

Relational Reasoning Model

We present a probabilistic model for Caren and Alison’s Relational Reasoning experiment and the results obtained with it.

The Model

We use a hierarchical model with three levels: the *theory* level, the *hypotheses* level, and the *data* level. At the *theory* level, there is a single variable t indexing the different theories. The *hypotheses* level has a richer structure, amounting for the hypotheses corresponding to the different theories and number of blocks needed simultaneously. Finally, at the *data* level, we describe actions (placing an arbitrary number of blocks on the machine) together with the results (either the machine going or not), and the bold notation describes many single datapoints. We allow for blocks of an arbitrary number of shapes n_s to be present.

The *theory* level

We consider three types of theory: $t = 0$, in which individual blocks activate the machine, $t = 1$, in which two blocks of equal shape are needed to activate the machine, and $t = 2$, in which two blocks of different shape activate the machine. [What happens here with theories in which any two blocks activate the machine?].

The prior probabilities for these theories are indexed by parameters α and β as follows:

$$\begin{aligned} p(t = 0) &= 1 - \alpha - \beta \\ p(t = 1) &= \alpha \\ p(t = 2) &= \beta. \end{aligned} \tag{1}$$

The *hypotheses* level

Hypotheses here are specific combinations of shapes that one thinks activate the machines. Examples of hypotheses are “a single triangular shape will activate the machine”, or “the combination of two triangular shapes or two circular shapes will activate the machine”. They are indexed by a triad $h = (h_0, h_1, h_2)$, where h_0 indexes which type of theory the hypothesis corresponds to, that is, $h_0 = 0$ tells us that h corresponds to an individual-block theory, $h_0 = 1$ that it corresponds to the equal shape theory, and $h_0 = 2$ to the different shape one.

h_1 labels the number of different blocks (or equal/different pairs thereof) that activate the machine according to the hypothesis. For instance, $h_1 = 1$ means that a single shape activates the machine in the case $h_0 = 0$ (say triangles, but not squares or circles), and that a single pair of equal shapes activates the machine in the case $h_0 = 1$ (say two squares but not two circles, etc). The special case $h_1 = 0$ means that no shape can activate the machine. h_1 ranges between 0 and n_s for $h_0 = 0$ and between 1 and n_s for $h_0 = 1$ (since we already incorporated the special no activation case to the first theory). For $h_0 = 2$, h_1 ranges between 1 and $\binom{n_s}{2}$.

Finally, h_2 is the remaining label indexing the different possibilities for given h_0 and h_1 , and its range varies with the values of h_0 and h_1 . In general, we have $h_2 \in \{0, \dots, \binom{\text{range}(h_1)}{h_1}\}$, where $\text{range}(h_1)$ depends on the value of h_0 as detailed above. For instance, having $h_0 = 0$ (individual blocks) and $h_1 = 1$ (single shape), gives us $h_2 \in \{0, \dots, n_s - 1\}$, that is, there are n_s different shapes that could be responsible for activating the machine, each corresponding to a different hypothesis.

The theory-hypothesis likelihood

The (unnormalized) theory-hypothesis likelihood is defined as:

$$\tilde{p}(h|t) = \begin{cases} \gamma^{h_1} & \text{if } t = h_0 \\ 0 & \text{otherwise.} \end{cases} \quad (2)$$

where γ is a parameter in the range $[0, 1]$ and we used the tilde notation to remind us that this distribution needs to be normalized. This equation penalizes hypotheses with a big number of blocks (or pairs of blocks).

The *data* level and the data-hypothesis likelihood

Single datapoints are (*action*, *result*) pairs, where *action* is either bringing a single or a pair of blocks in contact with the machine and *result* $\in \{\text{True}, \text{False}\}$, indicates whether the machine lit up or not. The whole sequence of play \mathbf{d} is a collection of datapoints d . The different datapoints in the sequence are conditionally independent given the hypothesis, such that we need only look at the data-hypothesis likelihood for a single datapoint d :

$$p(d|h) = \begin{cases} 1 & \text{if } d \text{ is compatible with } h \\ \epsilon & \text{if it is not,} \end{cases} \quad (3)$$

where ϵ is a free noise parameter. Compatibility here means that the block in d satisfies the criteria specified by h for the machine to activate, if the state of the machine in d is active, or that the block fails to satisfy the criteria in h , and the state of the machine is inactive. Although this distribution is also not normalized, we don't need to normalize it explicitly, since the constant will cancel in our further computations (weak sampling). [Tom, please check this, in particular that the constant does not depend on h ... I made the calculation for a simpler case, but here the 'data space' differs for the different h 's.. In particular, when dealing with the 'different' theory, we have more possible datapoints than when dealing with the 'same' one..].

Full joint distribution

The full joint distribution then simply factorizes as:

$$p(\mathbf{d}, h, t) = p(\mathbf{d}|h)p(h|t)p(t), \quad (4)$$

keeping in mind that $p(\mathbf{d}|h) = \prod_i p(d_i|h)$, where \mathbf{d} is a sequence of individual datapoints d_i .

Predictive probability

We are interested in predicting whether a new choice of block (shape) will activate the machine. For this, we need to compute the probability of a new datapoint given a history of previously observed data. Calling d_n the new (predicted) datapoint, and \mathbf{d}_o the previously observed sequence, we have:

$$\begin{aligned} p(d_n|\mathbf{d}_o) &= \sum_h p(d_n|h)p(h|\mathbf{d}_o) \\ &= \sum_{h,t} p(d_n|h)p(h|\mathbf{d}_o, t)p(t|\mathbf{d}_o) \\ &= \sum_{h,t} p(d_n|h) \frac{p(\mathbf{d}_o|h, t)p(h|t)}{p(\mathbf{d}_o|t)} p(t|\mathbf{d}_o) \\ &= \sum_{h,t} p(d_n|h)p(\mathbf{d}_o|h)p(h|t) \frac{p(t)}{p(\mathbf{d}_o)}. \end{aligned} \quad (5)$$

Here, in going from the third to the last line, we used the fact that, conditioned on hypotheses, the data are independent of the theory. Finally, we need an expression for $p(\mathbf{d}_o)$:

$$p(\mathbf{d}_o) = \sum_{h,t} p(\mathbf{d}_o|h)p(h|t)p(t). \quad (6)$$

Choice

Since we want to model the children’s choices, we still need to include in our model a recipe for the choice. Children are offered two options of action in the experiment, which we denote by a_1 and a_2 . We model the probability of choosing action a_1 as:

$$p_{choice}(a_1) = \frac{p(\text{active}|a_1, \mathbf{d}_o)}{p(\text{active}|a_1, \mathbf{d}_o) + p(\text{active}|a_2, \mathbf{d}_o)}, \quad (7)$$

where again \mathbf{d}_o is the previously observed data, and we compute the probability of activation given an action as:

$$p(\text{active}|a, \mathbf{d}_o) = p(d_n^{\text{active}}|\mathbf{d}_o), \quad (8)$$

where d_n^{active} is a single datapoint formed by joining action a with an *active* (or True) result.

Results

Experiment data

For the moment, we focus on reproducing the average number of correct choices in the two *same/different* conditions for Experiment 1 (no manipulation) and Experiment 2 (negative evidence for single object given). Because the complexity of the model grows exponentially with the number of available shapes, we simplify the treatment by presenting a single piece of evidence of each kind, so that in the *same* condition the model sees a pair of identical shapes activating the machine and a pair of different shapes not activating it, and viceversa for the *different* condition. The actual children see two independent instances of each, but attempting to include this renders the model intractable. In modeling Experiment 2, we add to this the evidence of single block non-activations, identical in both conditions, prior to seeing the conjoint evidence.

The actual success probabilities from the experiment are:

$$\begin{aligned} p_{corr}^{E1,same} &= 0.46, \\ p_{corr}^{E1,diff} &= 0.43, \\ p_{corr}^{E2,same} &= 0.79, \\ p_{corr}^{E2,diff} &= 0.5. \end{aligned} \quad (9)$$

Manual minimization

Our model has four free parameters that we need to choose: α , β , γ and ϵ . We vary these parameters by hand to minimize the sum of the squared differences of the four target probabilities, model minus data. The range of the parameters chosen is:

$$\begin{aligned} \alpha &\in \{0.01, 0.05, 0.2, 0.33, 0.5, 0.9\}, \\ \beta &\in \{0.01, 0.05, 0.2, 0.33, 0.5, 0.9\}, \\ \gamma &\in \{0.01, 0.1, 0.5, 0.9, 0.99\}, \\ \epsilon &\in \{0.001, 0.01, 0.05, 0.1, 0.25\}. \end{aligned} \quad (10)$$

Parameters α and β were always chosen such that $\alpha + \beta \leq 1$. The choice among these values that minimizes the error is:

$$(\alpha, \beta, \gamma, \epsilon) = (0.33, 0.01, 0.99, 0.25), \quad (11)$$

and the probabilities they yield are:

$$\begin{aligned} p_{corr}^{M1,same} &= 0.55, \\ p_{corr}^{M1,diff} &= 0.54, \\ p_{corr}^{M2,same} &= 0.65, \\ p_{corr}^{M2,diff} &= 0.51, \end{aligned} \quad (12)$$

where we substituted M for E to indicate that these are model results. This shows that, although the numbers are not exactly the same, the general effect observed in the experiment can be recovered by the model. In particular, we see an increase in the probability of a correct choice for the second experiment only in the *same* condition, which is the crucial effect in the study.

A note is in place however regarding the parameter values, since three of them β , γ and ϵ are on the boundary of their allowed region. Although one can extend this region in an attempt to improve the match between model and data even further, we see that the values are already too extreme. In particular, a value of $\epsilon = 0.25$ seems like an unreasonable amount of noise. On the good side, however, we find that with a less extreme choice of parameters as $(\alpha, \beta, \gamma, \epsilon) = (0.3, 0.02, 0.9, 0.05)$, we can still coarsely find the desired effect, finding correct-choice probabilities of $(0.60, 0.59, 0.87, 0.67)$ (in the same order as above).