Retrospective overview

Topics in Cognitive Modelling
Chris Lucas

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Goals of this course (I)

• Examine the Big Questions of cognitive science through the lens of computational modelling
  • Is cognition a collection of separate domain-specific abilities or an interacting whole?
  • How much of cognition is innate?
  • Are mental representations symbolic or distributed?
  • Are mental processes based on rules or associations?
  • To what extent are our cognitive abilities determined by our physical body and environment, i.e., grounded/embodied?
Goals of this course (I)

Is cognition a collection of separate domain-specific abilities or an interacting whole?
Goals of this course (I)

Pro-modularity:

- Plunkett: labels are special
- Also: UG + parameters account of language learning
- Few of the papers we’ve read argue for modularity
Goals of this course (I)

Pro-domain-generality:

• Grammar learning
  • Chunking and memory limitations (MOSAIC)
  • Hierarchical structure (Bannard et al.)

• Categorization and development
  • Categories emerge from statistics (French et al.)
  • No special status for labels (Gliozzi)
Goals of this course (I)

How much of cognition is innate?

We can frame this with the bias-variance trade-off, so the question becomes “What is the bias?”
Goals of this course (I)

Higher bias: less sensitive to experience.

Extreme cases:

- Imprinting
- “Fixed action patterns” like egg-rolling

Examples:

- Itti et al. (1998): Static features and computations
- Quillian’s hierarchical categories.
- Another example: “function learning”, where models assume strong linearity bias.

Tinbergen, 1951; Lorenz, 1937
Goals of this course (I)

**High-variance:** behavior/inferences highly sensitive to input. Accurate generalization requires more data.

**Examples:**
- French et al. (2004): categories due to distributional properties in environment, not prior knowledge.
- Most connectionist models.
Goals of this course (I)

Are mental representations symbolic or distributed?
Are mental processes based on rules or associations?

• **Connectionist models**: Distributed [mostly]! Associations!
• [Traditional] **algorithmic models**: Rules!
• **Probabilistic models**: Varies – sometimes all of the above.

Not necessarily a hard distinction between these rules and associations: one can be mapped onto another.
Goals of this course (I)

To what extent are our cognitive abilities grounded/embodied?

• We didn’t cover this much. Further reading:
  • Clark (1999): Review in *TiCS* with a computational focus
  • Wilson (2002): Popular & high-level review
Goals of this course (2)

• Learn about different modelling approaches and how they relate to these Big Questions
  • Connectionist
  • Bayesian/probabilistic
  • Algorithmic/mechanistic
  • Dynamical systems
  • Cognitive architectures
Goals of this course (2)

Connectionist approaches

• Distributed, [kind of] domain-general.
• Biases not always clear
• Appeal to neural plausibility
  • Some cases more convincing than others…
• New applied work (e.g., deep belief nets) and neurobiological results (imaging, multi-unit recording…)
Goals of this course (2)

Bayesian/probabilistic approaches

• Usually expressed as computational-level models (Marr, 1982)
  • Complementary to algorithmic and neural explanations
• Bias tends to be explicit.
  • Though prior, likelihood, decision rules interact – may not be identifiable
• Associated with assumptions of rationality/optimality
  • Recent trend: reconciling Bayesian models with time/memory limitations (e.g., Sanborn et. al, 2010); inference by sampling
Goals of this course (2)

Algorithmic/mechanistic approaches

• Specify the processes by which mental representations are updated or constructed.
• Prior to connectionism, not many alternatives
• Bayesian and connectionist approaches entail algorithms, but often don’t commit to particular choices.
• Typically use rules and symbols.
Goals of this course (2)

Dynamical systems approaches

• The mind as a system with state that evolves over time

• Example: Elman’s simple recurrent networks

• Other examples (not covered):
  • “Decision field” model of decision-making
  • Infant perseverative reaching

(Beer, 2000; Roe et al., 2001; Thelen et al., 2001)
Goals of this course (2)

Cognitive architecture approaches

- Frameworks rather than specific models.
- Most are mechanistic, but connectionist and probabilistic approaches exist.
- Like Bayesian or connectionist frameworks, architectures themselves aren’t usually falsifiable.
Goals of this course (2)

Cognitive architecture approaches

Examples:

- ACT-R
  - Used in Ragni et al. (Reasoning)
  - Production system: rules fire when conditions are satisfied

- CHREST
  - Used in Freudenthal et al. (Grammar)
  - Used to model many phenomena in language
Other themes & questions

The importance of representation

• Choices among representations (e.g., Lachter & Bever’s TRICS, 1988)

• Where do features/inputs come from?
  • Active work in this field (e.g., Austerweil & Griffiths, 2013)
Other themes & questions

Other assumptions in models

- Objectives and loss functions
  - Error/output representation in connectionist models
  - Decision rules in Bayesian models
- Architectures of connectionist models
  - Numbers of nodes? Connectivity? Learning rules? Input encoding?
- Priors and likelihood functions in Bayesian models
  - Informative priors as testable theoretical claims
  - Often justified, trained, or estimated independently
Other themes & questions

What makes a model plausible?

• Fewer ad-hoc aspects/degrees of freedom
• Neural plausibility
• Resource demands & scalability
• Generality

... largely subjective! Simplicity depends on representational language.
Other themes & questions

**What makes a model evaluation convincing?**

- **Scope**: many data points, different kinds of evidence
- **Specific predictions**
- **Test sensitivity to incidental assumptions**
- **Predictions** – not just post-hoc explanations
- **Explicit comparisons to alternative models**
Discussion
References


References


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