Retrospective overview

Topics in Cognitive Modelling
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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?

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Goals of this course (I)

Is cognition a collection of separate domain-specific abilities or an interacting whole?

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Goals of this course (I)

Pro-modularity:

- Itti, Koch & Niebur (1998): vision-specific features, no top-down control or outside information.
- Plunkett: labels are special
- Also: UG + parameters account of language learning

(Few of the papers we've read argue for strong modularity)

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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)

[and more, e.g., shape bias]

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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?"

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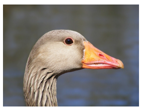
Goals of this course (I)

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

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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.
- Gopnik et al. (2004): "causal maps" depend on experience plus small set of assumptions.
  - Contrast: Michotte (1963).
- Many connectionist models.

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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.

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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

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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

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Goals of this course (2)

Connectionist approaches

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

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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

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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.

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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 (Grammar).
- Other examples (not covered):
  - "Decision field" model of decision-making
  - Infant perseverative reaching

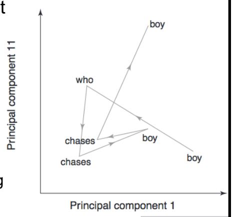

Figure: Beer, 2000

(Beer, 2000; Roe et al., 2001; Thelen et al., 2001) 15

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 as a whole, architectures like ACT-R aren't generally falsifiable.

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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
  - Current focus on neural correlates
- CHREST
  - Used in Freudenthal et al. (Grammar)
  - Used to model many phenomena in language

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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)

* "The representations it crucially supposes"

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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 better?

- Fewer ad-hoc aspects/degrees of freedom
- Predictive accuracy
- Generality
- Resource demands & scalability
- Compatibility with other evidence, e.g., neuroscience

Not always simple! Parsimony is subjective; real predictions often elusive.

Other themes & questions

What makes a model evaluation convincing?

- Scope: many data points, different kinds of evidence
- Specific **predictions** (not just post-hoc explanations)
- Examining assumptions
- Explicit comparisons to alternative models

Discussion

Thoughts?

References

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Image attribution

- Greylag Goose: http://en.wikipedia.org/wiki/File:GreylagGooseProfile.jpg

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