- Proof-of-concept vs “full” model
- Explain vs mimic vs surpass human
  - i.e. “intelligent” vs “human-like”
- For applications:
  - Support / Inform vs Replace people

Ways of classification

1. Levels of abstraction (incl. Newell, Marr, …)
2. Top-down vs bottom-up vs hybrid
3. Stand-alone or cumulative (incl. cog arch)
4. Which aspects/feature of cognition/behavior?
5. Embodied? Situated?
6. Number of agents
7. Origin of model (& audience)
8. What is goal/contribution?
9. ….. (more possible)

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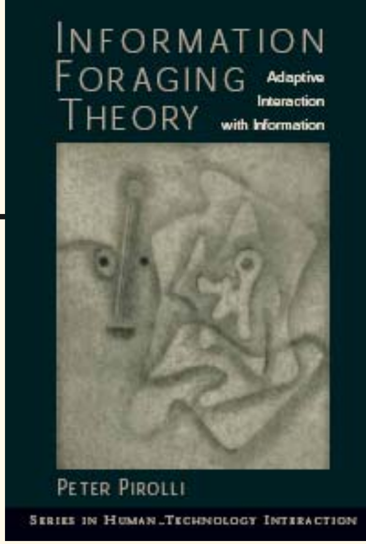
Making improvements to your model(s)

- No model is perfect! But hopefully valuable
  - See also McClelland (2009)
- There are more methods and techniques than was covered in this course
  - Hopefully a useful and broad subset
- How to improve?

Pirolli's perspective



Upward
Expand to larger time-scales & bigger applications

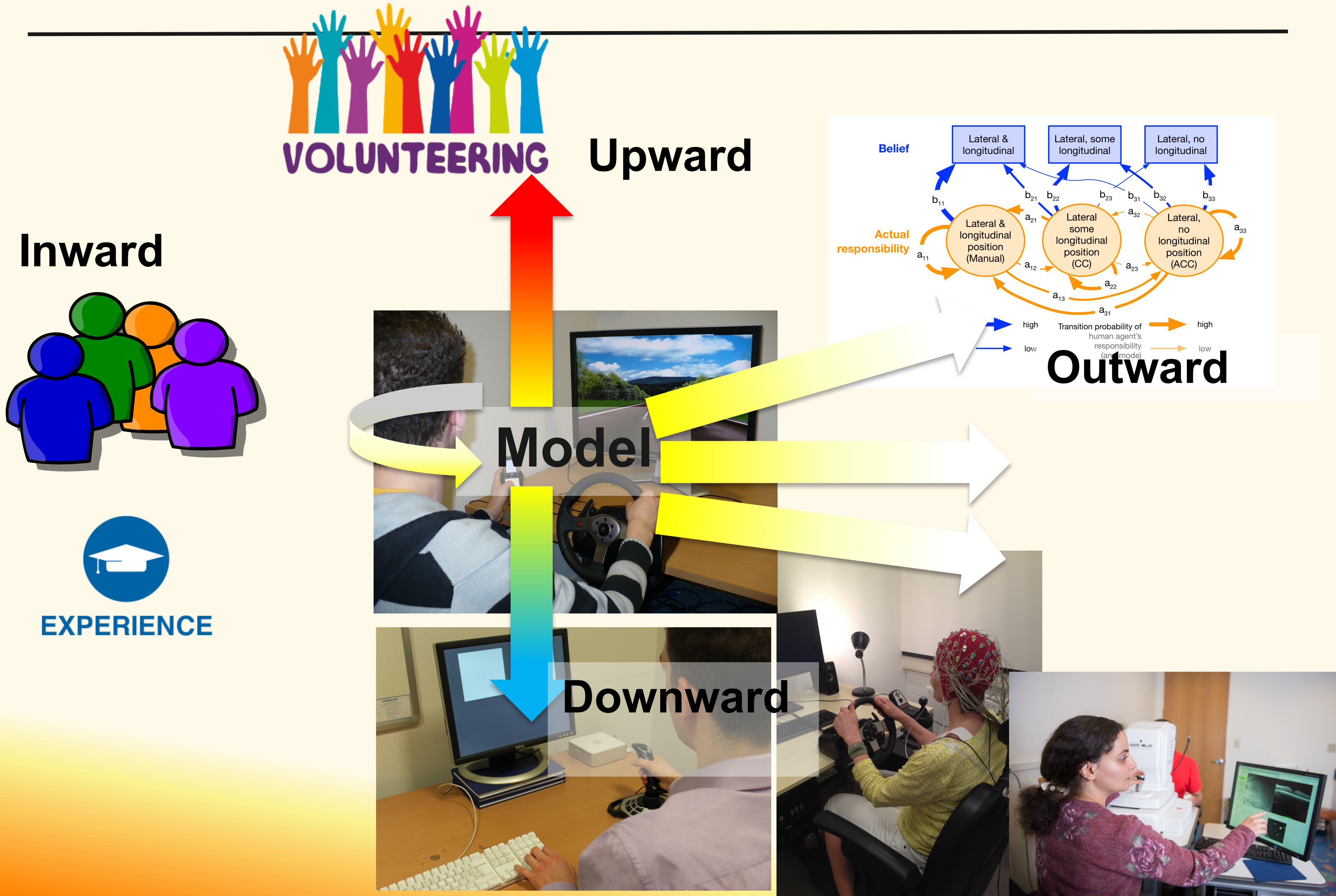
Inward
Eleborate on /improve existing model components,
(while staying close to timescale)
incl:
- Learning
- Individual differences

Model

Outward
Expand to new domains & phenomena

Downward
Gain more fine-grained details of model / process

Example: Driver distraction & efficiency



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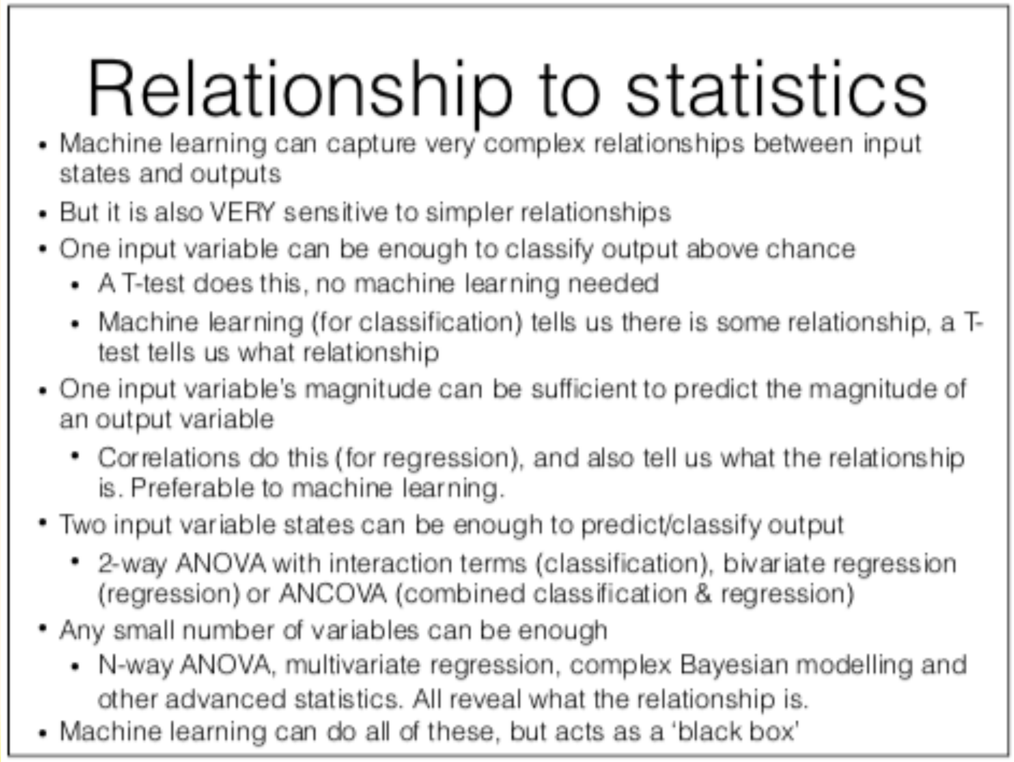
Role of statistics

- **Statistics and statistical techniques are integral in:**
  - **Model development**
  - **Model evaluation**
  - ***Model comparison***



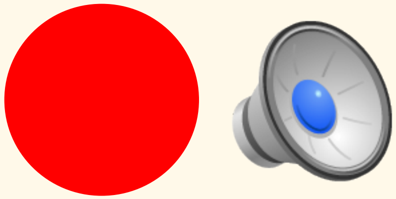
(Ben's slides ->)

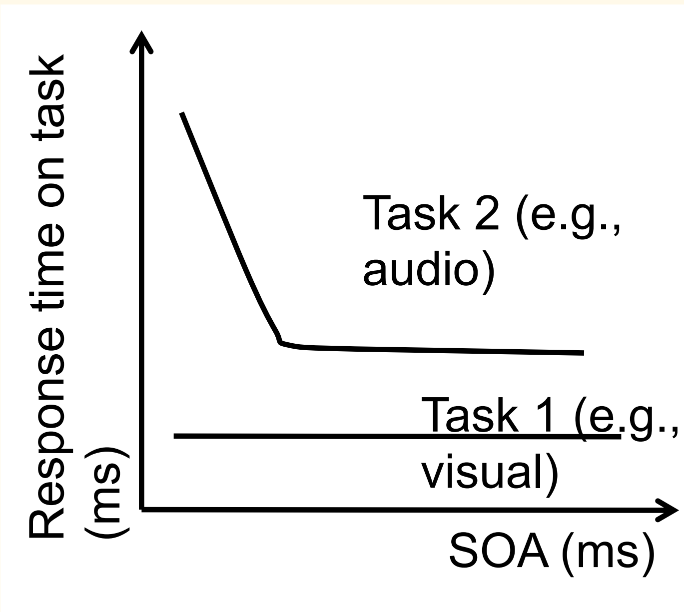
How good is a model fit?

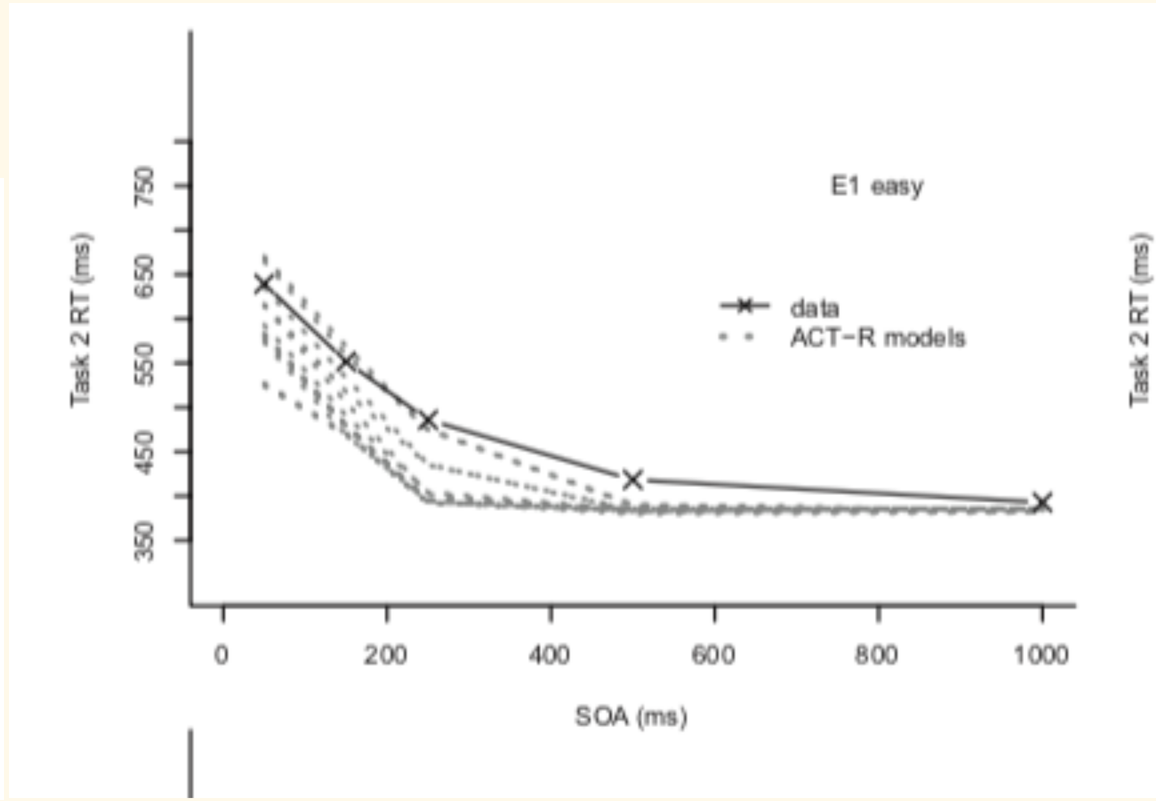
- **Qualitative description:**
  - Is there nothing "strange" (sanity check)
  - Does it capture theoretical trend?
- **Quantitative description:**
  - RMSE
  - R2
  - LOOCV score
  - Etc

- **What is a good value?**
  Requires a *comparison*

Example: PRP task (Lecture 1)





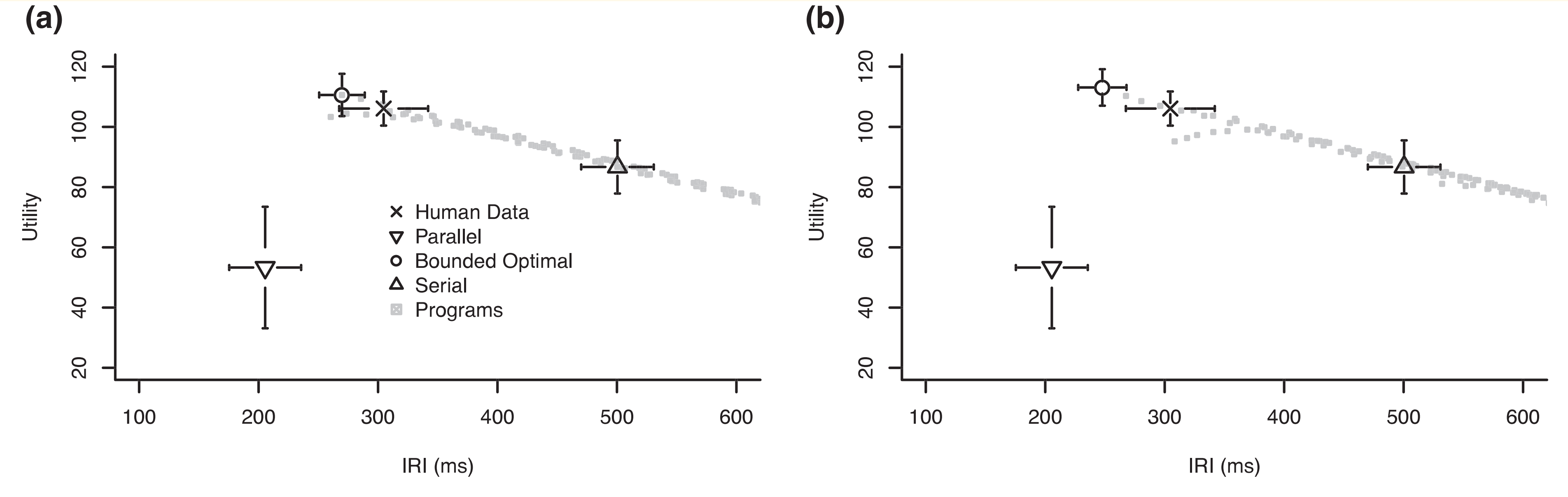


Qualitative good fit:

(Howes, Lewis, Vera, 2009, Psych Review)

- PRP curve is visible
- Sanity check: No strange effects (e.g., not observed that there were very accurate repsonses for low RTs)

PRP task: qualitative comparison is limited

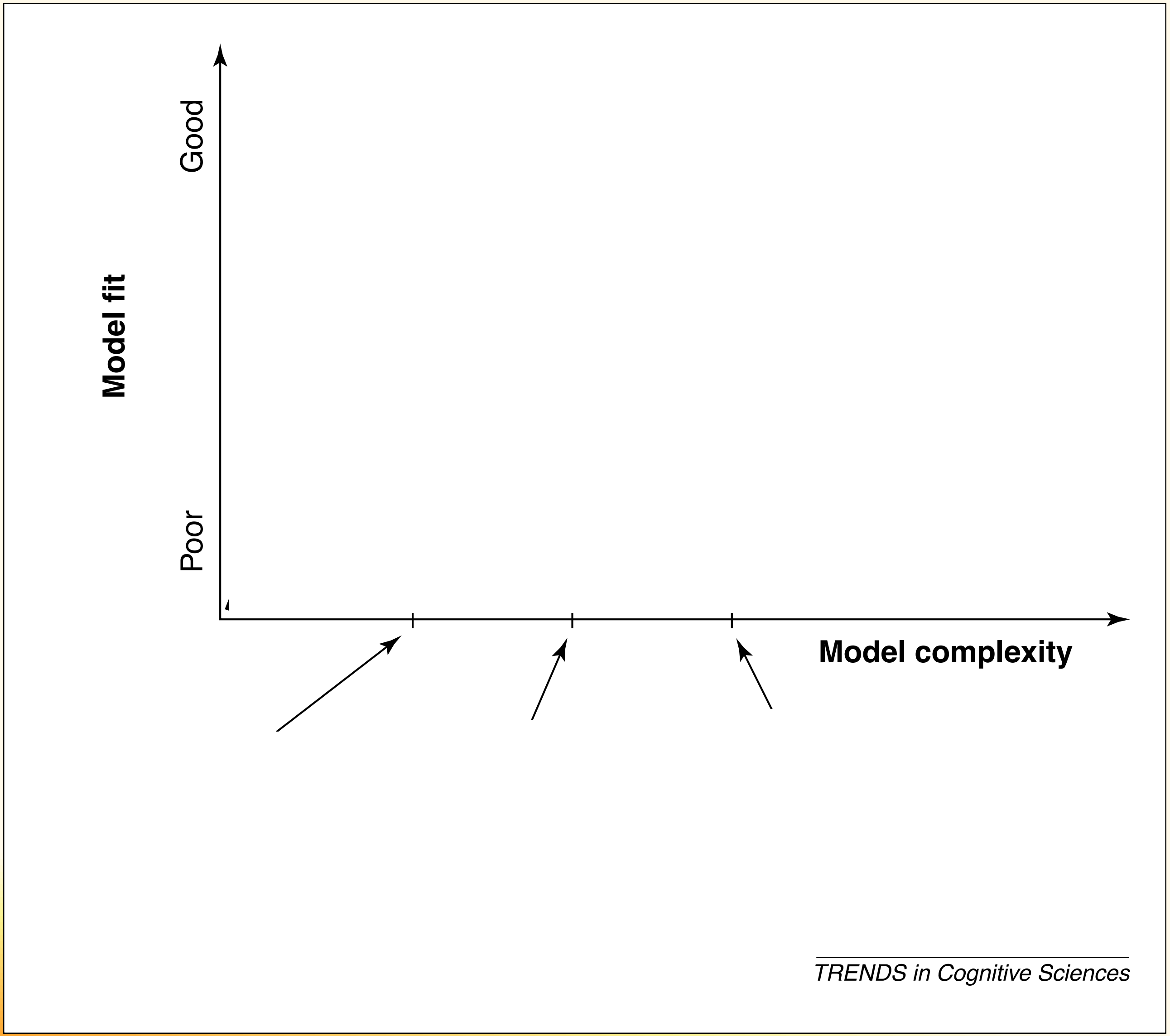


- **Two different model types fitted same pattern**
- **Exploration of more models and their fit was needed → quantitative (discussed in qualitative manner during class)**

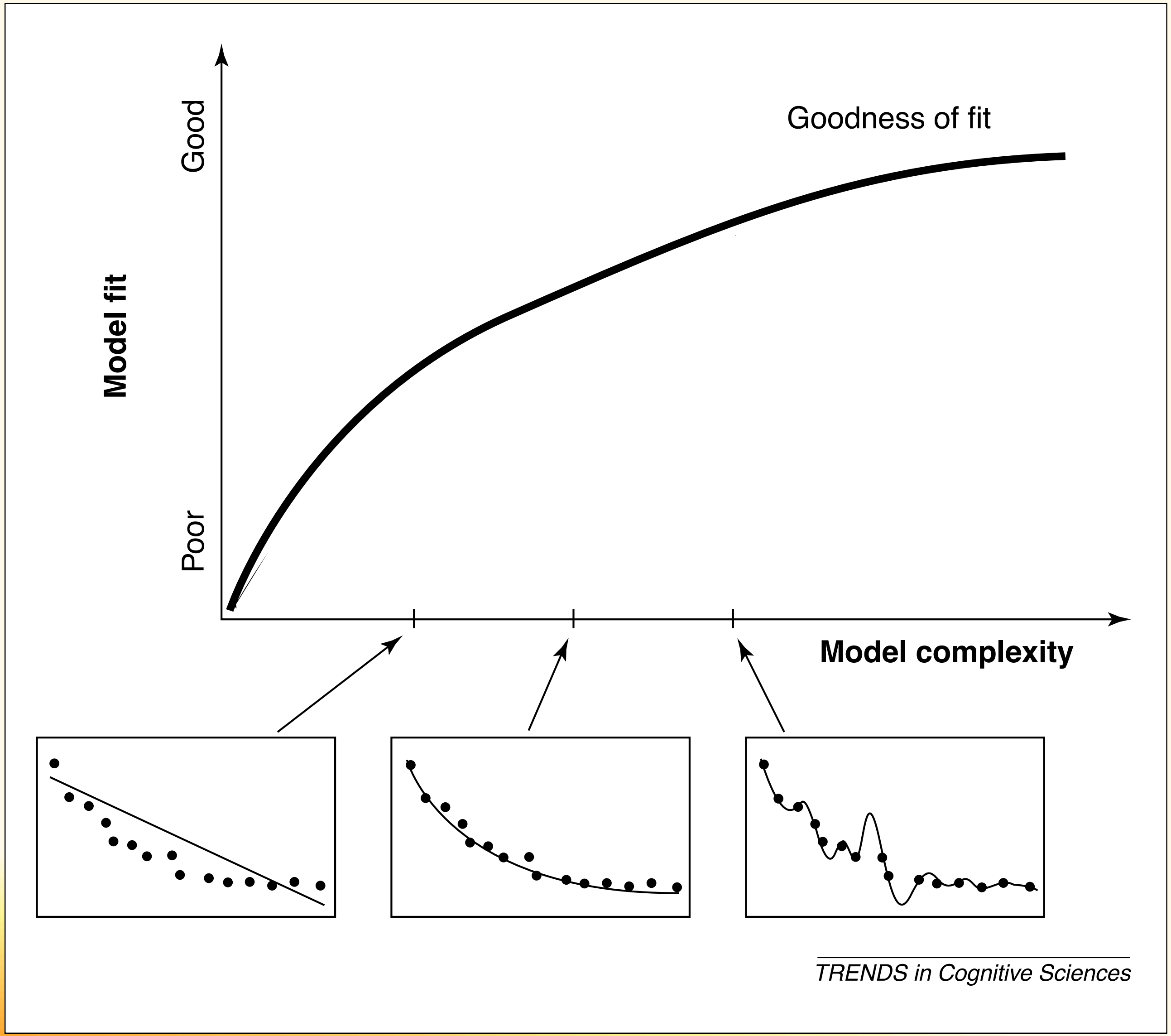
Model comparison

- **Relevant readings**
  - **Pitt & Myung (2002) When a good fit can be bad. *Trends in Cognitive Sciences***
  - **Roberts & Pashler (2000) How persuasive is a good fit? A comment on theory testing. *Psychological Review***

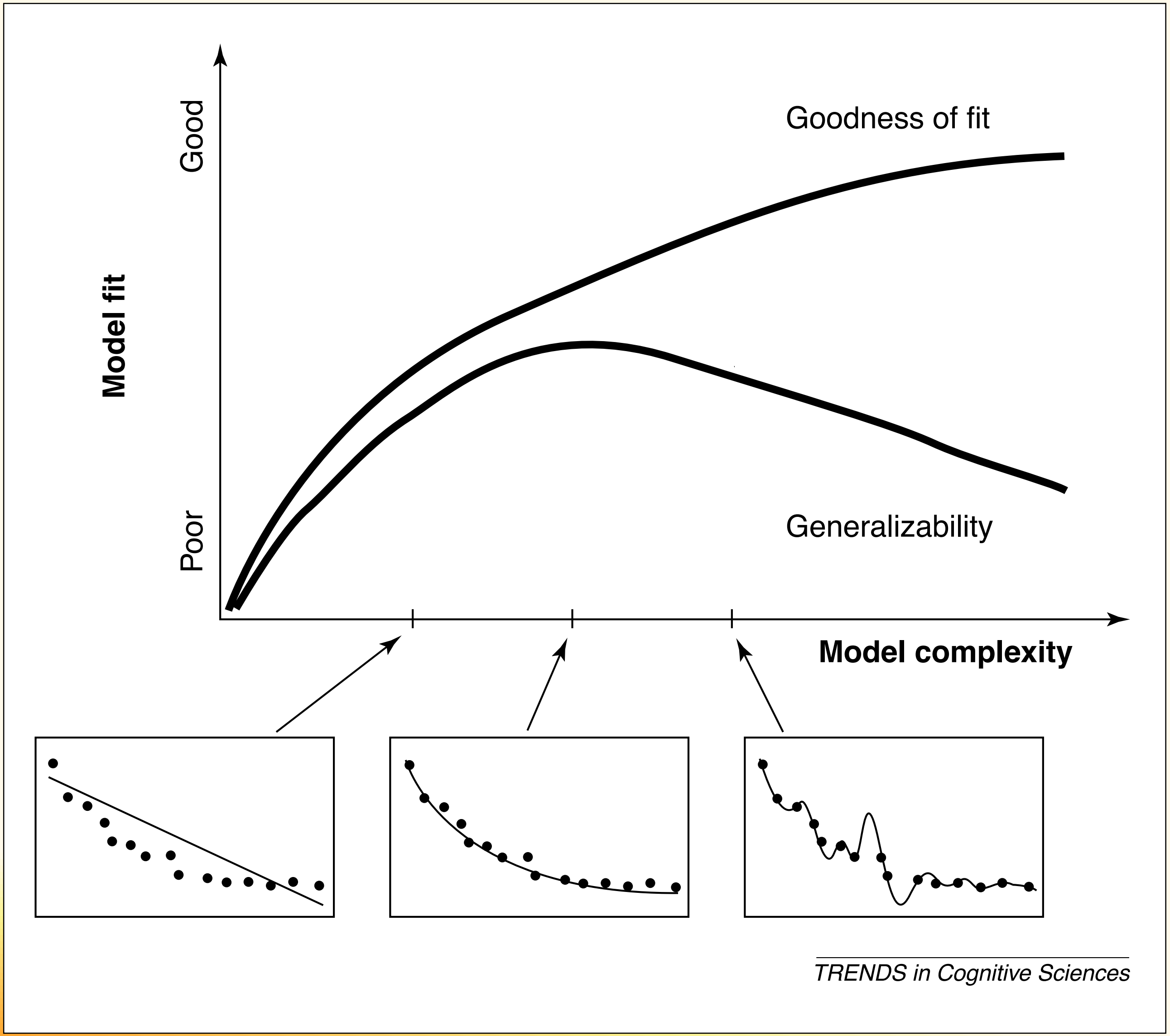
Pitt & Myung: Generalizability



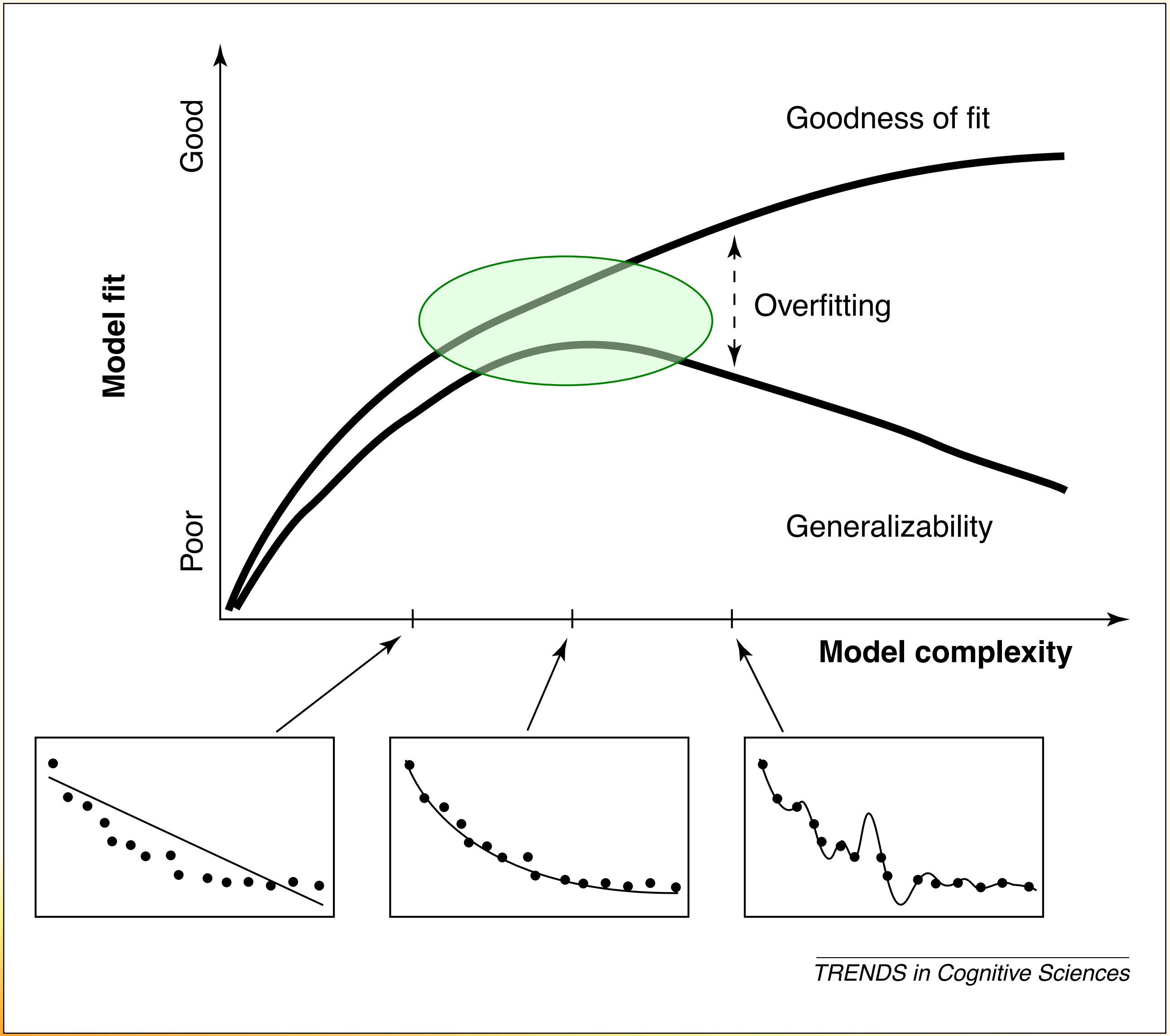
Pitt & Myung: Generalizability



Pitt & Myung: Generalizability



Pitt & Myung: Generalizability



Pitt & Myung: Generalizability

- Pitt & Myung paper provides various statistical procedures that consider fit in balance with model complexity. E.g.:
  - Akaike Information Criterion (AIC)
  - Bayesian Information Criterion (BIC)
  - Minimum Description Length (MDL)

- Easy to apply in parameterized models (e.g., ML, probabilisitc)
- Less straightforward to apply in process models. What is a parameter?

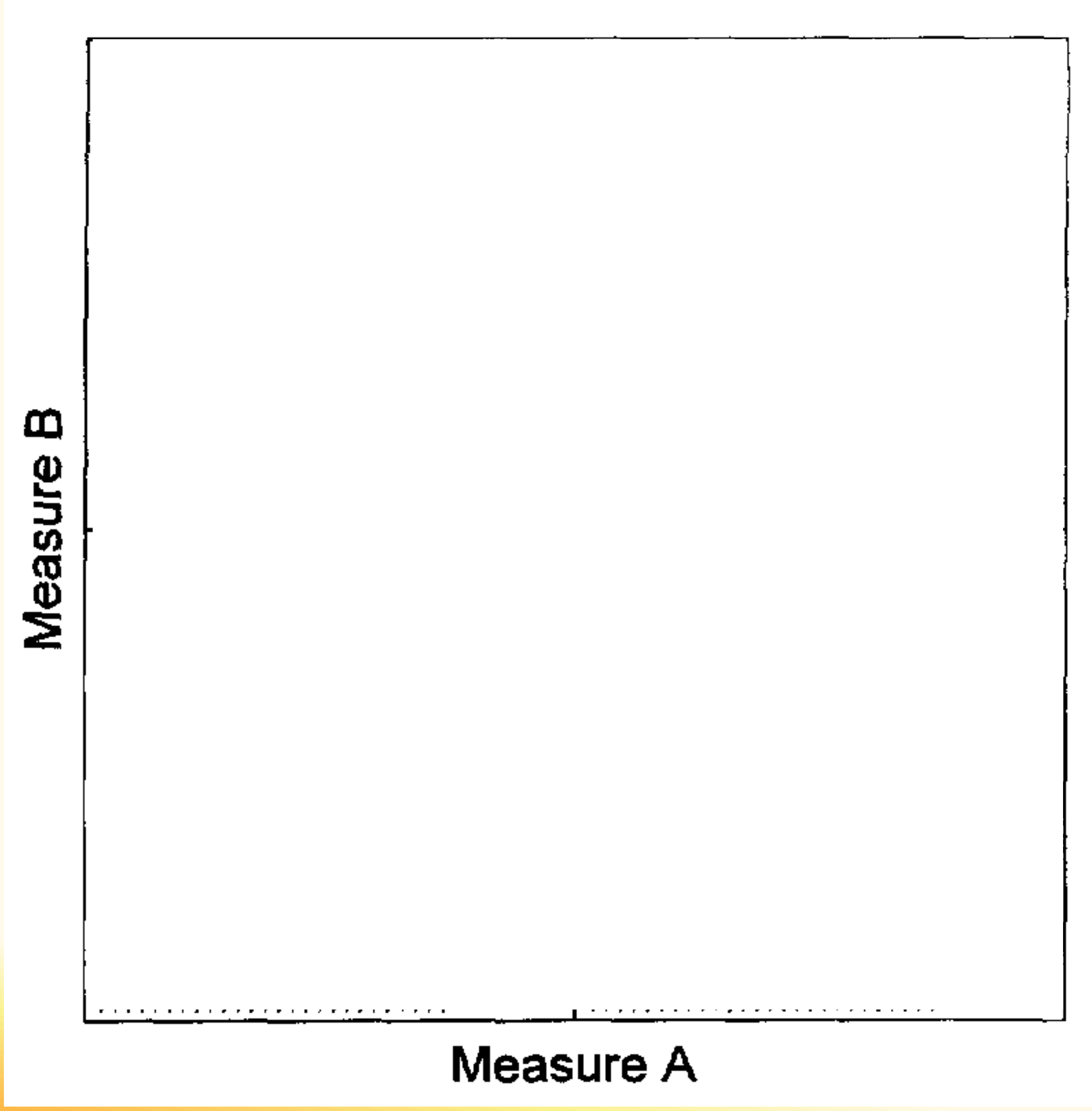
→ *Refer to this paper when doing your own modeling (thesis) project* ☺

Conclusion Pitt & Myung

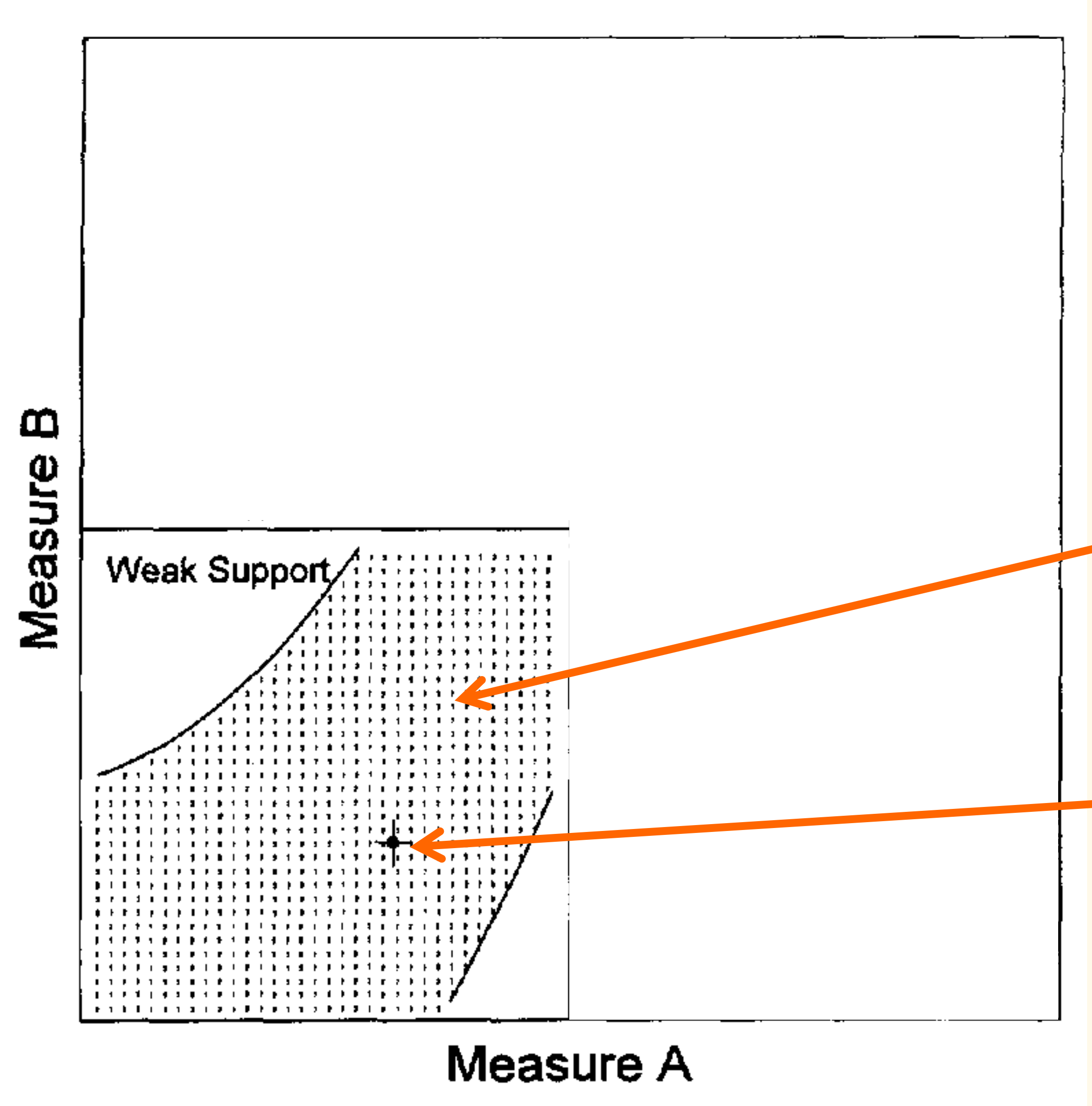
- “best fit” is not a goal in itself..
- “GoF” in relationship with complexity
  - Nr parameters
  - Functional form

Roberts & Pashler: How tight is the prediction?

Strong and weak support



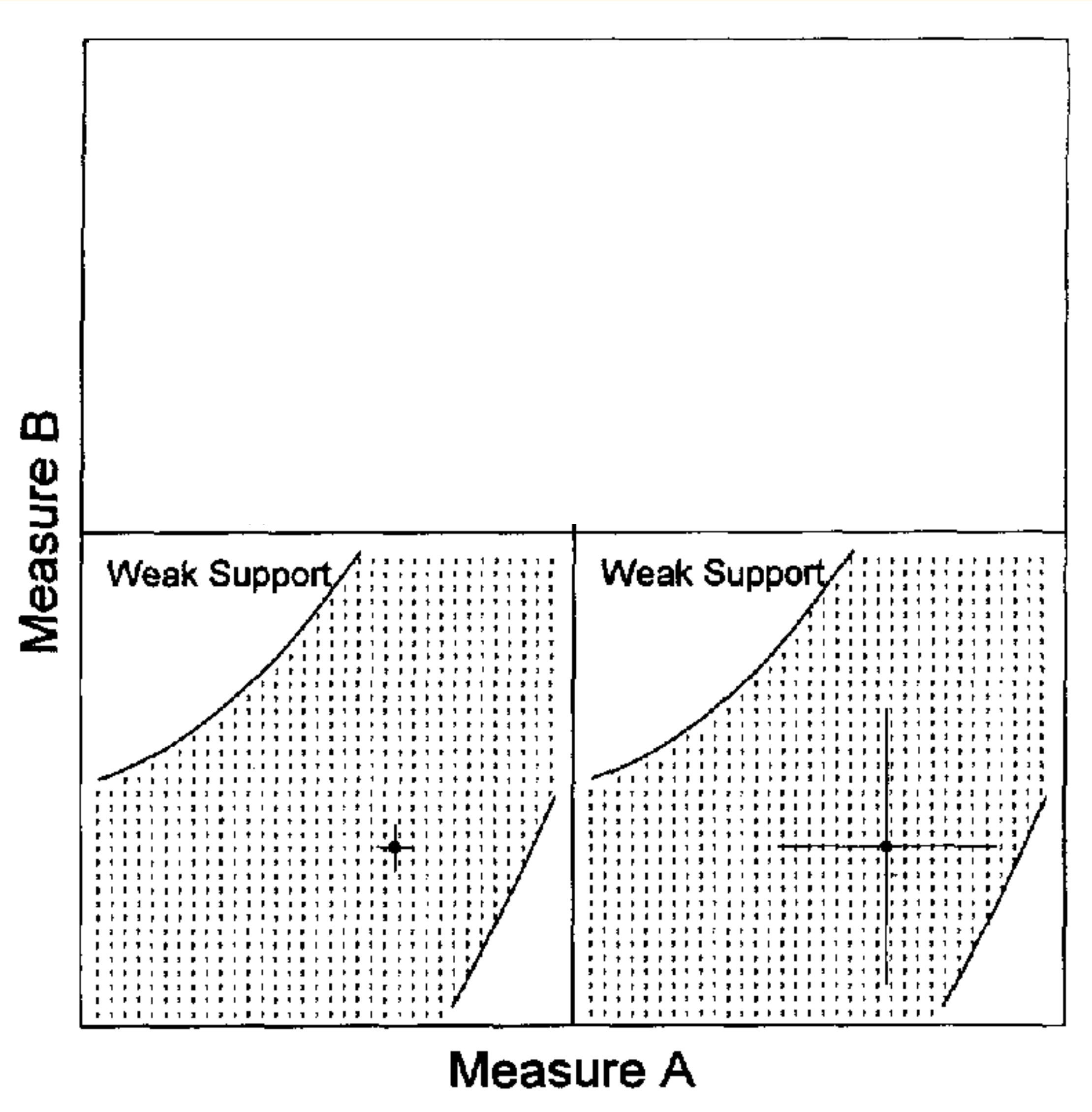
Strong and weak support



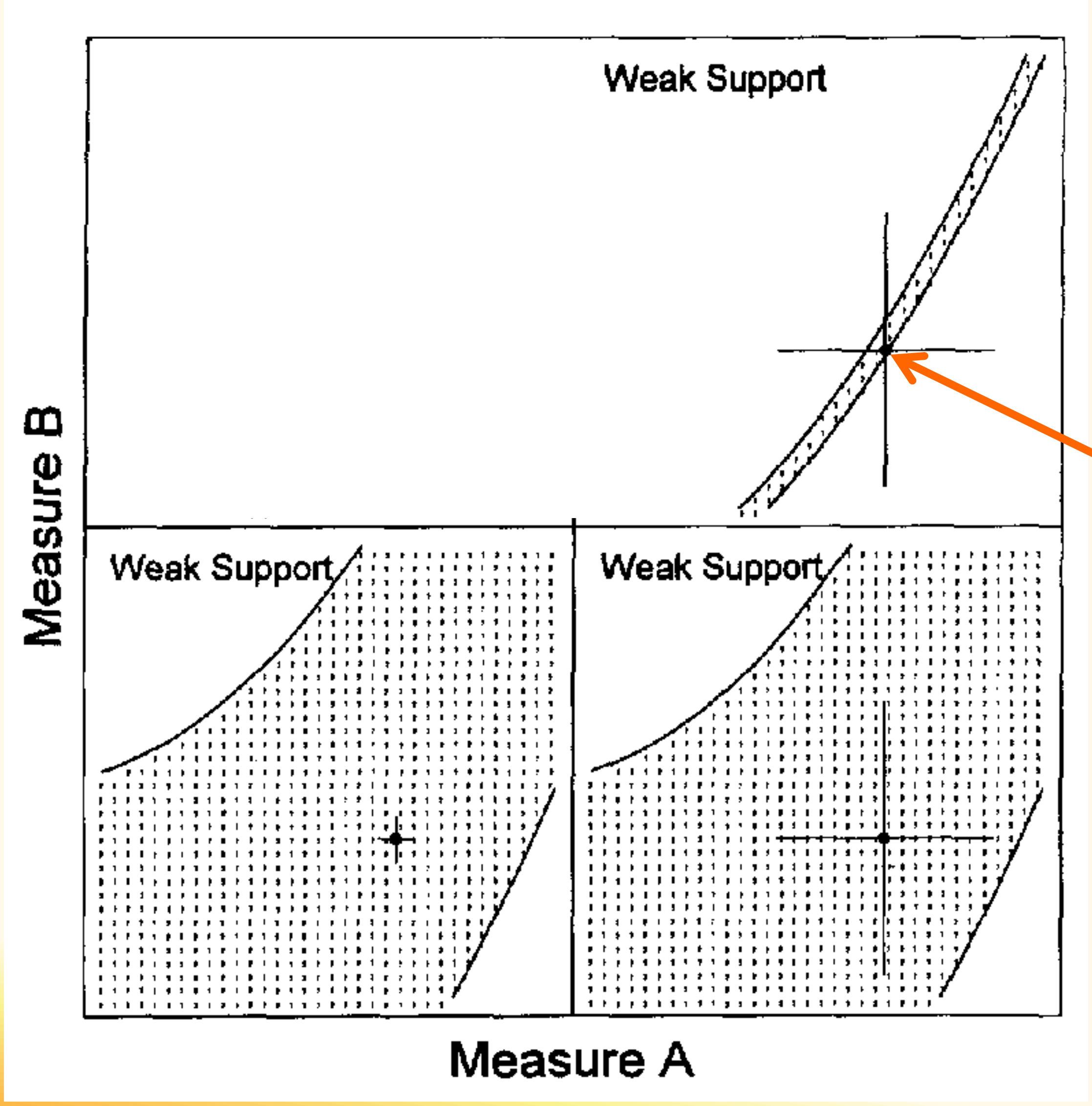
Model/theorie can explain and fit many results…

Human data

Strong and weak support

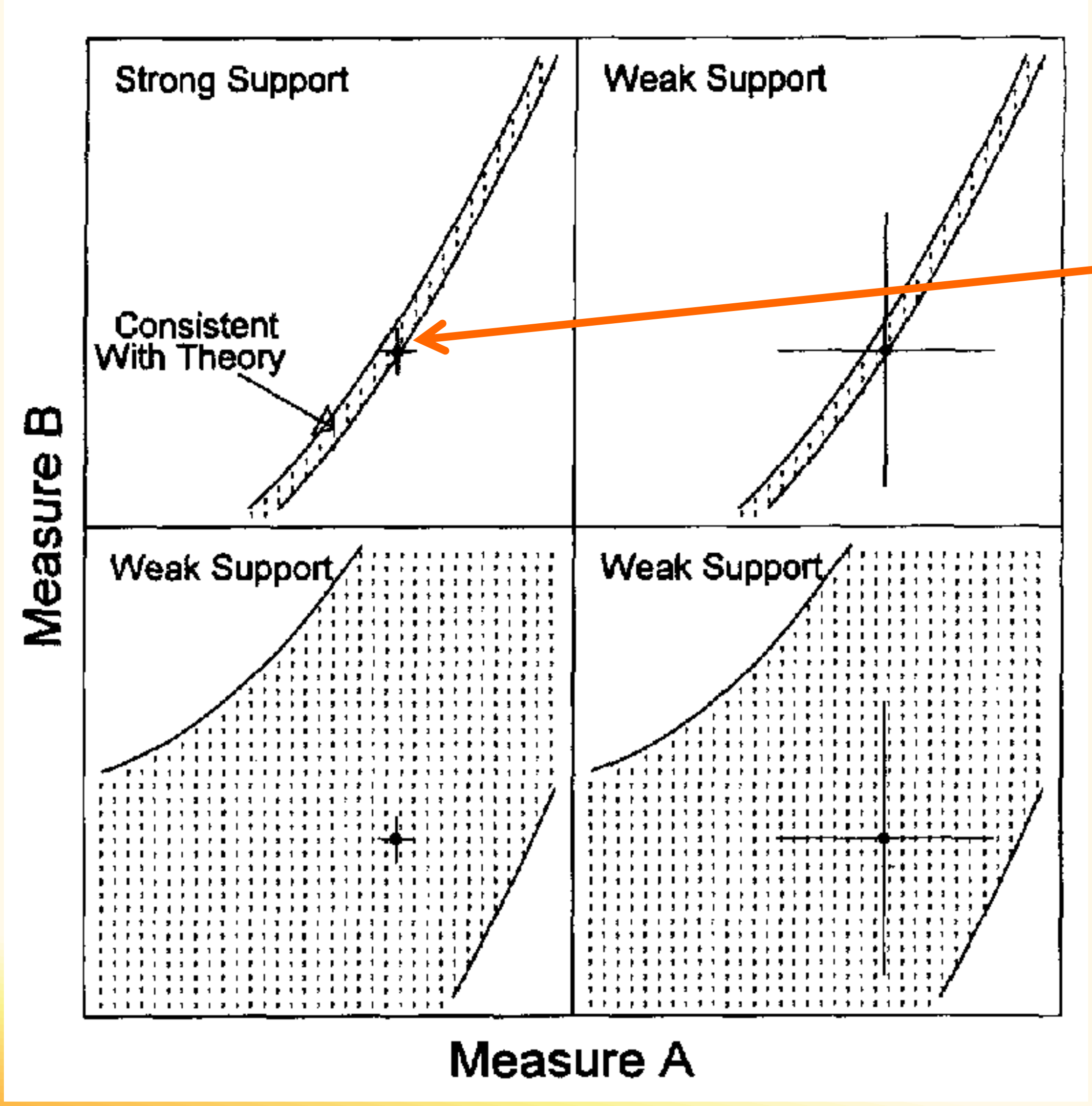


Strong and weak support



Humans show more variety than models. Easy to fit with a model.

Strong and weak support



Model predicts that humans can't do everything AND humans do (more or less) exactly and consistently what model predicts

Conclusion: Model comparison

- 1 model on its own not that interesting..
- Make a comparison between models
  - Often including a “base-line” or “random” model
  - Comparison with model results from previous papers where possible
- Comparison should
  - Be qualitative *AND* quantitative (know your stats)
  - Relate to balance of model fit with model complexity (Pitt and Myung)
  - Relate to theory and predictions; be explicit in what it does and does not *predict* (cf. Roberts and Pashler)

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  - **Model evaluation**
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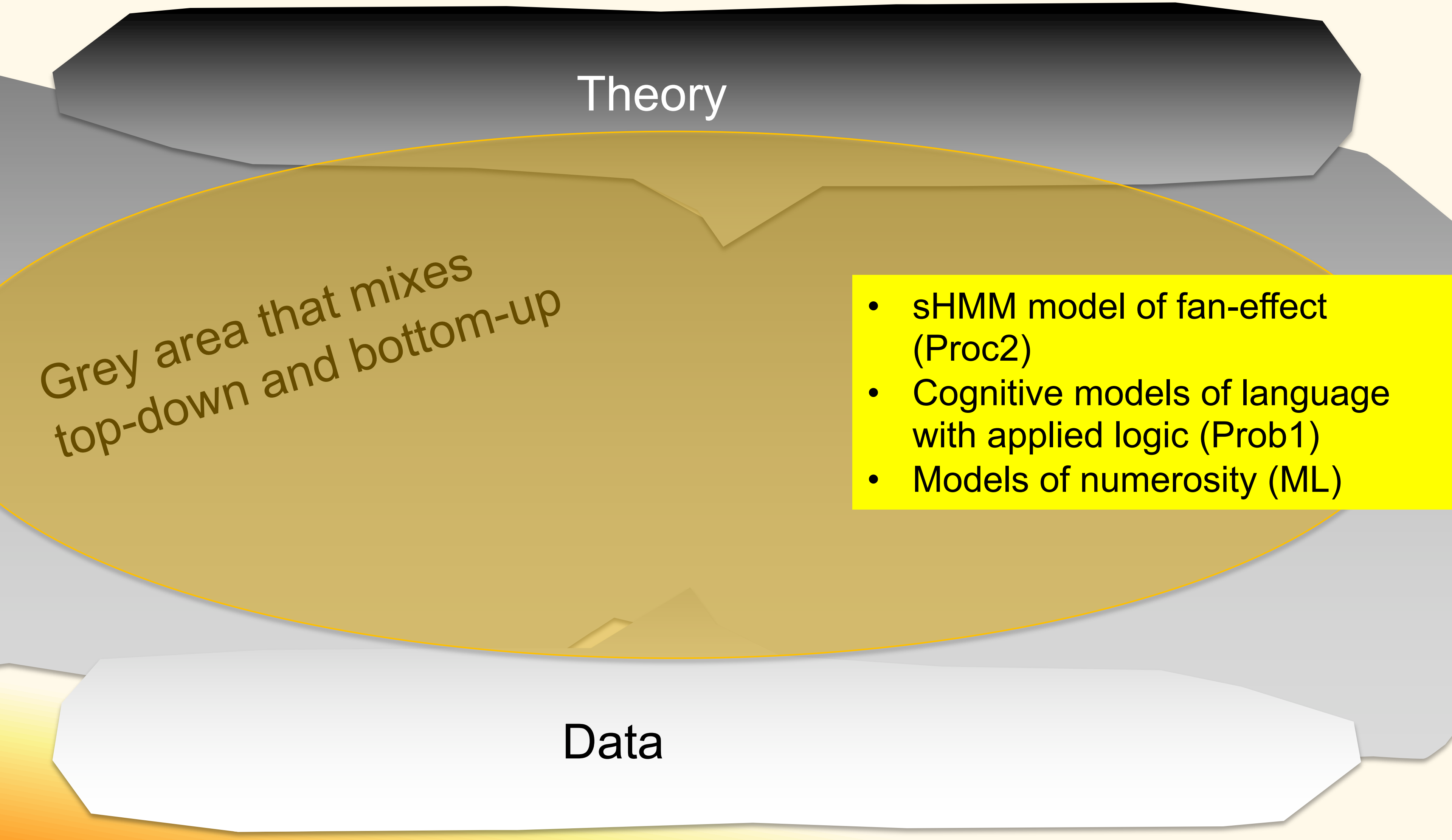
1. Variety

- ✓ Variety of models and frameworks
- ✓ Blends of models
- ✓ New models and frameworks

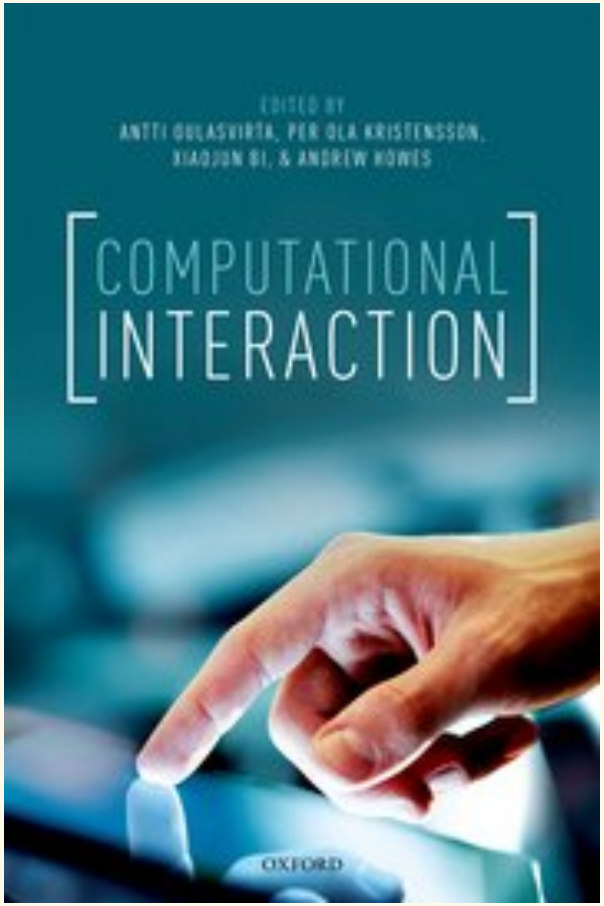
(see also McClelland)

2. Blend top-down & bottom-up



- sHMM model of fan-effect (Proc2)
- Cognitive models of language with applied logic (Prob1)
- Models of numerosity (ML)

3. Models for practice



Oulasvirta, Kristensson, Bi, Howes (2018)

Rise of model approaches in HCI

Understanding in many companies that models are useful

Not always theory driven models

Customization of apps (based on model)

See also:
Oulasvirta (2019) It's time to rediscover HCI models. *Interactions*
https://dl.acm.org/doi/10.1145/3330340

Side-note: Colloquium: 31 January

31 January, 16:00-17:00

Ruppert Rood

Prof. Antti Oulasvirta (Aalto U.)

Psychology as the science of design: what psychological theories do

Opportunity for interested students to meet in person and discuss his work on Bayesian modeling (see e-mail)

4. Companies & ML

- Hire "Machine learning" wizz-kids, but…
  - Do they know what these techniques are?
  - Might overlook value of empirical research including TESTS and STATISTICS

- Clever thinking (and theory) can save endless testing
  - This is how (some of) you can "beat the competition" on the job market!!

5. Processing models

- Combined with ML and Bayes/Probabilistic
- Application to applied domains

6. Probabilistic: Bayes

- (this course) For modeling
- (general) More and more for statistical inference incl hypothesis testing

Psychon Bull Rev
DOI 10.3758/s13423-017-1262-3

CrossMark

Introduction to Bayesian Inference for Psychology

Alexander Etz[1] · Joachim Vandekerckhove[1]

2017 Psychonomic Bulletin & Review

7. Machine learning

- Is deep learning "THE" solution??
  - Yes, it's wonderful
  - But… not "THE" solution
  - And … it is not entirely "new"

- Reading: Goodfellow, Benglio, Courville (2016) Chapter 1:
  - Provides some of the caveats
- A lot more on deep learning in course:
  - "Machine learning for human vision and language"

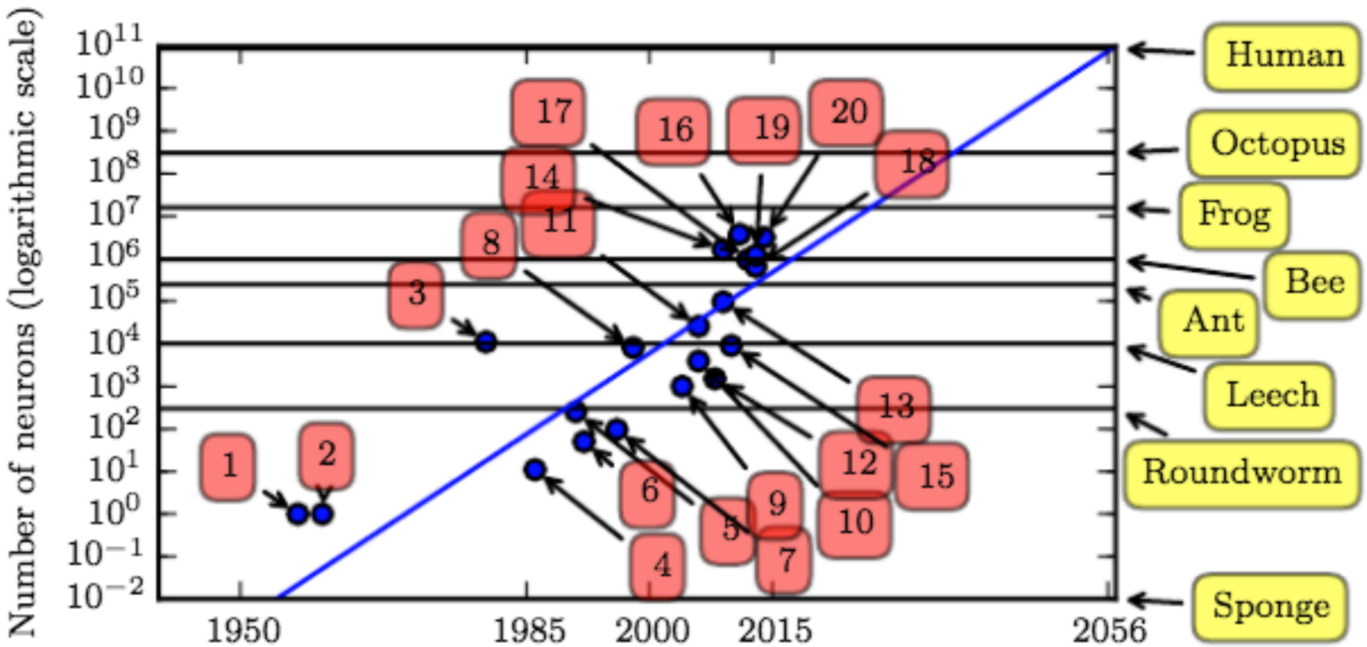


Figure 1.11: Increasing neural network size over time. Since the introduction of hidden units, artificial neural networks have doubled in size roughly every 2.4 years. Biological neural network sizes from Wikipedia (2015).

- Quite a while until same number of neurons as humans
- Have we overlooked important properties of brain? Simplified too much? (Goodfellow et al (2016) & McClelland (2009) both make this point)

8. Trends by McClelland (2009)

1. Models with greater fidelity to properties of real neural networks (downward, inward)

2. Models with richer knowledge bases (inward)

3. Increased complexity and capacity of situated cognitive agents (upward, outward)

Trends in field summary (1/2)

1. Variety of models and frameworks; Blends of models; New models and frameworks
2. Lots of "action" in blend of top-down mixed with bottom-up
3. Models applied in practice more (not always theory-driven; customization)
4. Companies overestimate Machine Learning Wizz-kids, underestimate value of clever experimentation (opportunity for you!)
   (of course: there are great exceptions in industry!)

Trends in field summary (2/2)

5. Processing specific: combined with ML and/or Bayes; Applications
6. Probabilistic specific: Bayes techniques are penetrating psychology, alternative to hypothesis testing
7. Machine Learning: Deep Learning is not “THE” solution, but seen as such (see book)
8. McClelland: greater fidelity; richer knowledge bases; increased complexity and capacity

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After this class

- Courses:
  - Experimentation in Psychology and Linguistics
  - Machine learning for human vision and language
  - Natural language generation
  - Natural language production
  - ...
- Develop, improve models
  - MLHVP
  - Capita Selecta
  - Smaller projects
  - Thesis projects

Revisiting course goals

- I hope you met your personal goal(s)

Revisiting course goals

At the end of this course, you can:

1. **Implement components of cognitive models in computer simulations**
2. **Evaluate the scientific literature on cognitive models**

Level: so you can learn more details after course and apply to other projects (e.g., MSc thesis)

Revisiting course goals

1. **Implement components of cognitive models in computer simulations**
   - Driving model: interpret existing theoretical model; adapting to new data (“noisy data set”)
   - Probabilistic, ML: create models “from scratch”

   - (I think we achieved)
     each of you challenged at your own level

Revisiting course goals

2. **Evaluate the scientific literature on cognitive models**
   - Various papers as part of exam
   - Poster presentation on various topics (different focus, different styles, different audiences)

   - Hopefully you know what exited you & understand better where various techniques stand within the wider pallet

Revisiting course goals

- **Level: so you can learn more details after course and apply to other projects (e.g., MSc thesis)**
  - **Some of you already applied for other projects ☺**
  - **Wide scope of topics provides broad introduction to go deeper.**
  - **Modeling yourself hopefully given confidence boost that you can go deep**

Your evaluation

- Please fill out the Caracal evaluation to help us further improve the course

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Exam material from this lecture

- **All material covered in class**
- **Articles:**
  - **McClelland, J. L. (2009). The place of modeling in cognitive science. *Topics in Cognitive Science*, 1(1), 11-38.**
  - **Goodfellow, I., Bengio, Y., & Courville, A. (2016). Chapter 1: Introduction. *Deep learning*. MIT press.**
    (Chapter can be accessed at:
    http://www.deeplearningbook.org/)

Study questions (not bullet proof)

- Understand the various ways of classification & be able to apply them to case studies
  (i.e., be able to classify a model yourself)
- Understand the downward, upward, inward, outward framework and be able to apply this to case studies
- Understand how Process, Bayesian, and Machine Learning models are positioned relative to each other and in the wider field of cognitive modeling
- Understand current developments and (projected) future directions of the field
- Understand power and limitations of deep learning (see also article)
- Understand article McClelland (2009), understand chapter 1 of Goodfellow et al (see also own questions)

- Be able to apply this to case studies as well

Study questions about McClelland (not bullet proof)

- What's the purpose of modeling in Cognitive Science according to McClelland?
- Why is simplification essential?
- What are downsides of simplifications?
- Why was the invention of the computer essential for cognitive science? And what were limitations to this?
- Why is care needed when interpreting successes and failures of models?
- How should a cognitive model be judged (according to McClelland)
- Understand McClelland's take on Popper (i.e., modeling as "existence proof")
- What is McClelland's criticism on Marr's levels approach?
- What does McClelland see as trends (&future) in cognitive modeling?

- Be able to apply this to case studies as well

Study questions about Goodfellow et al (not bullet proof)

- What is the true challenge of AI according to the authors?
- Why is deep learning called deep learning (according to authors)?
- What are deep learning, representation learning, machine learning, and AI and how do they relate to each other?
- Is deep learning really new, or not? And why?
- Be able to recognize the various names that are used for and associated with neural networks as discussed in section 1.2.1
- Are deep learning models truly a model of the brain (i.e. inspired by neuroscience) or not?
- Are deep learning models the “killer solution” to all cognitive science at this time?
- How do increases in dataset size and model sizes explain the recent success of deep learning models?
- Can we expect deep learning networks to cover all aspects of the human brain soon?

- Be able to apply this to case studies as well

Questions?

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