Combining individuating and context-general cues in lie detection

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Talk outline

- The Adaptive Lie Detector theory (ALIED: Street, 2015)
- The ACT-R cognitive architecture (Anderson, 2007)
- Grounding ALIED in the representations and mechanisms of ACT-R

The Adaptive Lie Detector (ALIED) theory

ALIED: Main assumptions

- Judgements informed by two types of information:
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- II and CGI weighted based on perceived diagnosticity
- Diagnosticity of II varies:
  - High (e.g., Pinocchio's nose grows) $\longrightarrow$ weight II more for high accuracy (Blair et al., 2010; Levine & McCornack, 2014)
  - Low (e.g., poker face) $\longrightarrow$ weight prior CGI ("most people tell the truth in this setting") more

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- Truth bias not a cognitive disposition but an adaptive judgement in absence of diagnostic individuating cues

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- Training. Ps learn to associate four behavioural cues with probability of lying/telling truth (between 20% and 80%)
  - Voice pitch
  - Facial expression
  - Number of silent periods in sentences
  - Number of self-references such as 'I' and 'me'

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- Ps given game-playing scenario where people could cheat and then be truthful or lie when later questioned
- Three components:
- Suggest truth/lie base-rates. Ps told game was:
  - Easy (i.e., less cheating/lying)
  - Hard (i.e., more cheating/lying)

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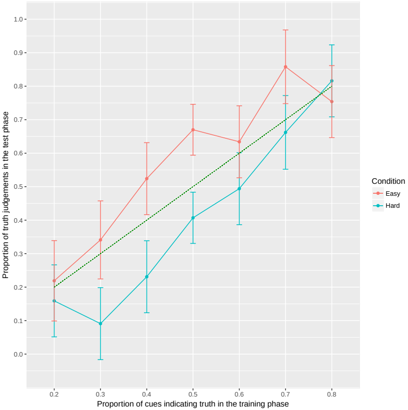
- Three components:

- Test. Ps presented with cues again and required to respond whether they indicated truth or lie

ALIED's predictions supported



Proportion of truth judgements for each cue diagnosticity in the test phase

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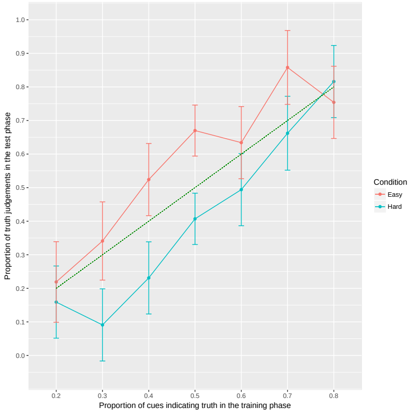

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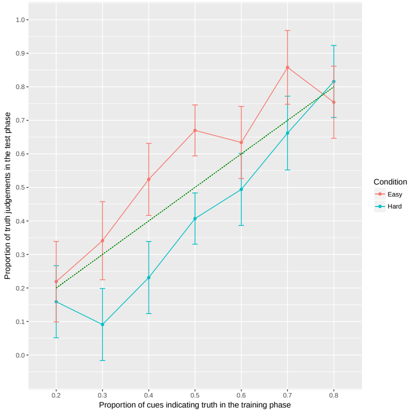

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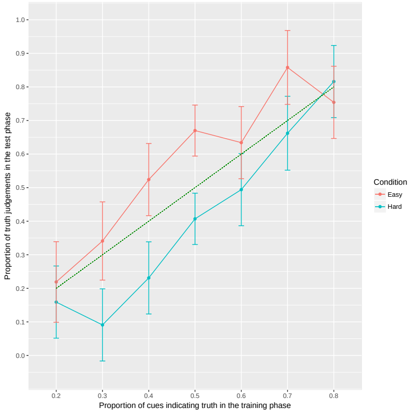

Proportion of truth judgements for each cue diagnosticity in the test phase

- Truth judgements increase as cues are more indicative of honesty
- Context information shifts judgements in predicted directions
- Effect of CGI increases as the individuating cue diagnosticity decreases

Developing a mechanistic account

- Demonstrates how judgements arise from interaction of:
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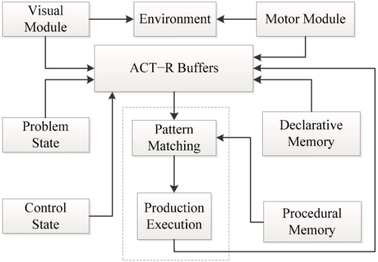
- Questions
  - How are the two types of information learned and cognitively represented?
  - What cognitive mechanisms can account for interaction?
- Cognitive process model
  - Developed within the ACT-R theory (Anderson, 2007)
  - Explains performance in terms of basic learning and retrieval mechanisms of declarative memory
  - Provides algorithmic level account consistent with ALIED

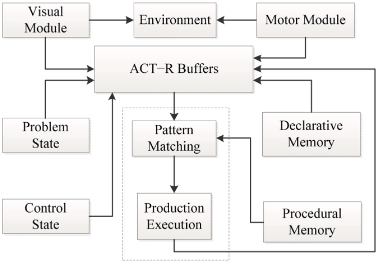
The ACT-R cognitive architecture

Key components of ACT-R



- *Core:* Two computational representations of memory
  - *Declarative* Network of "chunks" representing facts
  - *Procedural* "Production rules" representing actions
- Modules to simulate vision, audition, and motor action to interact with task environments

Key components of ACT-R



- *Rule-based sequential behaviour*
    - Every 50ms, snapshot of all buffer contents (goal state, visual object, retrieved knowledge etc.) is taken
    - Production rules matching buffer contents compete to "fire". Winner executes its actions (e.g., memory retrieval, motor actions, eye movements, update goal)

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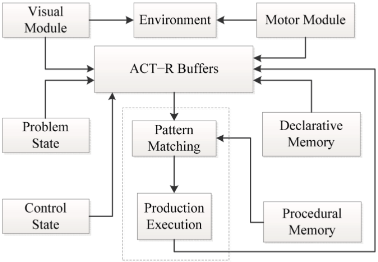


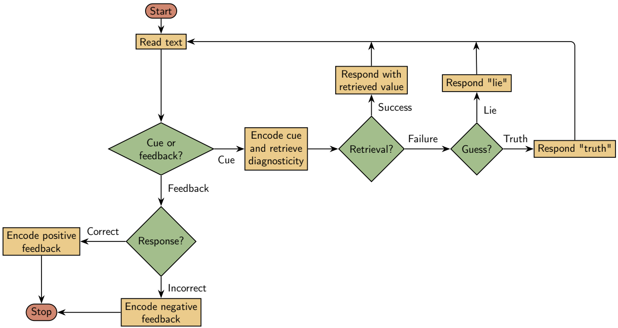
- *Equations that govern learning and forgetting*
  - Production rule "utility" learning. Productions involved in successful actions are reinforced
  - Chunk "activation" determines probability and speed of retrieval, forgetting etc.

Retrieving knowledge chunks from declarative memory

$$A_i = B_i + \sum_{j \in C} W_j S_{ji} + \sum_{l} PM_{li} + \epsilon$$

- Base-level activation reflects recency and frequency
  - Most recently and frequently used chunks have higher activation
- Partial matching component from retrieval cue
  - Retrievals don't require a perfect match to the cue
  - Chunks given a mismatch penalty based on similarity
- Noise component increases likelihood of erroneous response of chunk unrelated to retrieval cues

An ACT-R model of the experiment



- Model interacts with simulation of the experiment
- Code: github.com/djpeebles/act-r-lie-detection-model

An ACT-R model of the experiment

Before training

- 4 behavioural cues, differently diagnostic of truth/lie
- 8 chunks in declarative memory
- 2 per cue – one associated with “lie”, the other “truth”

Chunk	Activation
(voice-pitch truth)	0.0
(voice-pitch lie)	0.0
(facial-expression truth)	0.0
(facial-expression lie)	0.0
(silent-periods truth)	0.0
(silent-periods lie)	0.0
(self-references truth)	0.0
(self-references lie)	0.0

An ACT-R model of the experiment

During training

- Learn to associate cues with "true" and "lie" responses
- Use cue to retrieve associated chunks and make response
- Adjust chunk activations based on feedback

Chunk	Activation
(voice-pitch truth)	0.2
(voice-pitch lie)	0.0
(facial-expression truth)	0.1
(facial-expression lie)	0.3
(silent-periods truth)	0.4
(silent-periods lie)	0.0
(self-references truth)	0.1
(self-references lie)	0.0

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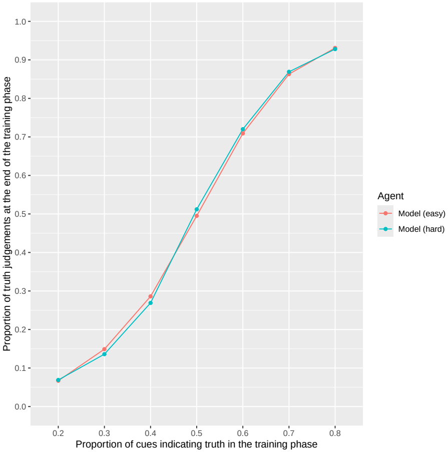
After training

- Chunk activations reflect learned associations between cues and responses
- Cue diagnosticity
  - High - large difference between true/lie chunks
  - Low - small difference between true/lie chunks

Chunk	Activation
(voice-pitch truth)	0.8
(voice-pitch lie)	0.2
(facial-expression truth)	0.3
(facial-expression lie)	0.7
(silent-periods truth)	0.4
(silent-periods lie)	0.6
(self-references truth)	0.5
(self-references lie)	0.5

ACT-R performance after the training phase



Proportion of truth judgements for each cue diagnosticity after the training phase

- Model over- and under-estimates truthful statement proportions as cue diagnosticity increases
- Due to non-linearities in ACT-R's equations, differences in activation between competing chunks

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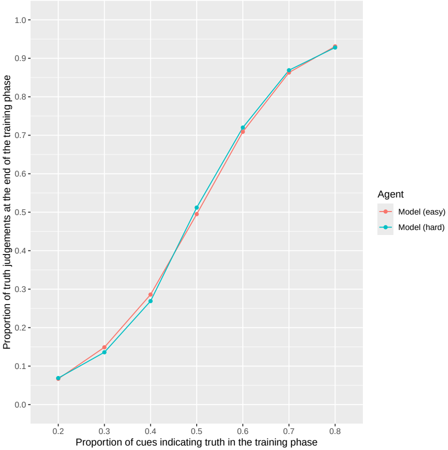

Proportion of truth judgements for each cue diagnosticity after the training phase

- Consistent with human probability learning with feed-back.
- People maximise responses rather than probability match (e.g., Barron & Erev, 2003; Shanks et al., 2002)

Providing the context information

- Between training and test, model provided condition information, “easy” or “hard”

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Providing the context information

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- Model retrieves from memory associated context-general response bias (“truth” or “lie” respectively)
- Response bias becomes an additional cue for retrievals in test phase

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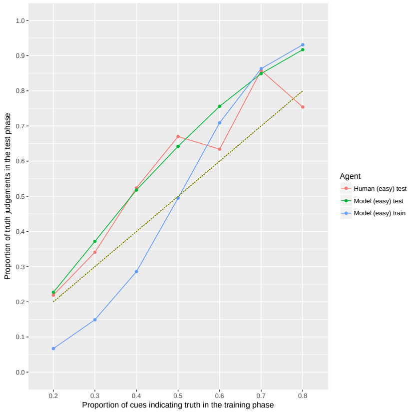
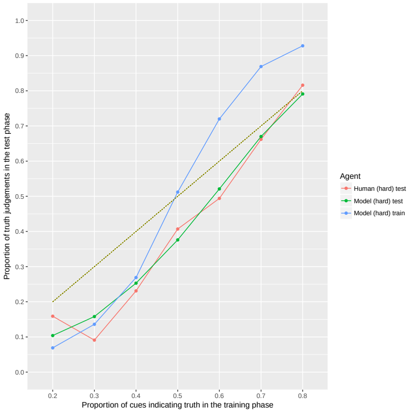
Comparing human and model performance



"Easy" condition. $R^2 = 0.92, RMSD = 0.08$



"Hard" condition. $R^2 = 0.98, RMSD = 0.04$

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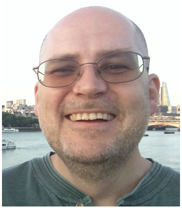
  - CGI has greater effect as diagnosticity of individuating cue reduces
  - CGI has weaker effect with strongly diagnostic cues
- Model supports compensatory strategy of integrating multiple cues rather than using only one (Gigerenzer & Todd, 1999; Newell & Shanks, 2003)

Acknowledgements



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