



THE UNIVERSITY of EDINBURGH
informatics

ilcc

Institute for Language,
Cognition and Computation



JRC for Logic

Tsinghua University – University of Amsterdam Joint Research Centre for Logic

MCMC

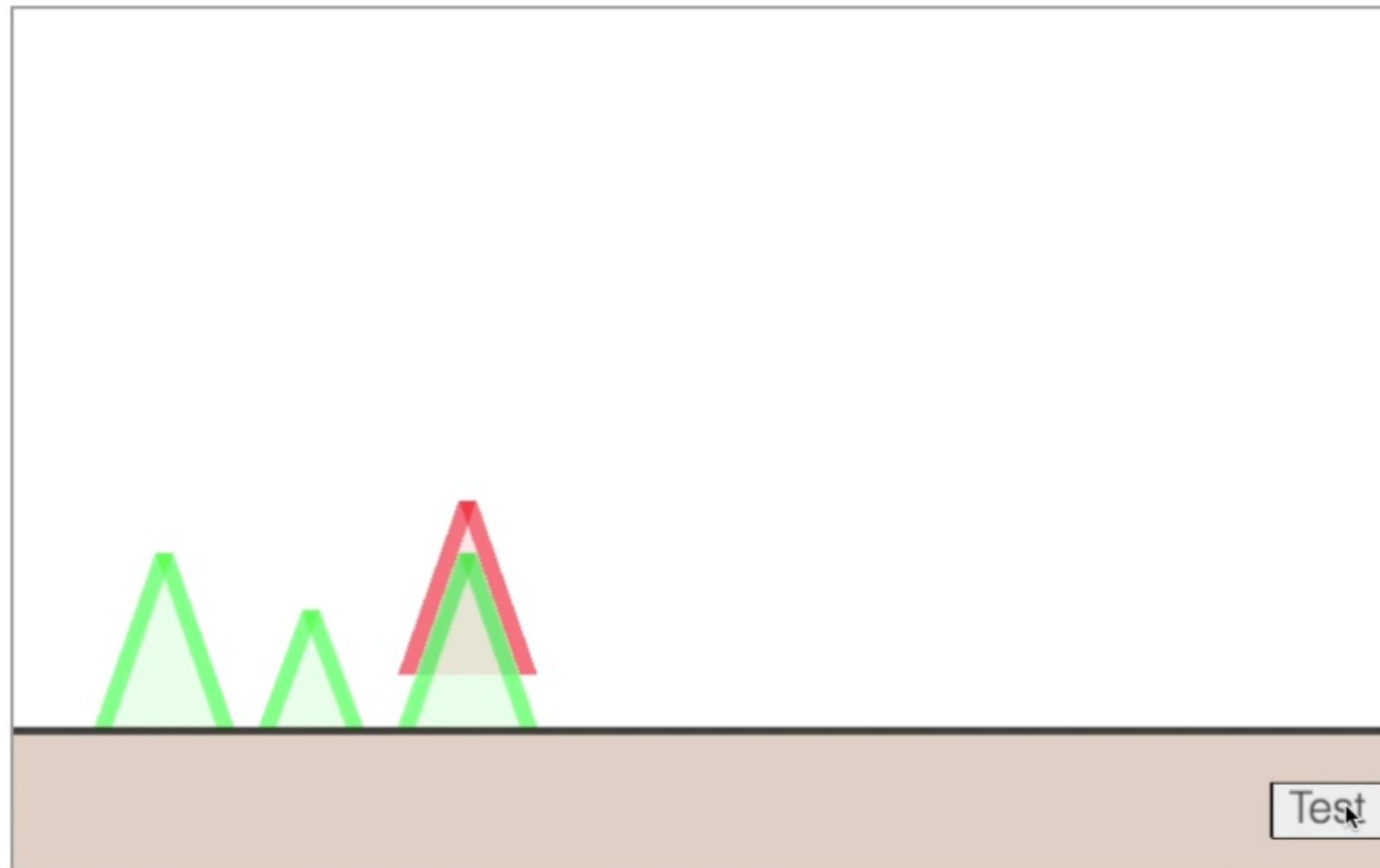
Bonan Zhao (b.zhao@ed.ac.uk)

Tsinghua Logic Summer School, July 2026



Experiment

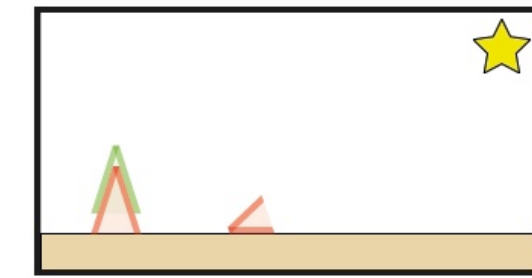
- 54 Children (8.9 ± 1.1) & 50 Adult mTurkers



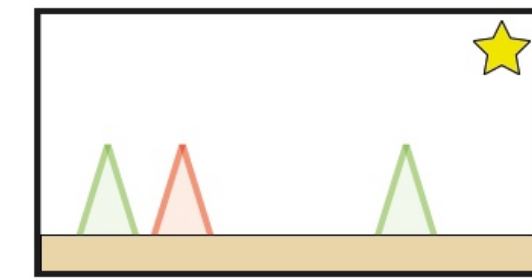
Different tasks:

Initial example

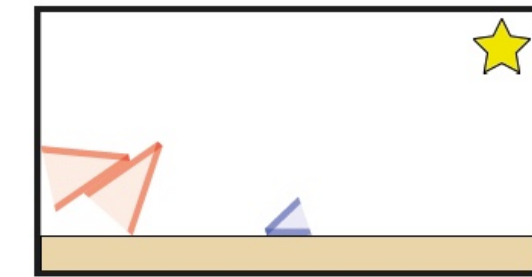
1. There is a red



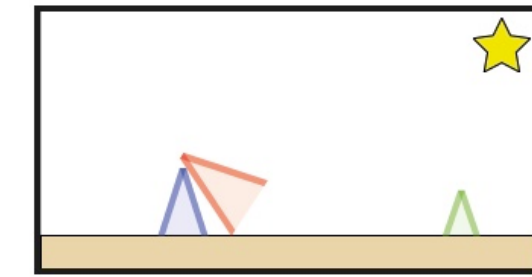
2. All same size



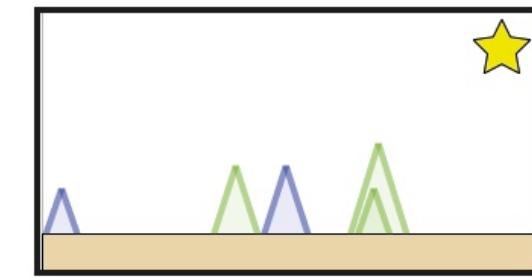
3. Nothing upright



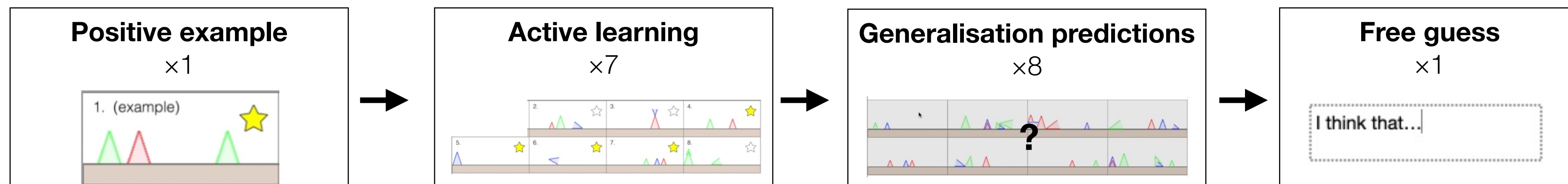
4. Exactly 1 blue



5. Something blue
& small



Procedure:



Model

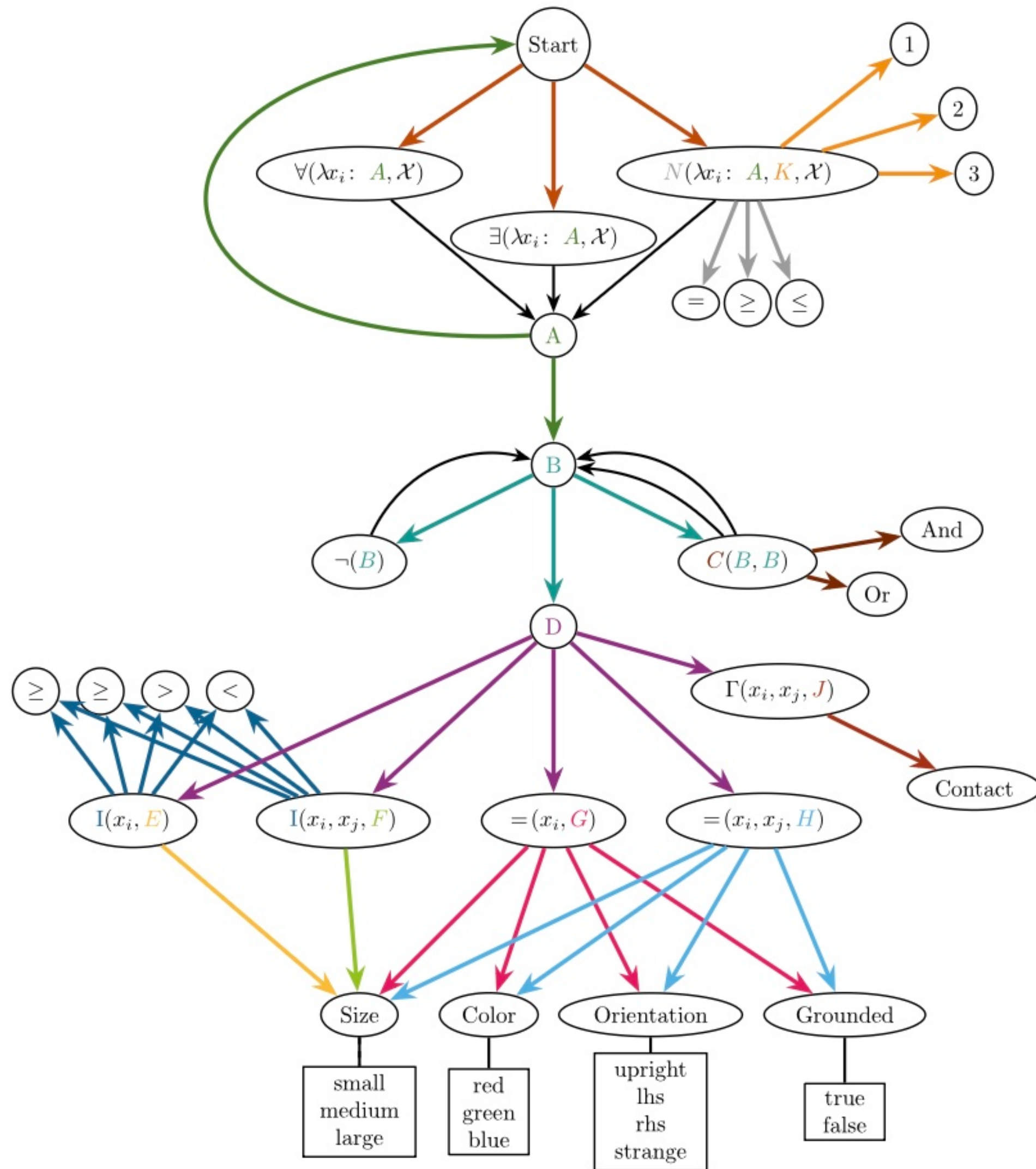
Concept Grammar.

There exists an object x_i such that...	$\exists(\lambda x_i :, \mathcal{X})$
For all x_i ...	$\forall(\lambda x_i :, \mathcal{X})$
There exist(s) {at least, at most, exactly} N objects x_i such that...	$N_{\{<, >, =\}}(\lambda x_i :, N, \mathcal{X})$
Feature f of x_i has value {larger, smaller, (or) equal} to v	$\{<, >, \leq, \geq, =\}(x_i, v, f)$
Feature f of x_i is {larger, smaller, (or) equal} to feature f of x_j	$\{<, >, \leq, \geq, =\}(x_i, x_j, f)$
Relation r between x_i and x_j holds	$\Gamma(x_i, x_j, r)$
Booleans {and, or, not}	$\{\wedge, \vee, \neq\}(x)$

Note that $\{<, >, \geq, \leq\}$ comparisons only apply to the feature size.

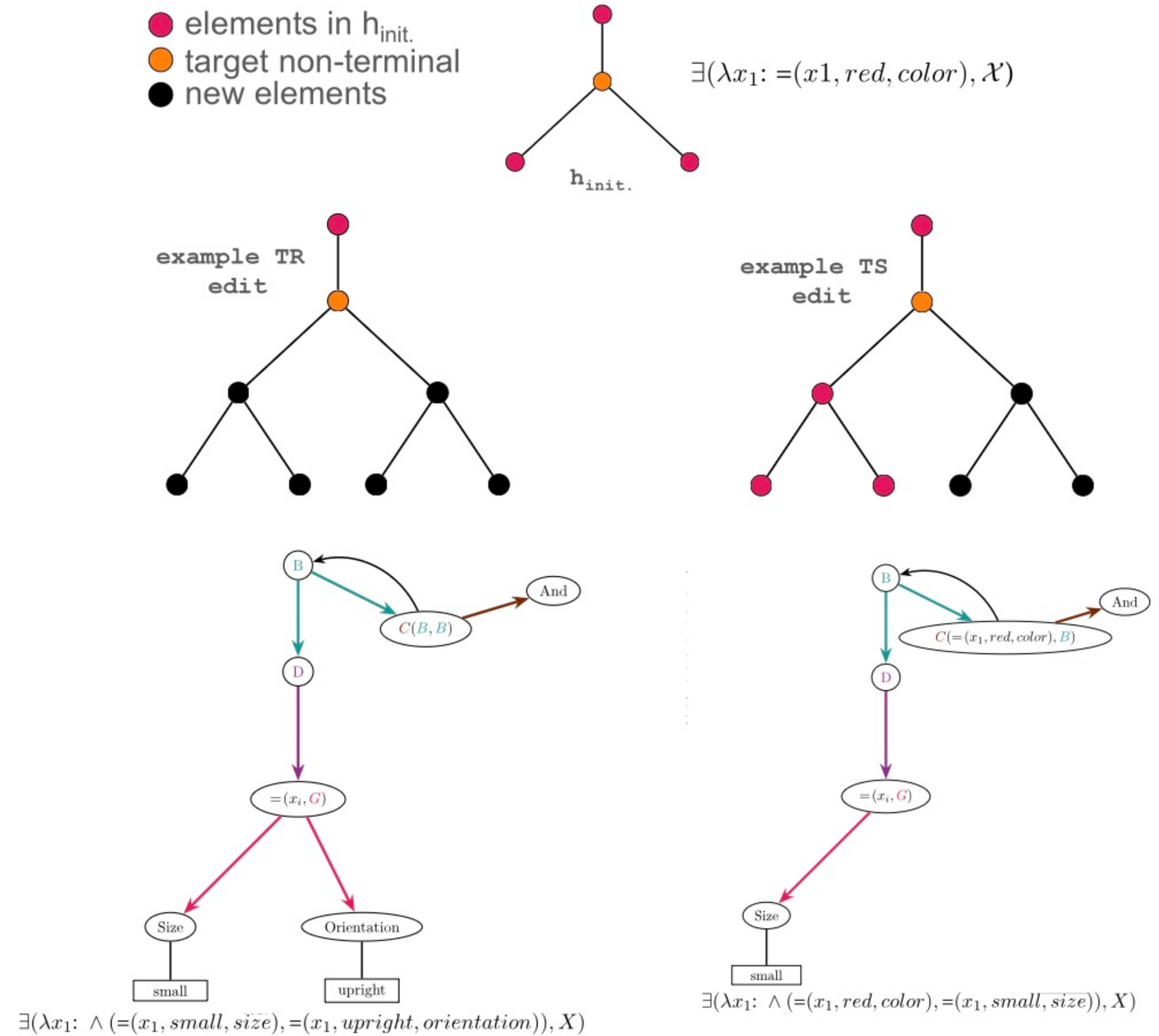
a)

Grammar

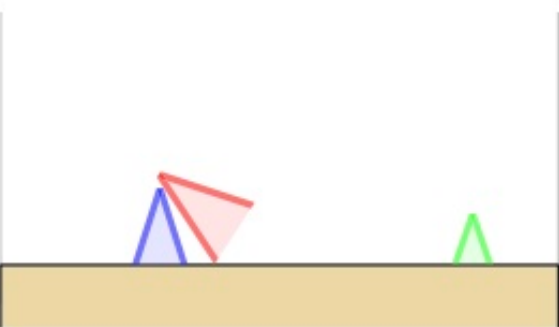
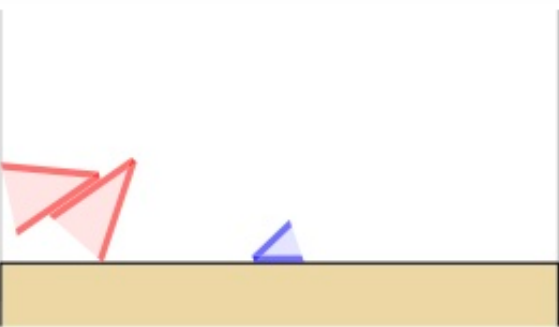
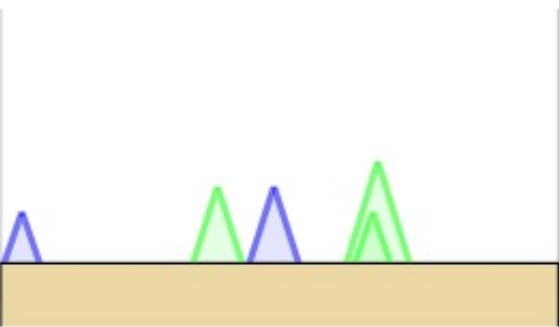
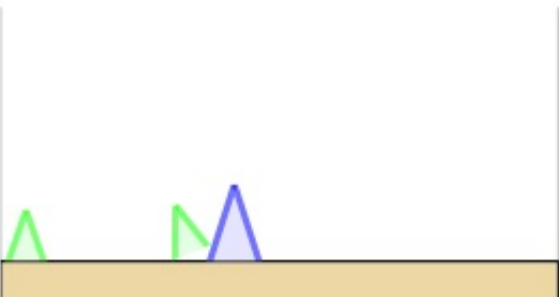


b)

Adaptation



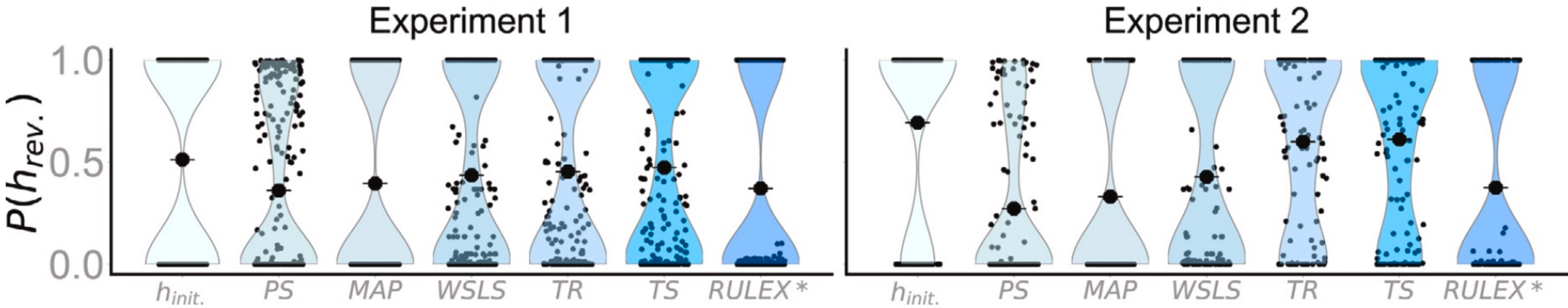
Five unknown test rules used during the main experiment.

Name	Rule	Prior Probability	Example
(1) Zeta	$\exists(\lambda x_1 : \quad =(x_1, \text{red}, \text{color}), X)$ (“there is a red cone”)	$\frac{\tau_{\text{color}}}{90}$	
(2) Iota	$N^=(\lambda x_1 : \quad =(x_1, \text{blue}, \text{color}), 1, \mathcal{X})$ (“there is exactly one blue cone”)	$\frac{\tau_{\text{color}}}{810}$	
(3) Upsilon	$\forall(\lambda x_1 : \quad \neg(=(x_1, \text{upright}, \text{orientation})), X)$ (“no cone is upright”)	$\frac{\tau_{\text{orientation}}}{270}$	
(4) Kappa	$\exists(\lambda x_1 : \quad \wedge(=(x_1, \text{small}, \text{size}), =(x_1, \text{blue}, \text{color}), X))$ (“there is a small blue cone”)	$\frac{\tau_{\text{size}} \times \tau_{\text{color}}}{450}$	
(5) Omega	$\forall(\lambda x_1 : \quad \vee(=(x_1, \text{small}, \text{size}), =(x_1, \text{blue}, \text{color}), X))$ (“all cones are small or blue”)	$\frac{\tau_{\text{size}} \times \tau_{\text{color}}}{450}$	

Best fitting model performances for participants' revised rule guesses ($h_{rev.}$).

Experiment	Model	Mean $BIC_{h_{rev.}}$	$N_{Best_{h_{rev.}}}$	b	λ
Exp. 1	$h_{init.}$	8.988	22.17	–	–
	Posterior Sample (PS)	9.817	6.00	5.0	–
	Maximum a posteriori (MAP)	11.164	4.17	7.0	–
	Win–stay, lose–sample (WSLS)	7.158	7.17	1.0	–
	WSLS with Tree Regrowth (TR)	6.368	12.17	3.0	10.0
	WSLS with Tree Surgery (TS)	5.917	15.17	5.0	10.0
	RULEX*	9.202	2.17	–	10.0
Exp. 2	$h_{init.}$	5.657	16.37	–	–
	Posterior sample (PS)	11.403	2.00	5.0	–
	Maximum a posteriori (MAP)	12.367	1.17	7.0	–
	Win–stay, lose–sample (WSLS)	6.573	0.37	1.0	–
	WSLS with Tree Regrowth (TR)	4.473	3.37	1.0	1.0
	WSLS with Tree Surgery (TS)	4.065	10.37	1.0	1.0
	RULEX*	9.220	2.37	–	3.0

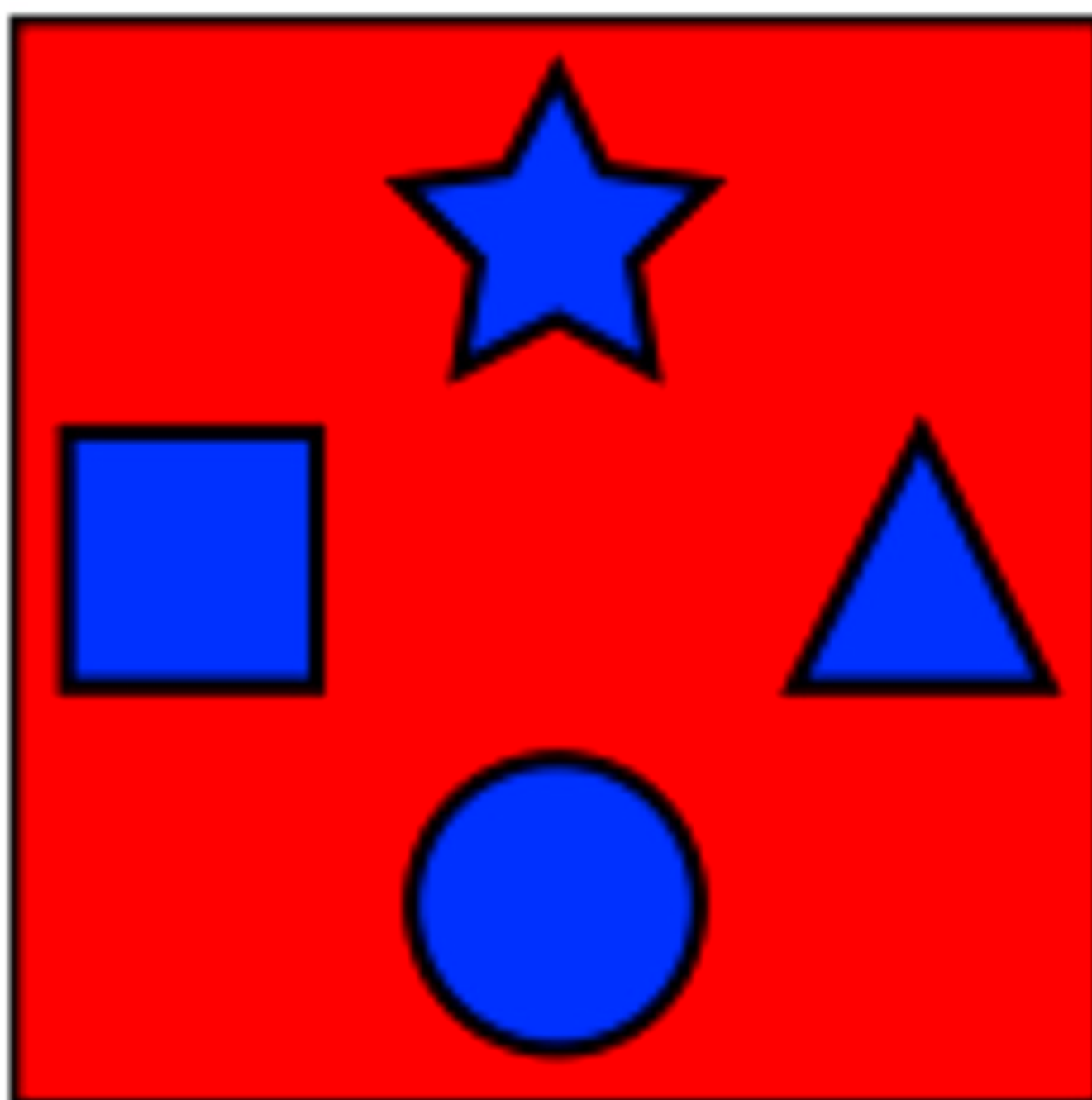
Predicting participants' hypotheses



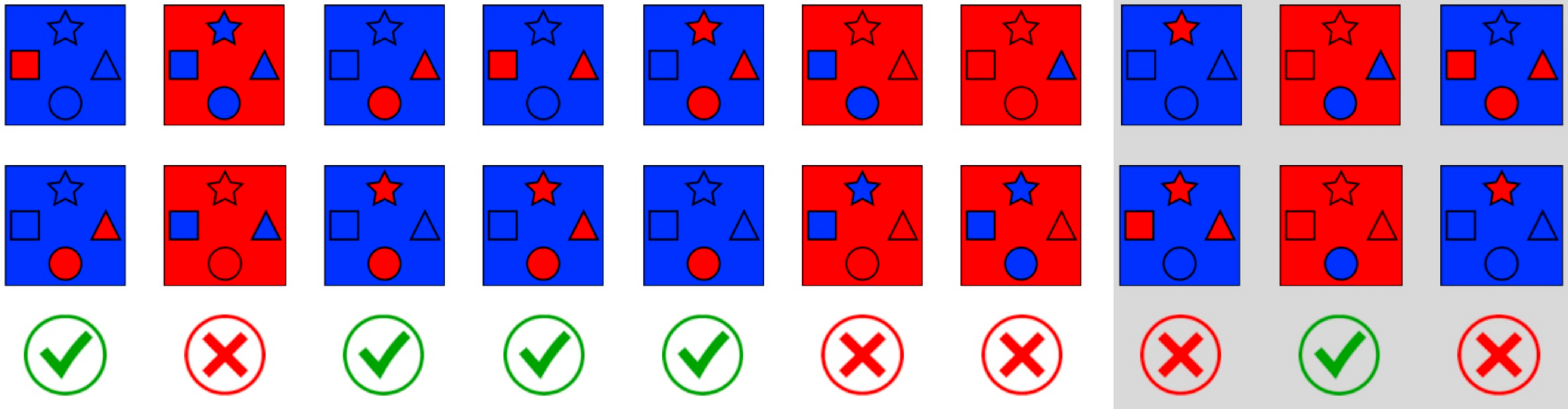
Reasoning about complex causal relations

With limited data

- People form rich and structured causal hypotheses.
- People update causal hypotheses locally.
- Local tree surgery provides a close account of human behavior.

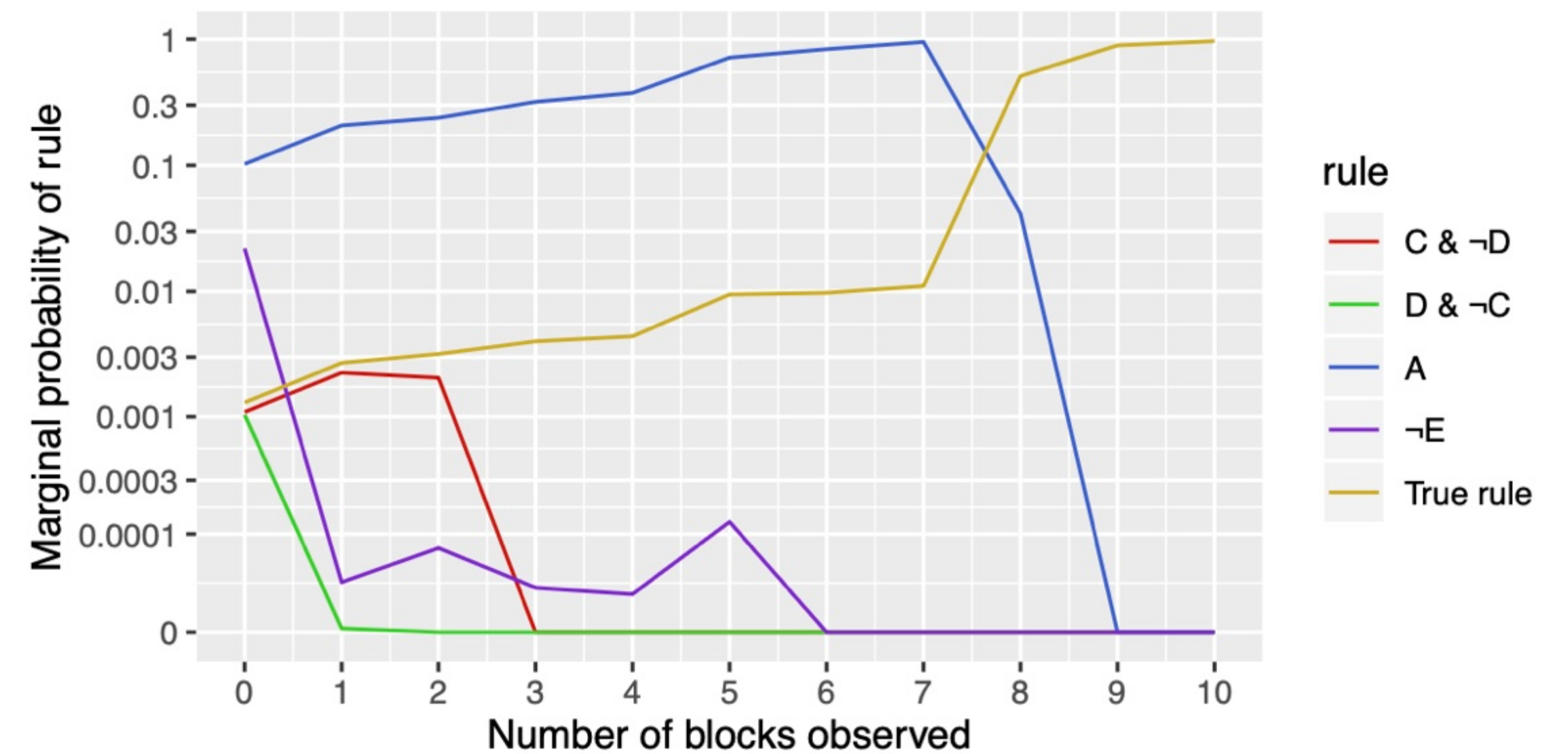
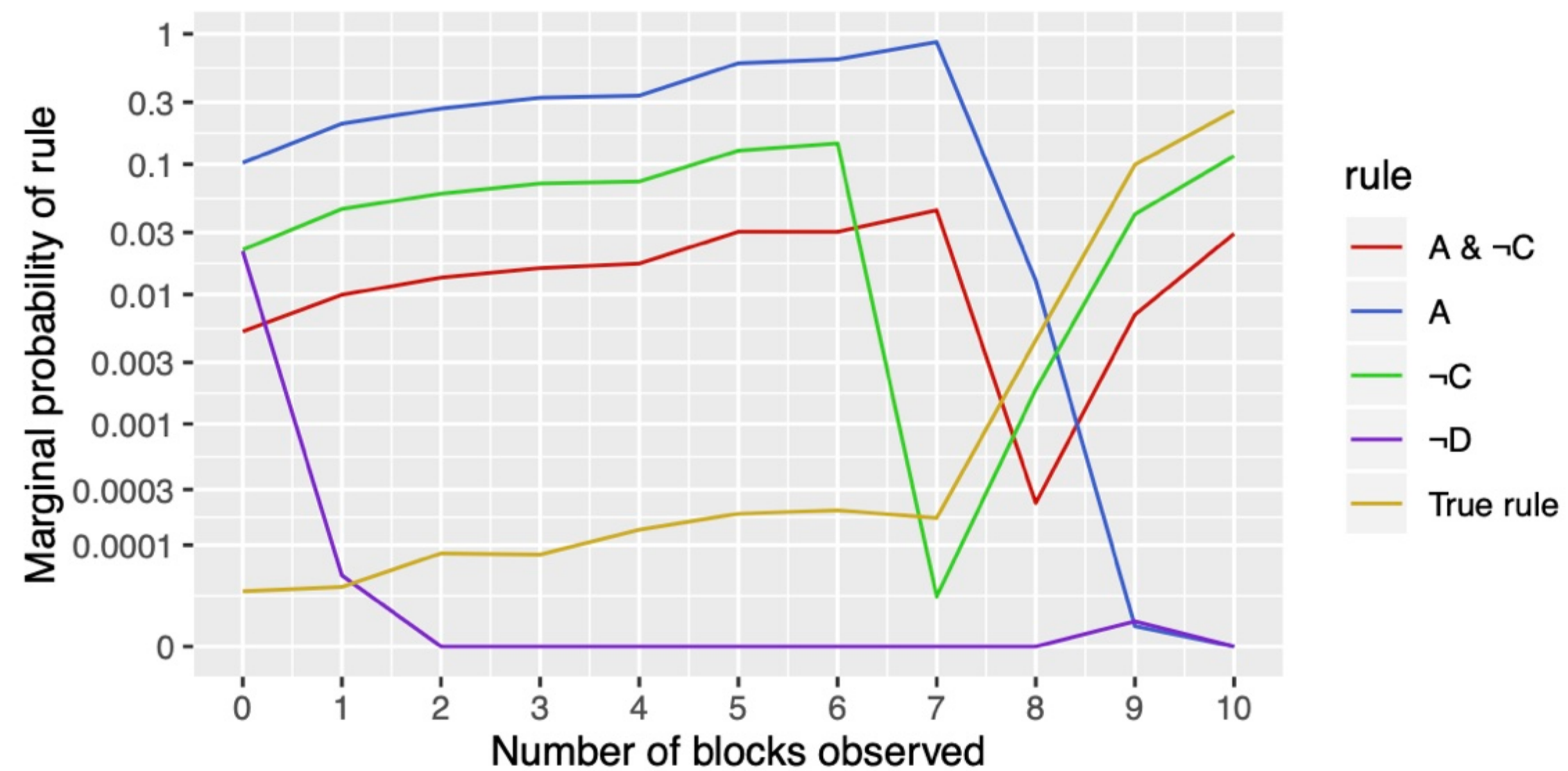


Distant, simpler true rule

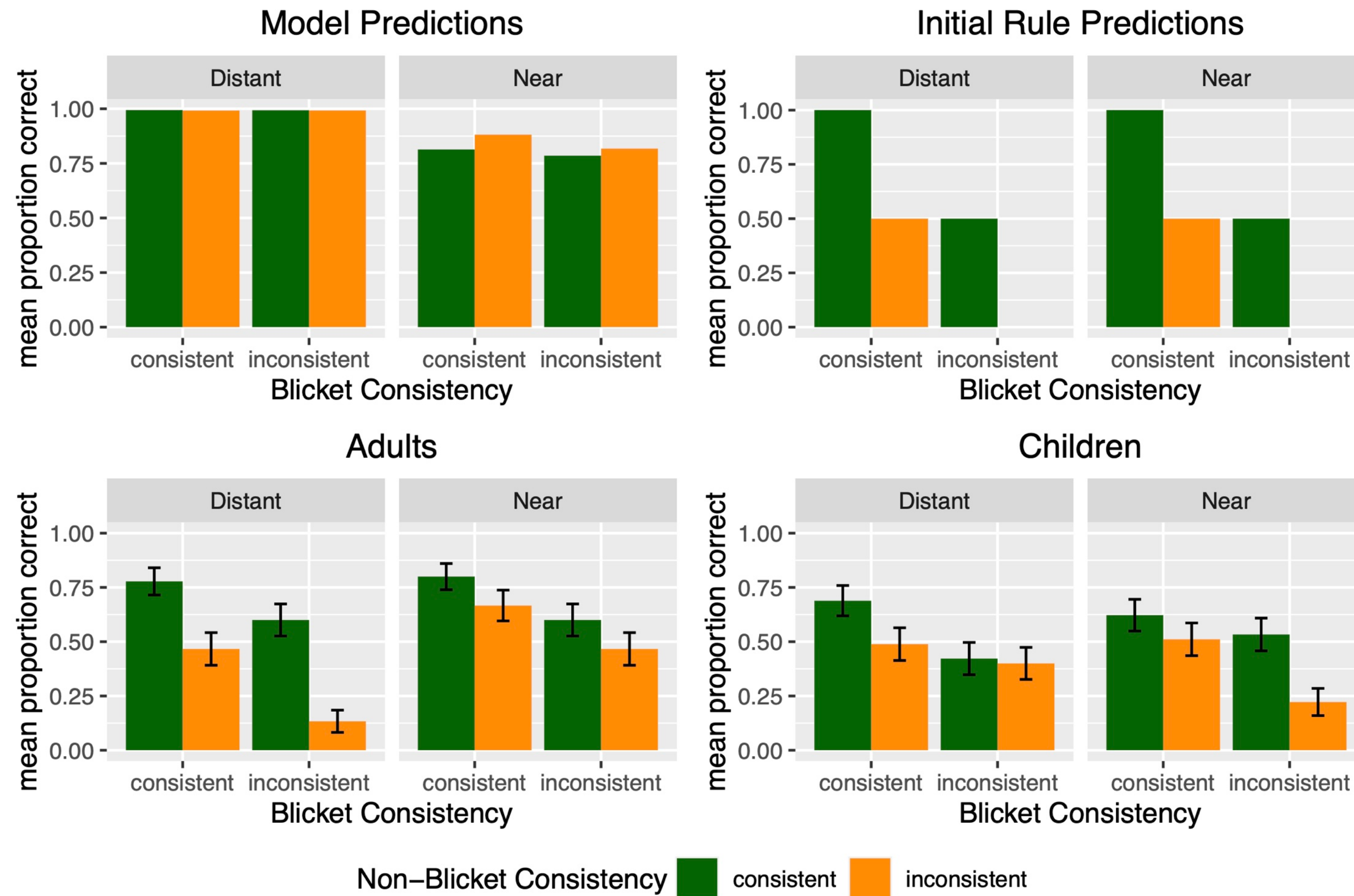


Near, longer true rule

Model Predictions



Main Result



Reasoning about complex causal relations

With limited data

- People form rich and structured causal hypotheses.
- People update causal hypotheses locally.
- Path-dependency.

Marr's Levels of Analysis

Computation

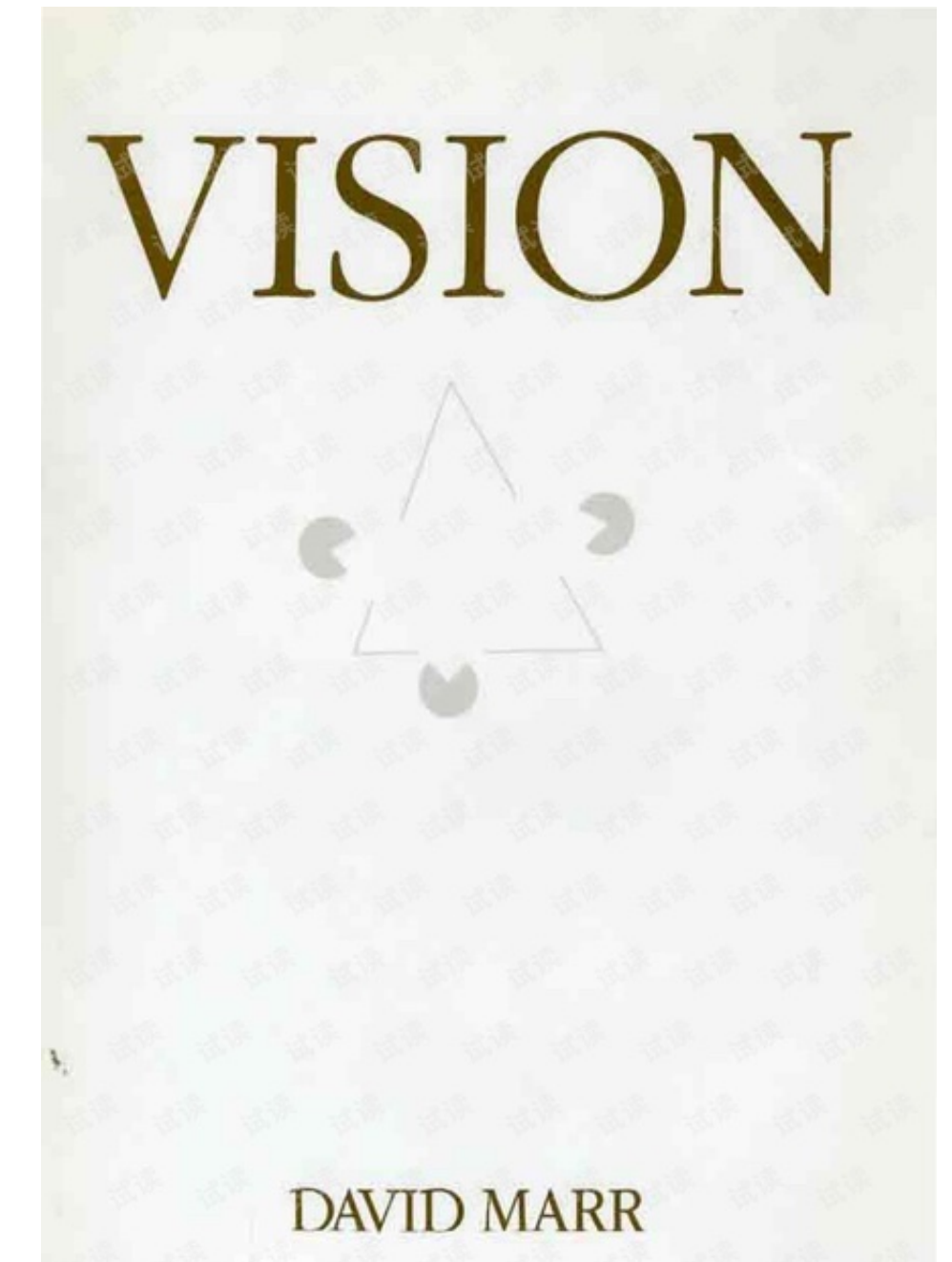
“What is the goal of the computation, why is it appropriate, and what is the logic of the strategy by which it can be carried out?”

Representation and algorithm

“What is the representation for the input and output, and the algorithm for the transformation?”

Implementation

“How can the representation and algorithm be realized physically?”



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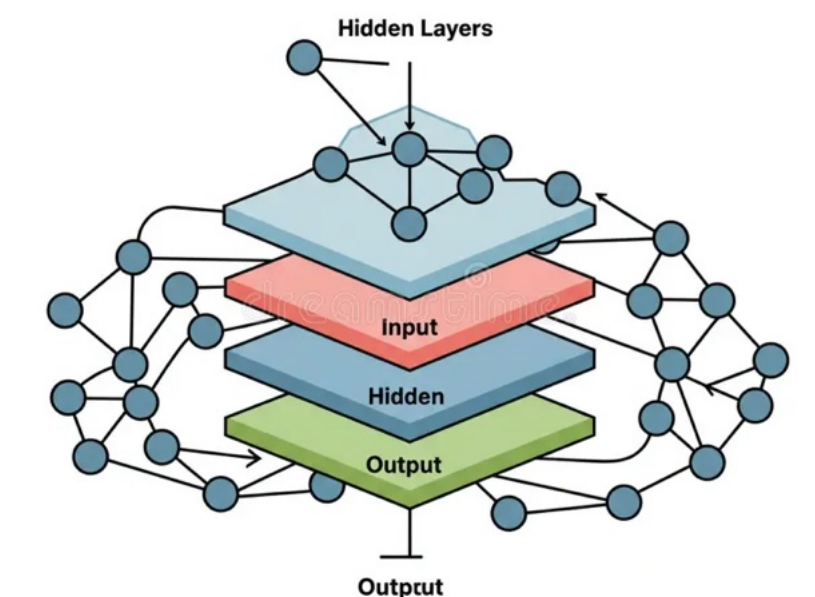
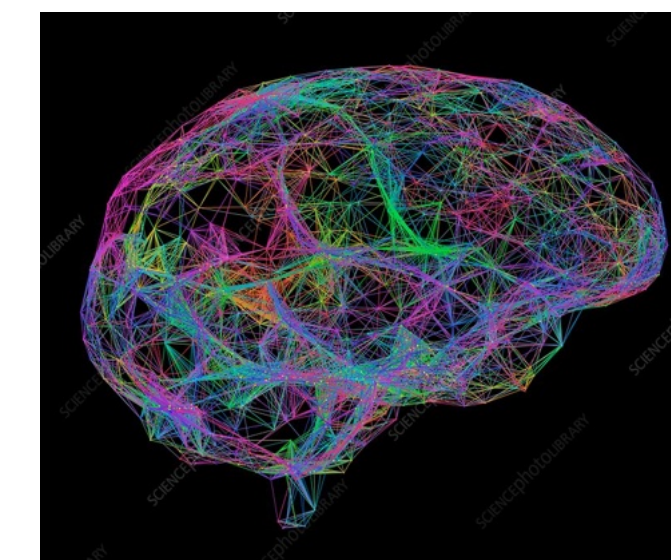
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$$P(h | D)$$

$$\hat{P}(h | D)$$



Learning about causal models

Or, the reverse inference of the true data generation function

- Causal model generates data
- Priors over possible causal models
- Using Bayes' rule to infer which causal model is the true one

Learning about causal models

Or, the reverse inference of the true data generation function

- Causal model generates data
- **Priors** over possible causal models
 - Evolutionary roots
 - Domain-specific knowledge
 - Open-endedness
- Using Bayes' rule to infer which causal model is the true one

Learning about causal models

Or, the reverse inference of the true data generation function

- Causal model generates data
- Priors over possible causal models
- Using Bayes' rule to **infer** which causal model is the true one
 - Approximation algorithms
 - Computational resource constraints

Tomorrow

- Going back to what we can do with causal models