

Modeling Part

Summer School on Modeling

Philosophy of the School

- We expect homogeneous learning outcomes for the conceptual stage
 - irrespective of prior knowledge

We encourage peer-assisted learning

- We accept heterogeneous learning outcomes for the technical stage
 - some people will master the material faster
 - this is difficult to avoid due to heterogeneous background

If we are here, we are available (even if we appear to be busy)

Interaction with mentors:
Start at 3pm today

Computational Modeling

				Track 1	Track 2		
12	Tue.	3	AM	Overview and Principles of Modeling		Ch. 1, 2 F&L	SL, JJ
			PM	From Verbal Theories to Computational Models		Ch. 1, 2 F&L	KO, MN
			3 PM	Project Time: Meet with Supervisors			All
13	Wed.	4	AM	Parameter Estimation, From Basics to Maximum Likelihood		Ch. 3, 4 F&L	GB, CL, LF
			PM	Parameter Estimation & Maximum Likelihood Exercises: Memory and Judgment/Decision-Making Models			GB, CL, LF
			4 PM	Project time			All
14	Thurs.	5	AM	Model Selection and Drawing Inferences from Models		Chapter 10 F&L	CD & SL

Overview for Today (Tuesday)

Time	Instructor	Topic
9:00 – 10:45	Stephan Lewandowsky	why models? inside a simulation
10:45 – 12:00	Jana Jarecki	scope, falsifiability, explanations, some terms
12:00 – 1:00	Klaus Oberauer	from models to instantiations
1:00 – 2:00		lunch
2:00 – 3:30	Michael Nunez	from models to instantiations
3:30 – dinner	All	meet mentors and discuss projects
6:30		dinner

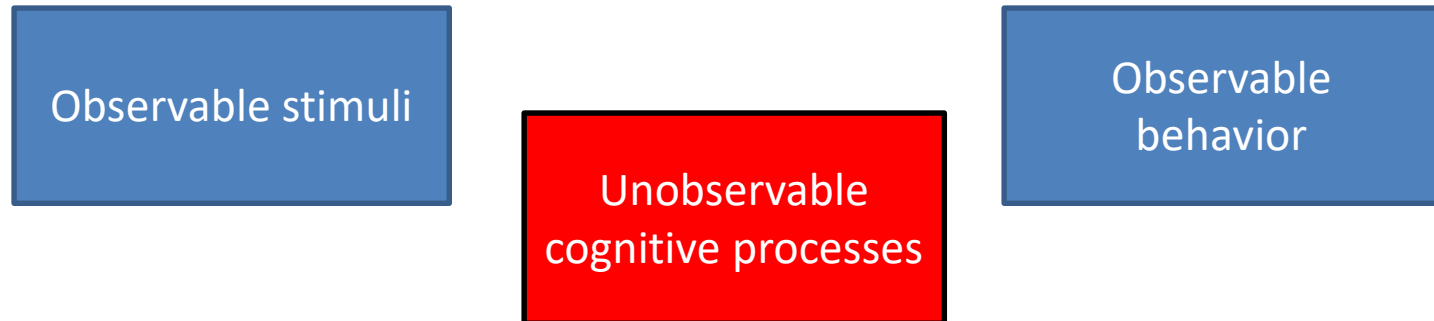
Yes, there will be breaks

Why Models?

Why *Computational* Models?

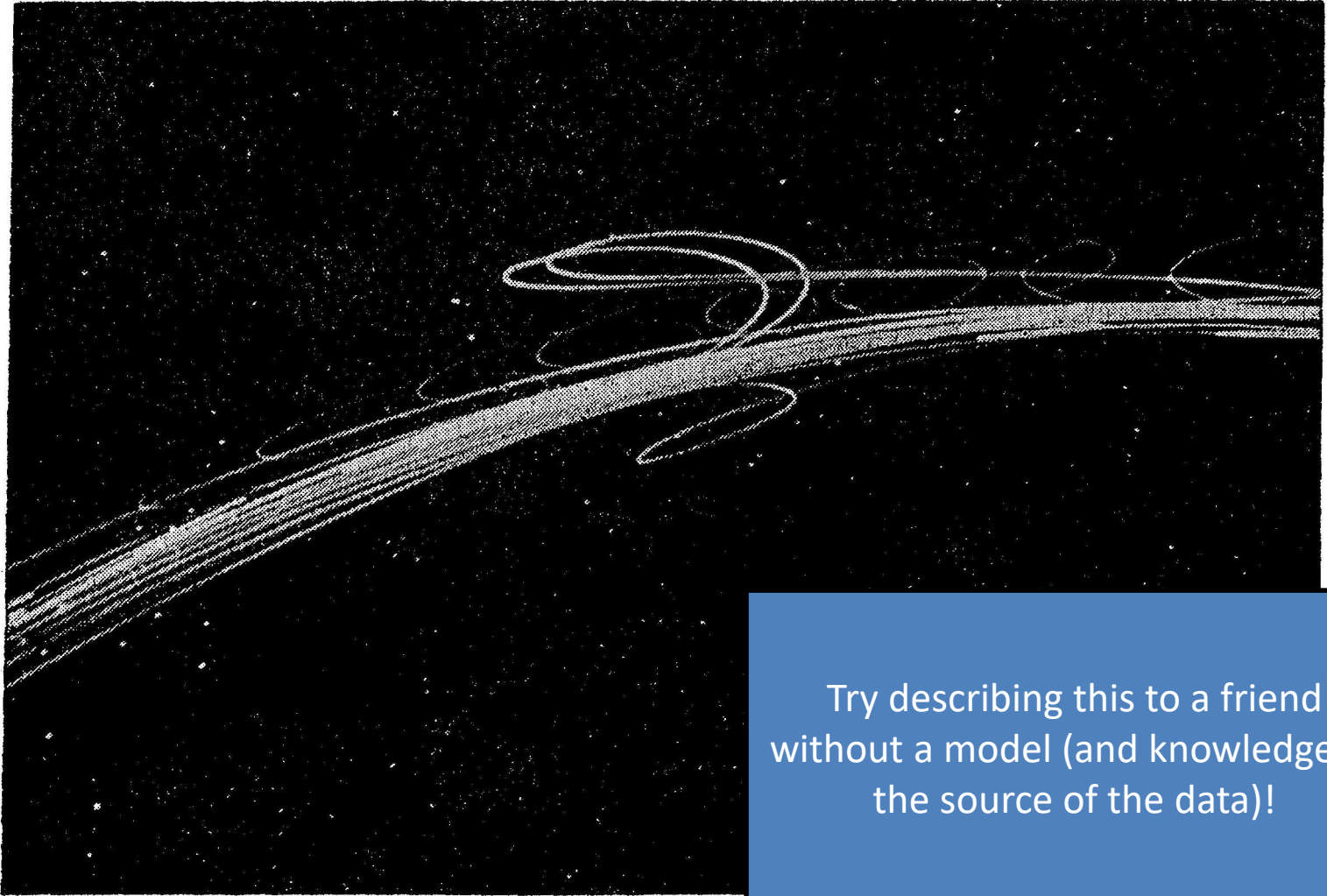
Why Cognitive Science?

- We seek to understand how the mind works



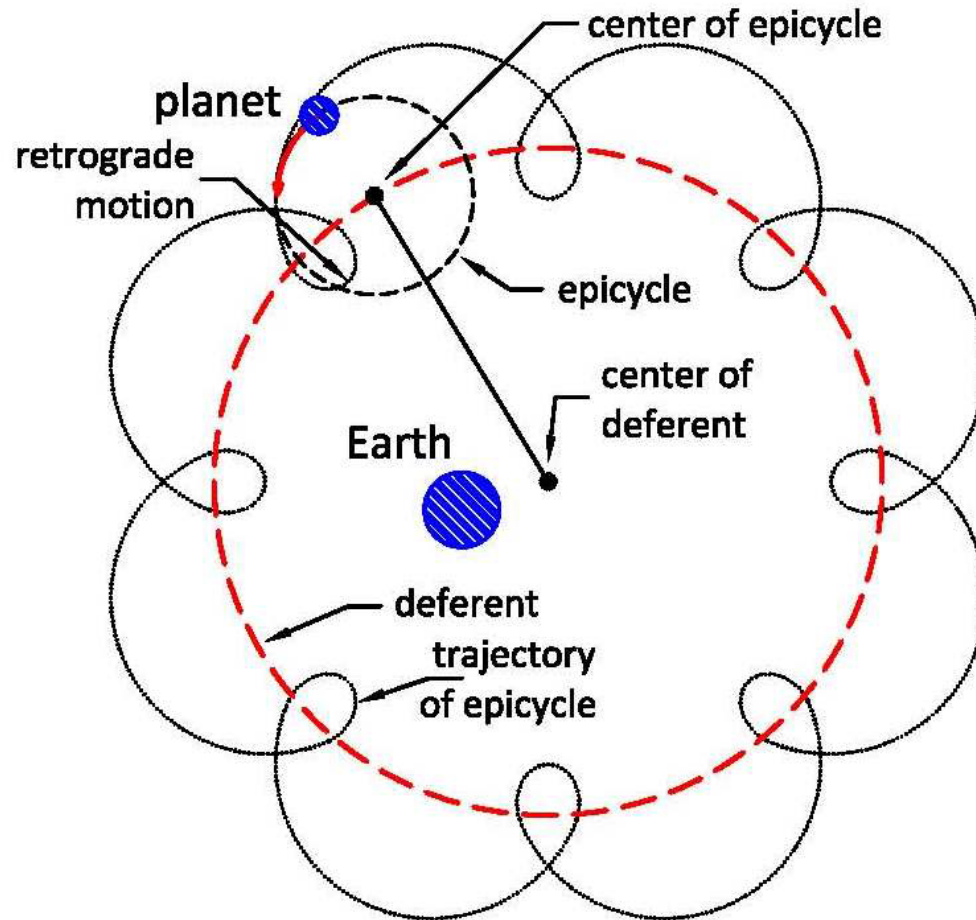
- Models are indispensable
- Nothing can be understood without a model

A Stellar Example

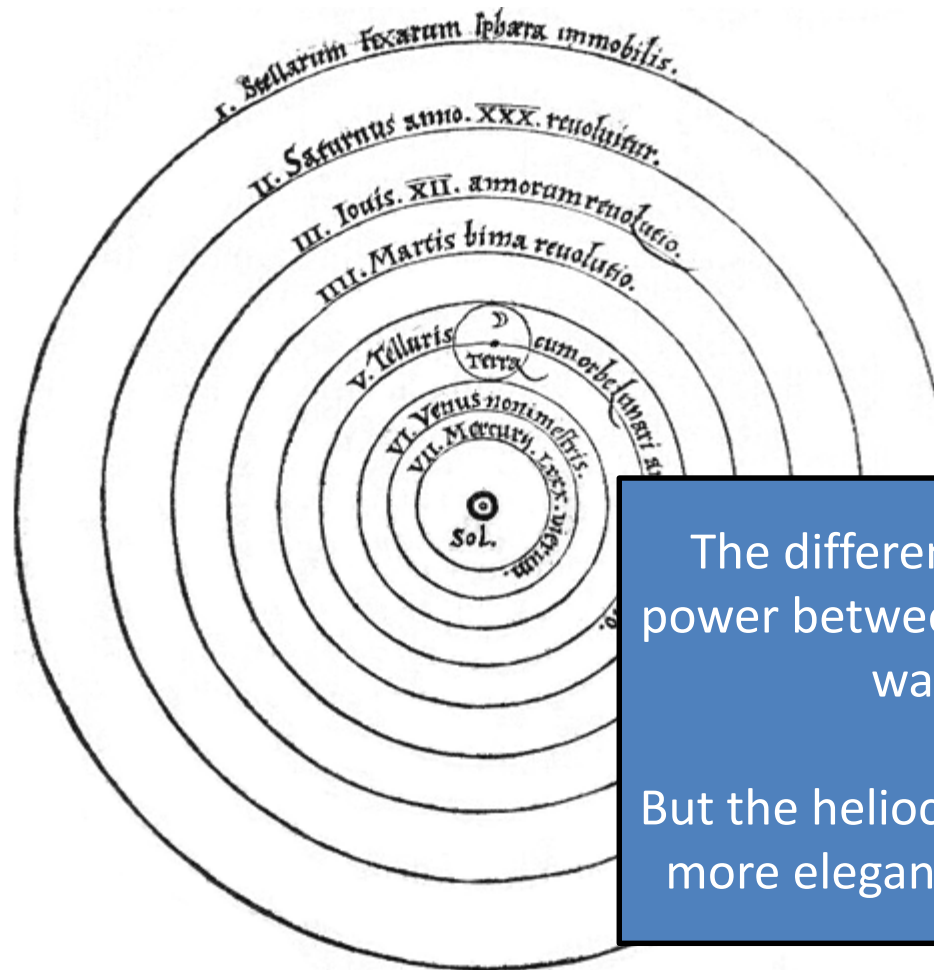
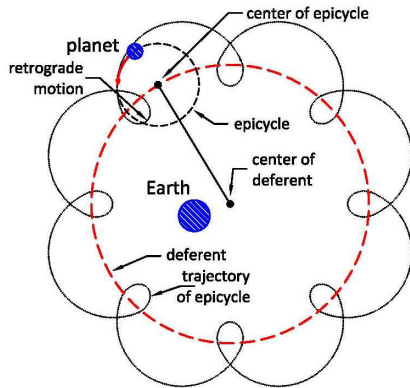


Try describing this to a friend
without a model (and knowledge of
the source of the data)!

1,300 Years of Modeling ...



... and Modernity



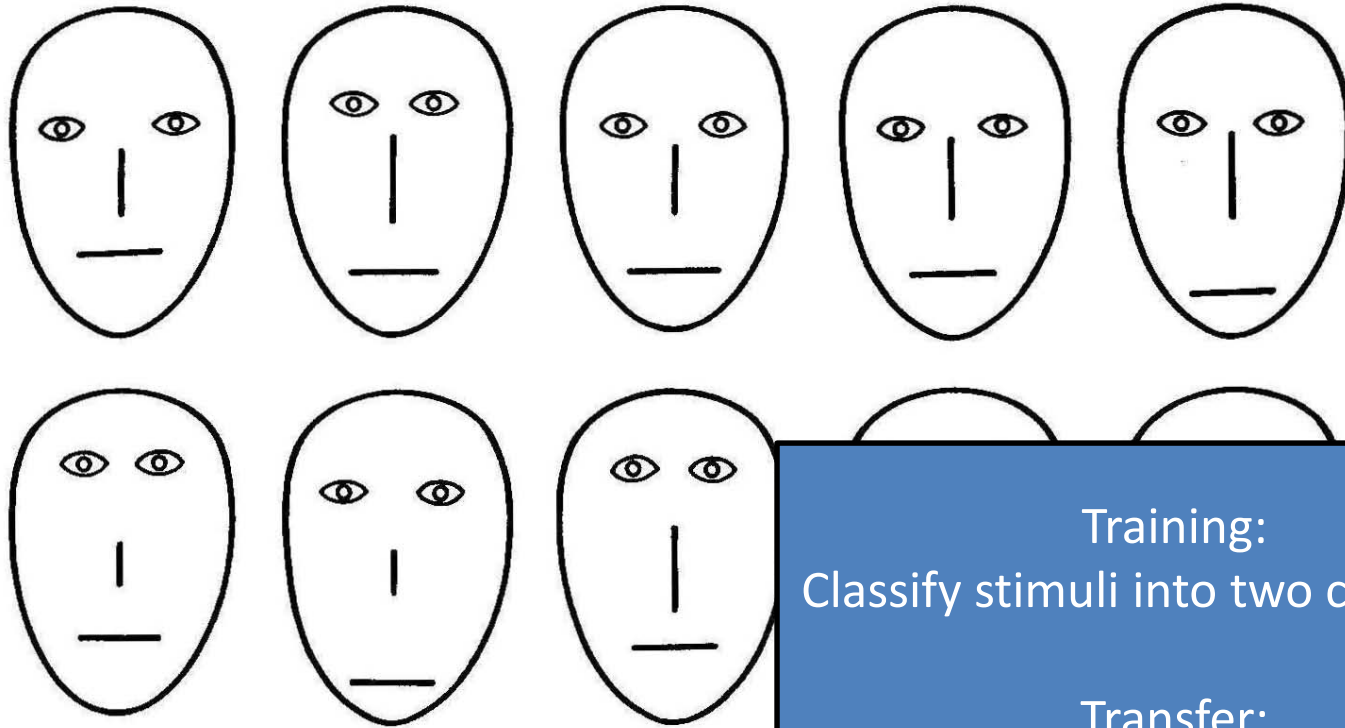
The difference in predictive power between the two models was *slight*!

But the heliocentric model is far more elegant and satisfactory

Conclusions (I.)

- Data never speak for themselves
- Nothing can be understood without a model
- There are always *multiple possible models*
- Choice between models based on
 - quantitative comparison
 - *and* intellectual judgment

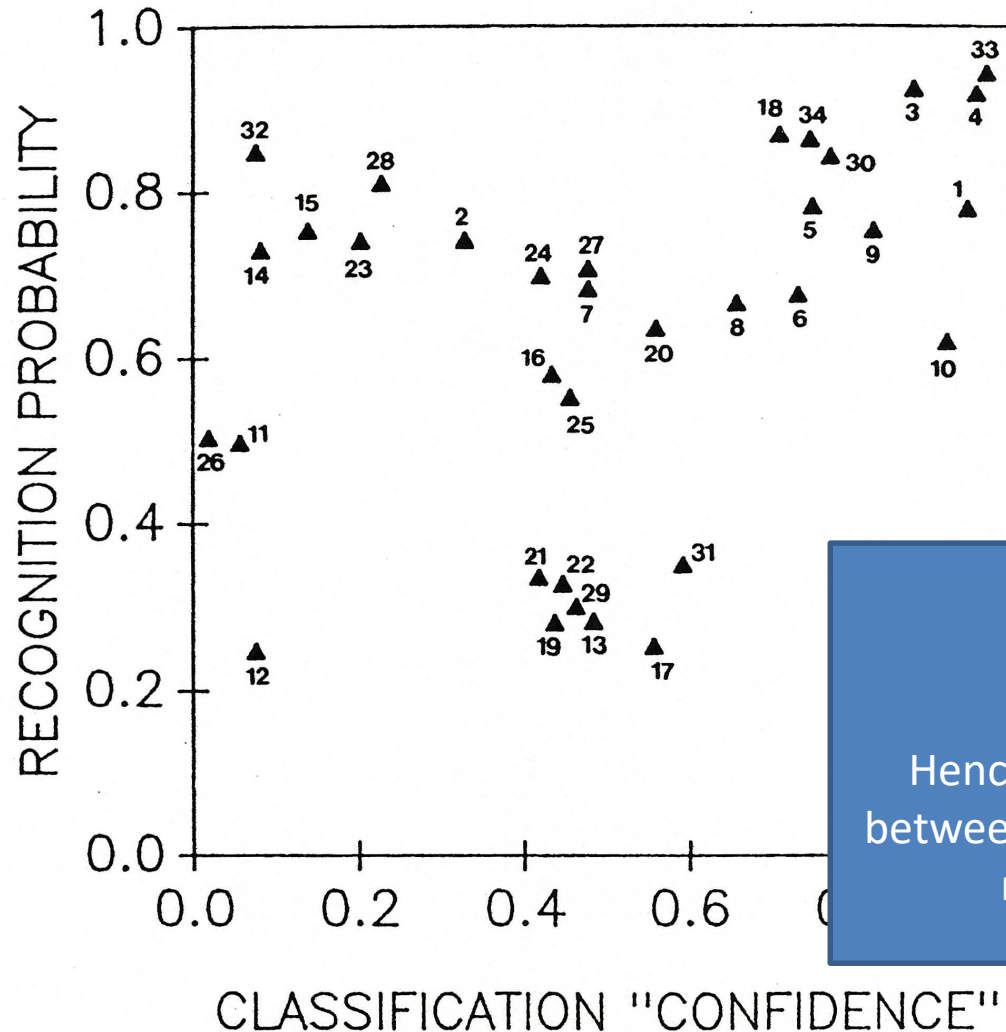
A Cognitive Example



Training:
Classify stimuli into two categories

Transfer:
Classify *and* recognize

A Cognitive Example

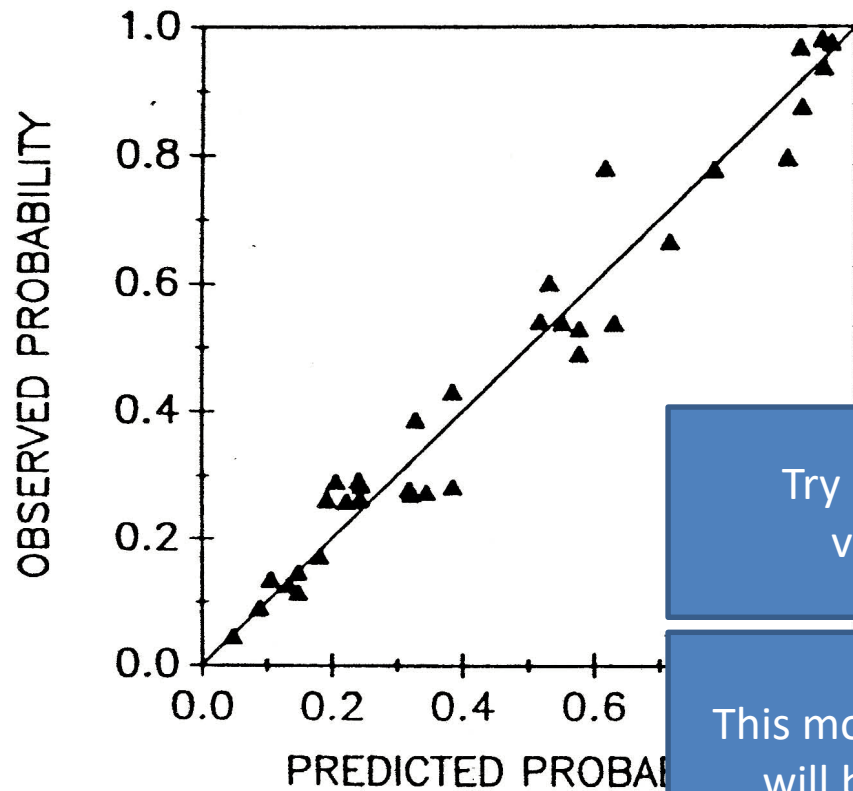


$$r = .36$$

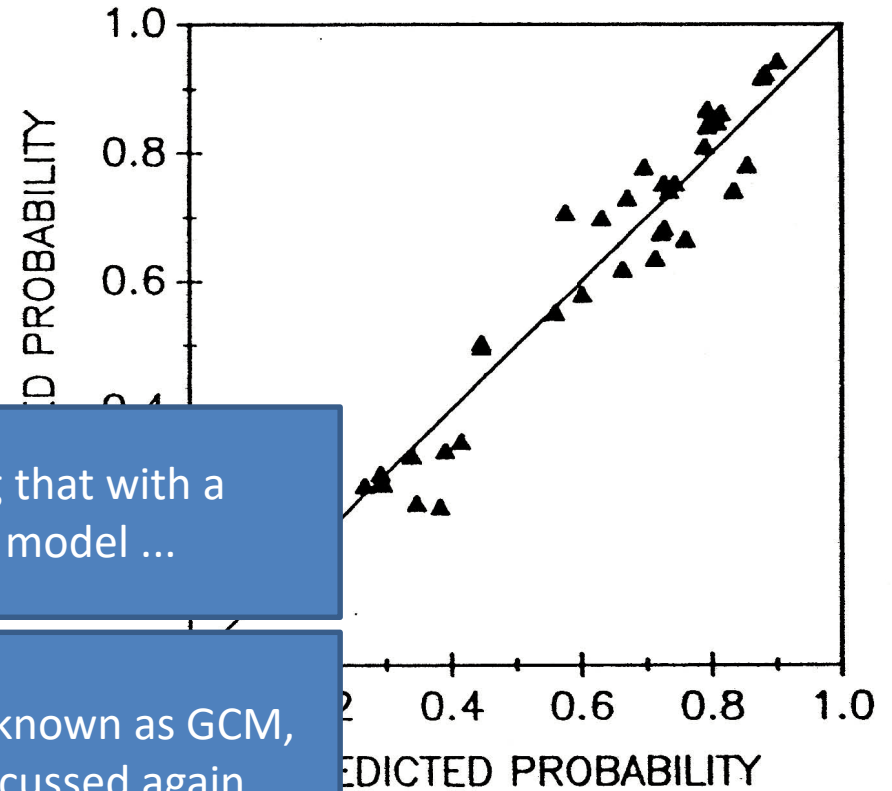
Hence no relationship
between classification and
recognition?

Uncovering a Hidden Relationship

CATEGORIZATION



RECOGNITION



Try doing that with a
verbal model ...

This model, known as GCM,
will be discussed again

Conclusions (II.)

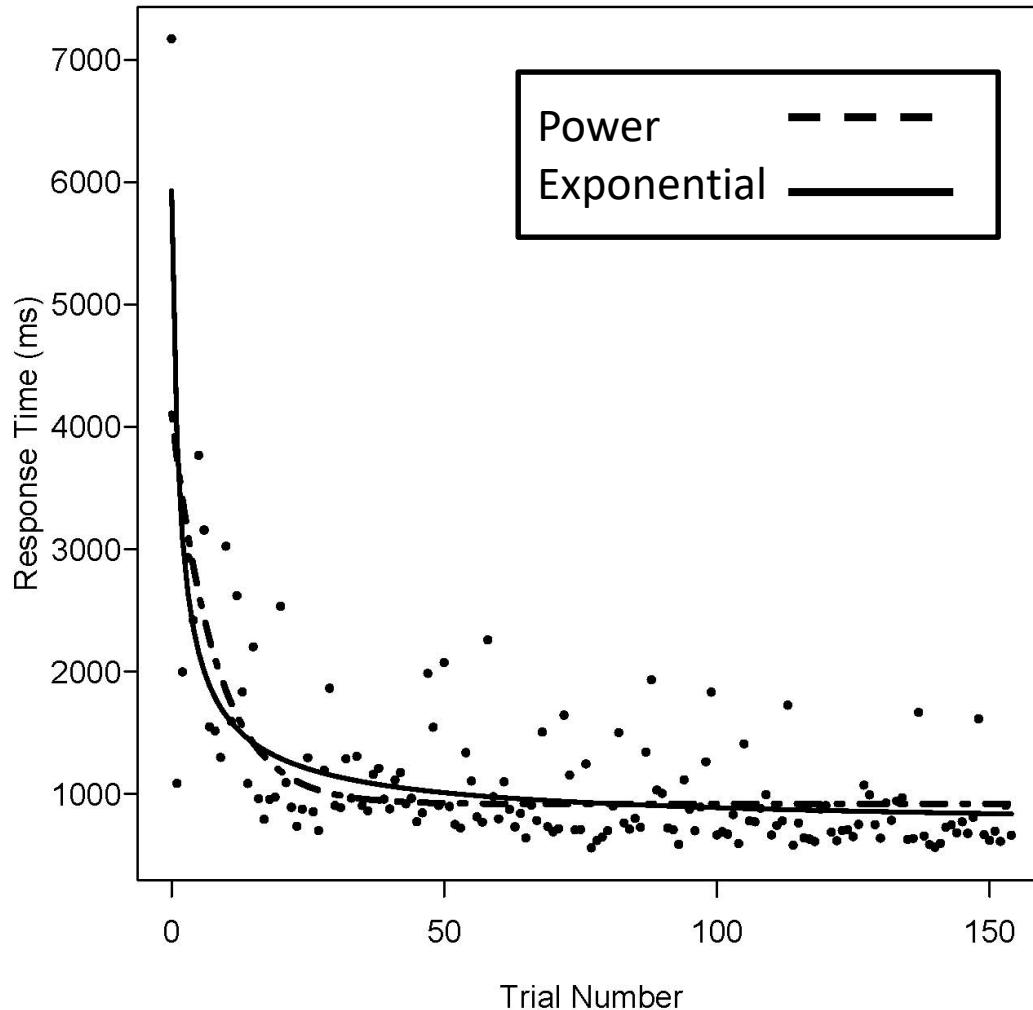
- Computational models can reveal relationships between psychological measures that would otherwise escape detection
- The model then *explains* performance in two disparate tasks
 - psychological model
 - explains rather than just describes data
- But not all models always explain....

Classes of Models

- Data description
 - focuses on data only
 - may have psychological implications
- Process models
 - look inside the “black box”
 - explain

Primary focus

Data Description: The Case of the “Power Law”



Exponential implies
constant relative rate of
learning

Power implies reduction in
learning rate with practice

Conclusions (III.)

- Data description can have psychological implications
 - “laws” of learning or practice
 - forgetting function
 - utility functions

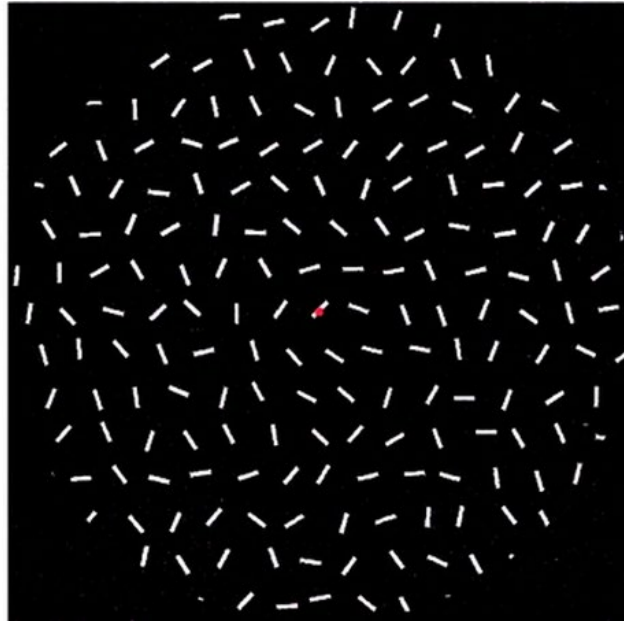
Where Does the Model Come From?

- Suppose we have a verbal theory
- We recognize the limitations of verbal theories
- We seek to instantiate the theory in a computational model
 - this forces us to be explicit about *everything*
 - and many decisions have to be made

Klaus & Michael:
Later today, in-depth
look at this process

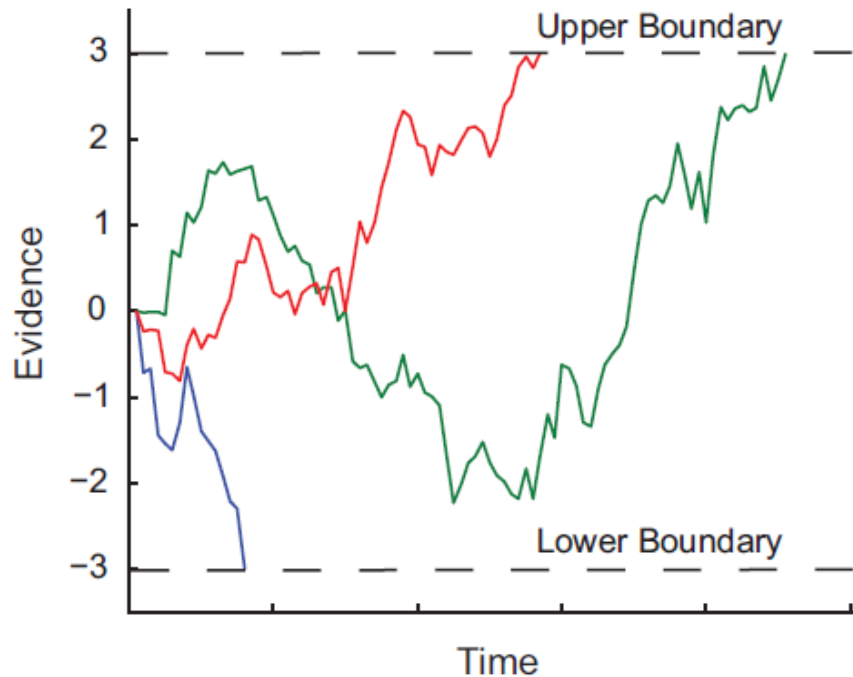
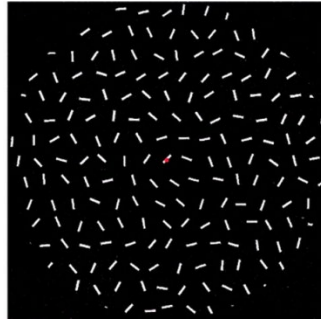
Inside a Simulation

How Do People Make Decisions?



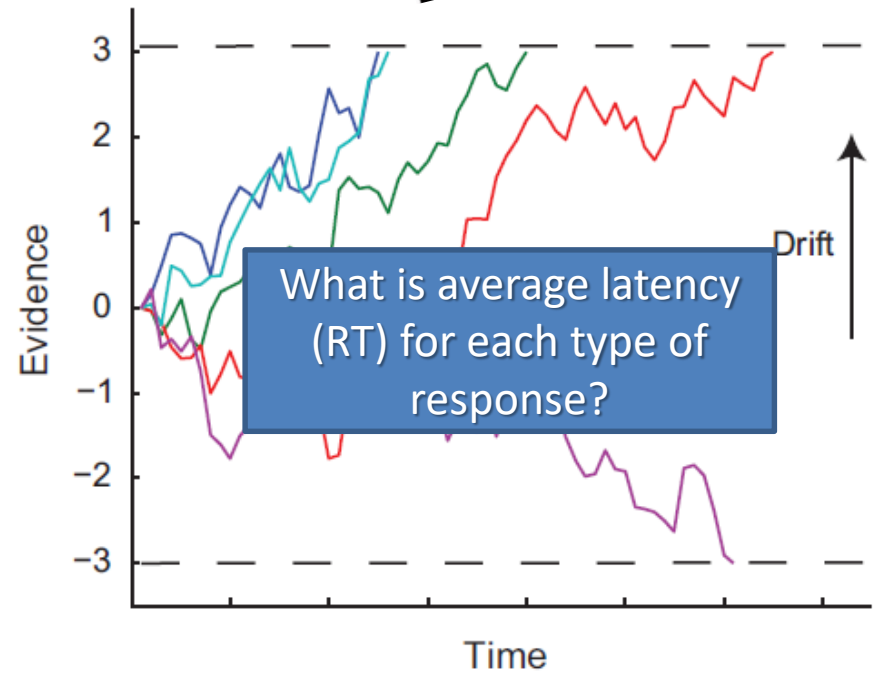
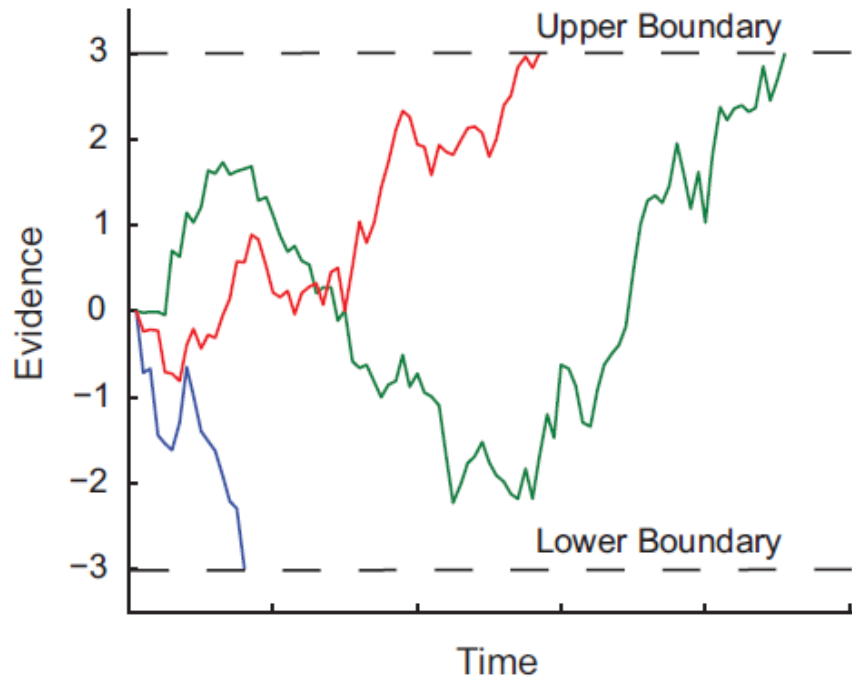
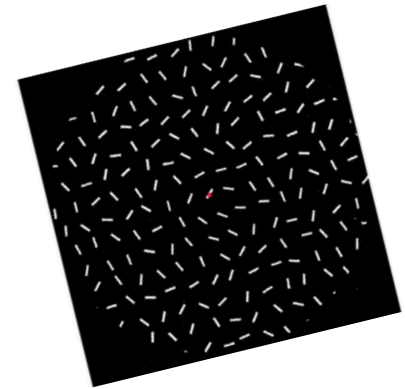
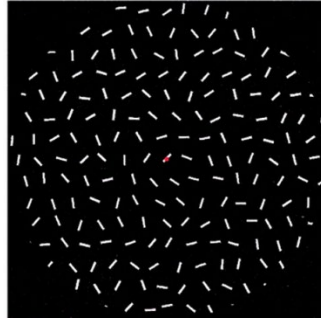
- Account for latencies and accuracies simultaneously
- Sequential sampling models
- “Random Walk”

Random Walk Model



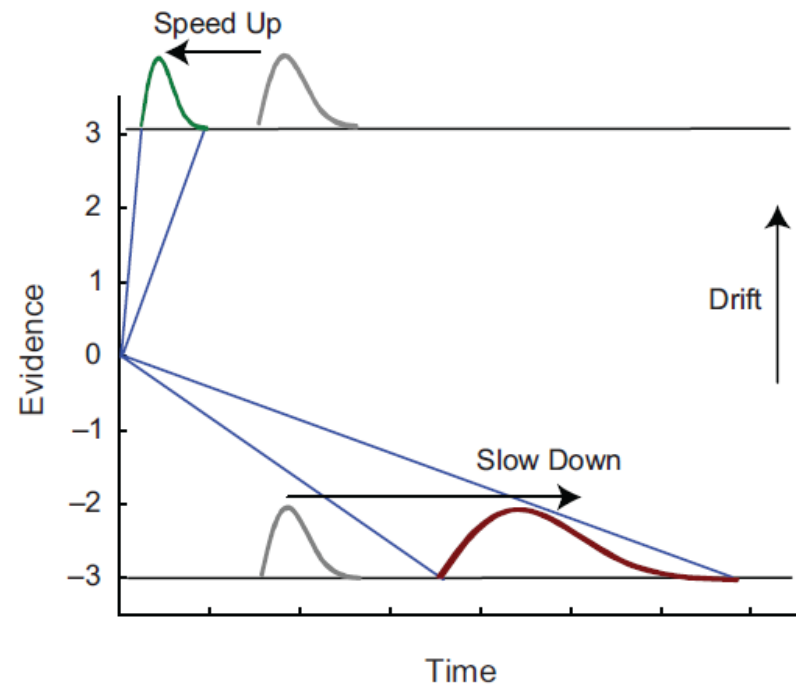
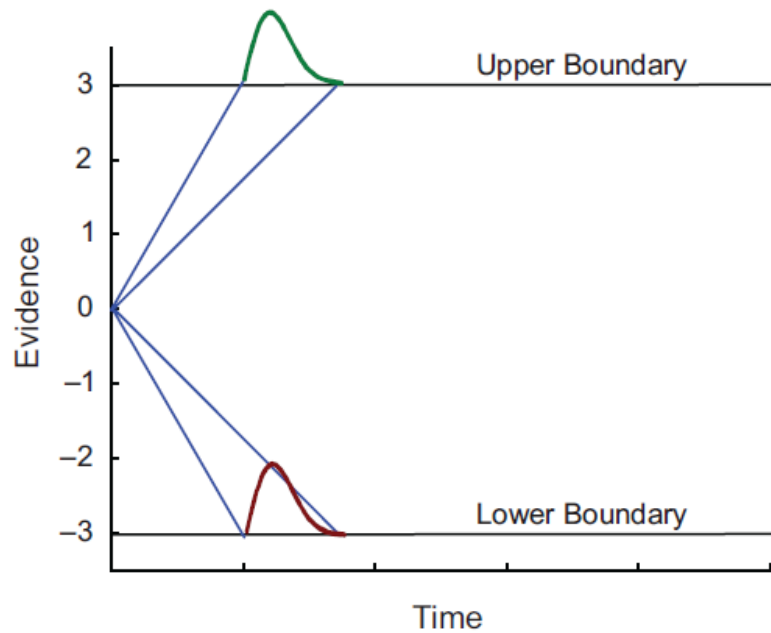
What is average latency
(RT) for each type of
response?

Random Walk Model



Random Walk and Errors

- What happens to error latencies if there is a non-zero drift rate?



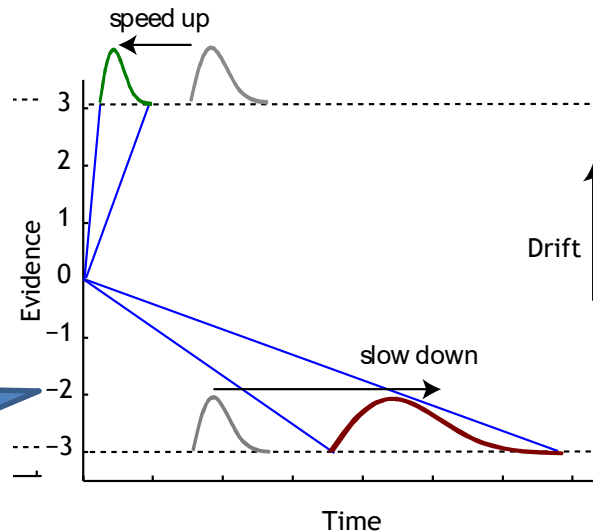
Testing our intuitions



RW: Why?

- Bottom boundary crossed only if series of samples, by chance, works against the drift
 - more time = more chance to drift to top
 - RW model agnostic about prior history (time already passed)

If you are here, time to bottom identical regardless of how you got there



Speed of Errors: Data

- Errors can be fast
 - faster than correct responses
 - when under time pressure and discriminability of stimuli is high
- Errors can be slow
 - slower than correct responses
 - when time pressure is relaxed and task more difficult
- Sequential sampling models?

From Data to Model ...



Speed of Errors in Random Walk

- Starting point trial-to-trial variability
 - fast errors when starting point by chance close to wrong boundary
- Drift rate trial-to-trial variability
 - low drift rate: slow errors and slow corrects
 - high drift rate: fast errors and fast corrects

50%
errors

10%
errors

Over to Jana ...