Predictive Modeling of Individual Human Cognition: Upper Bounds and a New Perspective on Performance

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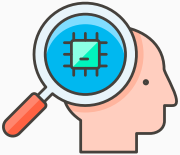
Human Reasoning

- Reasoning is one of the core abilities of humans
- Allows us to leverage available information to decide on the best course of action
- Research shows that human reasoning differs greatly from formal (first-order) logics

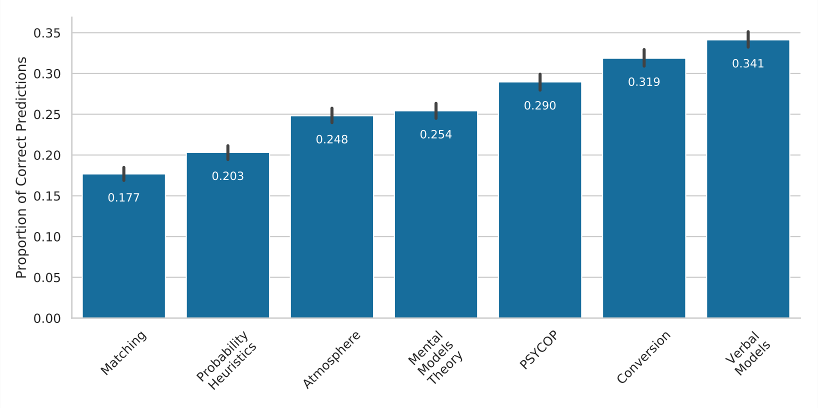


Theories for Human Reasoning

- Traditional goals of modeling:
  1. Satisfy psychological effects/phenomena
  2. Probabilistically describe population data
- Problem:
  Predictions derived from cognitive theories perform poorly in prediction scenarios[1]

[1] Riesterer et al., 2018

Predictive Performance for Syllogistic Models



Prediction data taken from Khemlani & Johnson-Laird (2012)

Research Question & Approach

Research Question

Is lacking performance due to noise in data or suboptimal theoretical assumptions?

Data-driven methods (neural networks) to empirically investigate upper bounds in predictive performance

- Automatically find and leverage structural patterns in the data
- Data which cannot be captured from the available features should be regarded as noise
- Here, neural networks are not considered cognitive models but tools for evaluation

Syllogistic Reasoning

- Categorical quantified assertions
- Four quantifiers:
  All, Some, Some ... not, No
- Two premises containing three terms
  researchers, logicians, professors
- Responses relate end terms (researchers, professors) via quantifier or NVC
- Total of 64 distinct problems with 9 possible conclusions each

Some researchers are logicians
Some logicians are professors

What, if anything, follows?

Research on Syllogistic Reasoning

- Rich history of modeling and analysis[2]
  - Prediction lists available for seven theories
  - Unclear which theory is to be preferred
- Recent evaluations have demonstrated shortcomings in predictive performance[3]

→ Establish prediction-based evaluation (preferably on trial-level) as core component of cognitive model evaluation

[2] Khemlani & Johnson-Laird, 2012
[3] Riesterer et al., 2018

Prediction-Based Modeling Task

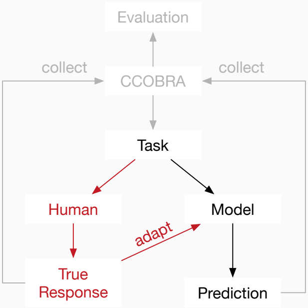
Goal of modeling:

Model should simulate the reasoning behavior of individuals.

- Predict specific conclusions instead of lists of possibilities
- Evaluation score based on proportion of correct predictions
- Verify models by performing crossvalidation

The CCOBRA Framework

- Cognitive Computation for Behavioral Reasoning Analysis (CCOBRA) framework[4]
- Procedure:
  1. Iterate over participants in the data
  2. Iterate over individual problems
  3. Query model for a specific prediction
  4. Provide model with true conclusion
- Learning/Fitting Phases:
  1. Pre-Training based on training data
  2. Adaption based on true conclusions



[4] https://github.com/CognitiveComputationLab/ccobra

Evaluation Setting

- Models:
  - Cognitive Models[5]
  - Neural Networks
  - Statistical Baseline Models
- Dataset: `Ragni2016` from CCOBRA
  - $N = 139$
  - Each participant was presented with all 64 tasks

[5] Khemlani & Johnson-Laird, 2012

Evaluation Models

Cognitive Models

- Atmosphere
- Conversion
- Matching
- Mental Models Theory (MMT)
- Probability Heuristics Model (PHM)
- PSYCOP
- Verbal Models

Neural Networks

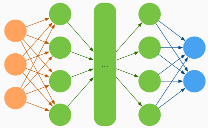
- Multilayer Perceptron (MLP)
- Autoencoder
- Recurrent Neural Network (RNN)

Statistical Baselines

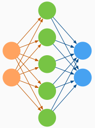
- Uniform guessing
- Most-Frequent Answer (MFA)

Network Models

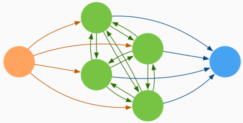
- Adaptive Multi-Layer Perceptron (MLP):
  - Problem-response mapping
  - Adapts by continuing training



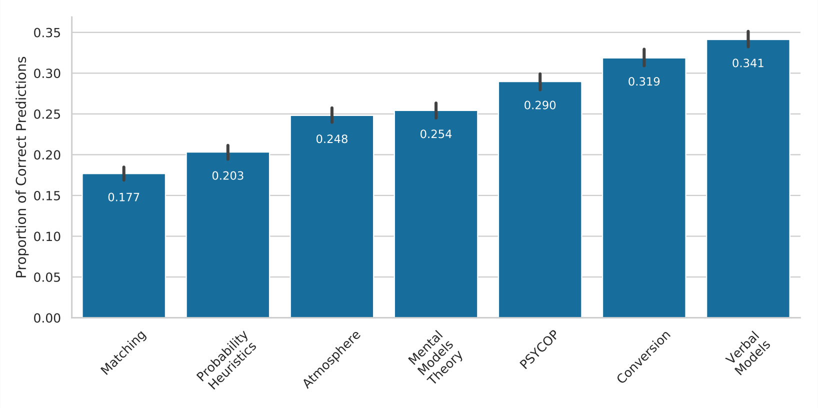
- Denoising Autoencoder:
  - Treats conclusions as *reasoner profile*
  - Imputes missing input information
  - Adapts by filling up reasoner profile



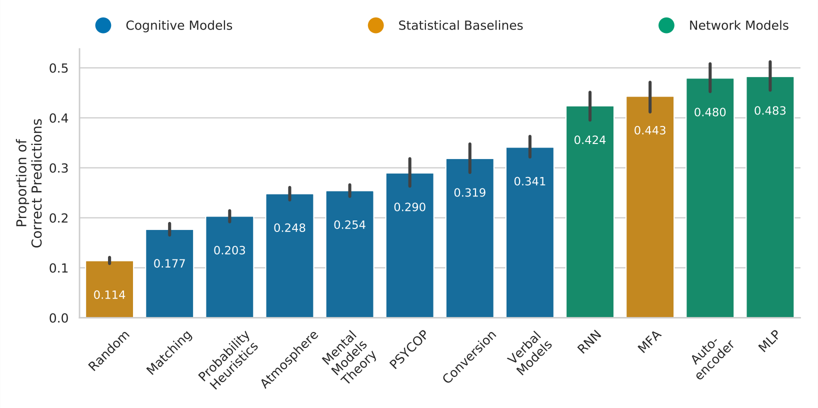
- Recurrent Neural Network (RNN):
  - Trained on experimental task sequence
  - Leverages sequential effects
  - Not adapted to the individual



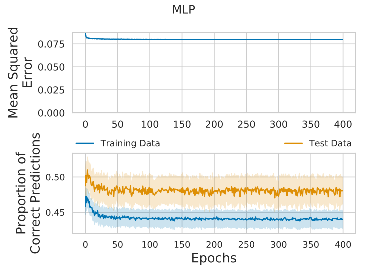
Predictive Accuracy

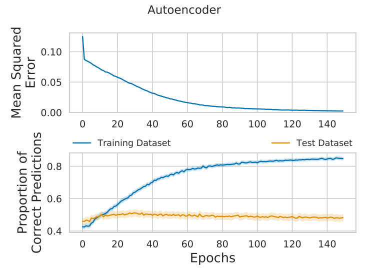


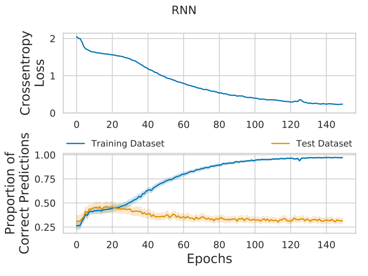
Predictive Accuracy



Network Training Performance







Conclusions

- Cognitive models perform poorly on the accuracy-based prediction task
  - Value of explanations rests on predictive accuracy
  - Shows limited applicability of the current theories
- Lacking performance of the models not entirely due to noise:
  - Neural networks able to better use structure in the data
  - Syllogistic domains still offers potential for future improvement
  - Individual differences exists and can be leveraged (adaptive networks)

Thank You!

References

Khemlani, S., & Johnson-Laird, P. N. (2012). Theories of the syllogism: A meta-analysis. *Psychological bulletin*, 138(3), 427.

Riesterer, N., Brand, D., & Ragni, M. (2018). The Predictive Power of Heuristic Portfolios in Human Syllogistic Reasoning. In: Trollmann F., Turhan AY. (Eds.) *KI 2018: Advances in Artificial Intelligence. KI 2018. Lecture Notes in Computer Science*, vol 11117. Springer, Cham (pp. 415-421).

Code on GitHub:

https://github.com/nriesterer/iccm-neural-bound