Can We Predict What *You* Will Conclude?

UNIVERSITY OF TECHNOLOGY
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Professorship of Predictive Analytics

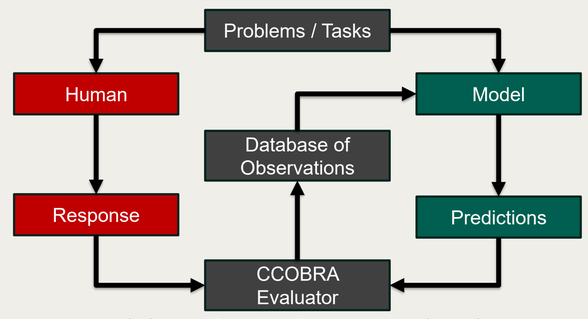
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Most cognitive models describe an "average reasoner". We test models by predicting *each individual's next response – before it is given* – across reasoning and decision domains.

① One Framework: Predict Every Response Before It Is Given

- **CCOBRA** presents tasks to a model one by one – the model predicts *this person's* response
- The true response is then revealed, so the model can **adapt to the individual**
- **Fair comparison:** leave-one-out cross-validation per task and participant
- Cognitive, statistical and data-driven models (recommender systems, neural networks) as **upper bounds**[1]
- Every model has to beat **strong baselines** (random, most frequent answer)
- Collecting comprehensive and datasets for benchmarking and evaluation of models[2]



github.com/CognitiveComputationLab/ccobra

② Domains: From Logic to Everyday Life

Syllogistic Reasoning

"All cooks are golfers. Some golfers are monks. What follows?"

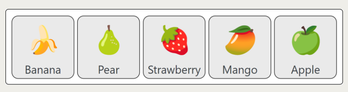
Traditionally 64 tasks · learned process models beat classic theories[3] · Variations of the task[4,5]

Conditional Reasoning

"If Joe cuts his finger, it bleeds. His finger bleeds. What follows?"

MP, MT, AC, DA · answers here predict syllogistic answers[2]

Spatial Reasoning



Five theories tested on individuals: **≈ 80 %** accuracy[6]

Selection Task (Wason)

"Which cards must you turn over to test the rule?"

Unified theory of selection tasks[7] · *individual prediction next*

Optimal Stopping

"Day 4: the flight costs 172 €. Buy now or wait?"

~400 people · **84.9 %** of buy/wait decisions predicted[8]

Misinformation

"Is this headline true? Accept or reject?"

3,794 people · hybrid models **79–84 %** accuracy[9,10]

Complex Problem Solving

"Run a simulated shirt factory for 12 months."

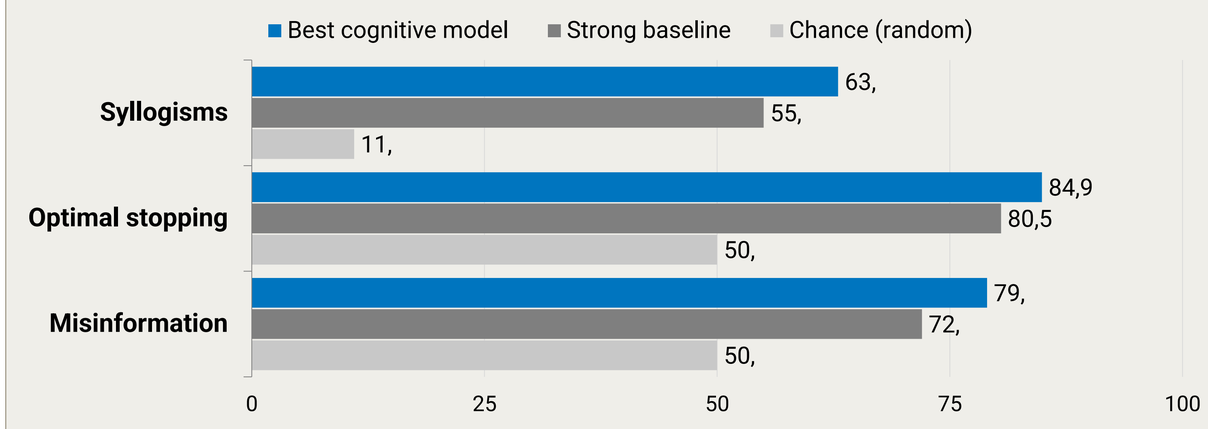
The first month predicts final success (R^2 = .25)[11]

Human–Machine Interaction

Automated driving, sense of agency

Predicting individual discomfort[12] and agency from facial expressions[13]

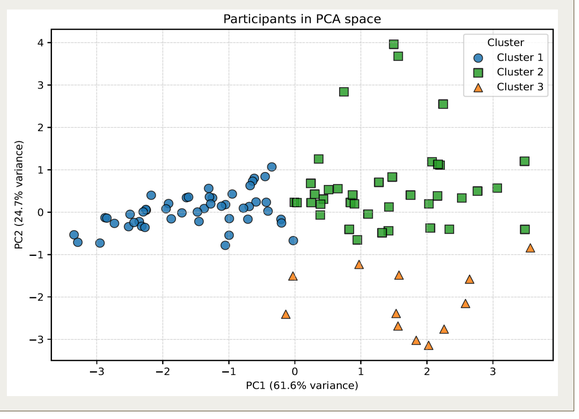
③ Models Beat Strong Baselines



Predictive accuracy (%) for individual responses. Strong baselines: correct categorisation (misinformation[9]), "never buy" (optimal stopping[8]), most frequent pattern (syllogisms[3]).

④ Is There an Average Reasoner? No.

- Same tasks, re-tested: three stable response profiles[14]
- **Cluster 1:** low variability, sceptical, 68 % correct
- **Cluster 2:** high variability, 38 % correct
- **Cluster 3:** moderate variability, 30 % correct
- Data-driven and statistically analysis of behavioral patterns identify different clusters of strategies[15]
- → **multiple processes and strategies**



⑤ Neural Correlates

- Meta-analyses of fMRI studies: relational, conditional and syllogistic reasoning recruit distinct fronto-parietal networks[16,17]
- Brain stimulation (tDCS) over the right parietal cortex **improves** spatial reasoning[18]

⑥ Explainable Cognitive Models

- Implementation and improvement of established theoretical explanations for cognitive effects as predictive models[3, 6, 19]
- Development of predictive cognitive process models[20]
- Testing and deriving hypotheses and explanations from models[21,22]

⑦ LLMs in Online Studies

- ChatGPT and Claude agents complete online reasoning studies on their own – often **more accurately** than humans[23, 24]
- LLMs are not able to convincingly simulate human behavior and errors
- Their uniform response times give them away → record interaction traces

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