Cognitive Modeling: Processing 1
Computational Rationality:
Modeling (sub-) optimality & efficiency

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Who am I? Who are you?

REVIEW

Computational rationality: A converging paradigm for intelligence in brains, minds, and machines

Samuel J. Gershman,[1*] Eric J. Horvitz,[2*] Joshua B. Tenenbaum[3*]

After growing up together, and mostly growing apart in the second half of the 20th century, the fields of artificial intelligence (AI), cognitive science, and neuroscience are reconverging on a shared view of the computational foundations of intelligence that promotes valuable cross-disciplinary exchanges on questions, methods, and results. We chart advances over the past several decades that address challenges of perception and action under uncertainty through the lens of computation. Advances include the development of representations and inferential procedures for large-scale probabilistic inference and machinery for enabling reflection and decisions about tradeoffs in effort, precision, and timeliness of computations. These tools are deployed toward the goal of computational rationality: identifying decisions with highest expected utility, while taking into consideration the costs of computation in complex real-world problems in which most relevant calculations can only be approximated. We highlight key concepts with examples that show the potential for interchange between computer science, cognitive science, and neuroscience.

Imagine driving down the highway on your way to give an important presentation, when

purpose ideal for decision-making under uncer-tainty. Second, maximizing expected utility is

Models of computa
on a base of inferenti
predicting, learning, a
tainty (1–3). Such infer
representations that e
dencies among variabl
of relevant states in th
ing streams of percept
procedures or approx
agate information an
probability distributio
Beyond base process
ities, models of compu
mechanisms for reas
and implications of a
the best action to take
predictions about how
fluence likelihoods of
tion of the value or ut
Learning procedures
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perceptual data and
ferences about likeli
the world.

Last, systems with
power must consider
precision and timeli
Thus, models of com
include policies or d
make inferences and d

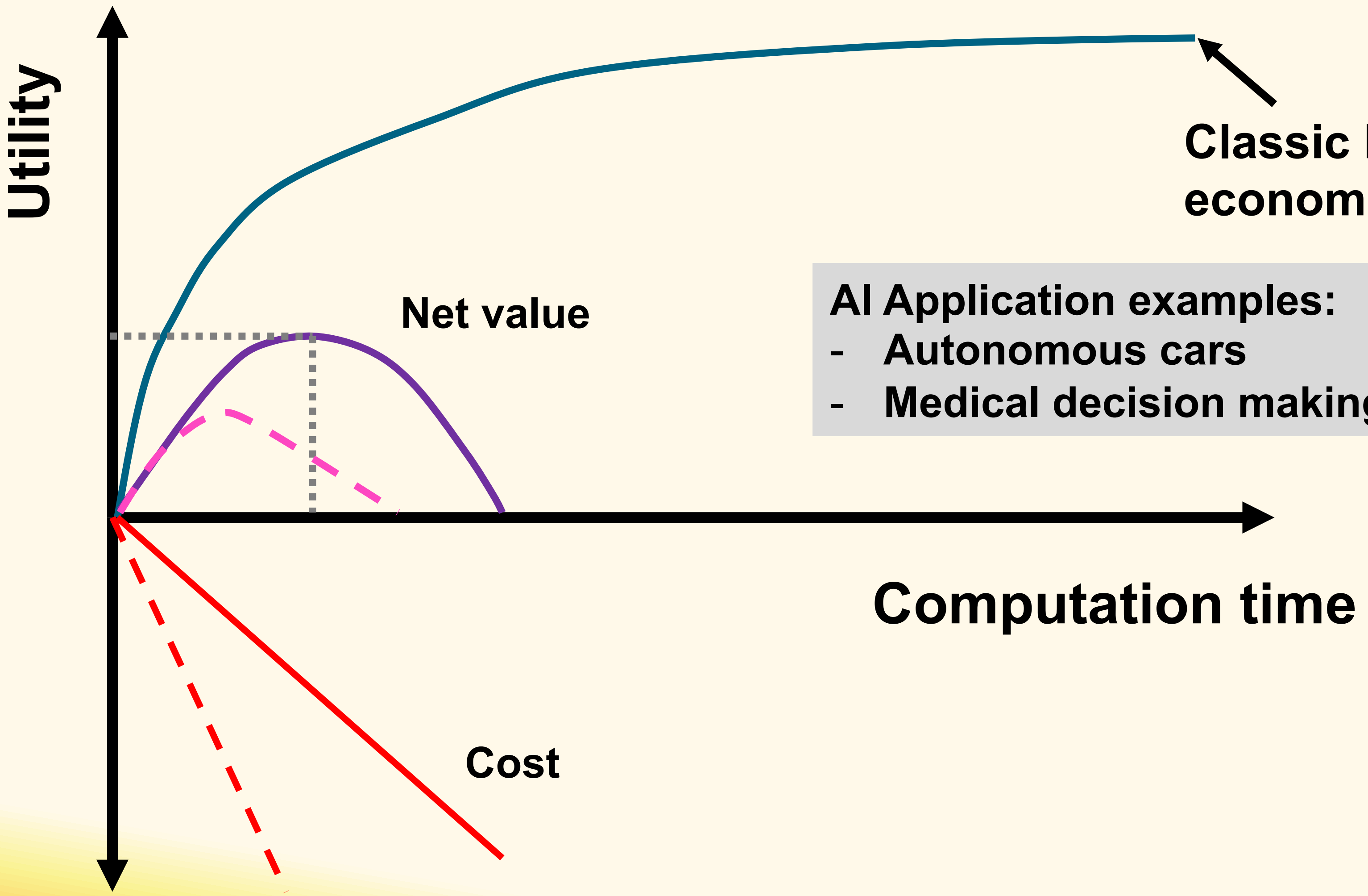
Example: Quick decisions

Calculate expected utility (internal)

Determine action with best expected utility

Consider trade-offs speed & accuracy

1. Why is Comp. Rationality important in AI?



AI Application examples:
- Autonomous cars
- Medical decision making

Paper section “Rational decisions under bounded..”

2. Why is Comp. Rationality important in CogSci?

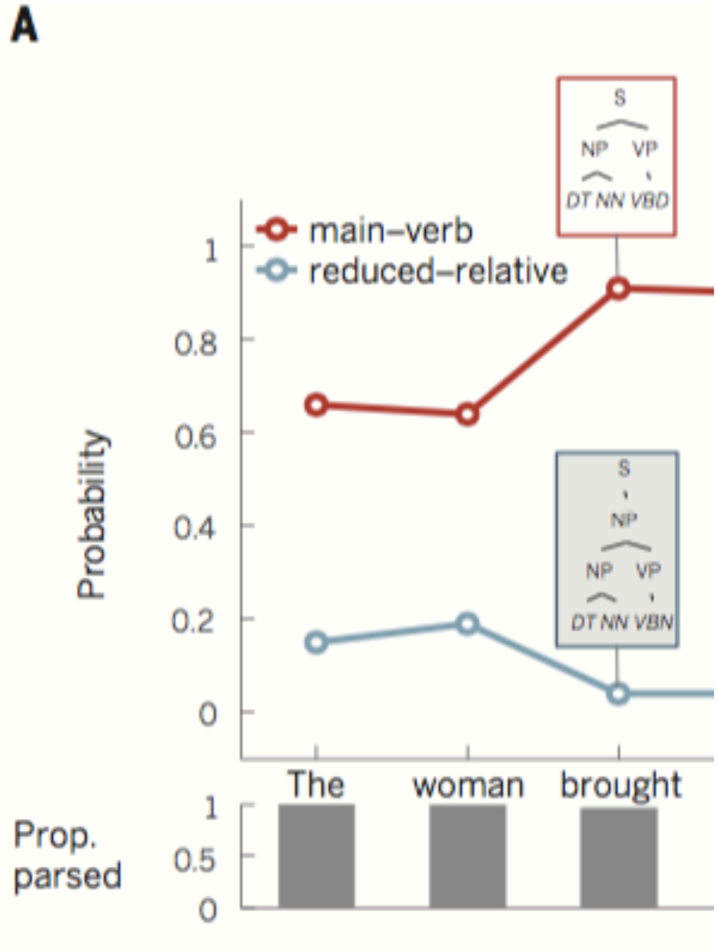
- **Human reasoning is not "perfect"**
- **Fallacies (Kahneman, 2011 "Fast and Slow")**
  - Wason Selection Task
  - Gambler's fallacy

- **(Comp. Rationality) models help to understand:**
  - ***Why*** (and when) such fallacies happen
  - ***What*** causes those fallacies
  - ***How*** they are implemented in the brain

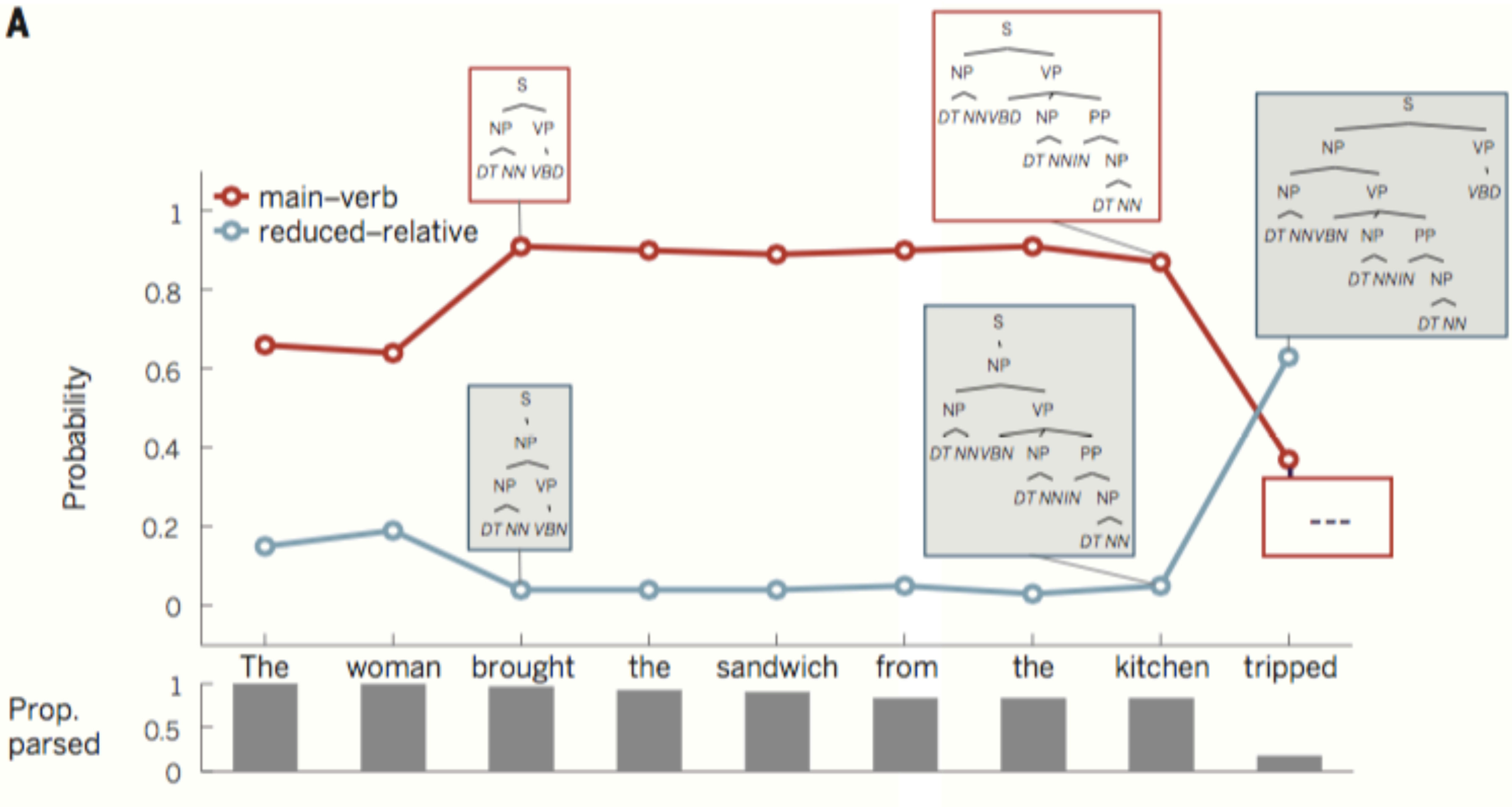
Paper section "Computational rationality in mind and brain.."

The woman brought the sandwich from the kitchen tripped.

2. Why is Comp. Rationality important in CogSci?



2. Why is Comp. Rationality important in CogSci?



2. Why is Comp. Rationality important in CogSci?

Computational rationality perspective:

- **Based on experience, we expect particular type of sentences**

- **Keeping track of all options takes time & memory (costs)**

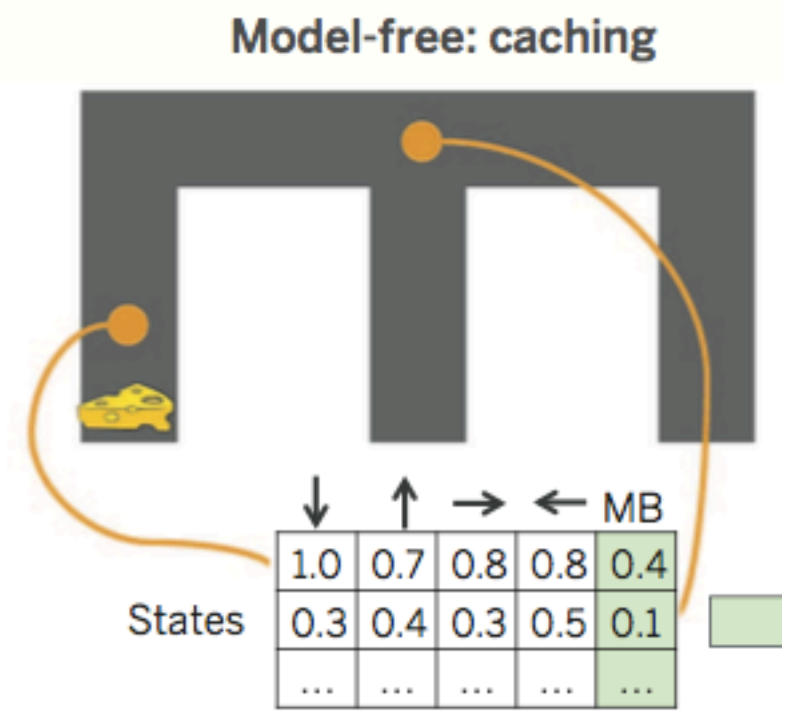
- **Do not keep track of options once you have sufficient evidence against it**

- **This helps performance, but can lead to errors**

3. Why is Comp. Rationality important in NeuroSci?

Paper section "Computational tradeoffs in sequential.."

3. Why is Comp. Rationality important in NeuroSci?



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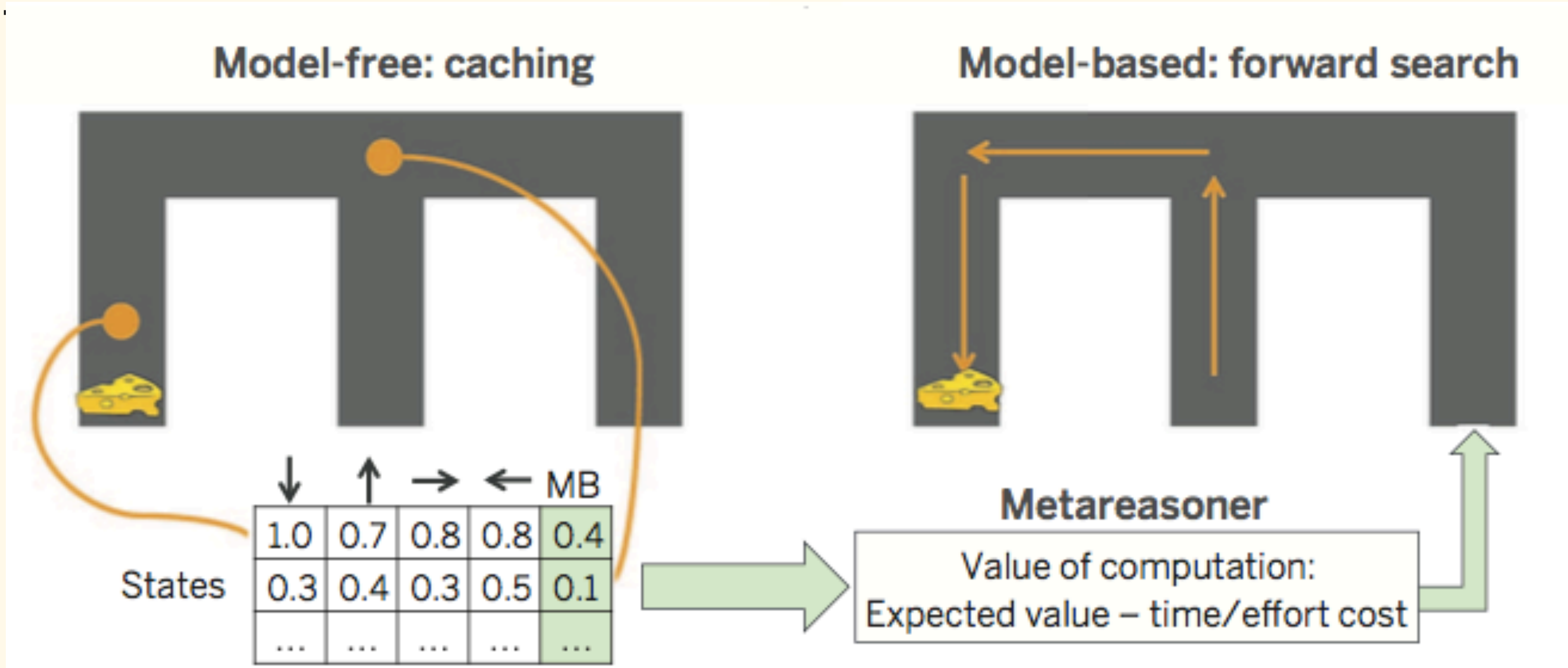

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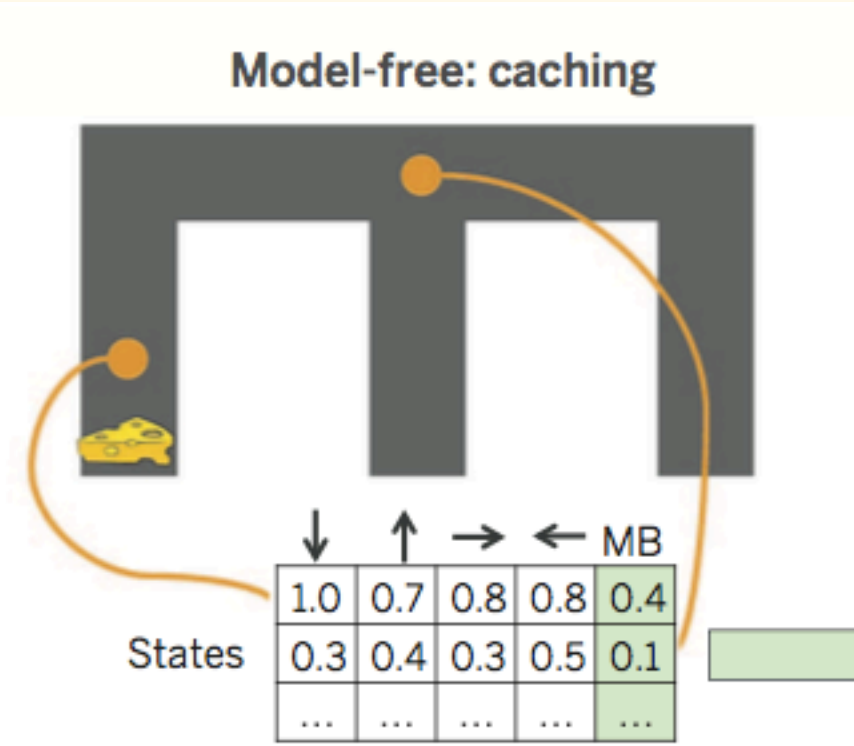

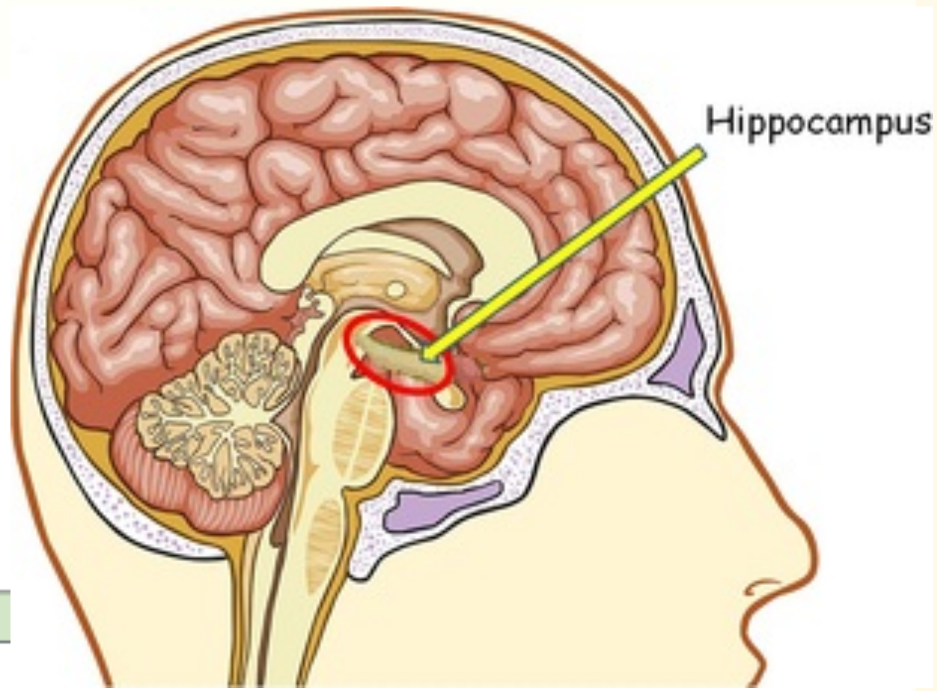

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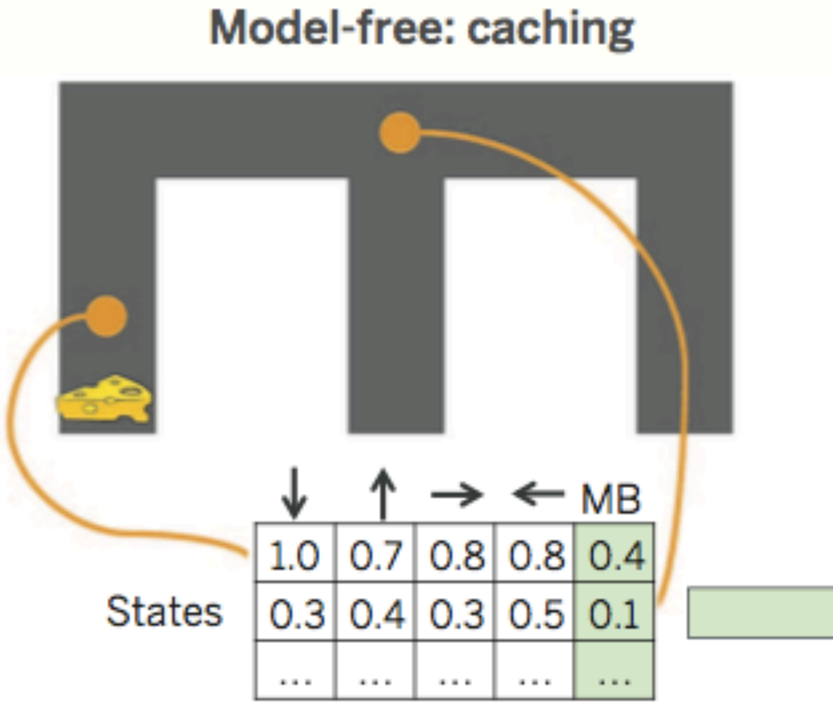
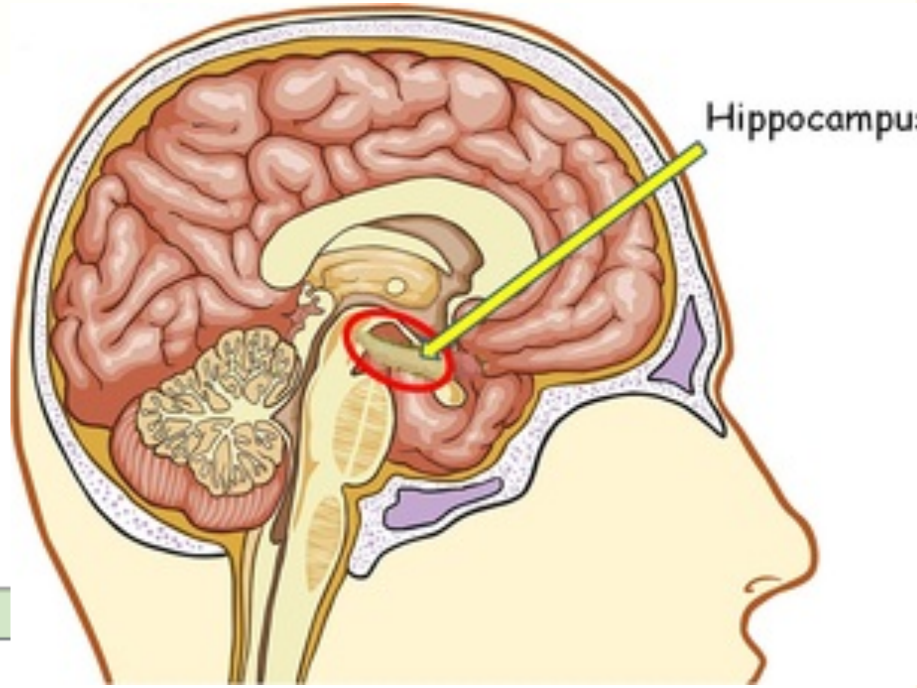
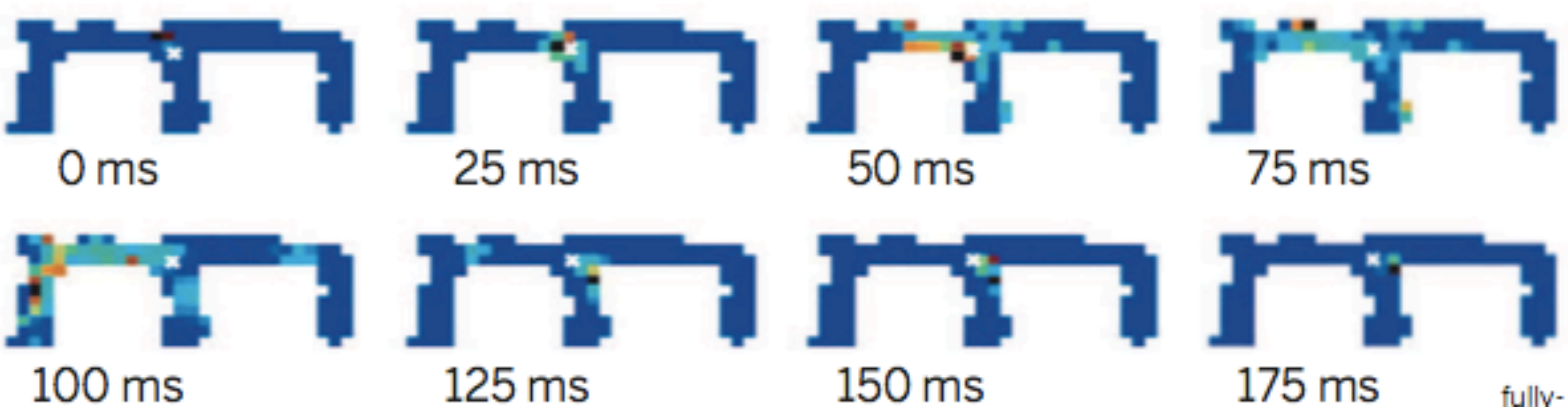
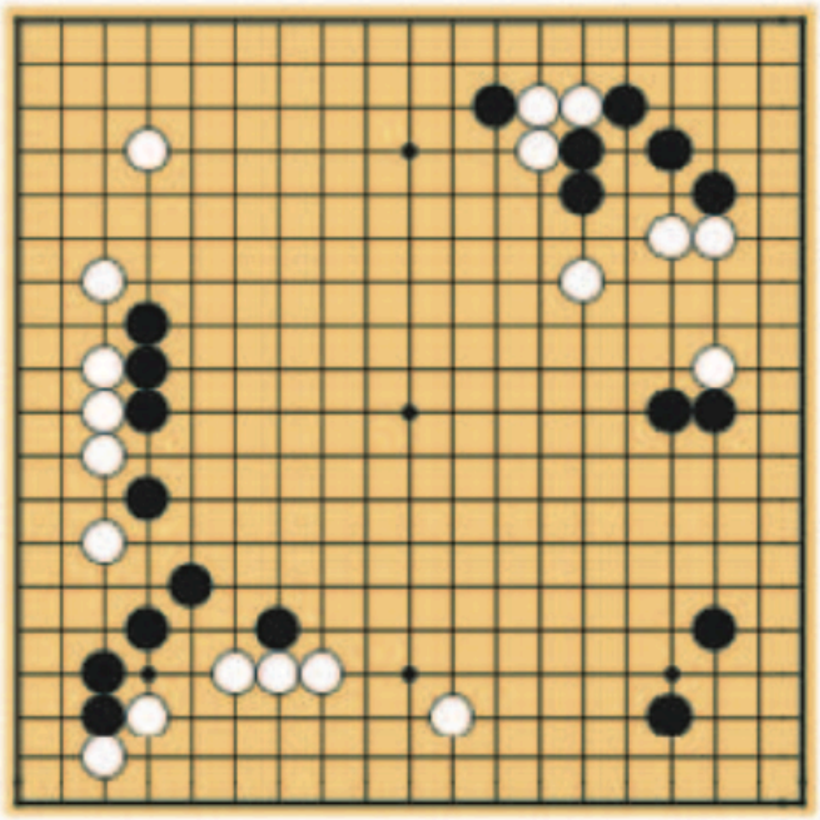






And back to AI…



Why do processing models matter here?

What is a process model?

- Describes steps (i.e., process) that mind goes through
  - Typically: algorithmic levels (Marr)
  - Typically: at cognitive band (Newell)
  - As you will see: cross connections with other levels
- Many varieties:
  - ACT-R
  - SOAR
  - EPIC
  - Cognitive Constraints (used in lab)
- MSc level: goal is NOT
  - explain 1 architecture in detail
  - explain all basic principles

Why do processing models matter in computational rationality? Science

- Describe *process* that agents go through

- Cognitive (neuro) science:
  - Why & *when* do errors occur? Which steps of process?
  - *What* are limitations of the mind?
  - *How* do these arise in the brain / implementation?
- AI:
  - How can we emulate human behavior?

Why do processing models matter in computational rationality? Applications

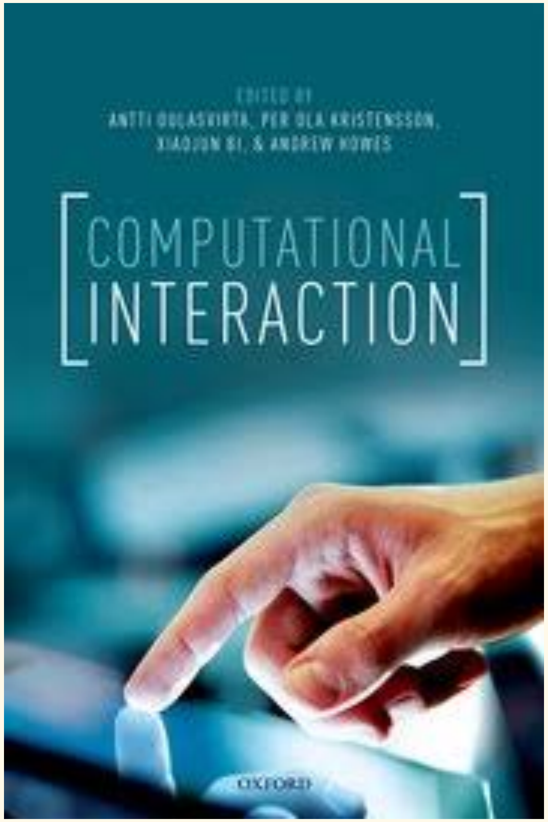
- Describe process that agents go through

- AI applications:
  - When is non-human support needed?
  - What & how should that be given?
  - Inspiration for robots and autonomous systems that take decisions in finite amount of time

- Other applications, e.g.:
  - Better interface design (minimize errors)
  - Tutoring and support systems (train to overcome errors)

Applied perspective

- **Book: Computational Interaction (Jan 2018)**
- **Editors: Oulasvirta, Kristensson, Bi, Howes**
  https://global.oup.com/academic/product/computational-interaction-9780198799603



31 Januari: colloquium Antti Oulasvirta

- 16:00-17:00
- Location: t.b.a.
- “Psychology as the science of design: what psychological theories do” http://users.comnet.aalto.fi/oulasvir/

Gershman et al.'s conclusion

Computational Rationality in Brain, minds, and machines:

1. **All form beliefs and plan actions in support of maximizing expected utility (MEU)**
2. **Ideal MEU may be intractable; rational algorithm might approximate**
3. **Algorithms *rationally adapted***

Today's topics

1. Gershman, Horvitz, Tenenbaum: Computational Rationality
   - Why does it matter for mind, brain, and machines?
   - Why are processing models useful?
- Intermezzo levels of abstraction
2. Lewis, Howes, Singh: Rational adapted
   - How is behavior formed? Optimality explanations
     - Type I: Optimality
     - Type II: Ecological-optimality
     - Type III: Bounded-Optimality
     - Type IV: Ecologically-Bounded-Optimality
   - Examples (Wason, PRP, Reading):
     - What is theoretical problem being studied? What is task/experiment? Why is this interesting?
     - What is "classical" model/approach
     - Why is this not sufficient?
     - Approach of computational rationality

Practical matters

- Read course manual (Blackboard)

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)

Examination

- Exam (40%)
- Lab assignments (40%)
- Poster presentations (20%)
  - Presenter (in group of 3 students)
  - Discussant (for 3 papers: individual!)

- Attendance: highly encouraged

- Course manual: deadlines (Multiple!), details on grading, minimum grades, …

Lectures

- Not always full 2 hours
  - To compensate for intense assignments
- About recordings..

This Friday

- Lab between 9 and 11
  - Only in room Bol 1.204
- Use time to:
  - Find a good paper to present with group
  - New to R? -> work through crash course
  - Start on assignment 1 (in team of 2)

- Other weeks: 9-13
  - Experience learns that students need the full session!

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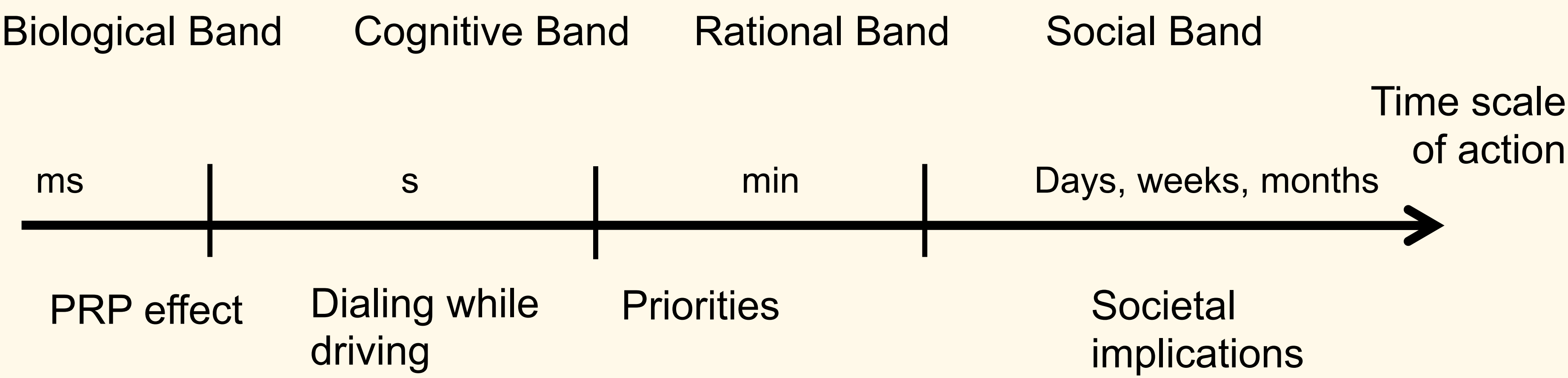
Intermezzo: levels of abstraction

- **Brief recap: Newell’s bands of cognition**
- **Extension: Marr’s levels**

Abstraction continuum

Abstraction continuum; time scale of action

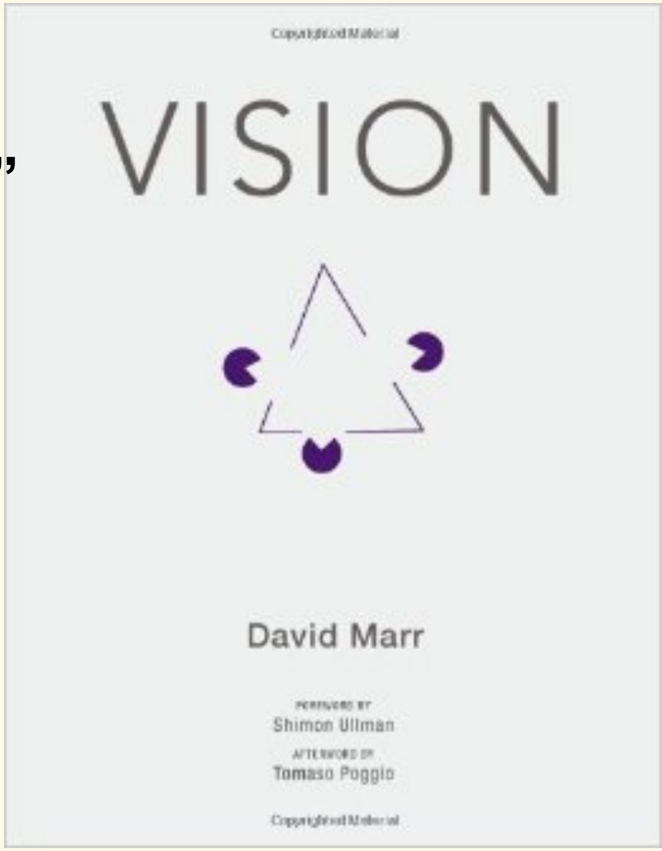


Abstraction continuum

- **Alternative view:**
  David Marr (1982) Vision Chapter 1
- **3 levels:**
  - Computational theory
  - Algorithmic theory
  - Implementation theory

"More detailed"

- **Each level is important**
- **Each level explains *different* aspects of behavior**



Marr: Computational level

- Goal
  "*WHY* do we do what we do"?
- Common characteristics:
  - Small set of equations explains behavior
  - Explanation involves characteristics of statistics of the environment (e.g., adaptive argument)

Example: computational level (with algorithmic level)

Driver distraction model used in lab session

Marr: Algorithmic level

- Goal :
  - How is a computational theory implemented?
  - What is the “input”, what is “output”
  - What type of algorithm/strategy solves this problem?
- Common characteristics:
  - Detailed algorithms
  - That describe aspects of the process

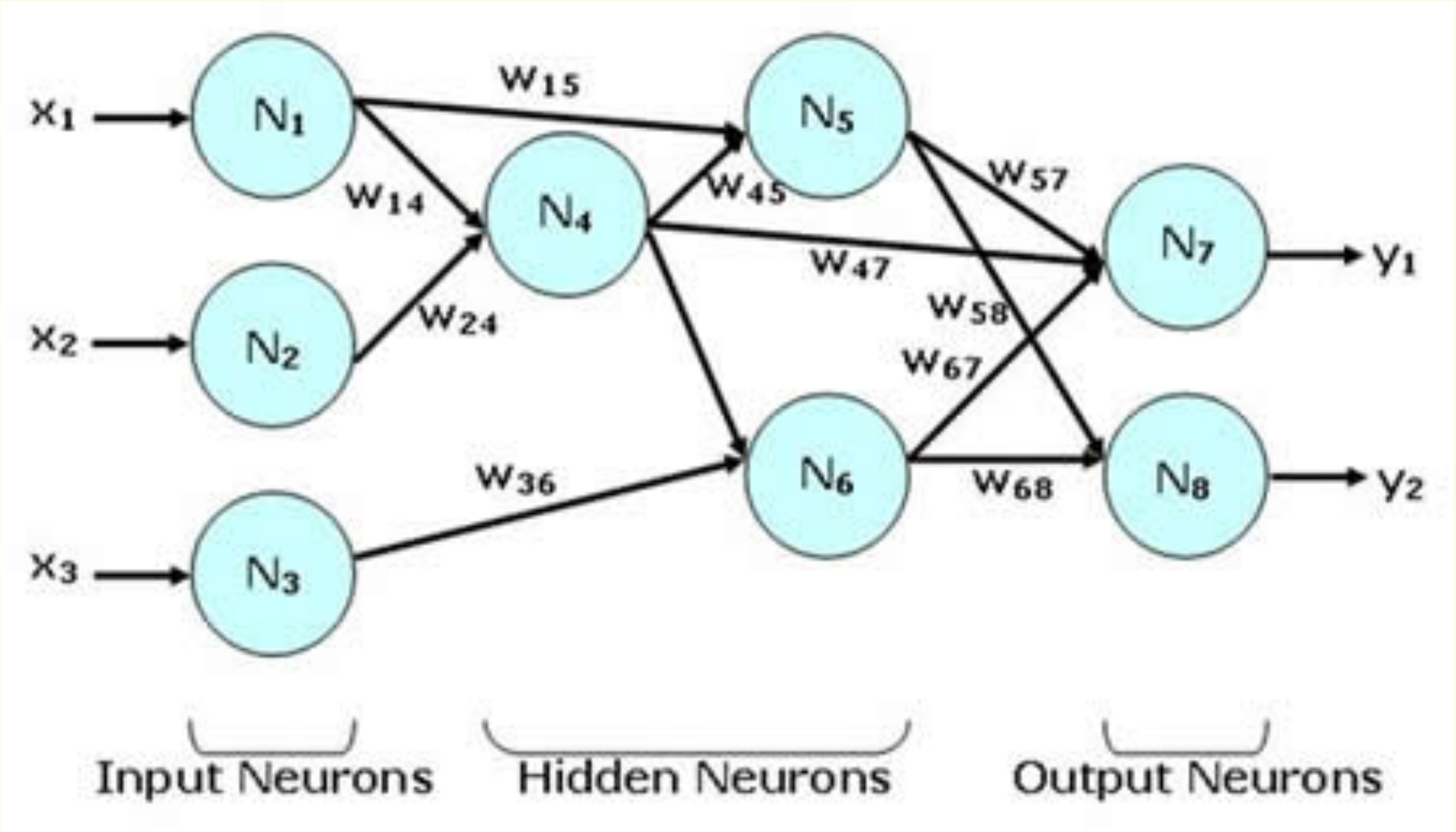
Example: Algorithmic level

Salvucci's distract-R
(distraction over time, composed of small production rules)

Marr: Implementation level

- Goal:
  - What is the physical implementation?
- Common characteristics:
  - Describe WHERE in the brain the process occurs
  - WHAT areas are connected to each other and HOW
  - Many many minor details, small time scale

Example: Implementation level



Abstraction continuum

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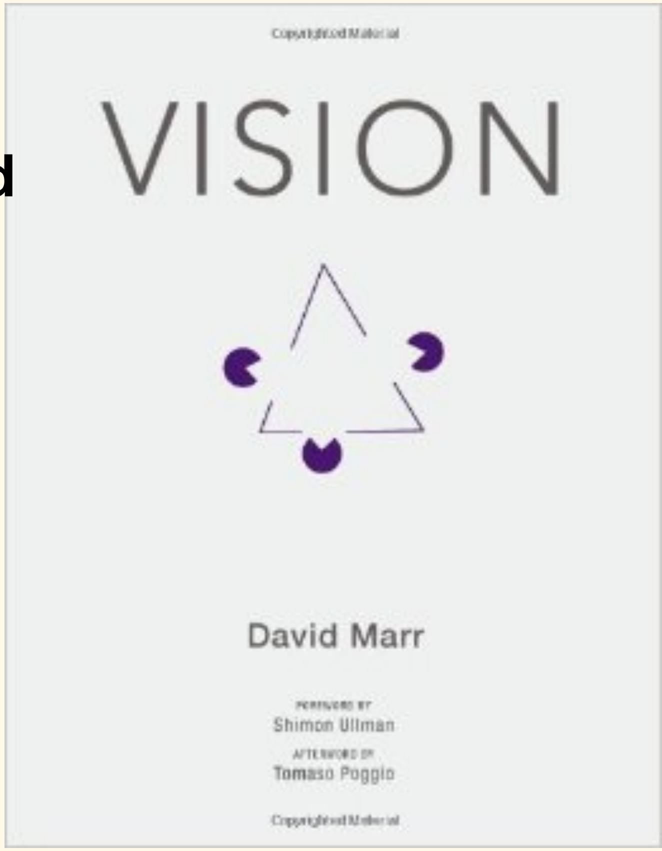
More detailed



- **Each level is important**
- **Each level explains *different* aspects of behavior**

But isn’t a model always…

- **Computational?**
  (because it is on a computer)
- **Algorithmic?**
  (Because it is an algorithm)
- **Implementation?**
  (because it is “implemented” in code)

NO!

Solution

- **Let go of thinking about the computer, think about the *research question* you want to answer.**
  (even if this concerns humans and not models)

- **Do I want to answer:**
  - ***Why* behavior occurs -> computational**
  - ***What* are information processing steps ->algorithmic**
  - ***How* physically realized in the brain -> implementation**

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TOPICS
TOPICS IN COGNITIVE SCIENCE

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Computational Rationality: Linking Mechanism and Behavior Through Bounded Utility Maximization

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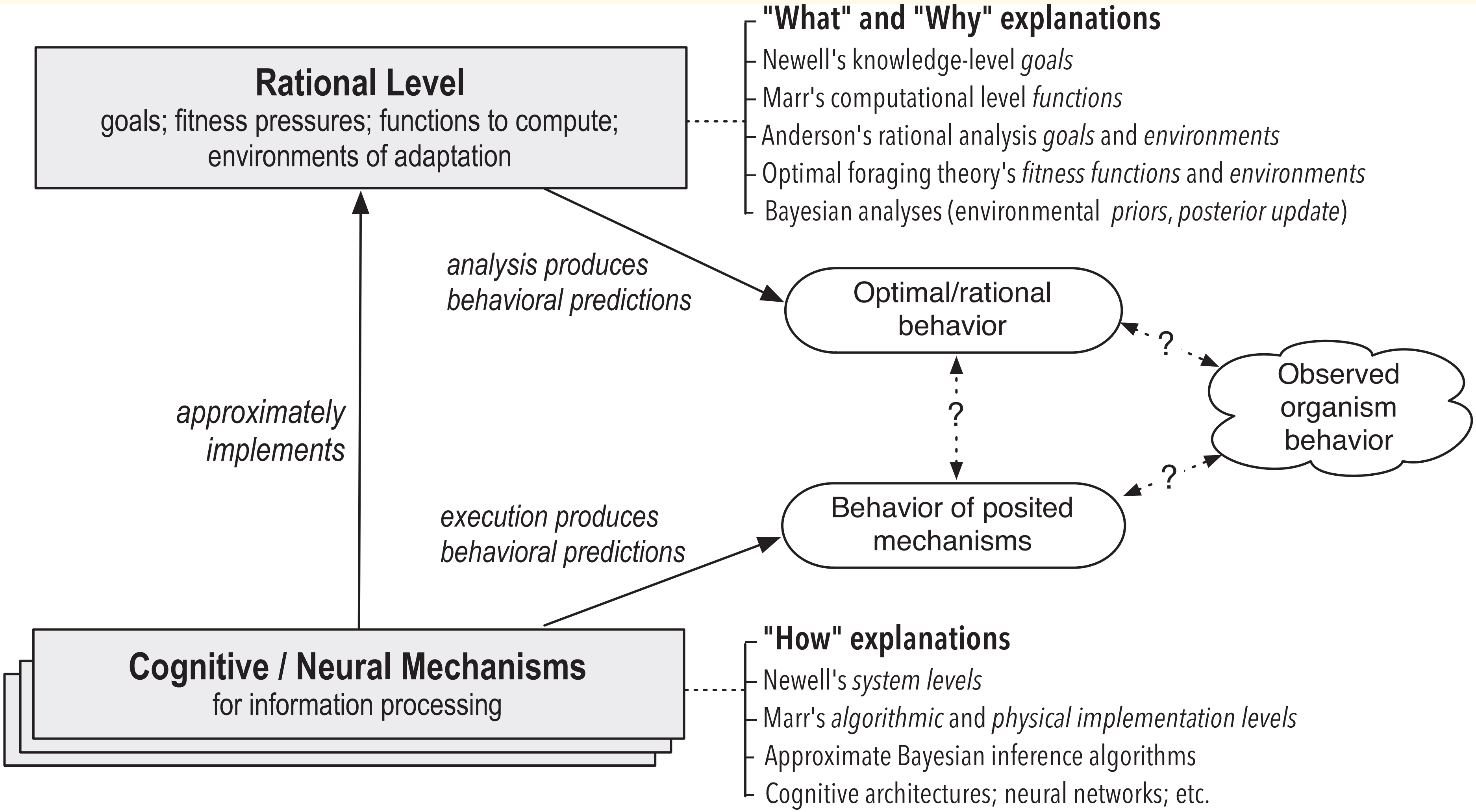
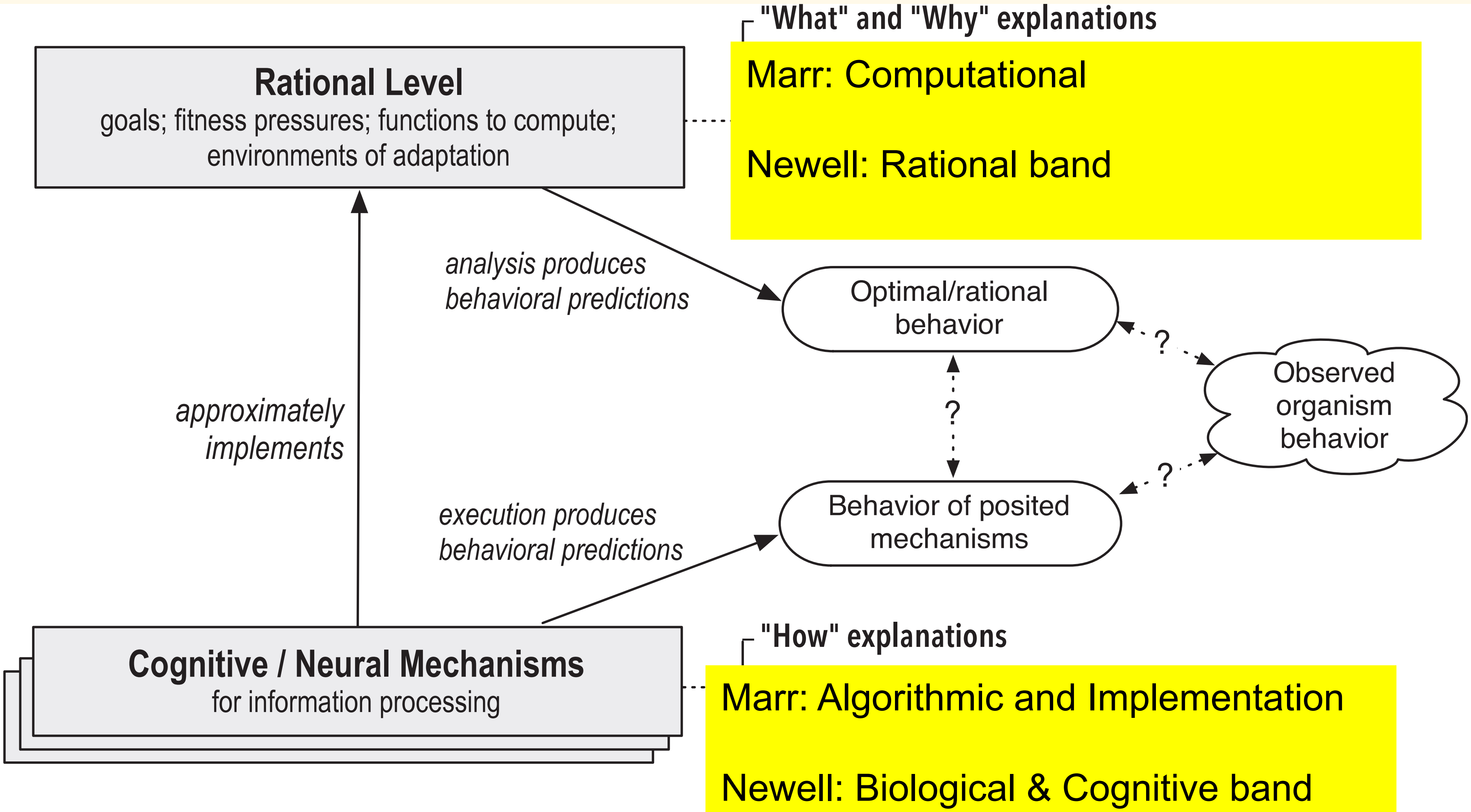
Received 11 December 2012; received in revised form 8 July 2013; accepted 16 July 2013

How is behavior formed?



How is behavior formed?



‘Sub-optimal’ behavior

- E.g. As observed in heuristics & biases research Kahneman & Tversky
  - Humans demonstrate problems in (logical and numerical) judgment & decision making

‘Sub-optimal’ behavior

- Mechanistic explanation:
  - Limitations in ability to calculate optimal solution
    - “Not enough time”
    - “Not enough memory”
    - “Not enough knowledge of (full) problem”
- Is this really ‘sub-optimal’?

‘Sub-optimal’ behavior

- **Mechanistic explanation:**
  - Limitations in ability to calculate optimal solution
    - “Not enough time”
    - “Not enough memory”
    - “Not enough knowledge of (full) problem”

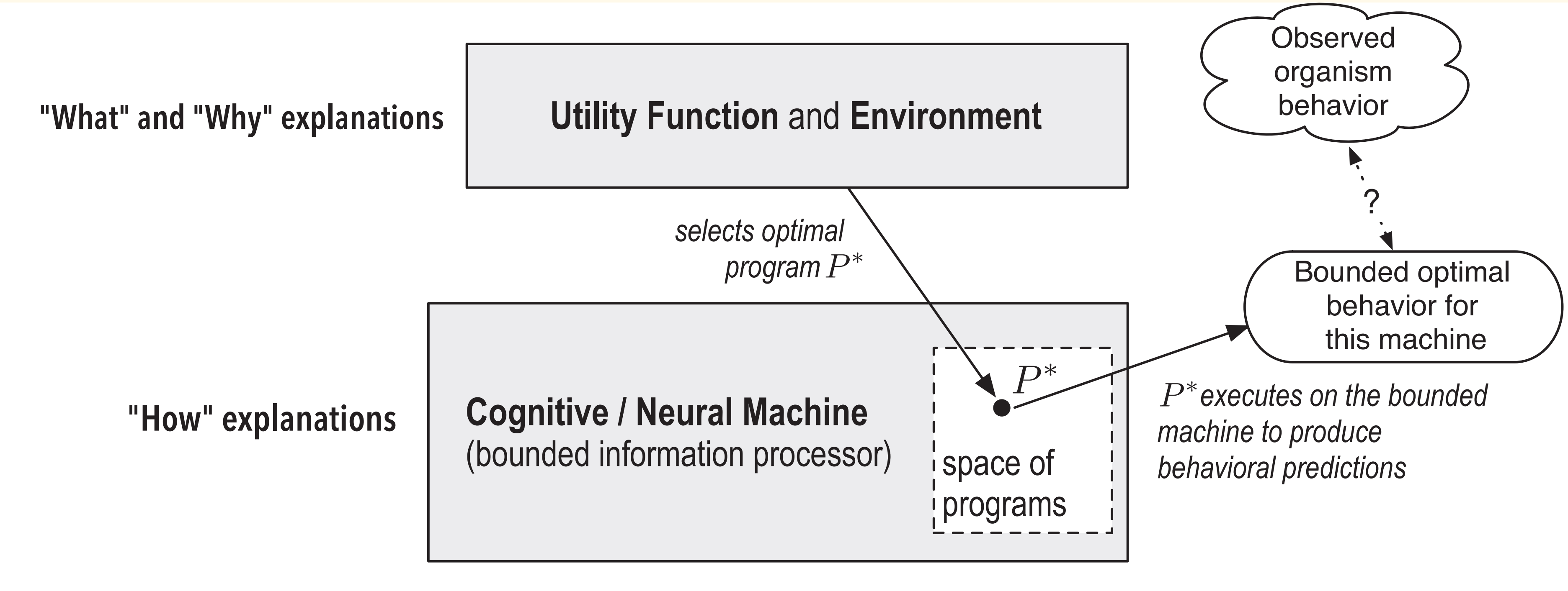
- **Rational explanation:**
  - Situation is ill described:
    - People have other goals (in broader context)
    - Environment in daily life is different from experiment

Core of paper

- *Mechanism* ('agent') and rationality (utility and environment) matter:
  - "propose a framework for including *information-processing* bounds in rational analyses"
  - "application of bounded optimality to the challenges of developing theories of *mechanism* and behavior"
  - Computational rationality: application of bounded optimality (Russell & Subramanian, 1995) to psychology
  - "What should a rational (utility-maximizing) agent, with its available *information processing mechanisms*, do in this environment?"

Proposal in paper

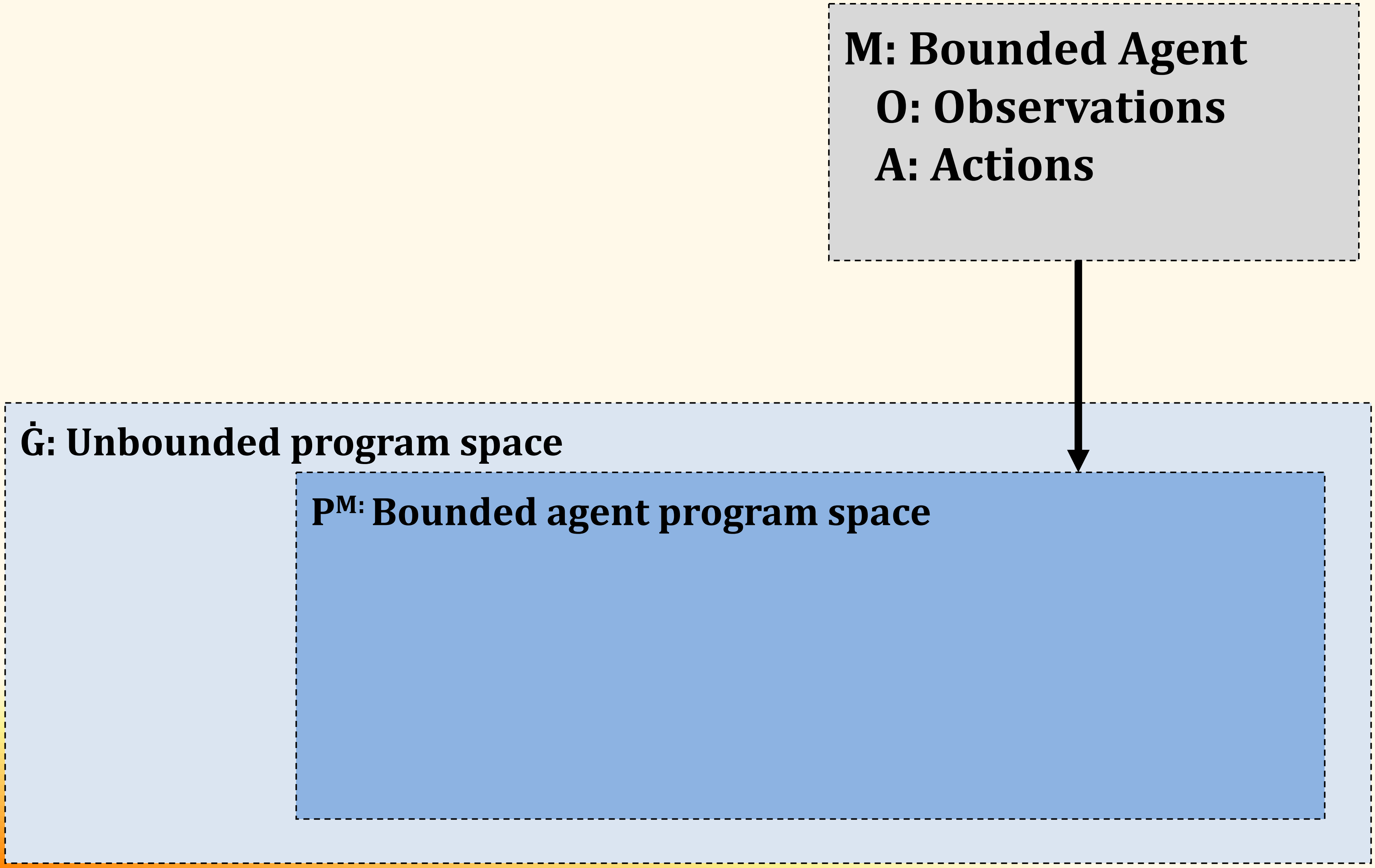
- **Both environment & agent count**



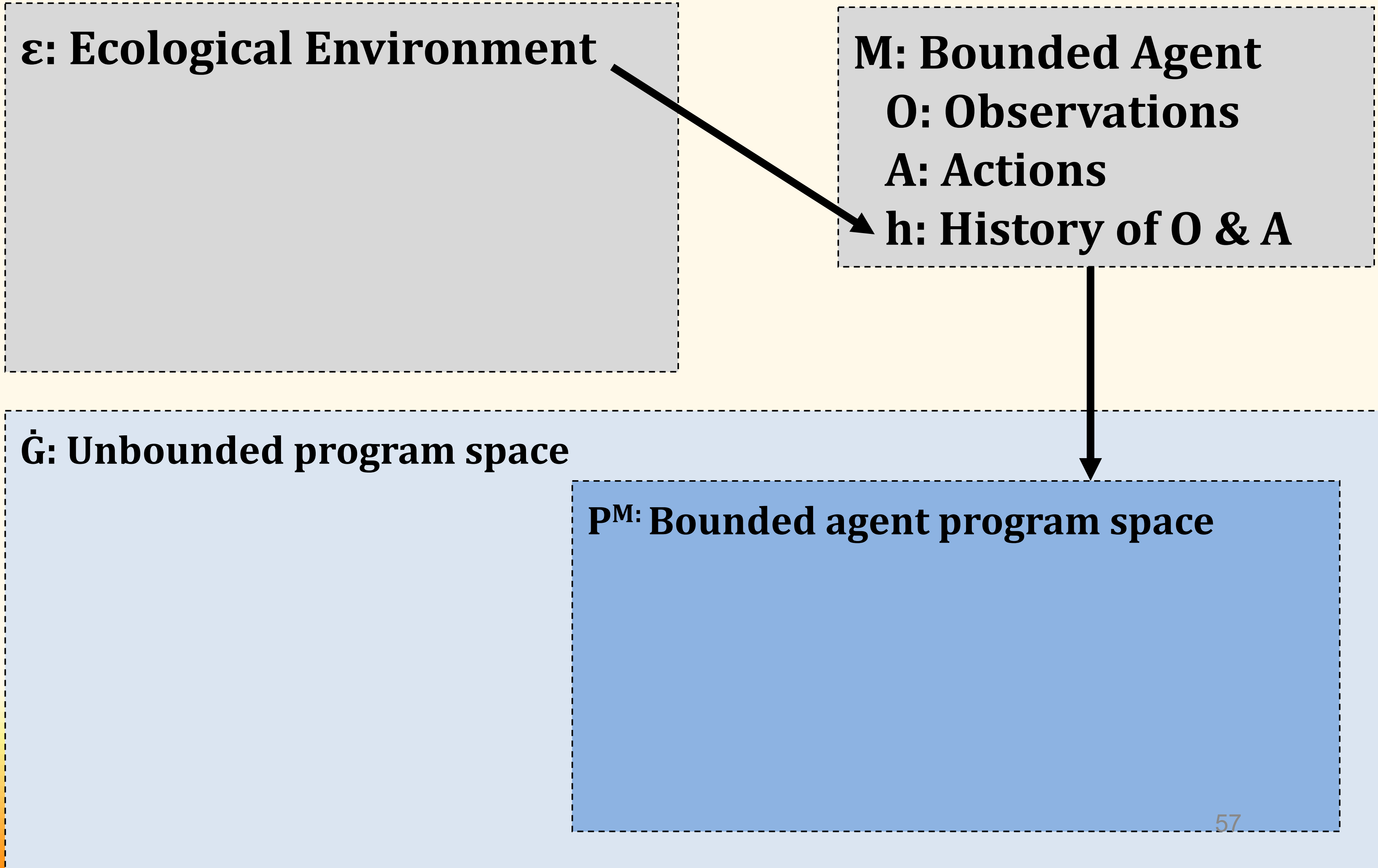
Computational Rationality

Ġ: Unbounded program space

Computational Rationality



Computational Rationality



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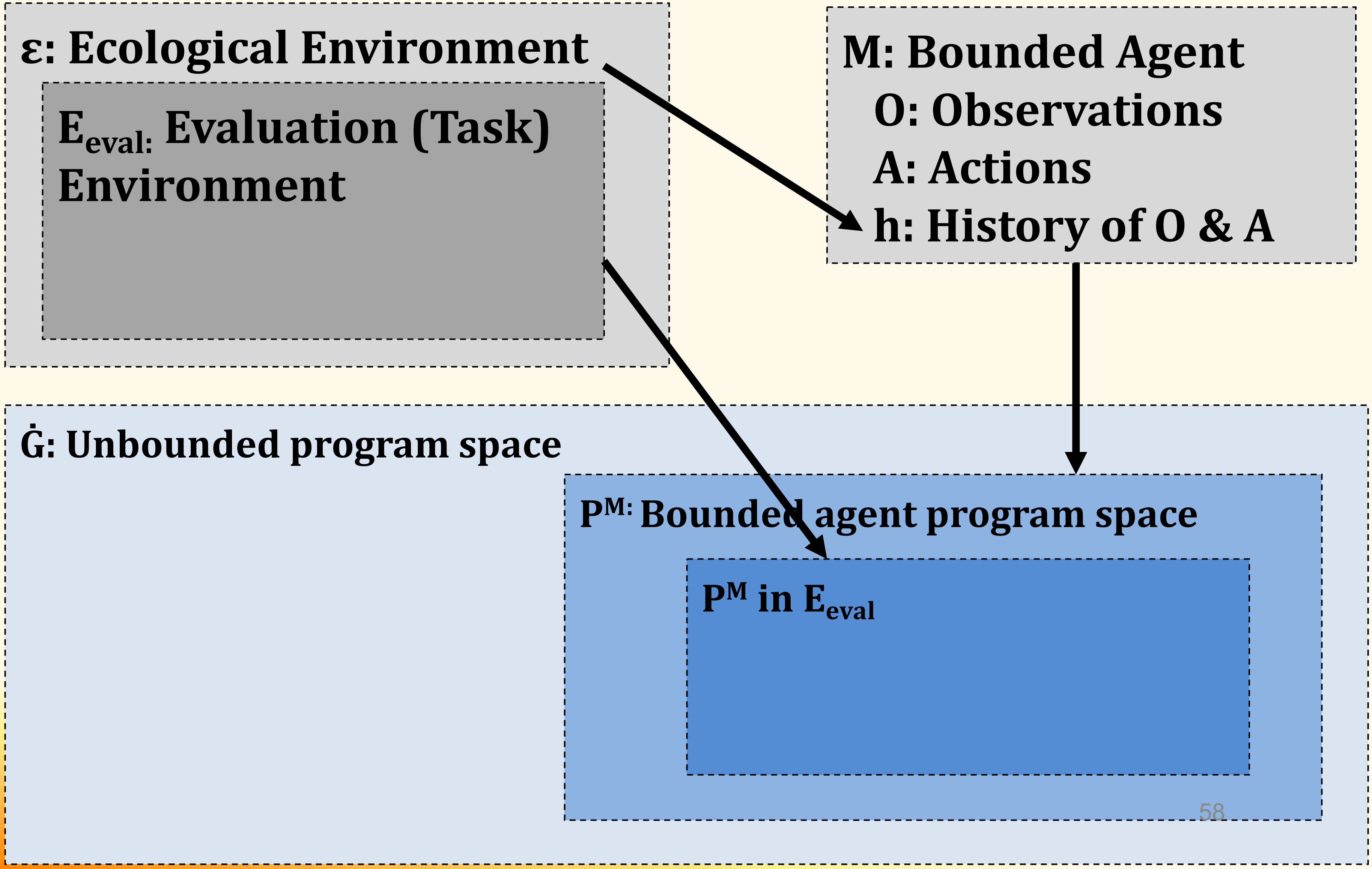

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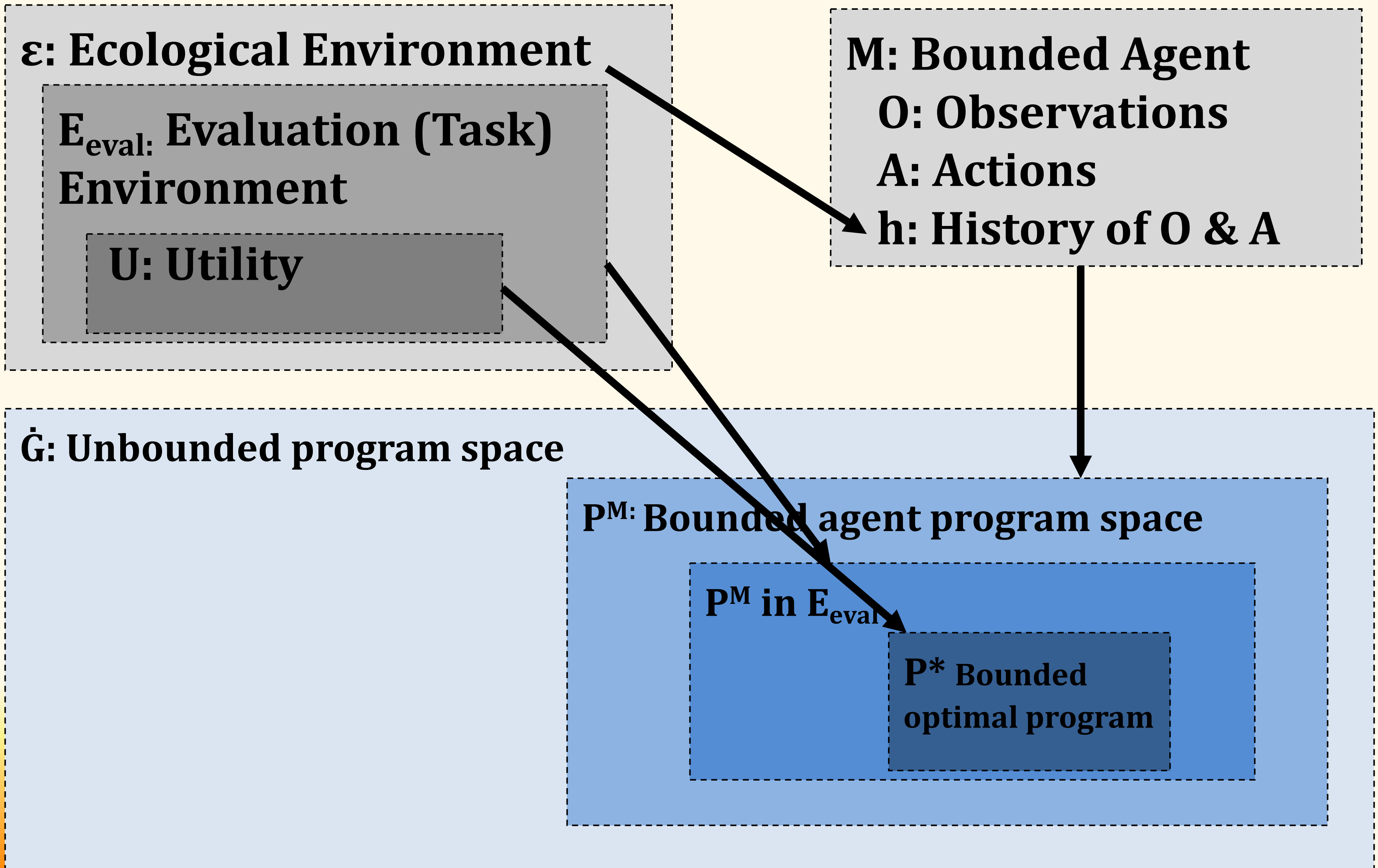

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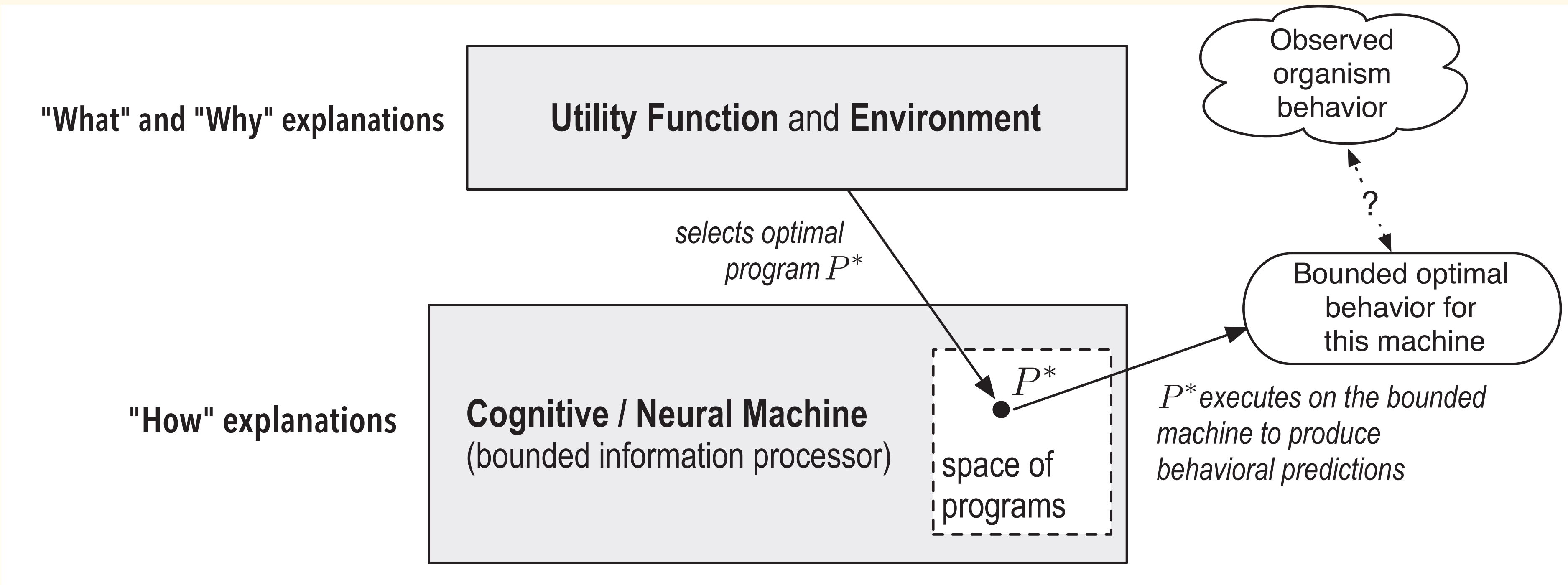


Optimality explanations

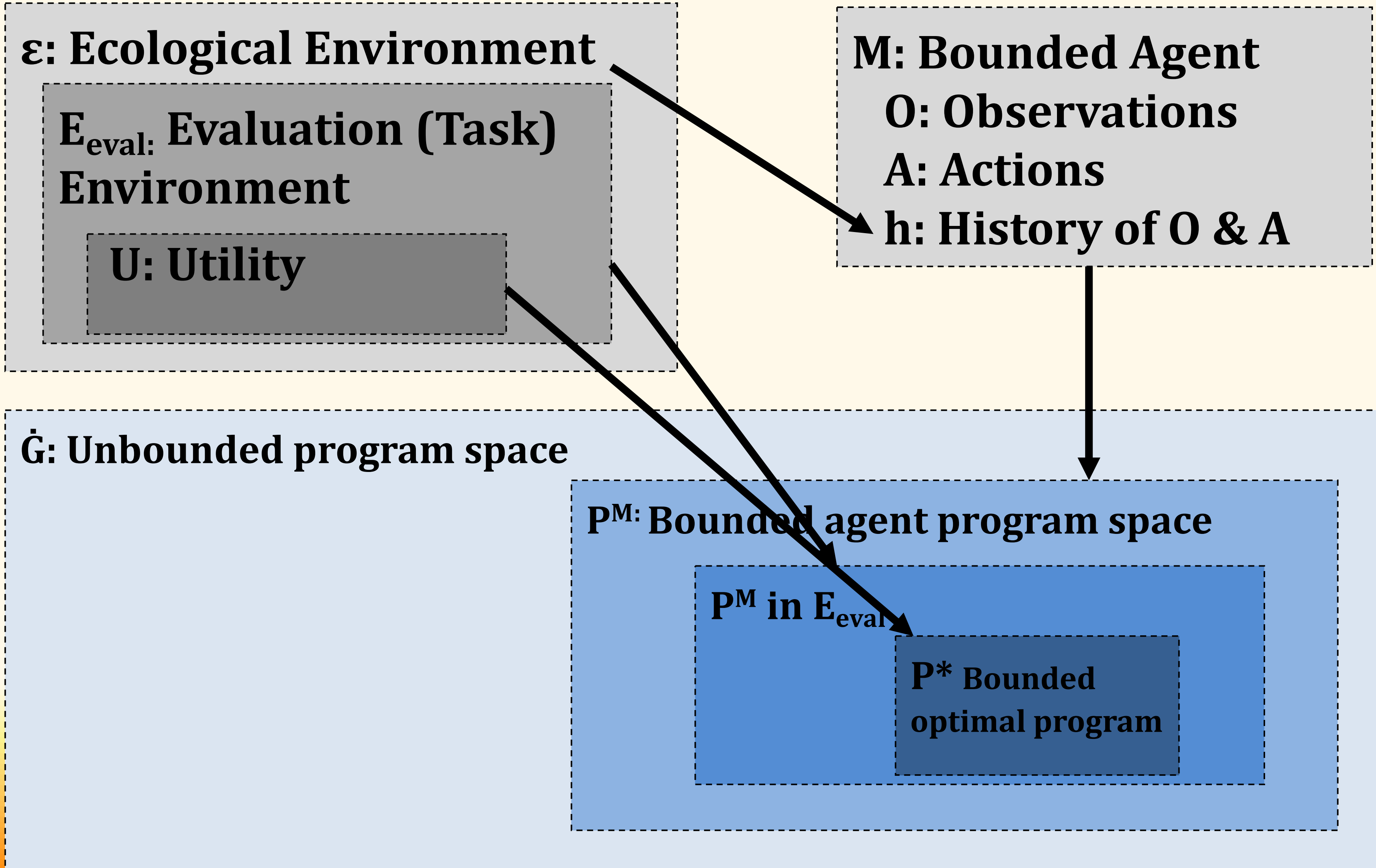
- **Type I: Optimality**
- **Type II: Ecological-optimality**

Computational Rationality approaches:

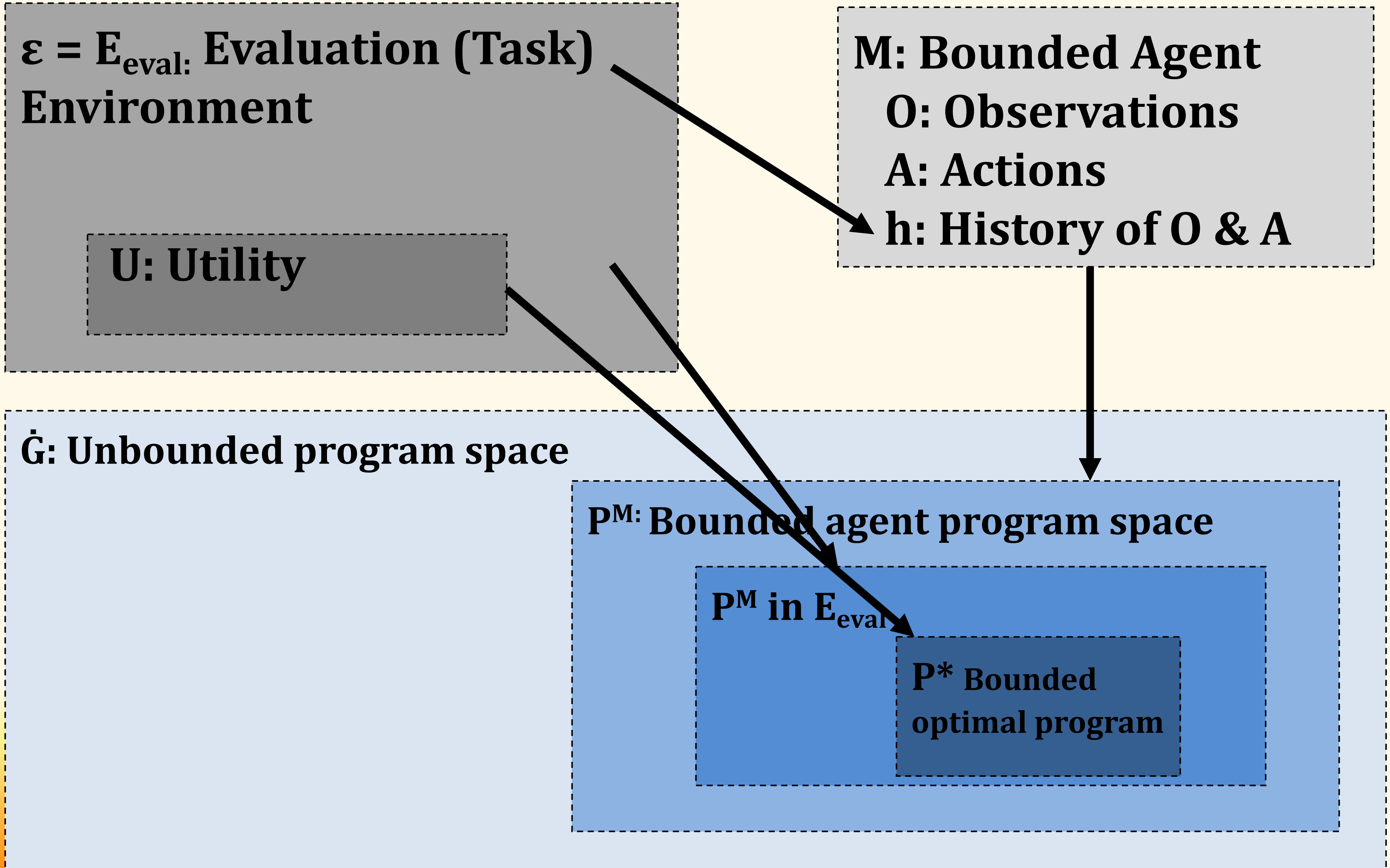
- **Type III: Bounded-optimality**
- **Type IV: Ecological-bounded-optimality**

- **Type I & II:**
  - study on your own (incl Wason example)
  - See Appendix of presentation for support slides

Computational Rationality



Type III: Bounded optimality explanation

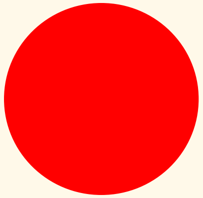


PRP task

- **Who has heard of this task before?**

PRP task

- Respond as fast as you can to each stimulus
- *Always respond to visual stimulus first*
  - *More points when fast*
  - *0 points if “response reversal”*
- Visual:
  - Left hand up when RED

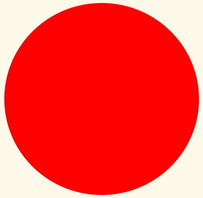


  - Right hand up when BLUE

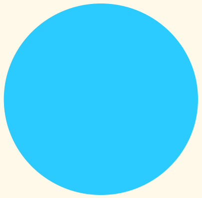
- Audio:
  - Say “yes” when high pitched tone

  - Say “no” when low pitched tone

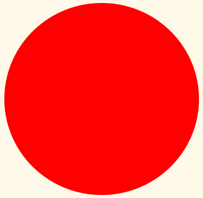
PRP task: trial 1



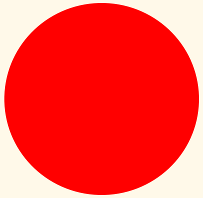
PRP task: trial 2



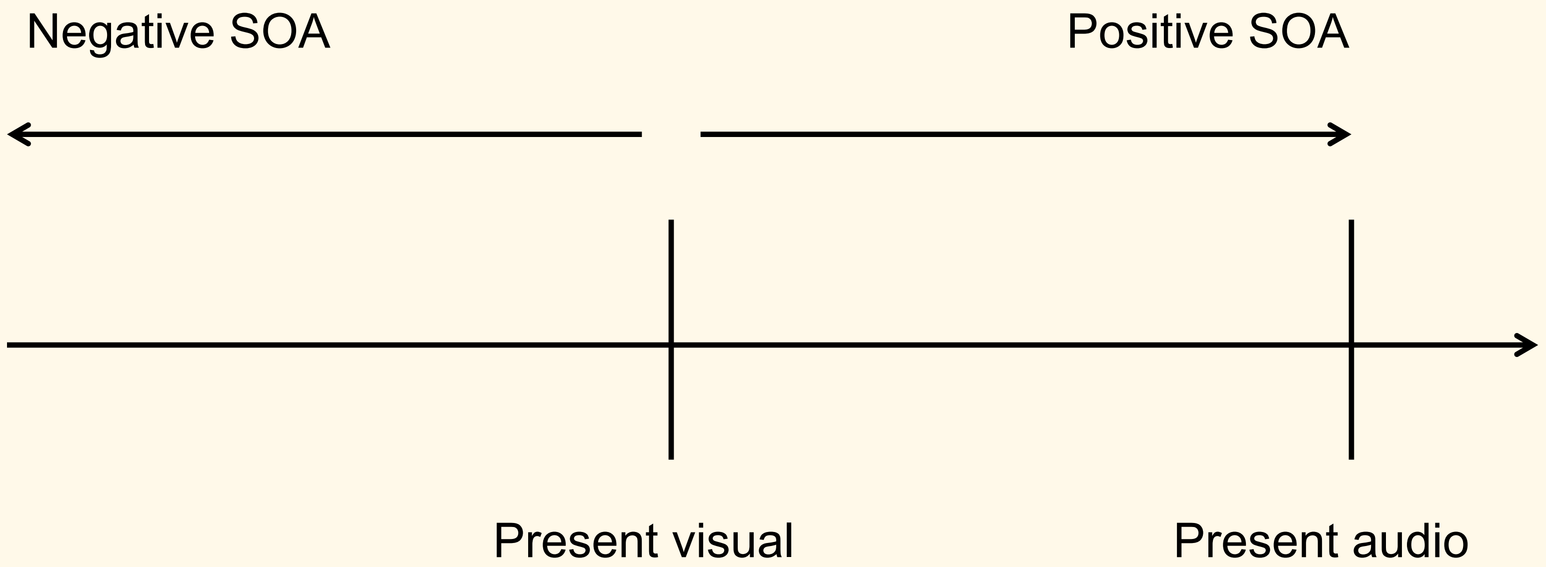
PRP task: trial 3



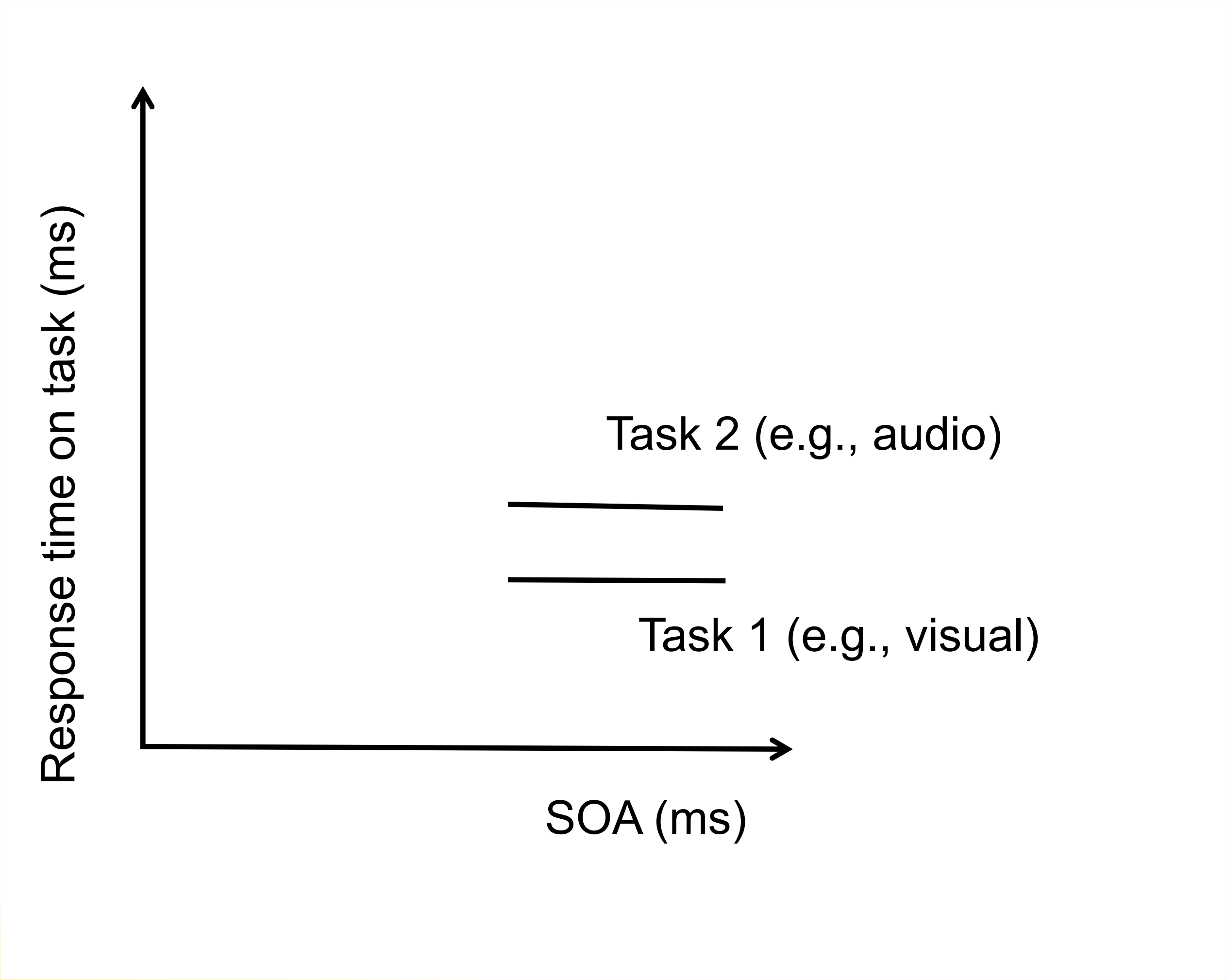
PRP task: trial 4



PRP task: Stimulus Onset Asynchrony



PRP task: Classical effect



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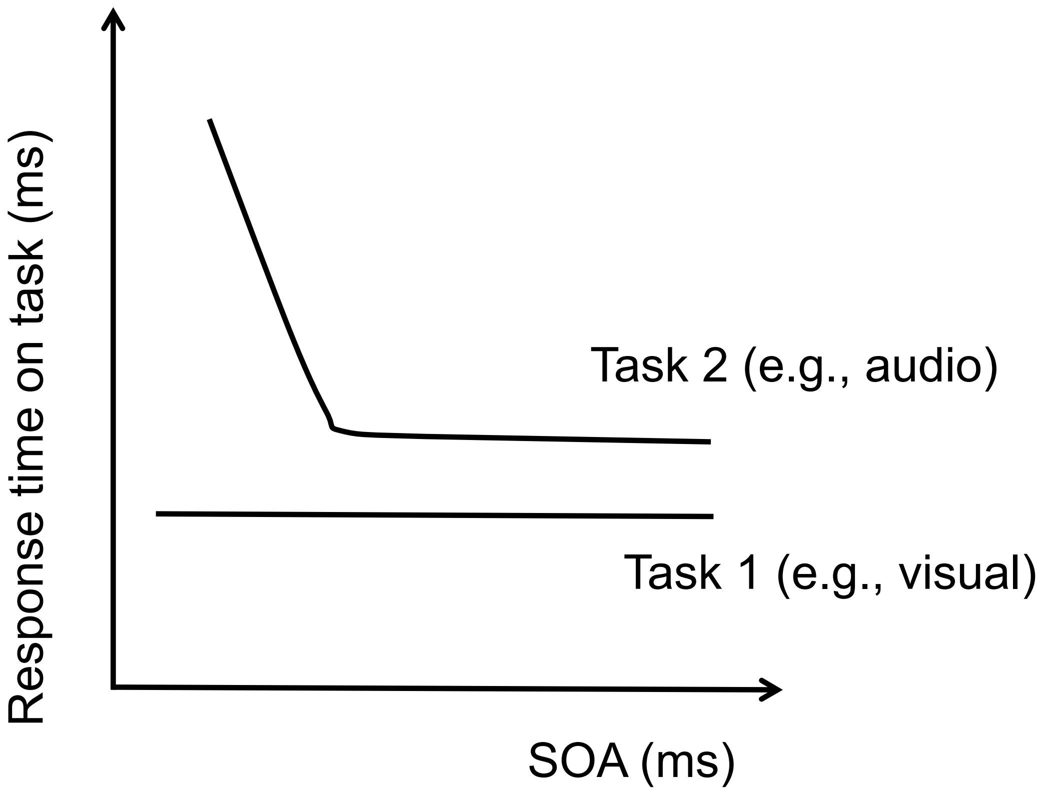
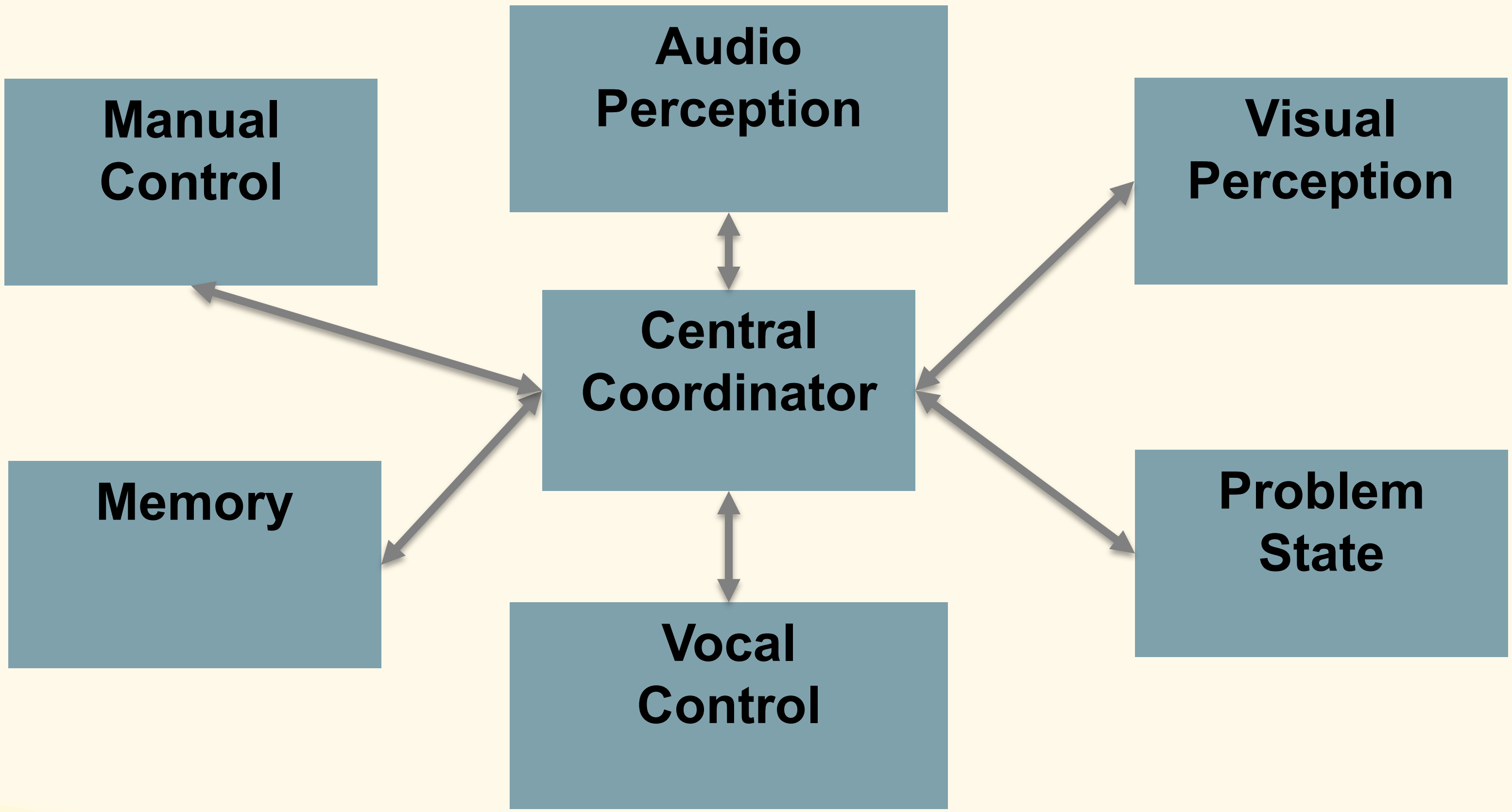


PRP task: classical model

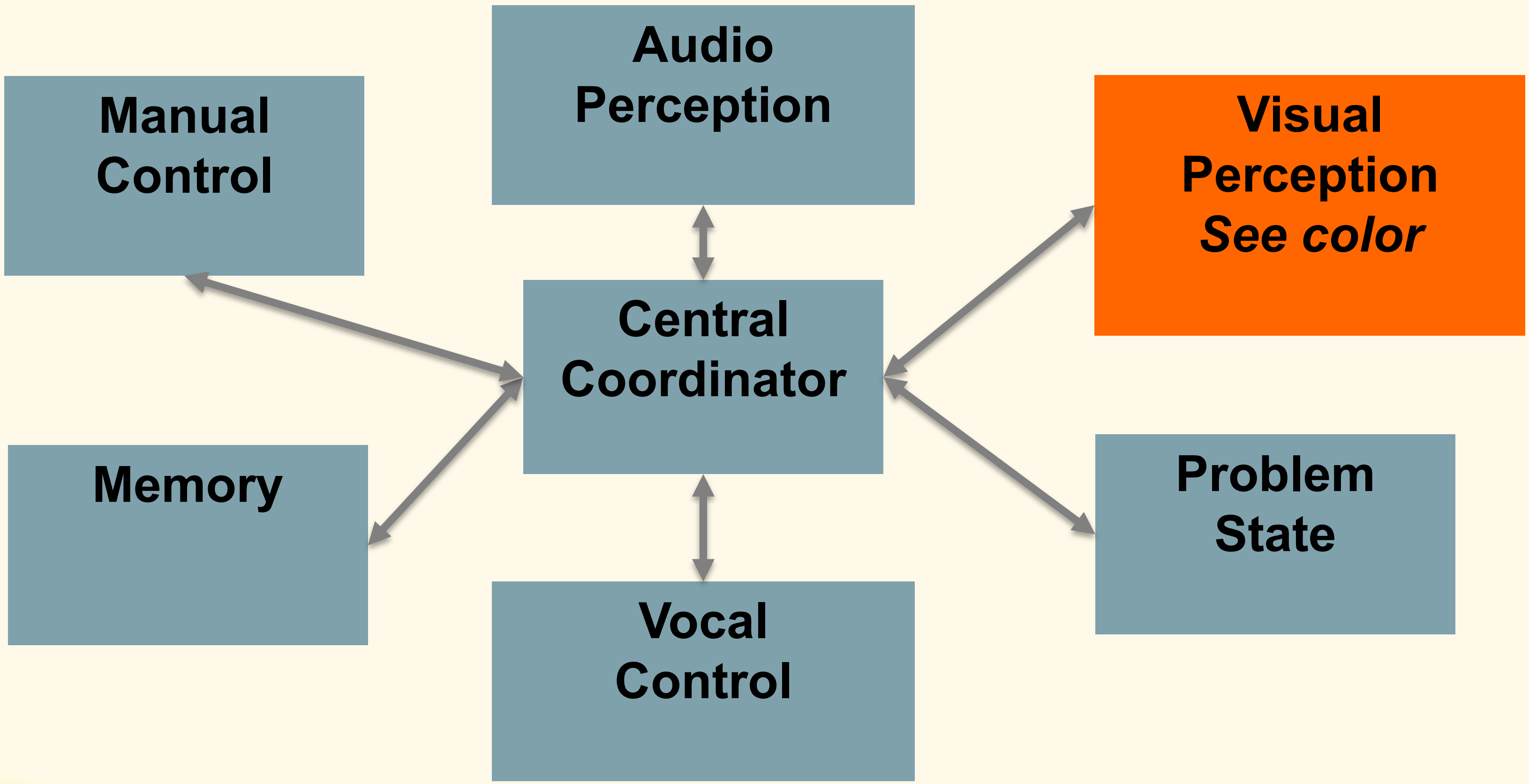
- Response bottleneck



ACT-R: With Short SOA, central coordinator can only start audio processing after visual-manual response is initiated

PRP task: classical model

- Response bottleneck



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PRP task: classical model

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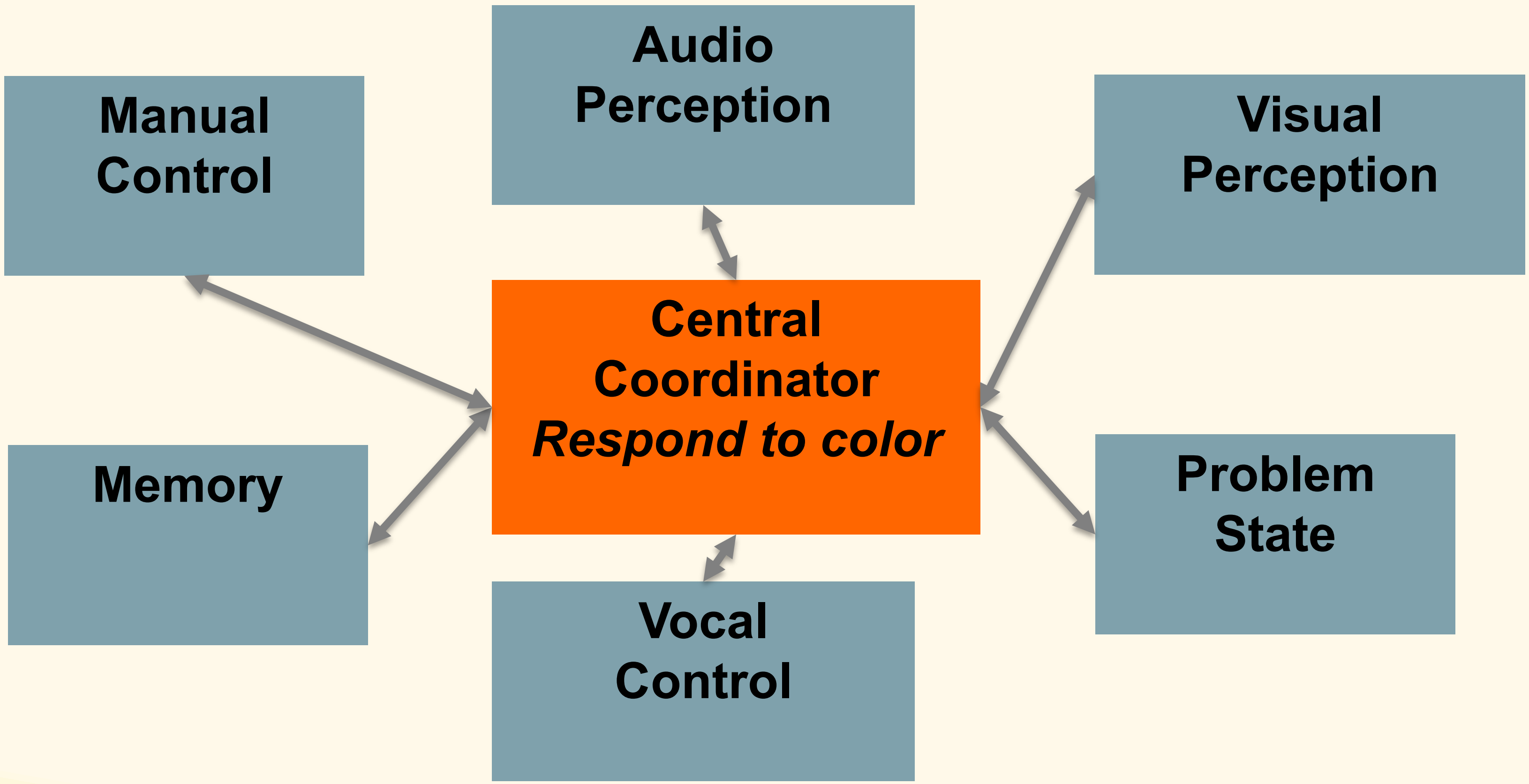

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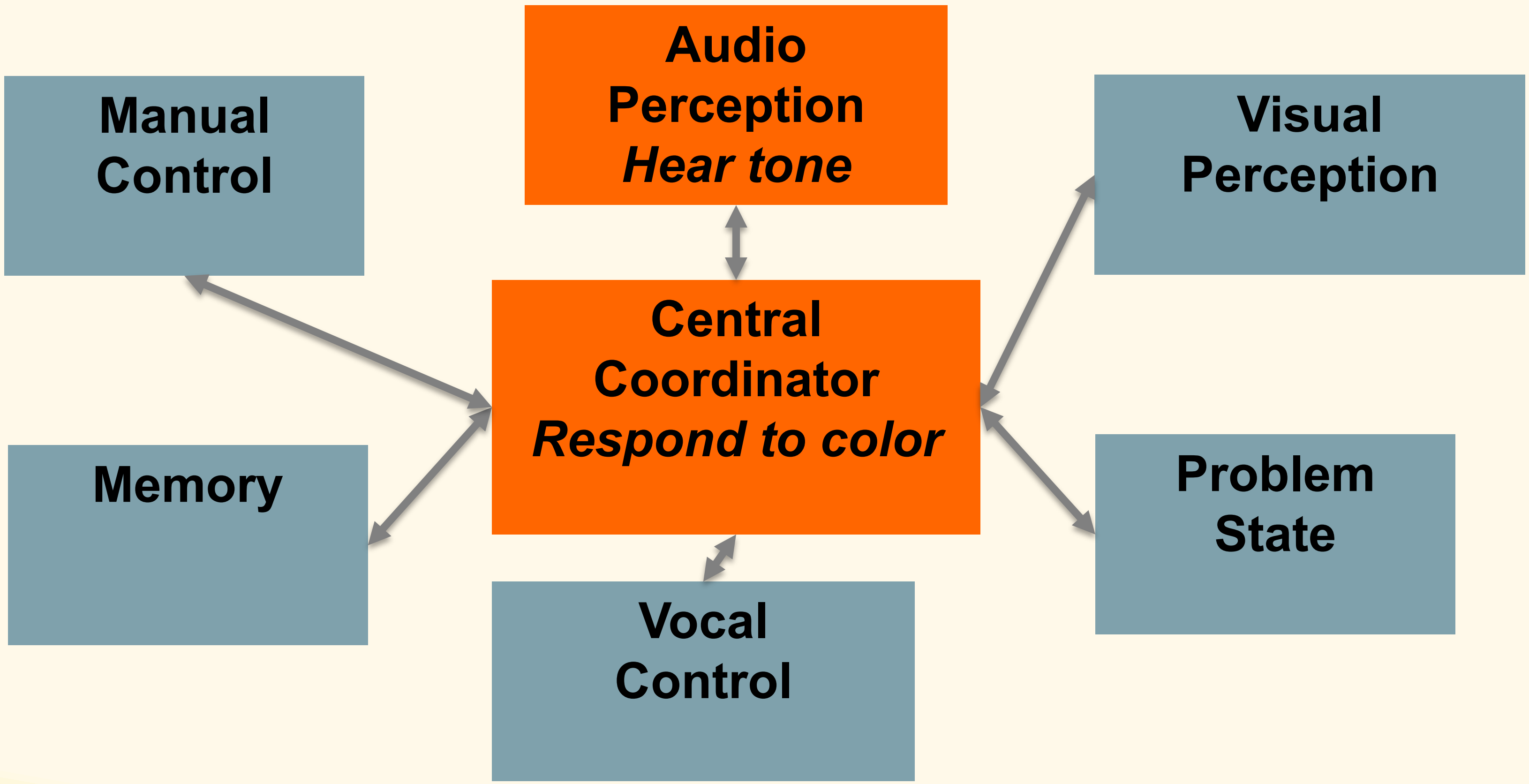
PRP task: classical model

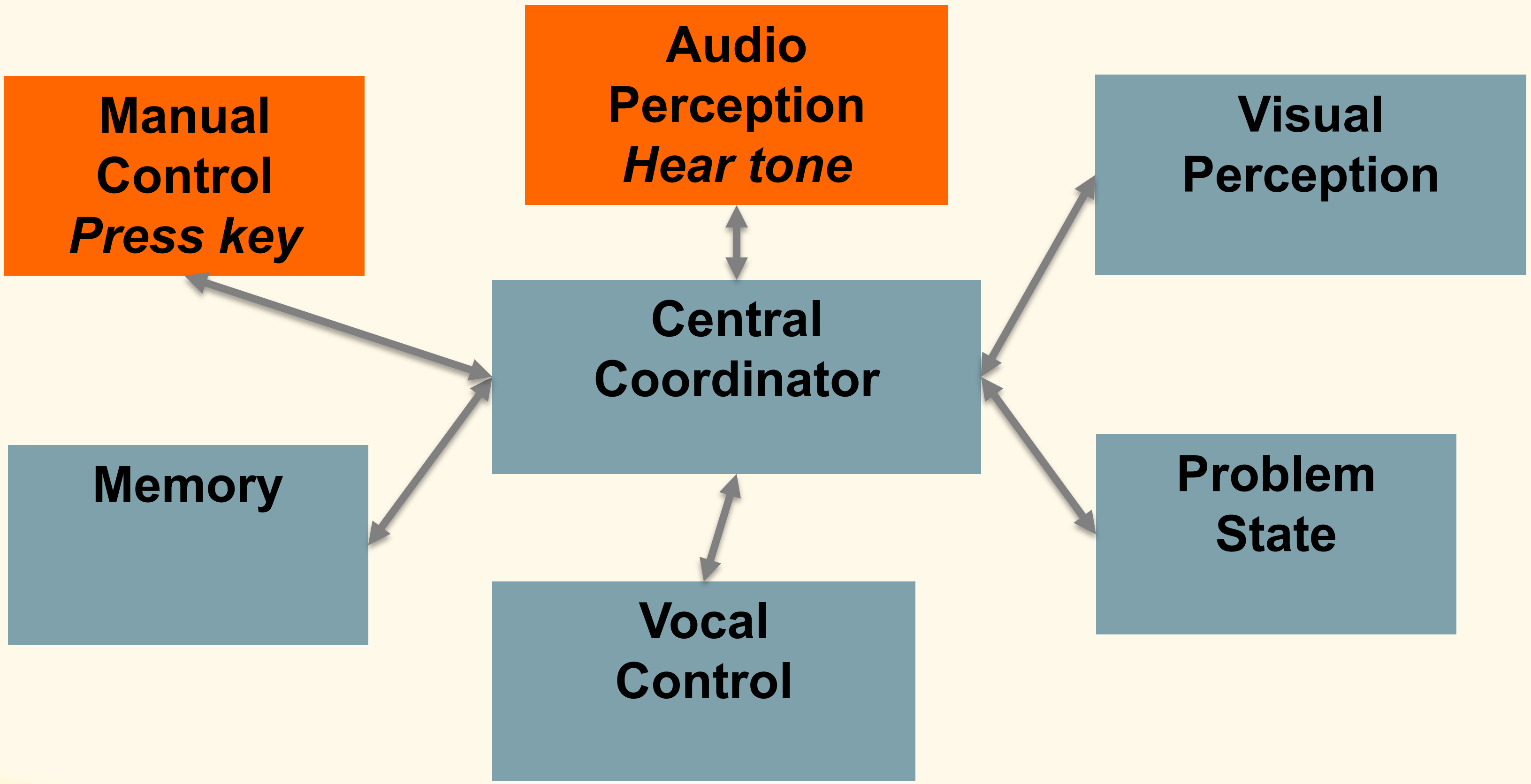
- Response bottleneck



ACT-R: With Short SOA, central coordinator can only start audio processing after visual-manual response is initiated

PRP task: classical model

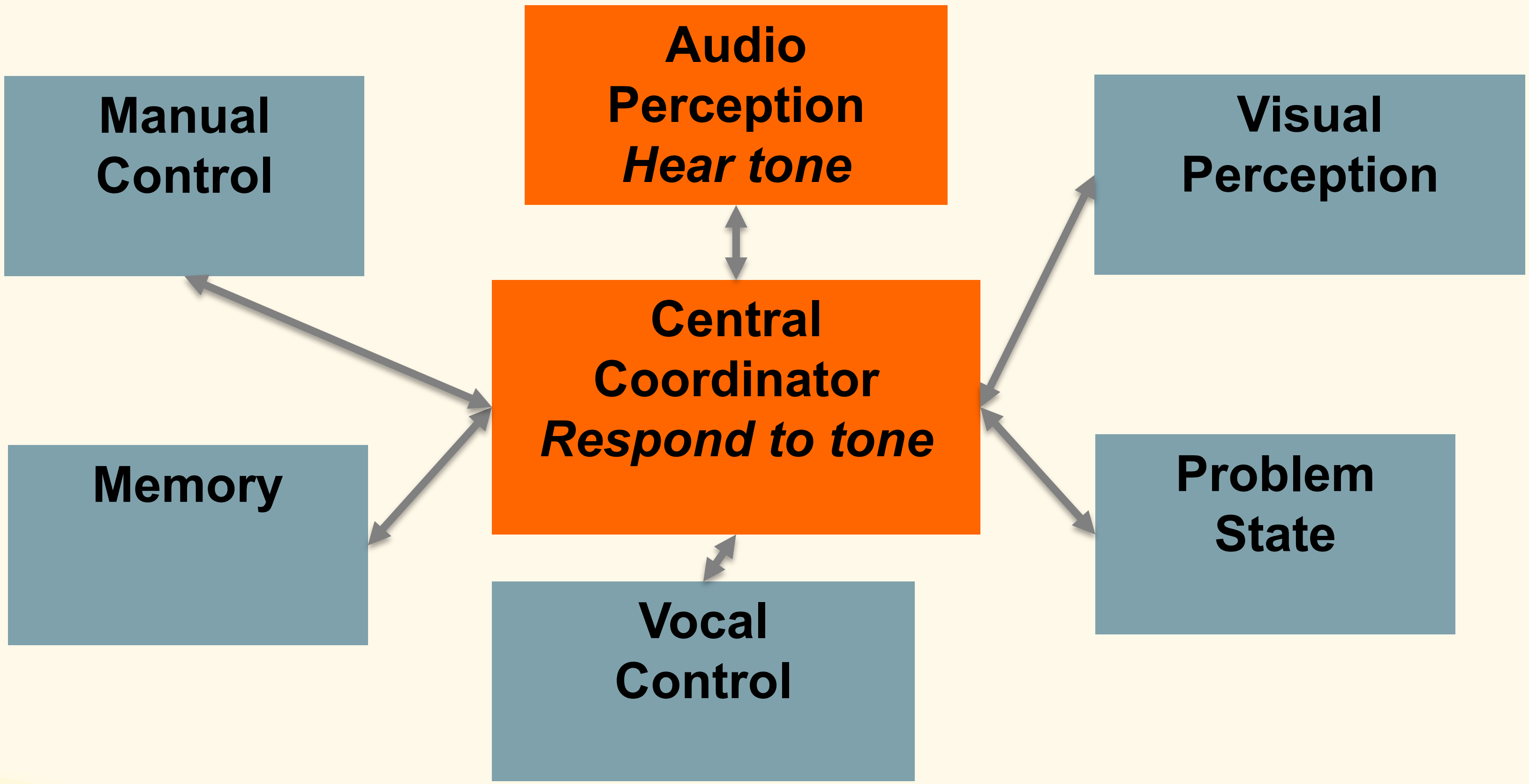
- Response bottleneck



ACT-R: With Short SOA, central coordinator can only start audio processing after visual-manual response is initiated

PRP task: classical model

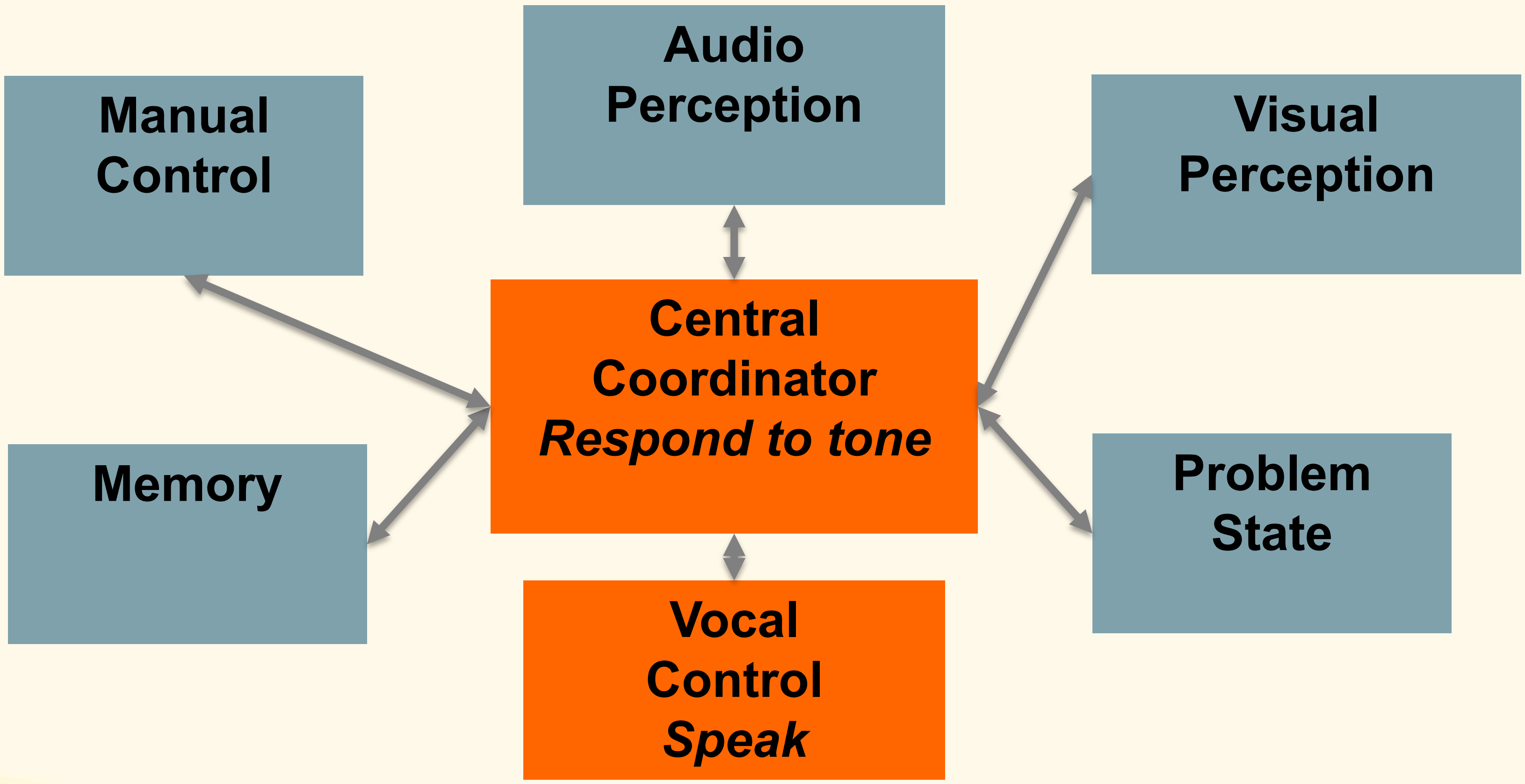
- Response bottleneck



ACT-R: With Short SOA, central coordinator can only start audio processing after visual-manual response is initiated

PRP task: classical model

- Response bottleneck



ACT-R: With Short SOA, central coordinator can only start audio processing after visual-manual response is initiated

Alternative model: EPIC

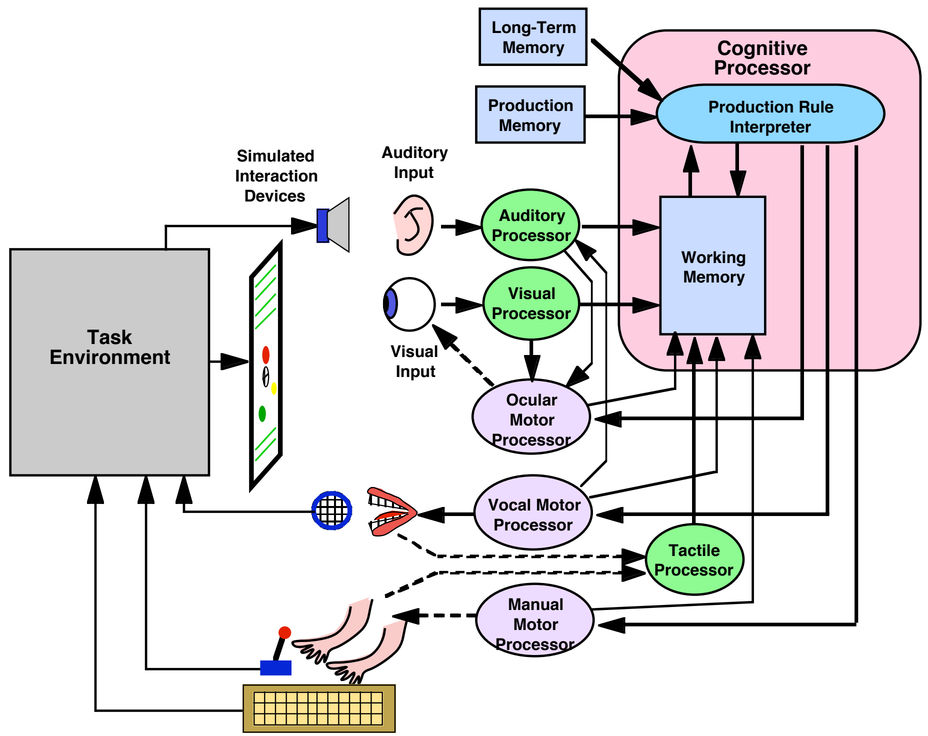
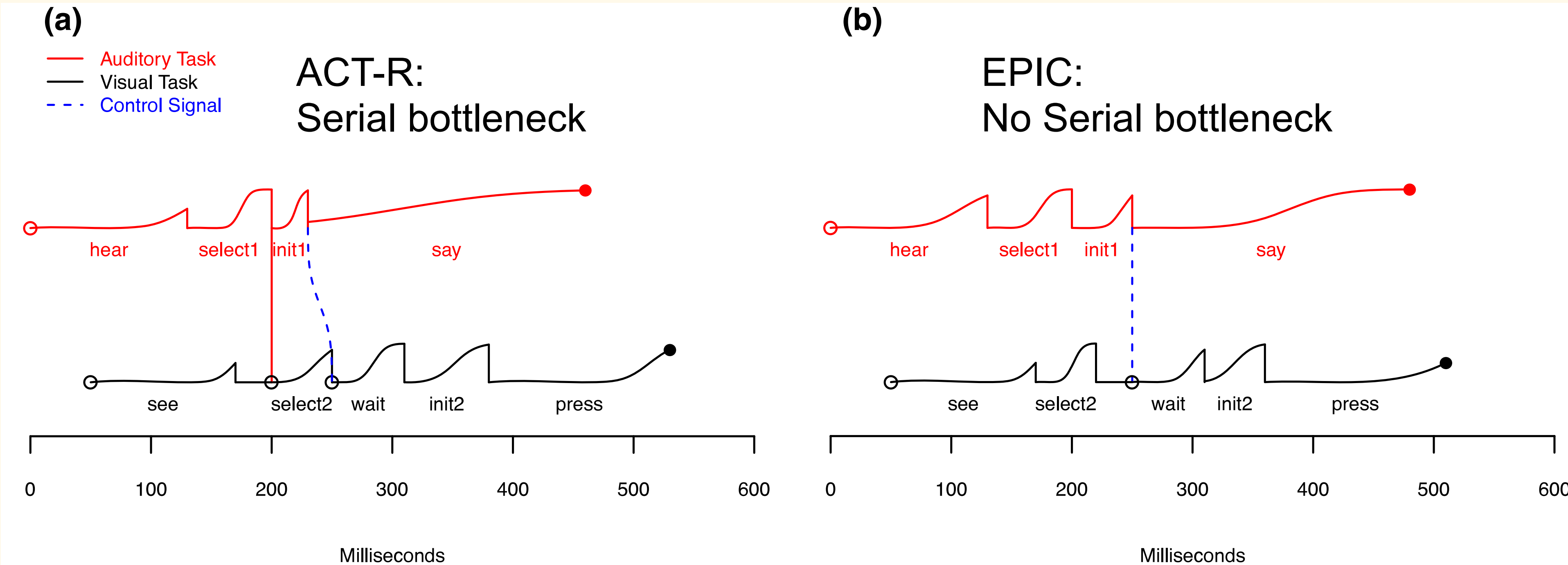


Figure 2. The EPIC architecture in simplified form. The simulated environment, or device, is on the left; the simulated human on the right.

- **Cognitive processor can start multiple processes in parallel**
- **NO bottleneck**
- **Delay through coordinating strategies**

Kieras (2007) in Gray (ed) Integrated Models

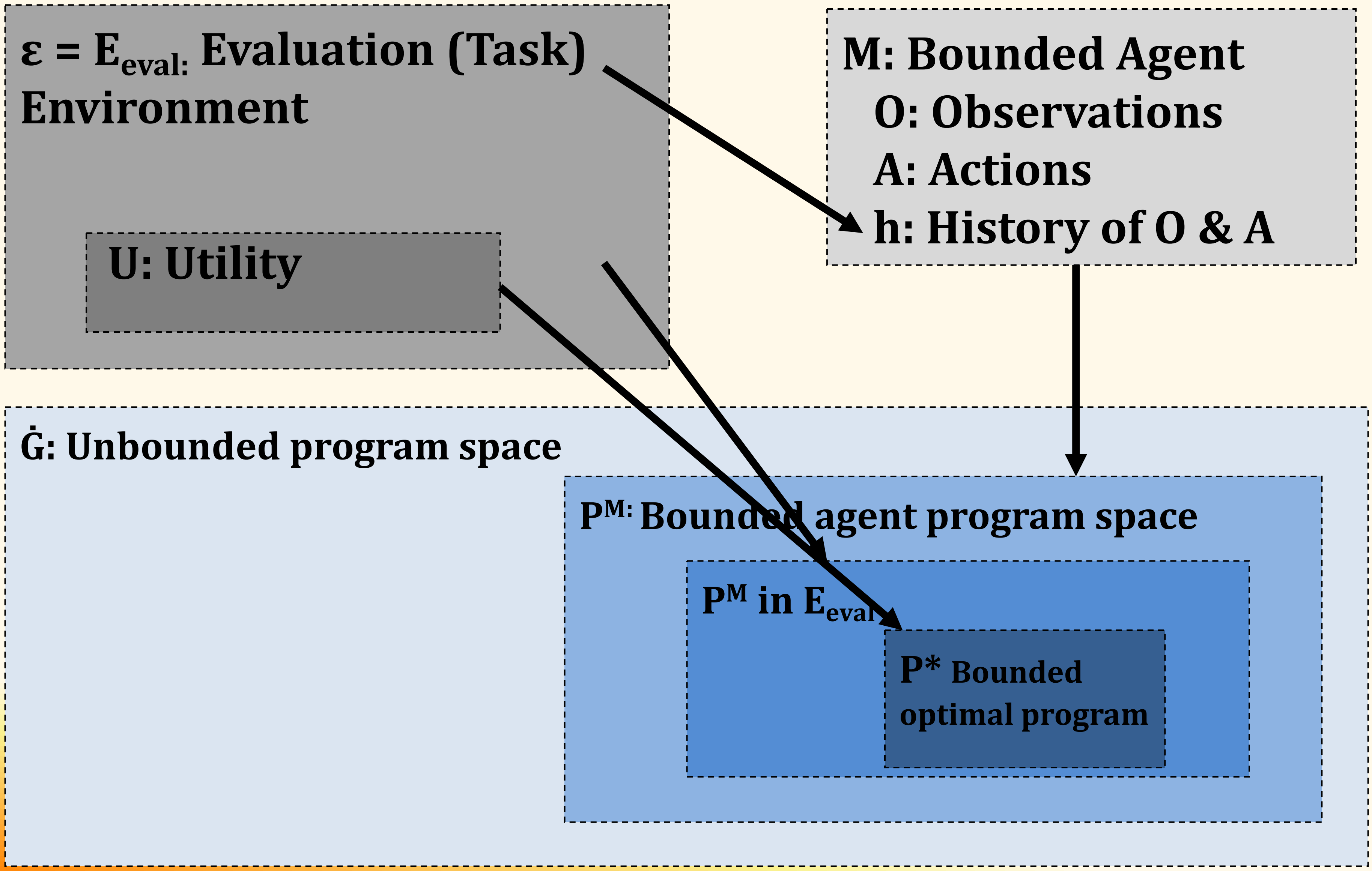
Predictions of models



- **Different process models; same result**
- **Which one is ‘better’?**

Figure from Lewis et al (2014)

Type III: Bounded optimality explanation



Type III: Bounded optimality

1. **Machine: bounded**
   - **Model captures "steps of central controller" ("production rules" / "condition action-pairs")**
   - **Explicit exploration of different strategies that are serial or parallel: *12 different models in total (see Figure in Appendix of slides)***
   - **Capture individual differences: duration of each step fit to data from longest SOA condition**

Type III: Bounded optimality

2. Environment

$$\varepsilon = E_{eval} = E_{schumacher}$$

- That means: similar SOAs were experienced as in Schumacher, no assumptions about learning outside of task

Type III: Bounded optimality

3. Utility function

- $U_{schumacher}$

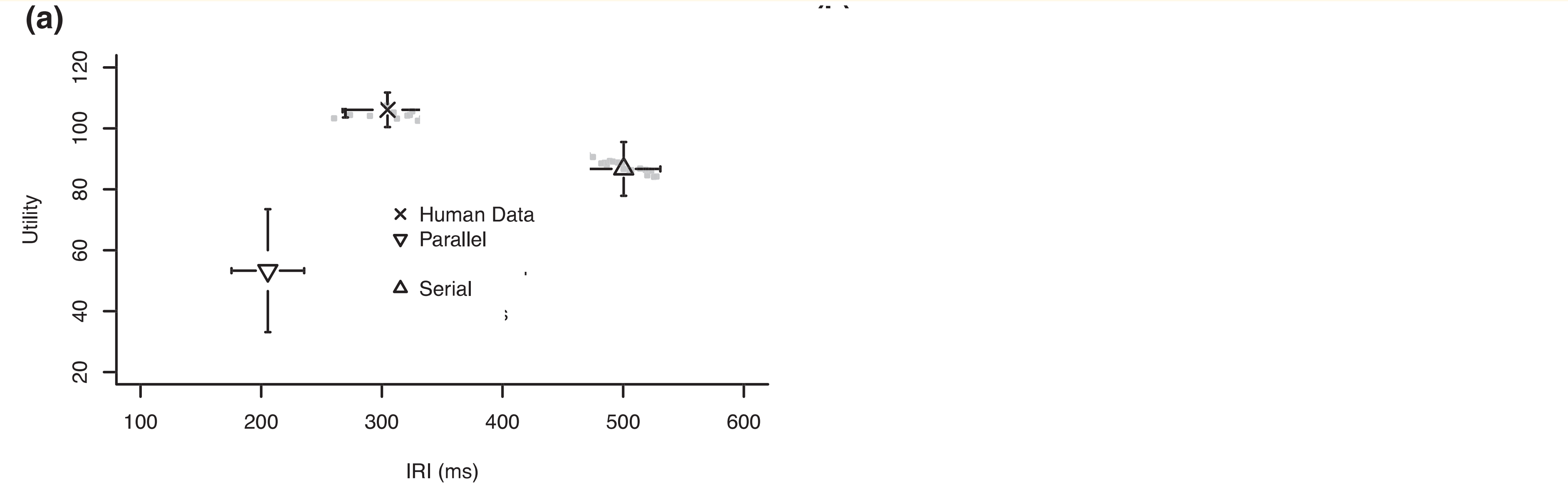
- Overall Utility of strategy: average over utilities/scores achieved on all SOAs

Type III: Bounded optimality

- **Generating predictions:**
  - Which of the strategies are in line with fully serial?
  - Which are in line with fully parallel?
  - Which models fit best given a particular architecture (i.e., ACT-R: bottleneck; EPIC: no bottleneck)?
  - Which is in general the best?

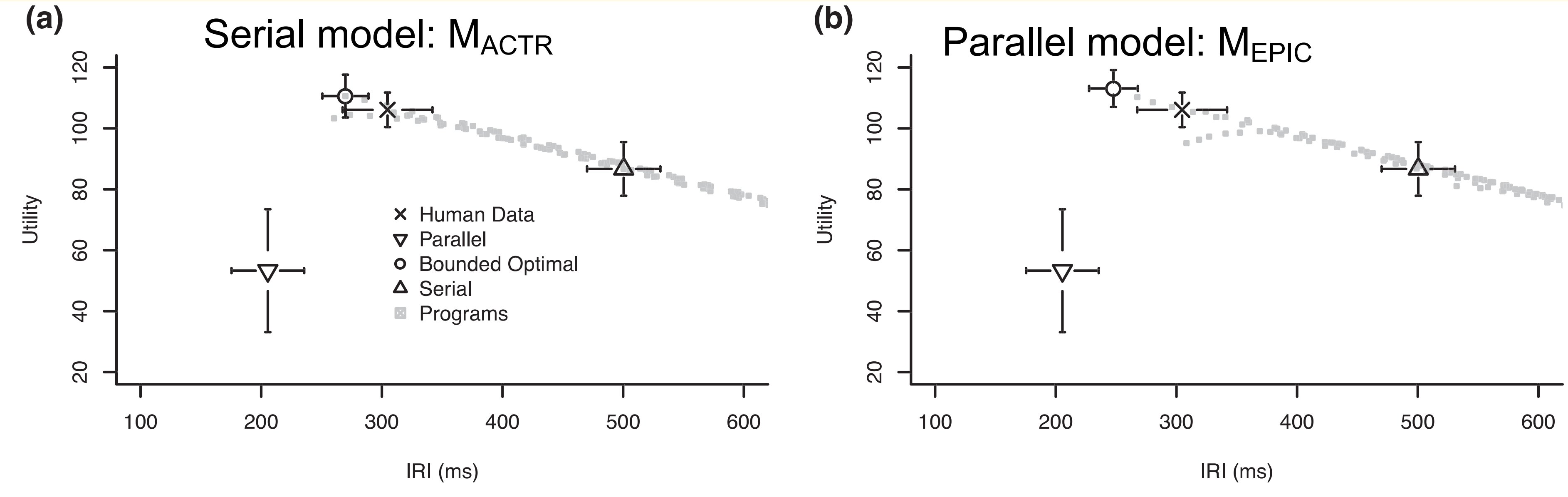
Type III: Bounded Optimality

- **Results: Different way of representing** (Lewis et al 2014)



Type III: Bounded Optimality

- **Results: Different way of representing (Lewis et al 2014)**



Conclusions:

1. **Bounded-optimal prediction of both M_{ACTR} and M_{EPIC} fit data.**
2. **M_{ACTR} slightly better (more overlap error bars).**
3. **Response slowing (PRP curve) is no definitive evidence for serial bottleneck**

Reflection on model type

- **Why not use Type I model?**
  - **Humans deviate from "ideal response time" (i.e., predicted by fully parallel model)**
- **Why not use Type II model?**
  - **Environment alone ($E_{schumacher}$) is not enough**
  - ***Assumptions about agent*** **(internal process) are needed**
  - **And these assumptions can differ between theories (ACT-R vs EPIC)**

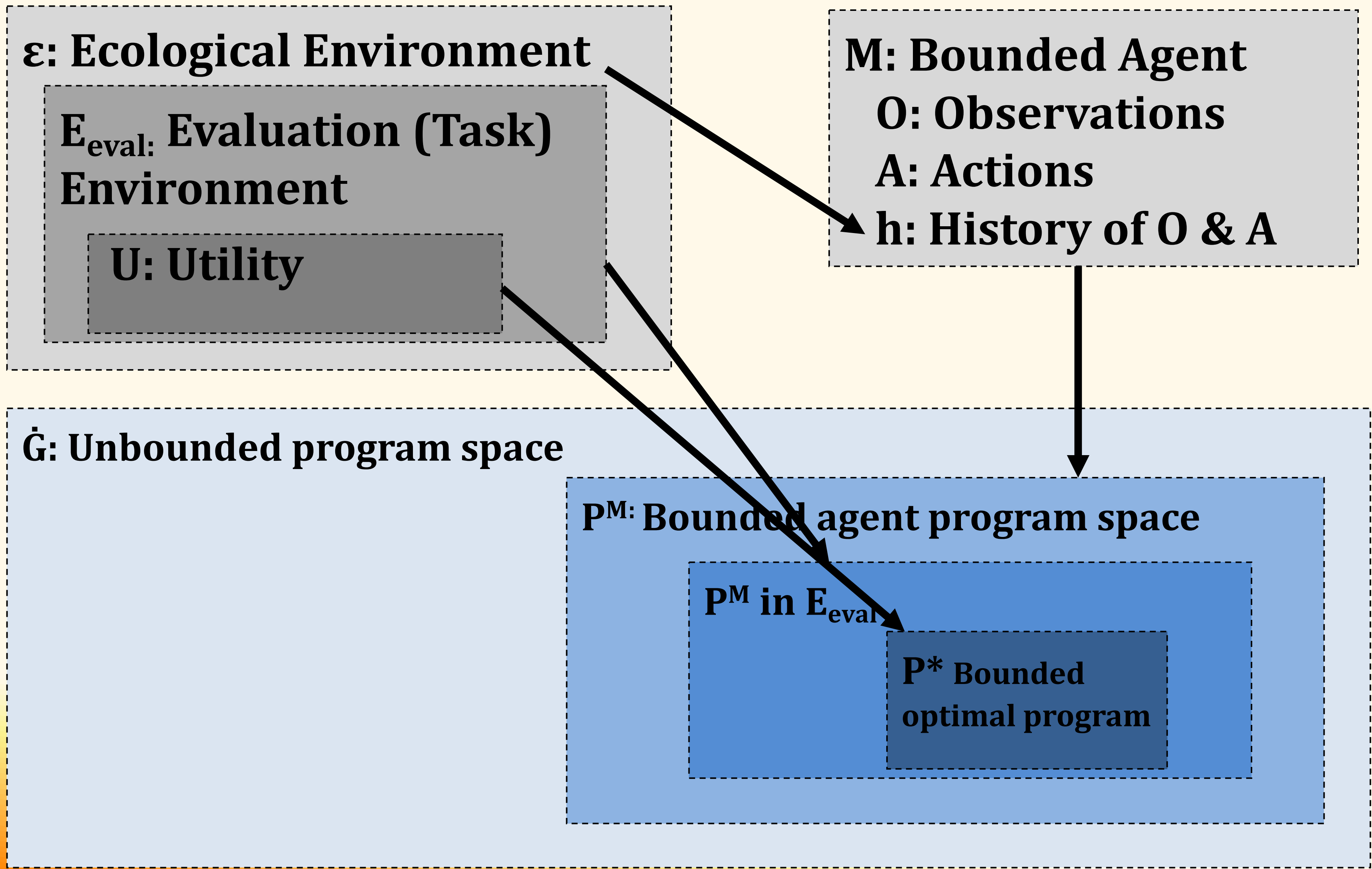
Who should use type III model?

- When details of agent matter:
  - What humans can and can’t do
  - i.e.: psychological research!

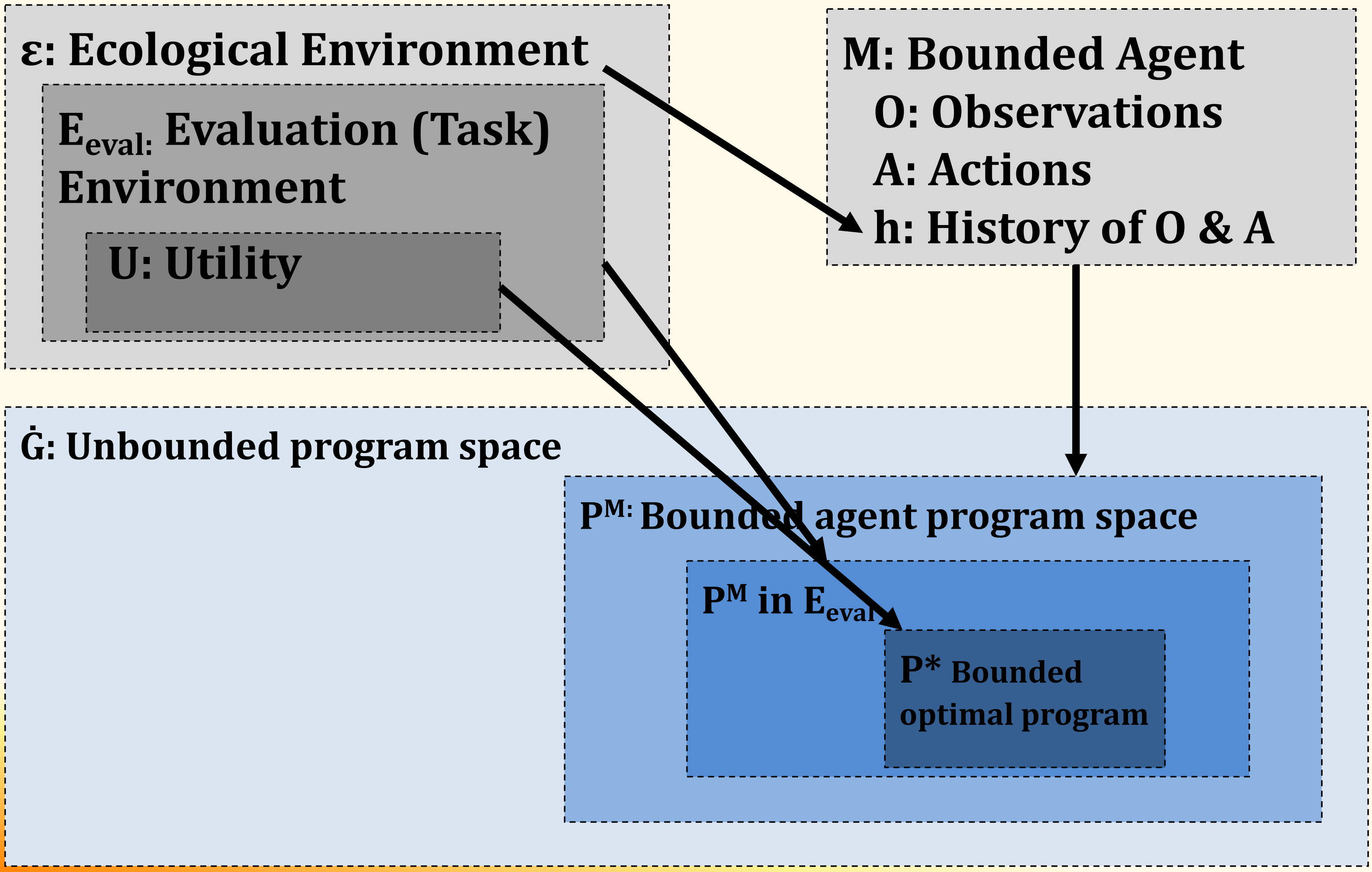
Why is this a ‘process model’?

- Describes the internal process that agent goes through
  - Which steps in which order?
  - What affects length of those steps?
  - Which steps parallel / serial?

Computational Rationality



Type IV: Ecological-Bounded optimality explanation

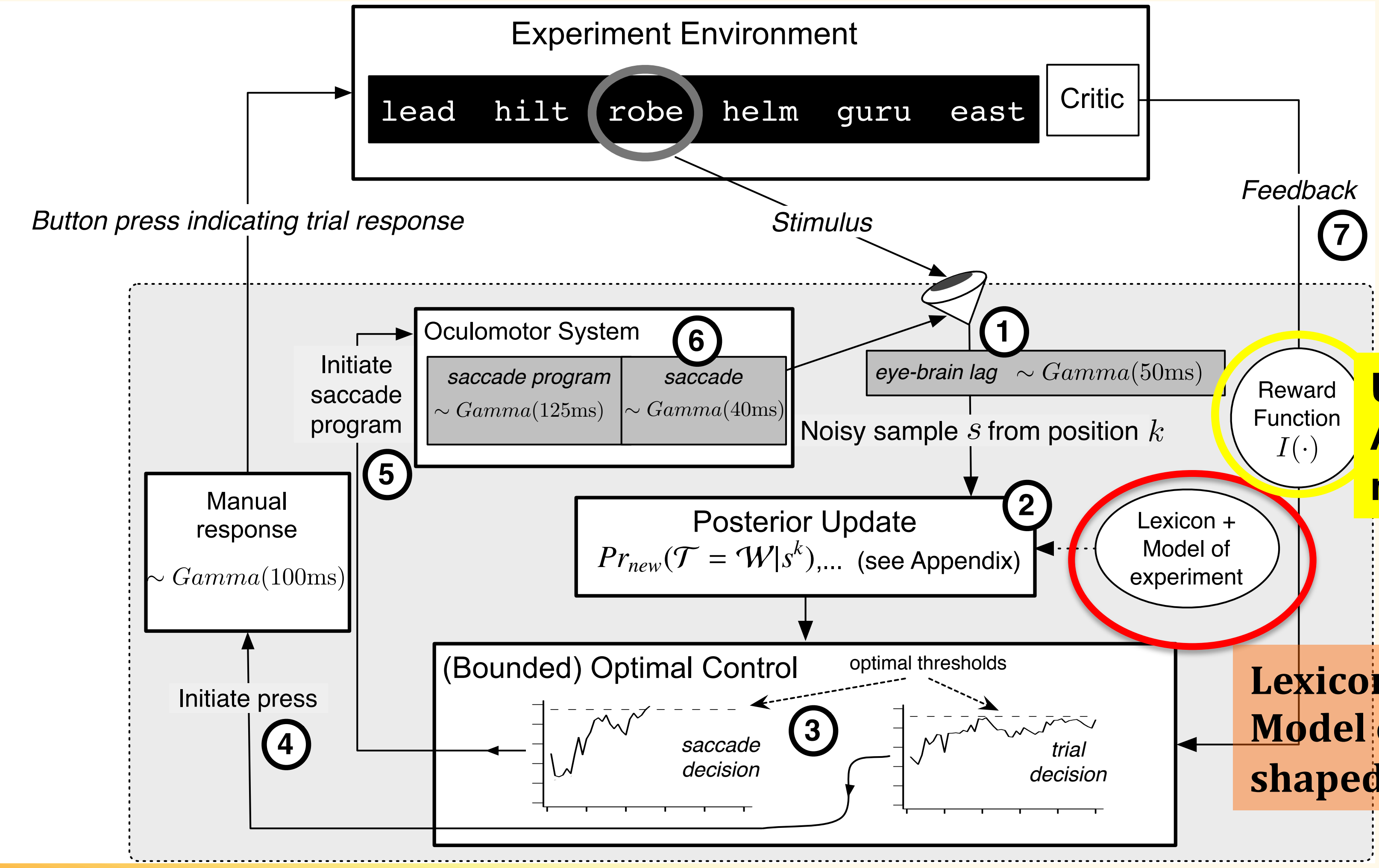


Lexical decision task (extension of Meyer & Schvaneveldt, 1971)

- **Is there a “non-word” in the list?**

fill	garb	stay	tool	dial	germ

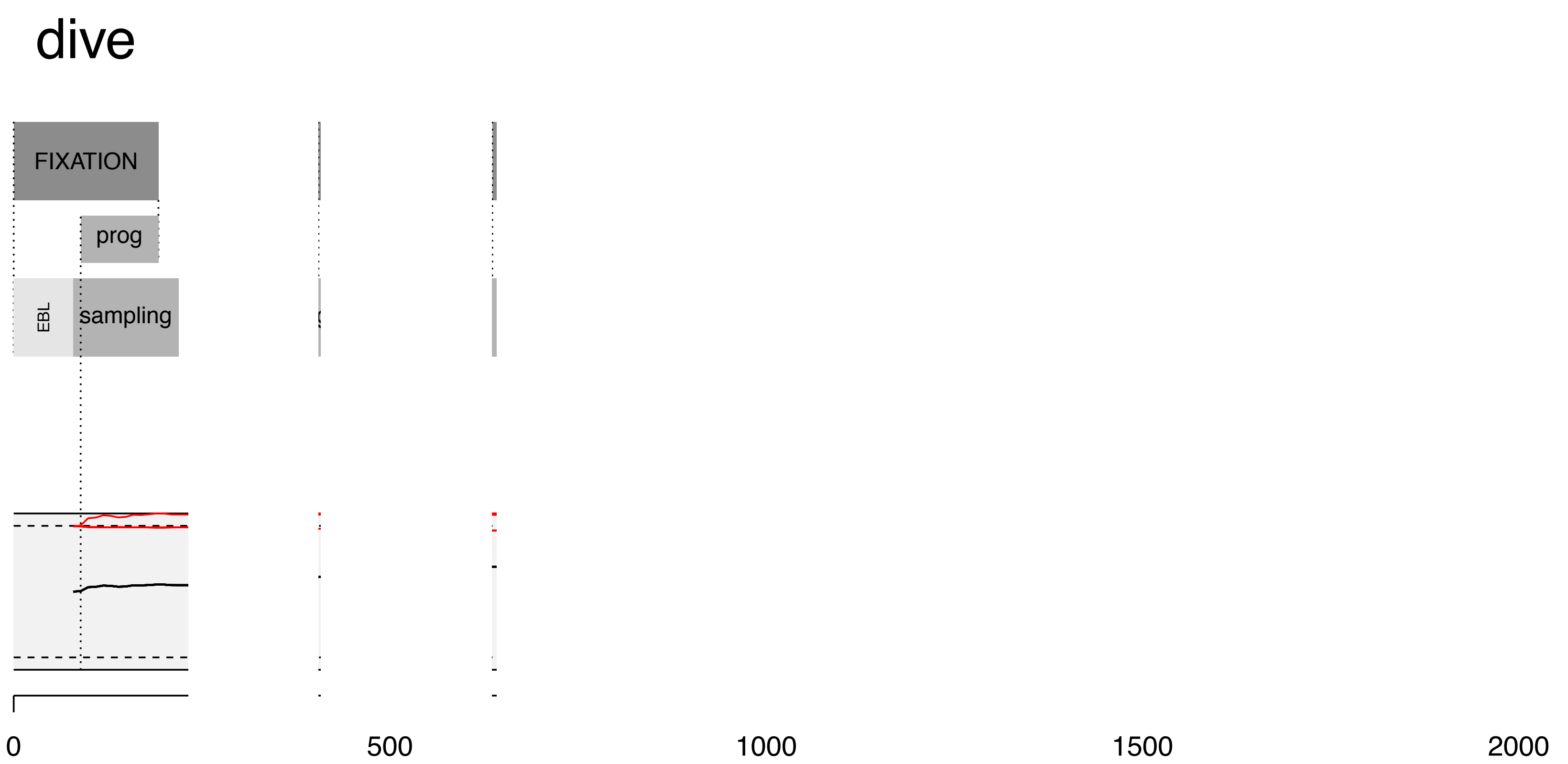
Model: Summary (Lewis et al 2013, Topics)



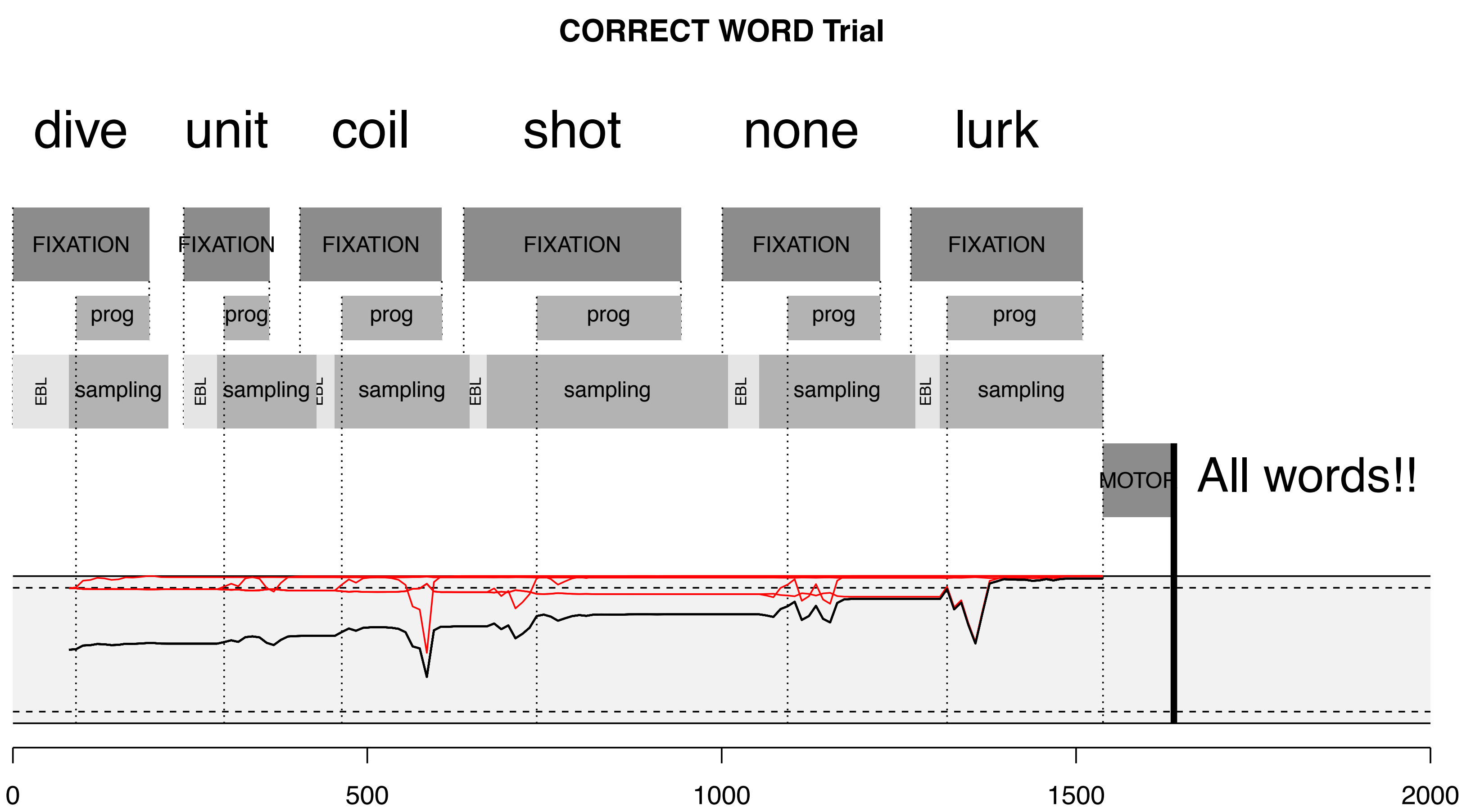
Utility: speed Accuracy, medium

Lexicon shaped by ε Model of experim. shaped by E_{eval}

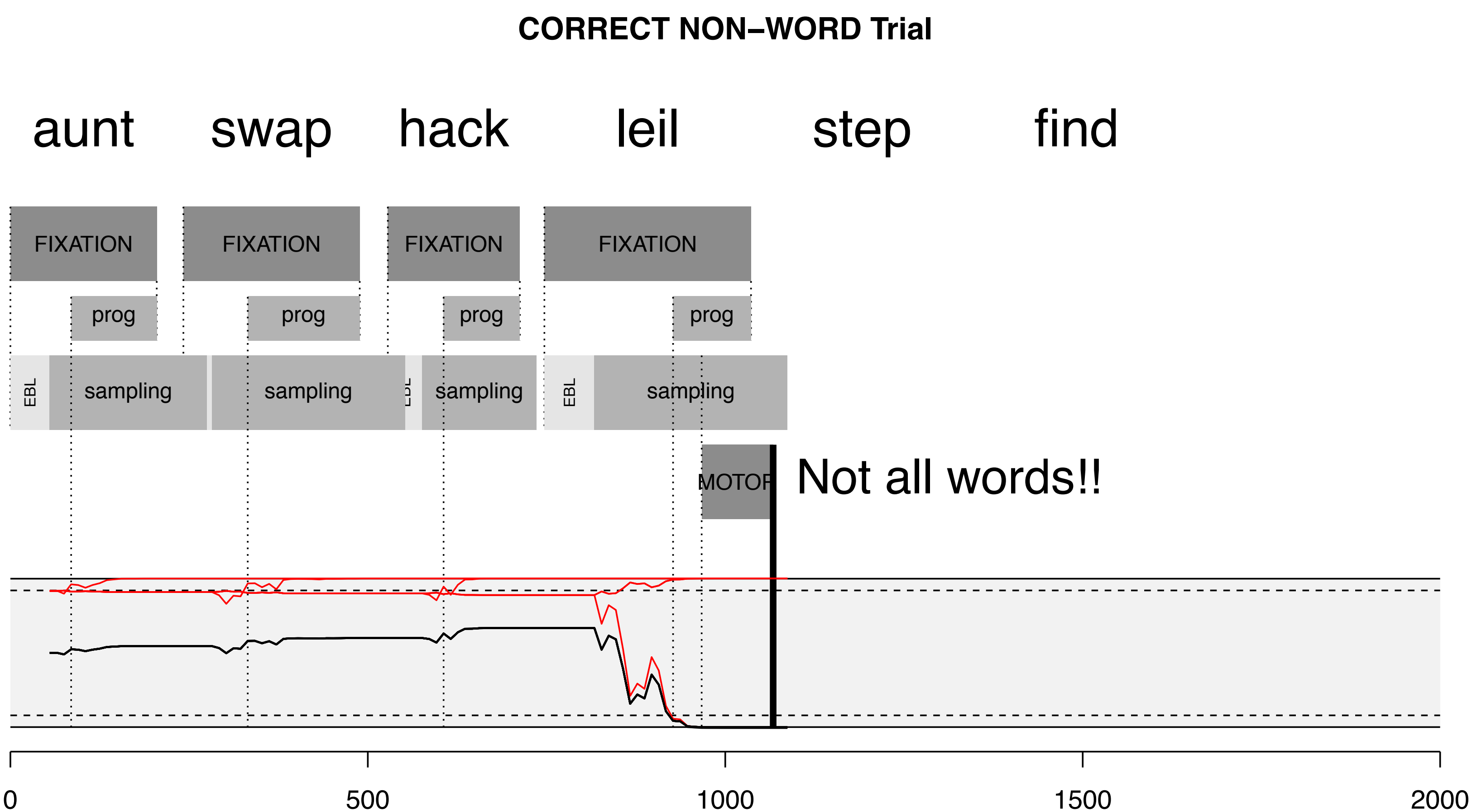
Model predictions



Model predictions (Lewis et al 2013)



Model predictions (Lewis et al 2013)



Bounds

- **Bounded machine:**
  - Next action is only taken once ***threshold*** (saccade, decision) is reached through ***noisy accumulation*** process
- **Bounded ecological environment:**
  - Recognition of individual word depends on lexicon (i.e., experience in the world)
- **Bounded by task environment:**
  - Expectation of non-word depends on trial statistics (1/2 trials non-word, then only 1 word incorrect)

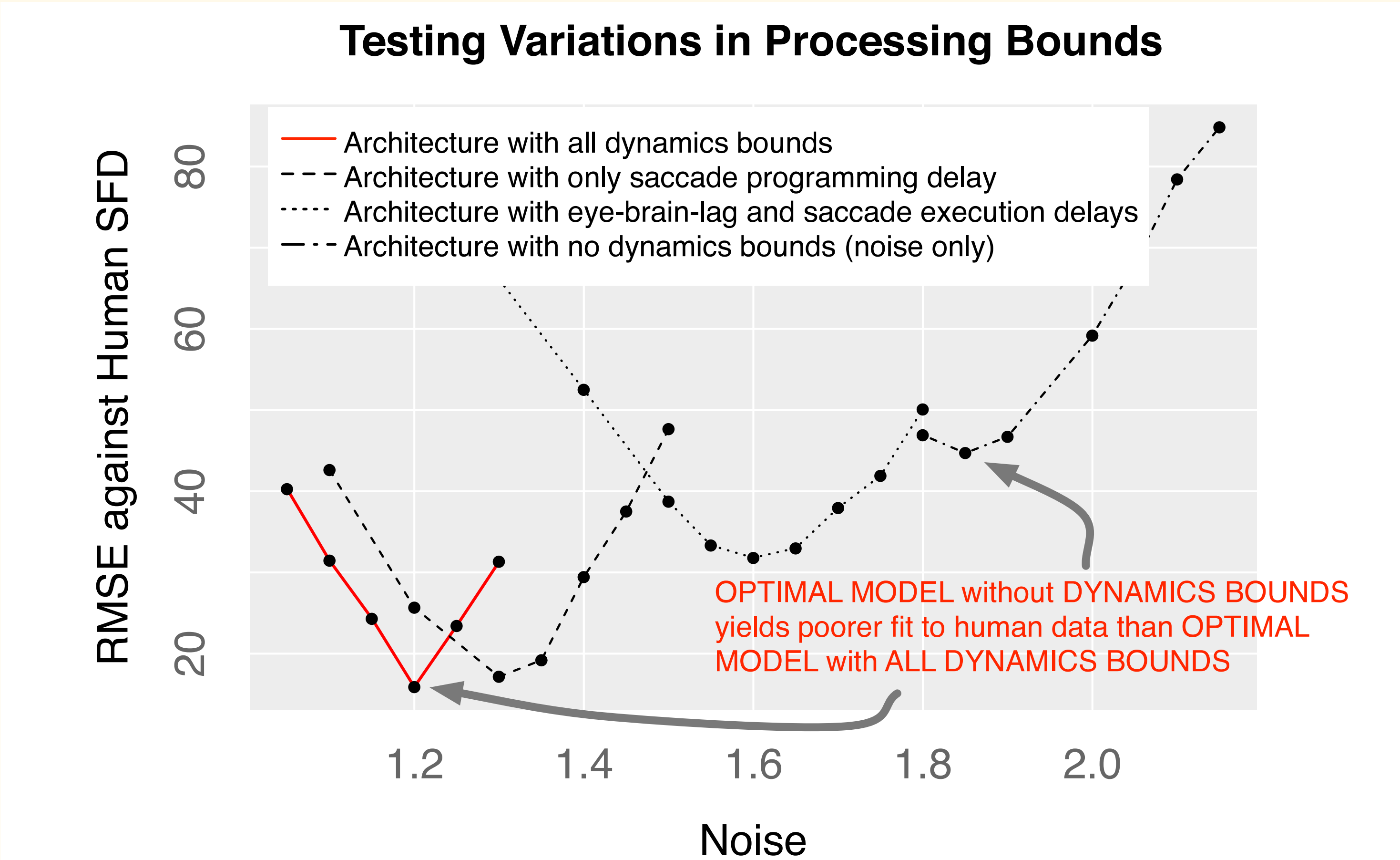
Results

- See paper & appendix of slides

Reflection on model type

- **Why not use Type I model?**
  - Humans do not get 100% correct
- **Why not use Type II model?**
  - Misses component of agent: how information is accumulated over time
- **Why not use Type III model?**
  - Misses adaptation to experienced words: lexicon

Reflections on model type



- **Bounds improve model correspondence with human data (lower RMSE)**

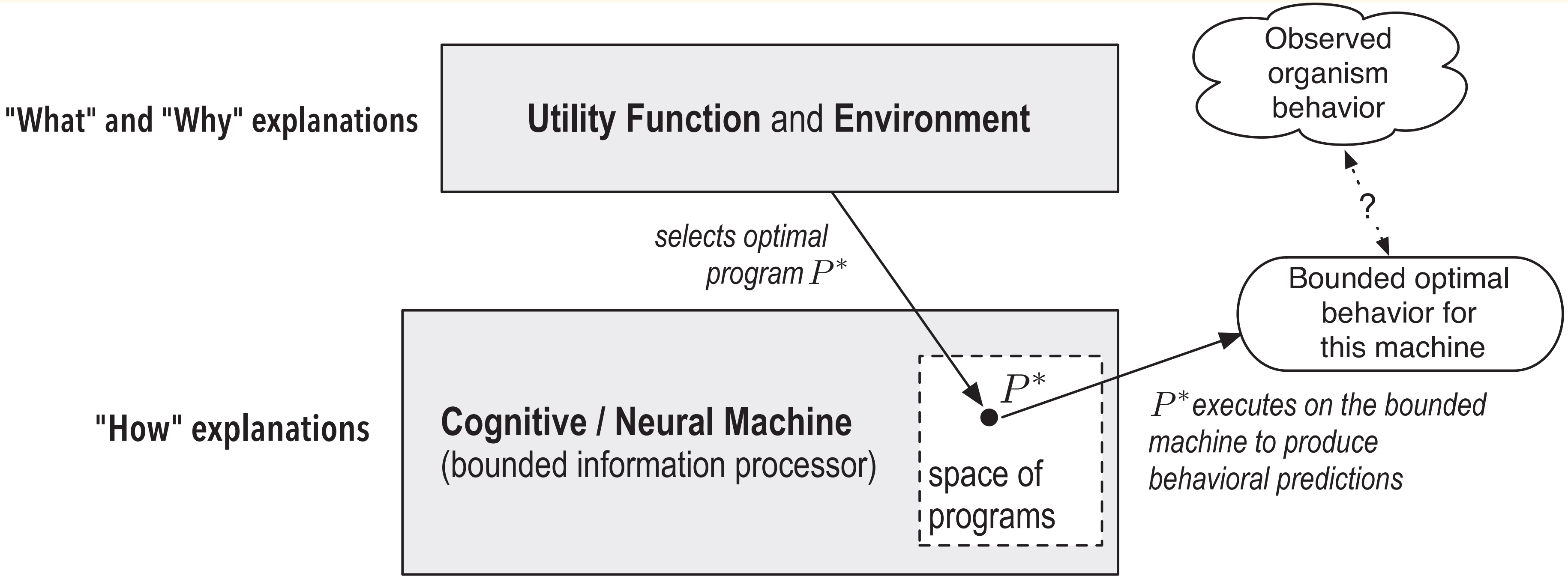
Who should use type IV models?

- When studying how agent and environment impact performance
  - Tasks that are influenced by history outside of lab
  - Tasks that are influenced by characteristic of agent

Why is this a ‘process model’

- **Describes the internal process that agent goes through**
  - **Which steps in which order?**
  - **What affects length of those steps?**
  - **Which steps parallel / serial?**

General Discussion



Environment + Mechanism / Agent shape programs

Role of levels: why, what, & how matter
'What' benefits from a processing account

To do

- Read course manual
- Prepare for lab:
  - Install R
  - If you already know R: read assignment 1
  - Think about paper to present
- Friday:
  - Decide on paper (discuss your ideas with me & Krista)
  - Sign-up for presenter and discussant role
  - Get started on assignment 0 or 1

Exam material from this lecture

- All material covered in class
- Articles:
  - Anderson, B. (2014). Chapter 1: An introduction to the ideas and scope of computational methods in psychology. *Computational neuroscience and cognitive modelling: a student's introduction to methods and procedures*. Sage.
  - Gershman, S. J., Horvitz, E. J., & Tenenbaum, J. B. (2015). Computational rationality: A converging paradigm for intelligence in brains, minds, and machines. *Science*, *349*(6245), 273–278. http://doi.org/10.1126/science.aac6076
  - Lewis, R. L., Howes, A., & Singh, S. (2014). Computational Rationality: Linking Mechanism and Behavior Through Bounded Utility Maximization. *Topics in Cognitive Science*, *6*(2), 279–311.
- Next week:
  - Anderson, J. R., Zhang, Q., Borst, J. P., & Walsh, M. M. (2016). The Discovery of Processing Stages: Extension of Sternberg's Method. *Psychological Review*.

Today's topics

1. Gershman, Horvitz, Tenenbaum: Computational Rationality
   - Why does it matter for mind, brain, and machines?
   - Why are processing models useful?
- Intermezzo levels of abstraction
2. Lewis, Howes, Singh: Rational adapted
   - How is behavior formed? Optimality explanations
     - Type I: Optimality
     - Type II: Ecological-optimality
     - Type III: Bounded-Optimality
     - Type IV: Ecologically-Bounded-Optimality
   - Examples (Wason, PRP, Reading):
     - What is theoretical problem being studied? What is task/experiment? Why is this interesting?
     - What is "classical" model/approach
     - Why is this not sufficient?
     - Approach of computational rationality

Study questions: Britt Anderson chapter 1(not bullet proof)

- This chapter includes many thinking questions. I encourage you to think about the questions the author poses.
- What are the goals of computational modeling for pscyhology and neuroscience?
- What are the advantages of cognitive models?
- What are the limitations of computational models?
- Do cognitive models require computers?
- Do cognitive models need to be neurally plausible?
- How can the success of a model be evaluated?

- Be able to apply this to case studies as well

Study questions: Gershman et al context (not bullet proof)

- Why does the study of computational rationality matter for (i) AI, (ii) cognitive science, and (iii) cognitive neuroscience? (know for each)
- When provided with an example in either of these fields, be able to explain why a computational rationality approach might be useful
(i.e., why not calculate the overall optimum?)
- What are the advantages of a computational rationality approach for these fields?
- Why are *processing models* useful for computational rationality problems?

- Be able to apply this to case studies as well

Study questions Lewis et al (not bullet proof)

- What are the 4 types of optimality explanations that Lewis et al describe, and what are their characteristics?
- For each type: when is it a (in-)sufficient explanation for behavior? Or: why is a particular type needed when?
- What are the various elements of a "computational rationality" model? (you don't need to know the equations)
- How do these models relate to Marr's three levels?
- For each of the three experiments Wason; PRP; Linguistic task (when available):
  - What are the classical explanation(s)/model(s)
  - What type of model do Lewis et al propose for the task. Why is such a model needed? What is the added value?
  - How are these models (dis-)similar from "classical model"?
- What are the "misconceptions" of computational rationality?
- Be able to apply your knowledge to case studies

Questions?

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Additional slides

What can the various components entail?

Bounded information-processing Agent

Can define (p 286):

1. Entire cognitive architecture
2. Comprehensive architecture
3. Machine architecture
4. Particular model for specific problem
5. Processing bounds at low level (*implementation*)

Different architectures
Newell: Different time-scales
Marr: Implementation and algorithmic level

Ecological environment

- **“The optimality, or otherwise, of an adaptive system should be partly determined by the statistics of the ecological environment to which the agent has adapted”**

Ecological environment

Can define (p 287):

1. Experiment
2. Rational analysis
3. Evolutionary biology

Utility function

Can specify (p 287):

1. Task goals (as instructed)
2. Internal subjective utility
3. Speed-accuracy trade-off
4. Assumptions of fitness

Bounded optimal program & behavior

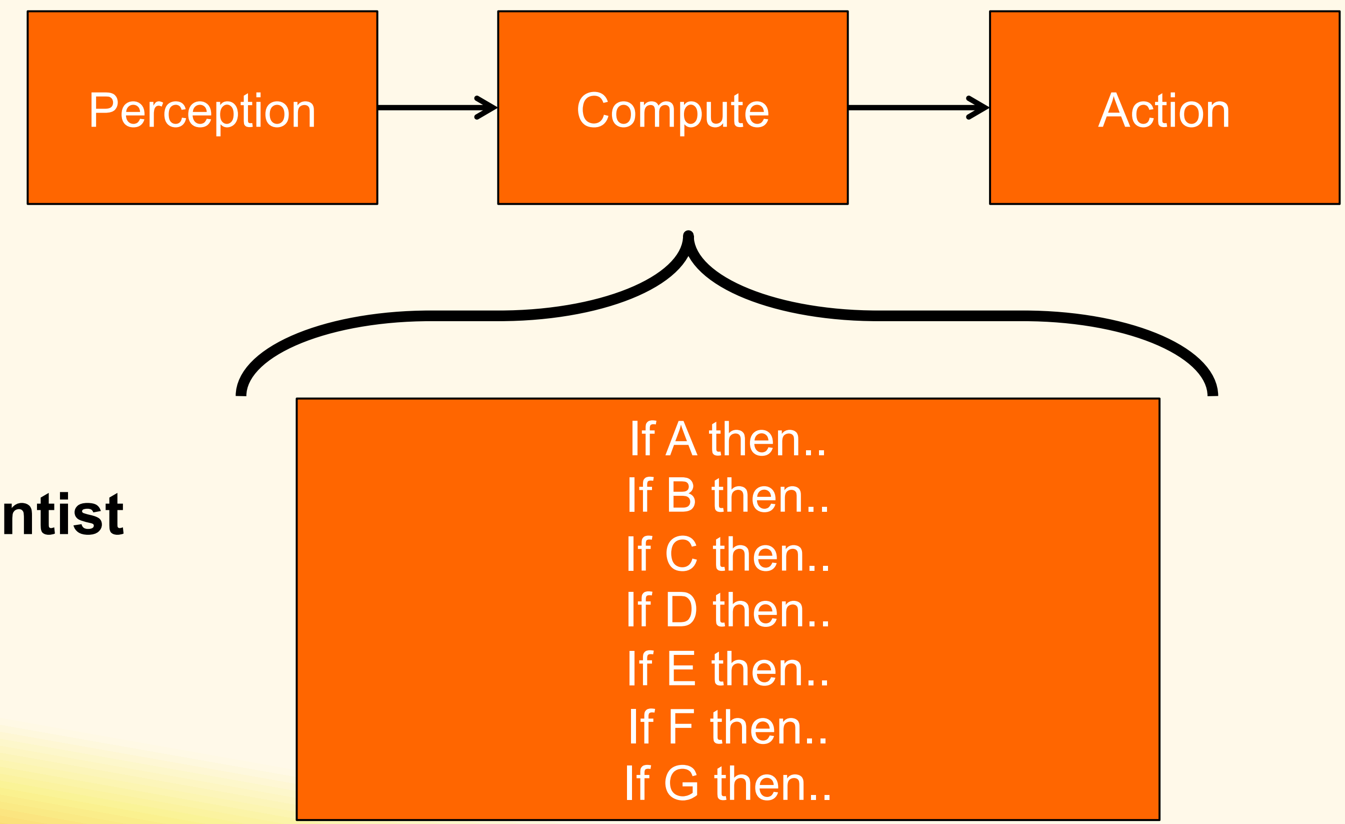
- **Uses (p 288):**
  - **Identify limits of adaptive processes (from agent, environment, utility): what *should* people do in particular environment?**
  - **Compare with what people do**

Slides explaining misconceptions

Misconceptions (p 288-289)

1. Cost of deriving optimum != cost of executing it

What person does:



!= What analyzer/scientist does:

Misconceptions (p 288-289)

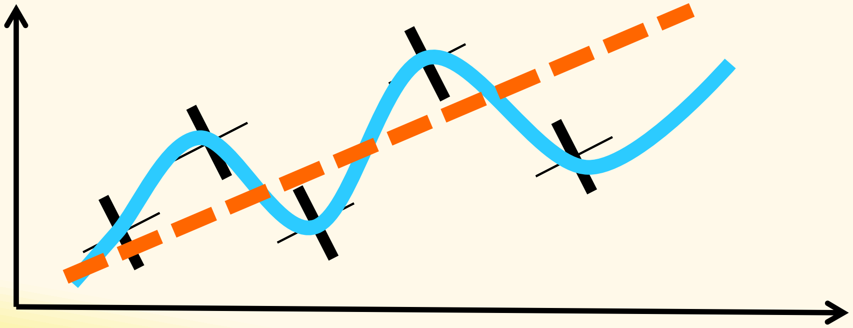
1. Cost of deriving optimum != cost of executing it
2. Optimal program vs optimal choice

A or B?	D or E?	G or I?	L or M?
Optimal Choice	Optimal Choice	Optimal Choice	Optimal Choice

Optimal program when considering everything in the long-run

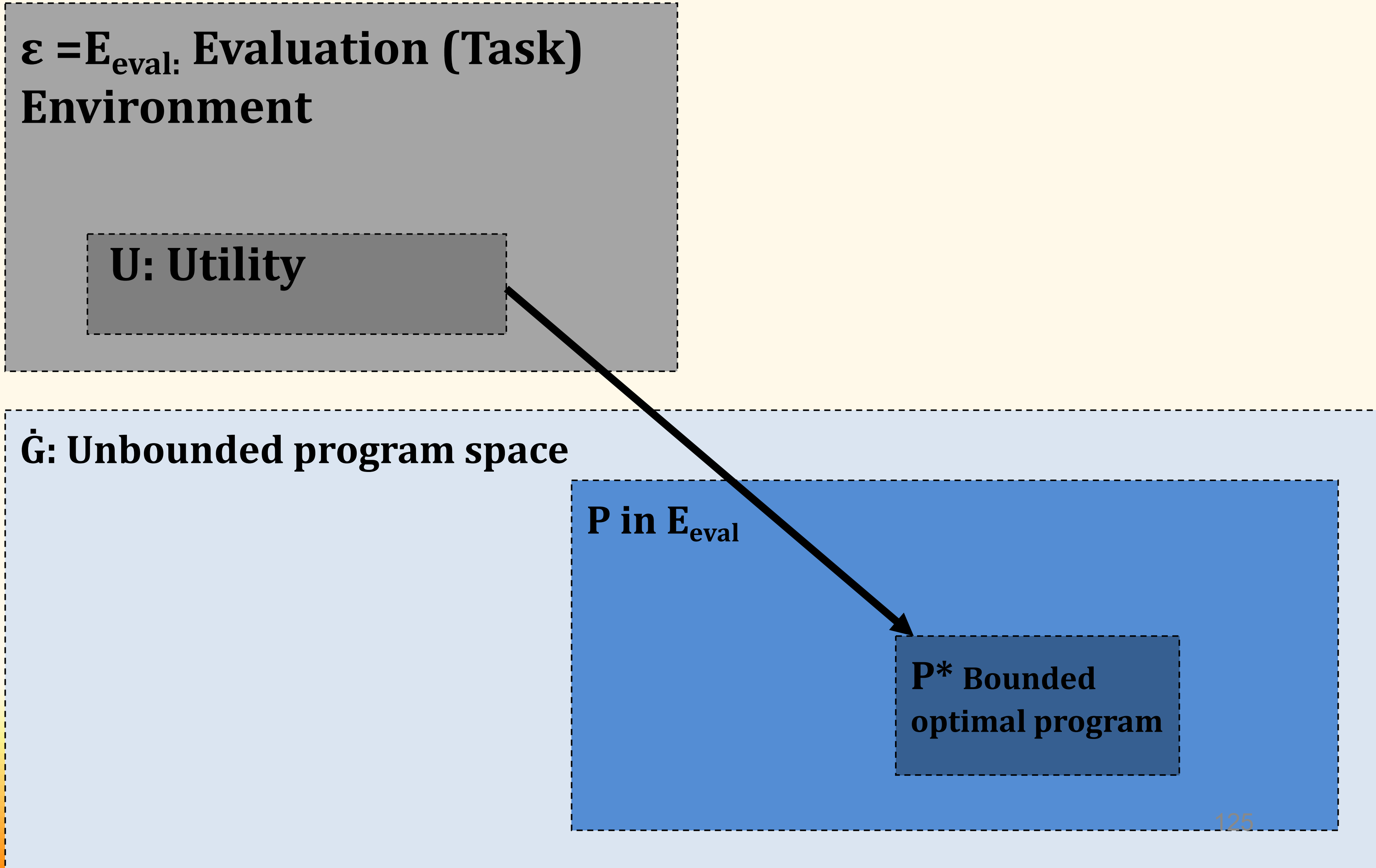
Misconceptions (p 288-289)

1. Cost of deriving optimum != cost of executing it
2. Optimal program vs optimal behavior
3. Data are not used for “model fitting”
   - Parameters of model can vary, might not be theoretical grounds for value
   - Fitting: select parameter that give “best fit” (without considering theoretical grounds)
   - Not done here



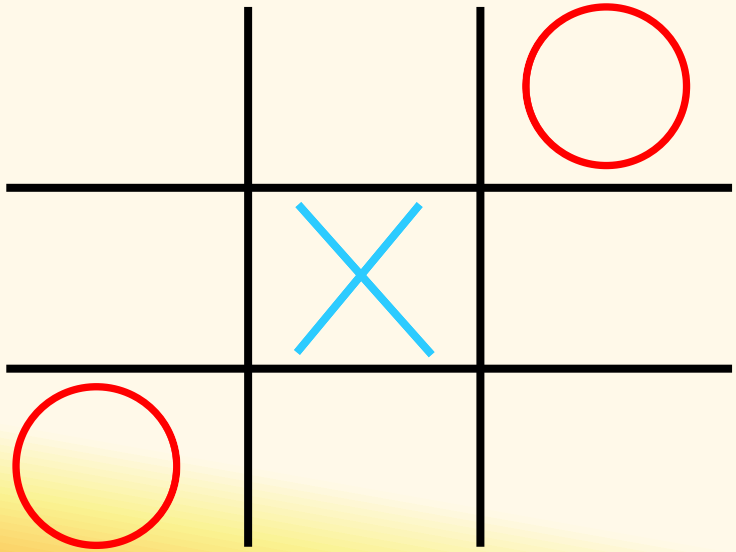
Slides explaining type I optimality

Type I: Optimality explanation



If humans show type I optimality

- Definitive proof: people are optimal ("could not be done better")
- No bounds required for explanation
  - Therefore: cannot be used as proof for bounds
  - Agent acts in local context



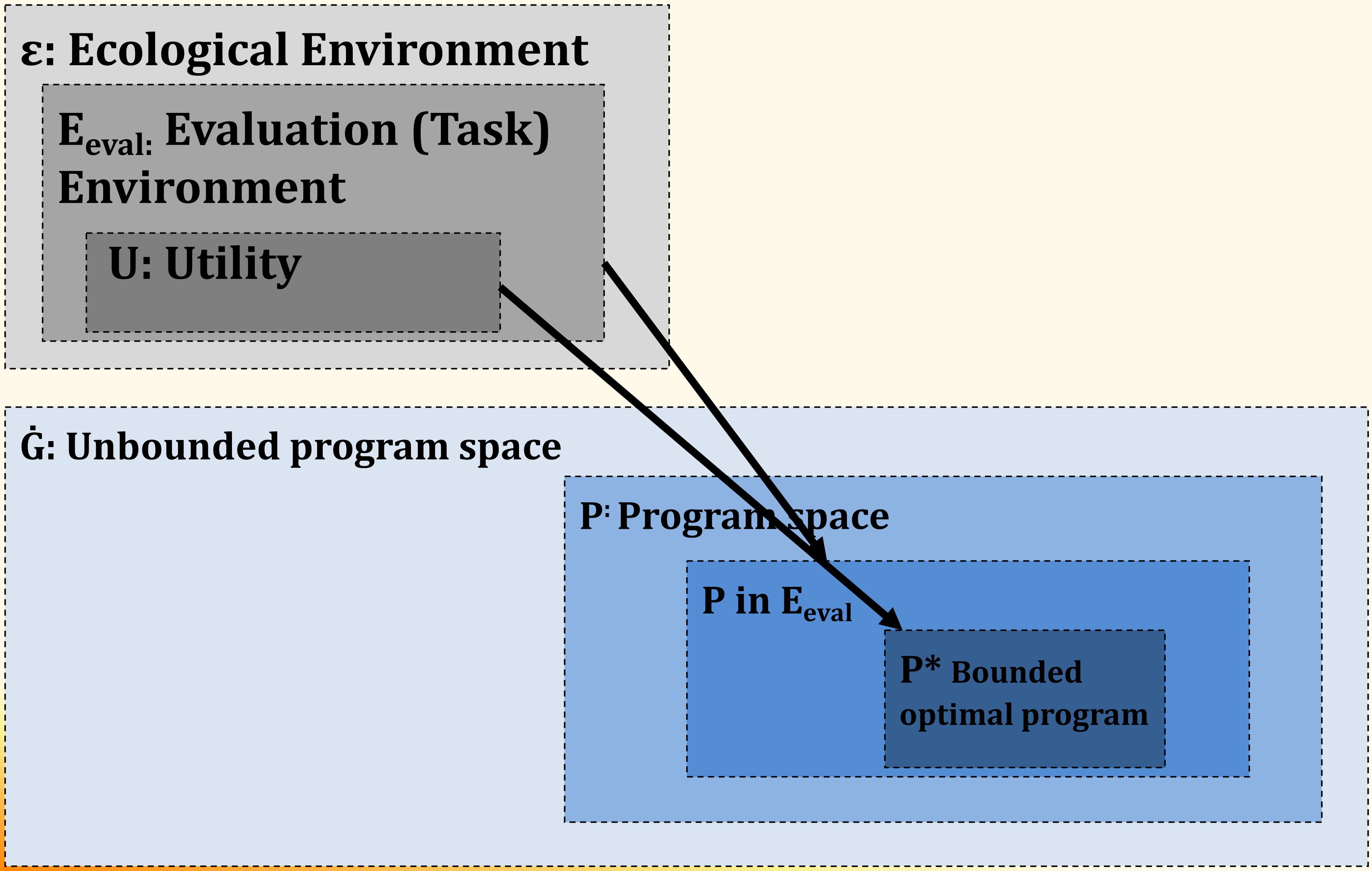
Who should use Type I theories?

- If the ‘best choice’ matters a lot:
  - Investors making a long-term investment
  - Politicians drawing up important policy
  - Scientists looking for exact solution to a problem (not looking for “how do humans do this”)

- Typically not used in psychological research:
  - Typically places people under challenging conditions
  - To assess floor/ceiling of behavior

Slides explaining type II optimality

Type II: Ecological optimality



Type II: Ecological optimality

- **Example discussed in paper:**
  - Considering Wason Selection Task from rational analysis perspective

- **Read example on your own**
  - see slides in appendix for extra material

When use Type II model

- When Type I does not suffice
- When experiment can not be considered "isolated incident"
  - Tasks that mimick real life strongly
  - Tasks that 'trick' people
    by changing statistics/expectations
    (i.e.: Kahneman approaches NOT correct)

Wason’s task

- **What is smallest set of cards to test :**

“If there’s a vowel on one side, then there’s an even number on the other side”

A	D	4	7

(each card has one letter, one digit)

Wason (1966) In: New Horizons in Psychology

Griggs & Cox's task

- Police officer

"Only 18+ can drink a beer"

Beer	Coke	22	16

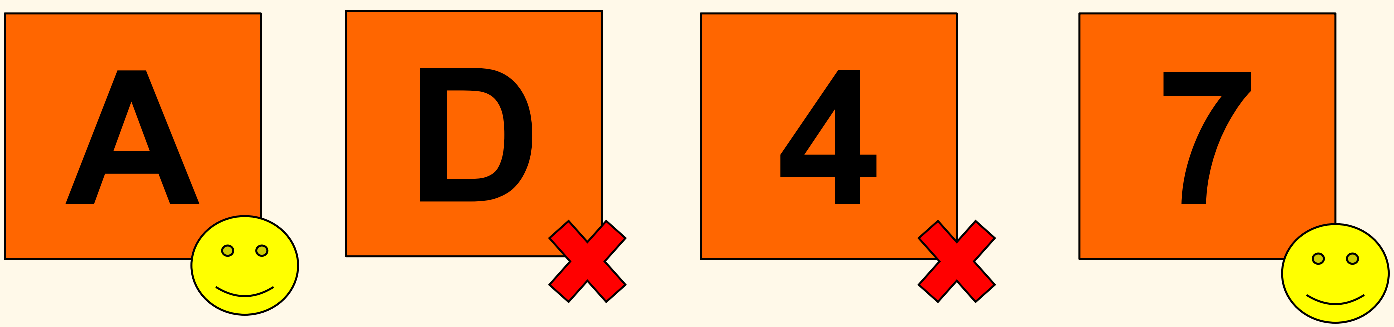
Each person has an age and is drinking something

Griggs & Cox (1982) British Journal of Psychology

Wason’s task

- **What is smallest set of cards to test :**

“If there’s a vowel on one side, then there’s an even number on the other side”

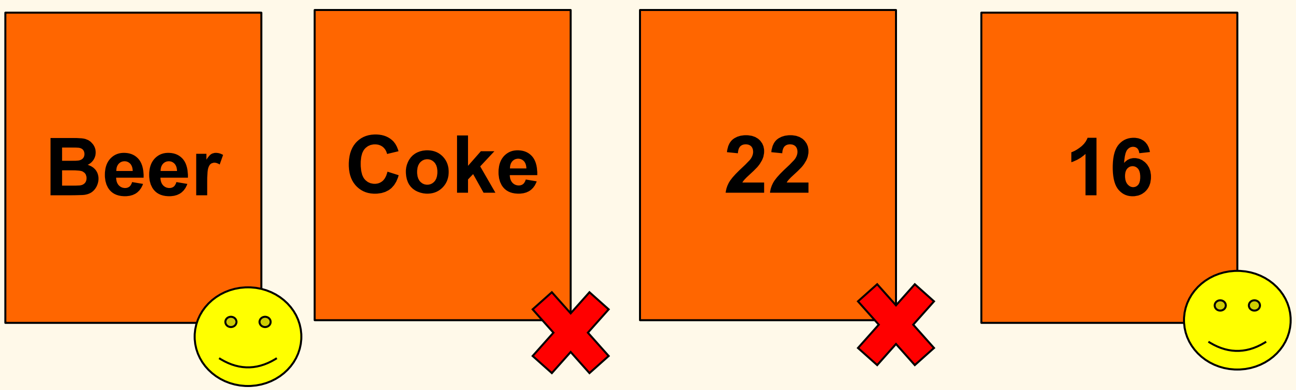


<10% participants correct (Johnson-Laird & Wason , 1977)

Griggs & Cox's task

- **Police officer**

"Only 18+ can drink a beer"



Why use a model for this task in the 1st place?

- **Behavior is not perfect**
  - **"illogical conclusions/choices"**

- **Model: try to understand *why* & *how***

Classical interpretation

- **"Mental Models" Philip Johnson-Laird**

If *p* then turn to see if q

If *!q* then ~~turn to~~ see if !p

A: instance of p

D: instance of !p

4: instance of q

7: instance of !q

A **D** **4** **7**

Which choices are (not) made →
which knowledge or logical rule is missing?

Why is a type I model not sufficient?

- People don’t choose the objective “optimal” solution

Alternative explanation: Rational analysis (Oaksford & Chater, 1994)

Rational analysis entails (Anderson, 1990):

1. Goal
2. Environment
3. Computational cost
4. Optimization

Note: specification of agent is implicit (computational cost)

Properties are rare

Bang!

q = rare

p = rare

If there is a vowel on 1 side (p), then there is an even number on the other side (q).
I see 7 (!q)
Should I check for p?

Rational analysis of Wason task

1. **Goal:**
   – Select data that is informative (not: provide falsification)
2. **Environment:**
   – Properties (p, q) are rare. Not seeing something (not q) is common
3. **Computational cost:**
   – Examining data takes time
4. **Optimization:**
   – Select minimum number of cards given time

Oaksford & Chater model

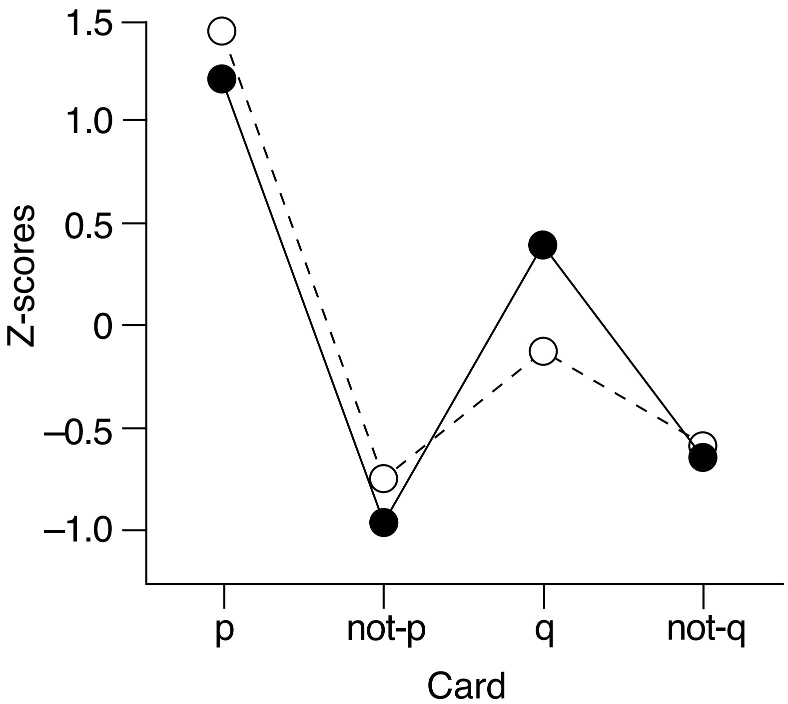
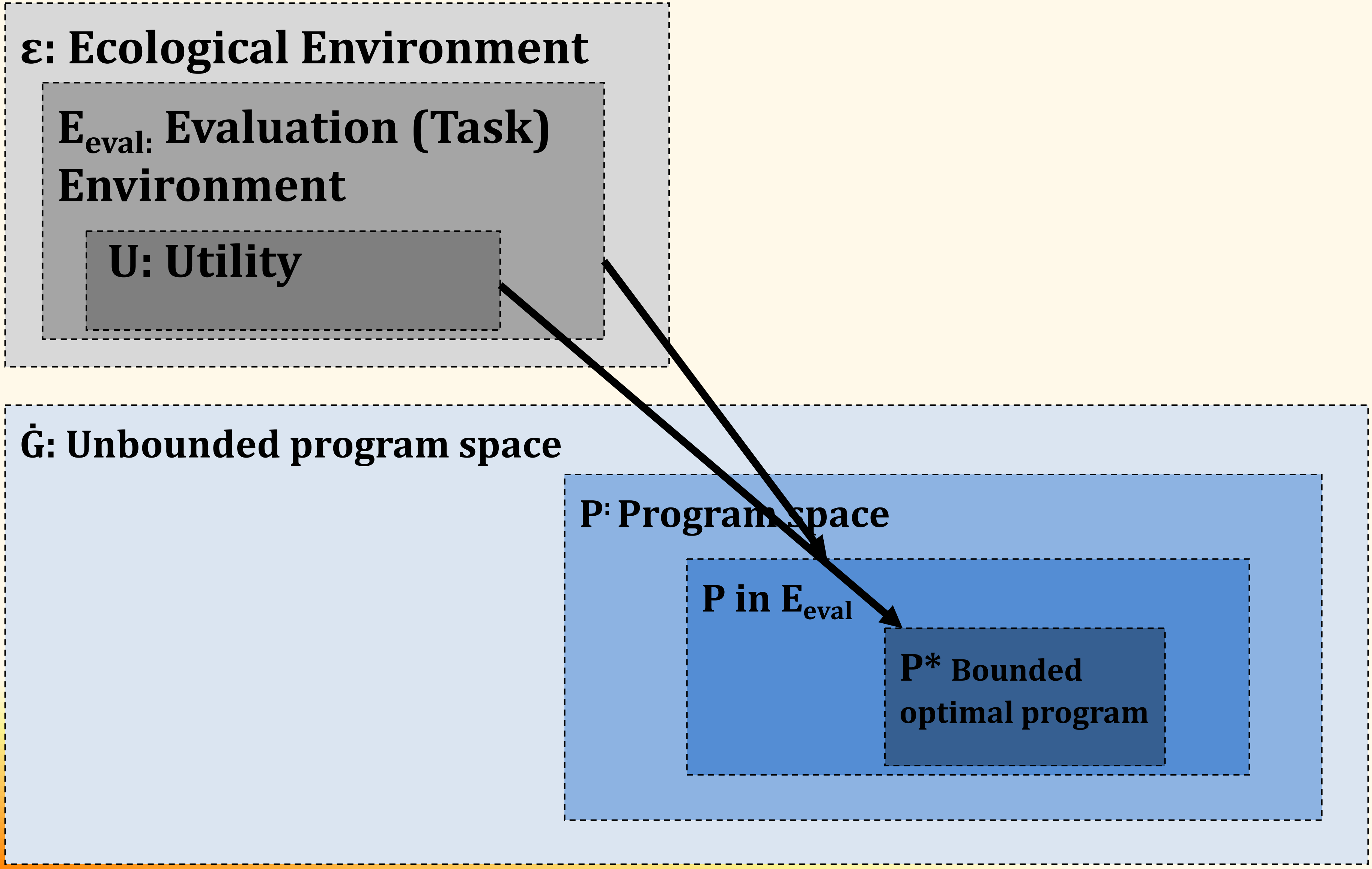


Fig. 2. Comparison of the expected information gain (dotted line) with the frequency of card selections in the standard abstract selection task (solid line). (For purposes of comparison both scales have been normalized.) These data are taken from the meta-analysis of the selection task reported by Oaksford and Chater[7].

Chater, N., & Oaksford, M. (1999).
Trends in Cognitive Sciences

Type II: Ecological optimality



Type II: Ecological optimality

1. Machine: Unbounded
    Possible action set:
    {none, p, q, p & q, p & !q, !p & q, !p & !q}

Type II: Ecological optimality

2. Environment: source of adaptation

	Environment	
	ε_{COMMON}	ε_{RARE} (per Oaksford & Chater)
Probability(p)	**0.6**	**0.1**
Probability(q)	**0.6**	**0.1**

Type II: Ecological optimality

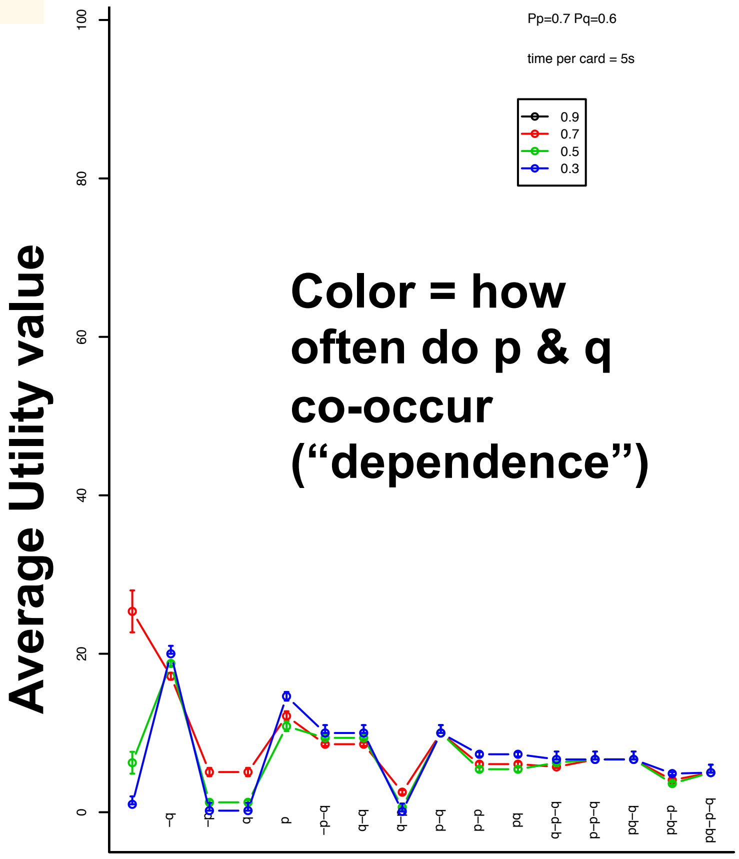
3. Utility function

- U_{info}: environment rewards correct falsification (as per Wason)
  100 points for selecting p & !q
  0 points otherwise

- U_{info}: environment rewards people for finding information (as per Oaksford & Chater)
  What is Prob(p) and Prob(q)?
  How dependent is occurence of q
  on occurence of p?

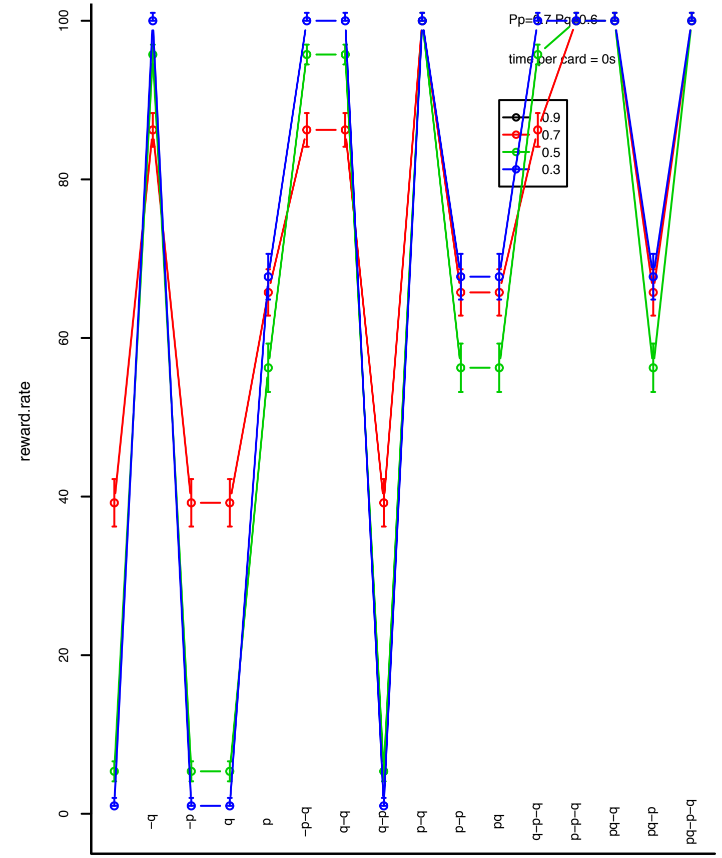
Values of utility$_{info}$

Each card takes 5 sec to inspect



Color = how often do p & q co-occur ("dependence")

Each card shown instantly ("easy access")



Which set of cards is turned around?

Result: Utility given

	U_{info}		U_{verify}	
				ε_{common}
p & q				76
p & !q				100

Wason's "ideal": check correct cards

Result: Utility given

	U_{info}		U_{verify}	
		ε_{common}		ε_{common}
p & q		46.34		76
p & !q		86.31		100

Wason's "ideal": check correct cards

Result: Utility given

	U_{info}		U_{verify}	
		ε_{common}	ε_{rare}	ε_{common}
p & q		46.34	99	76
p & !q		86.31	100	100

Wason's "ideal": check correct cards

Result: Utility given

	U_{info}		U_{verify}	
	ε_{rare}	ε_{common}	ε_{rare}	ε_{common}
p & q	36.43	46.34	99	76
p & !q	30.29	86.31	100	100

Wason's "ideal": check correct cards

Result: Utility given

	U_{info}		U_{verify}	
	ε_{rare}	ε_{common}	ε_{rare}	ε_{common}
p & q	36.43	46.34	99	76
p & !q	30.29	86.31	100	100

Wason's "ideal": check correct cards

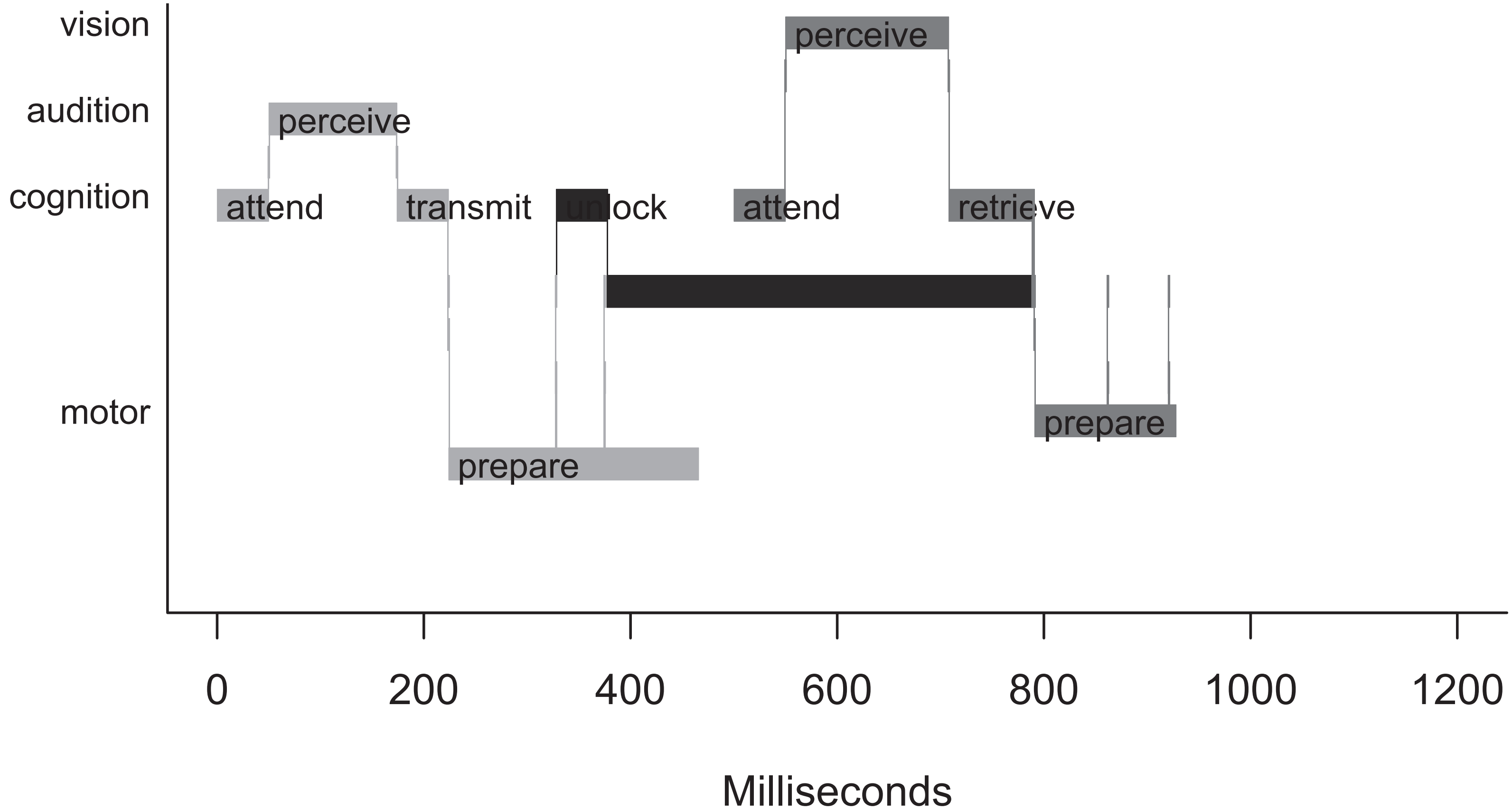
Yellow: conditions that are optimal. Note how there is some variety Wason's ideal solution is not always the "best"

Implication

- Experiences from our environment shape how we act (in the Wason selection task)

Extra slides type III rationality

Model implementation by Howes et al (2009)

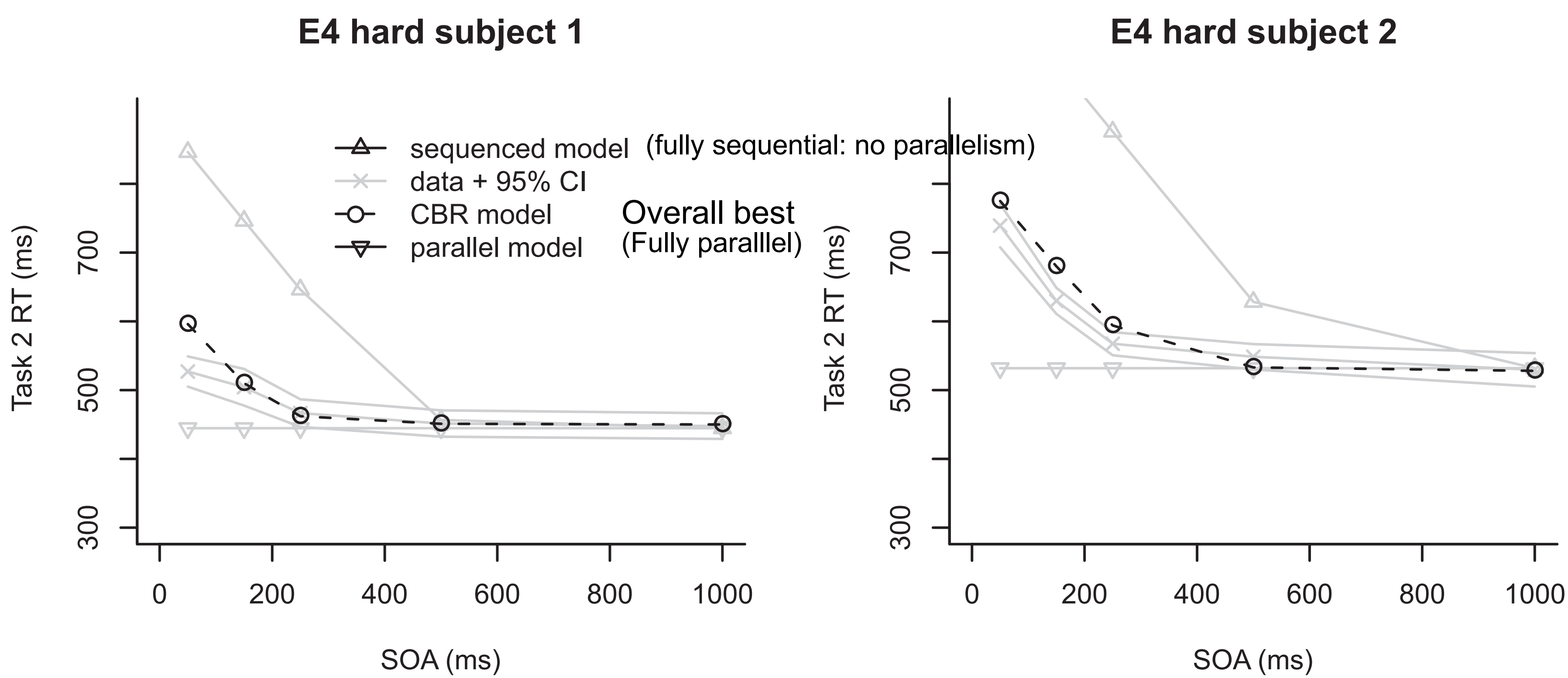


Strategic variation leads to 12 models – some serial, some parallel:

- **Does model wait for each of the "prepare" steps to start audio process yes/no (*2 options*)**
- **Is task 2 deferred? (a) yes: by unlock step, (b) yes: but not with unlock, (c) no (*3 options*)**
- **Is "attend" of task 2 deferred untill after response to task 1? (*2 options*)**

Type III: Bounded Optimality

- **Results**

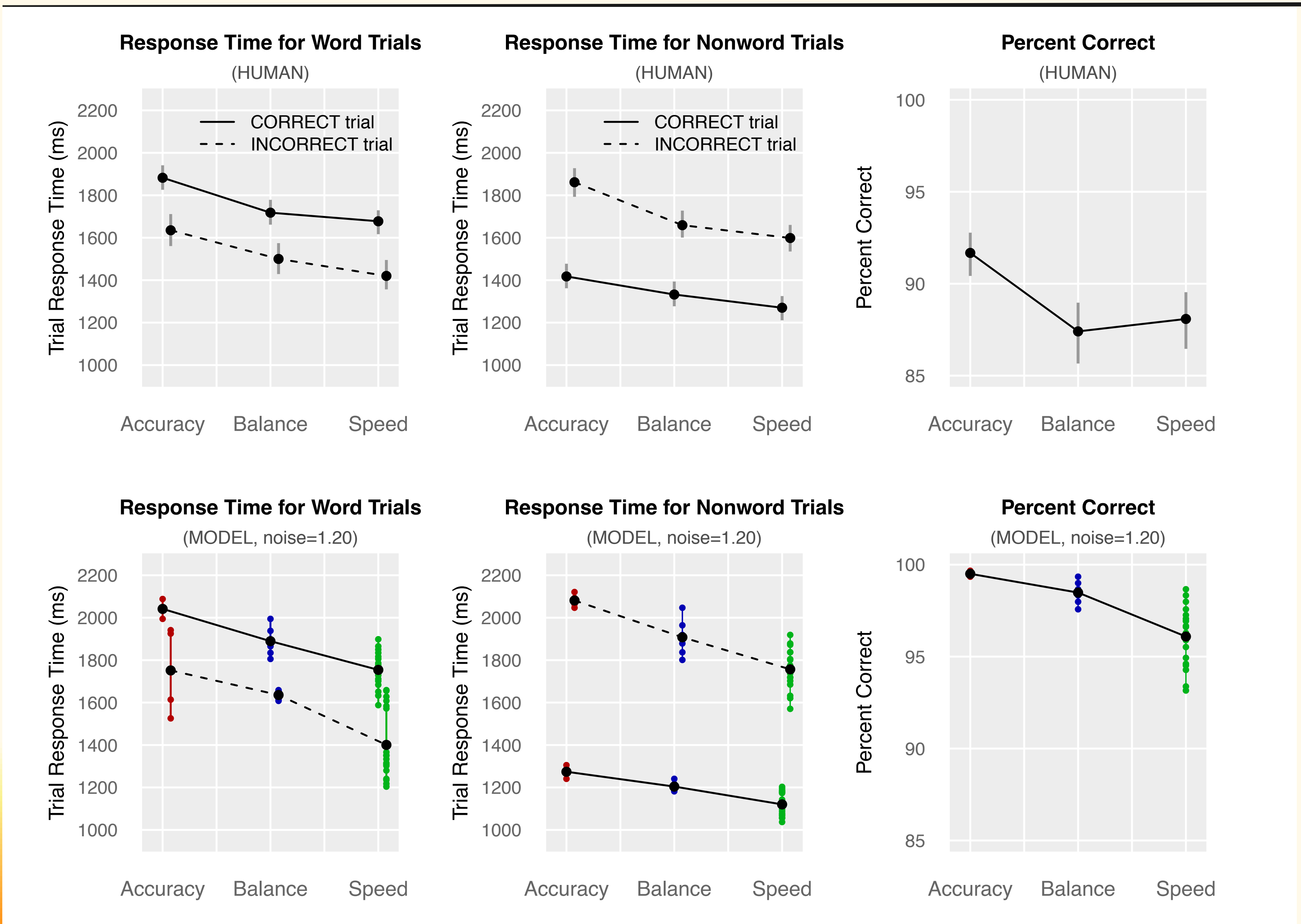


Howes et al. (2009)

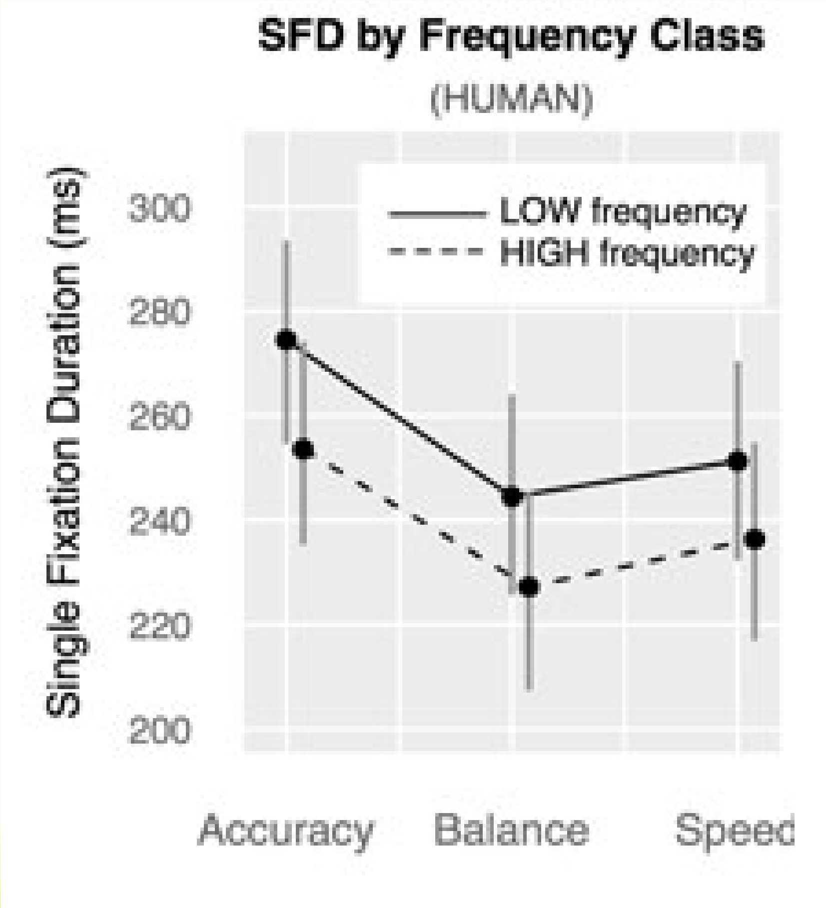
Model is made at the individual level:
Nicely captures individual differences

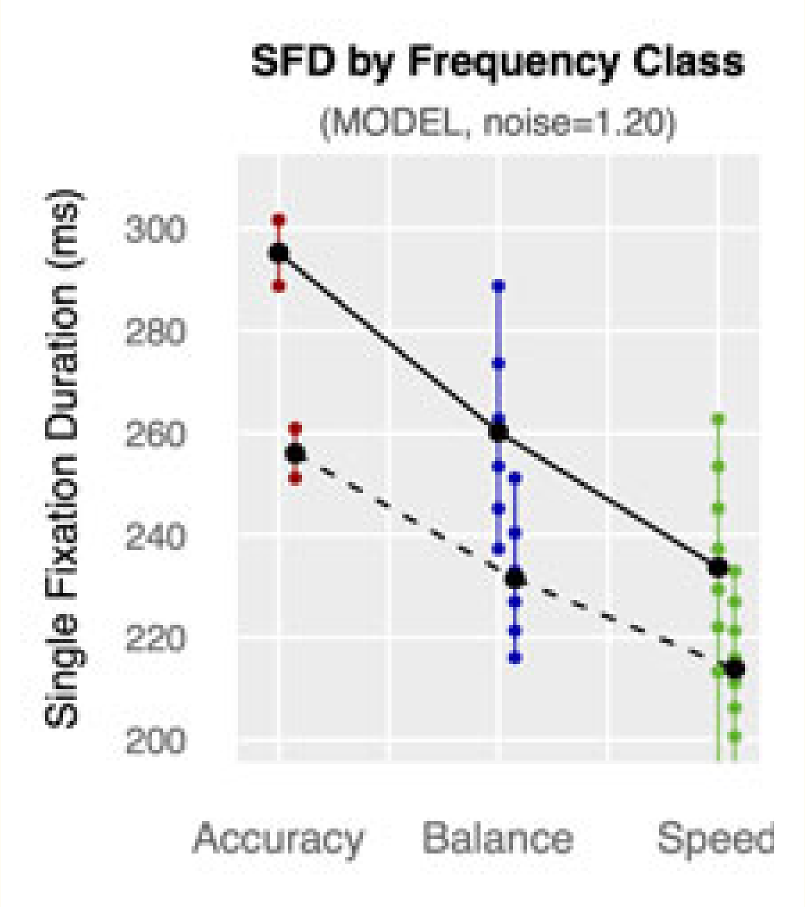
Extra slide type IV

General results model (from Lewis et al 2013)



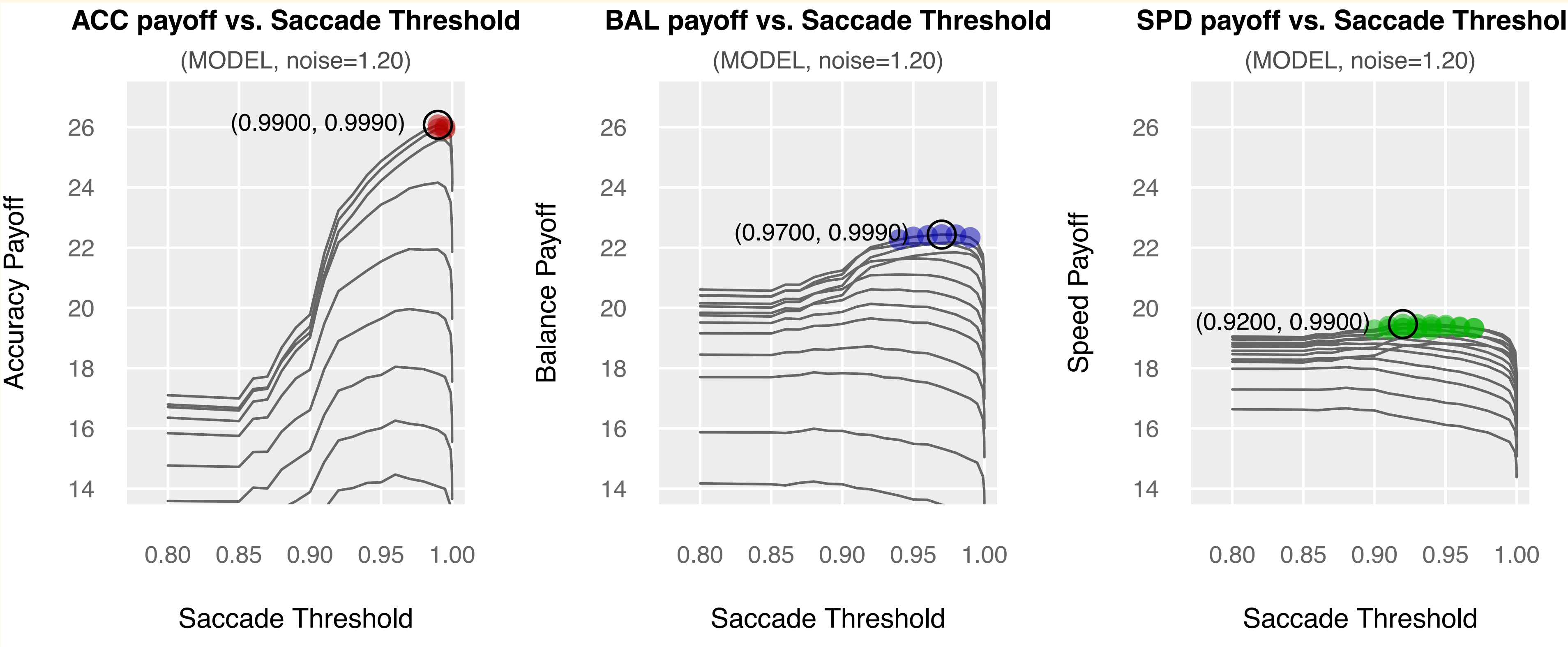
Bounded by ecological environment





Utility: How utility affects optimal threshold

Lewis et al (2013)



Utility function affects:

1. Shape of saccade-payoff function (shape of line)

2. What threshold is optimal

This influences fixation duration