



# A comprehensive model of development on the balance-scale task

Frédéric Dandurand<sup>a</sup>, Thomas R. Shultz<sup>b,\*</sup>

<sup>a</sup> Department of Psychology, Université de Montréal, 90 ave. Vincent-d'Indy, Montréal, QC H2V 2S9, Canada

<sup>b</sup> Department of Psychology and School of Computer Science, McGill University, 1205 Penfield Avenue, Montreal, QC H3A 1B1, Canada

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## Abstract

We present a new model of children's performance on the balance-scale task, one of the most common benchmarks for computational modeling of psychological development. The model is based on intuitive and torque-rule modules, each implemented as a constructive neural network. While the intuitive module recruits non-linear sigmoid units as it learns to solve the task, the second module can additionally recruit a neurally-implemented torque rule, mimicking the explicit teaching of torque in secondary-school science classrooms. A third, selection module decides whether the intuitive module is likely to yield a correct response or whether the torque-rule module should be invoked on a given balance-scale problem. The model progresses through all four stages seen in children, ending with a genuine torque rule that can solve untrained problems that are only solvable by comparing torques. The model also simulates the torque-difference effect and the pattern of human response times, faster on simple problems than on conflict problems. The torque rule is more likely to be invoked on conflict problems than on simple problems and its emergence requires both explicit teaching and practice. Overlapping waves of rule-based stages are also covered by the model. Appendices report evidence that constructive neural networks can also acquire a genuine torque rule from examples alone and show that Latent Class Analysis often finds small, unreliable rule classes in both children and computational models. Consequently, caution in using Latent Class Analysis for rule diagnosis is suggested to avoid emphasis on rule classes that cannot be replicated.

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## 1. Introduction

Ongoing debates between symbolic and neural-network models of cognition have often focused on development of children's performance on balance-scale problems, one of the most simulated tasks in developmental psychology. The symbolic view is that knowledge is represented in propositional rules referring to aspects of the world, that processing occurs as rules are selected and fired, and that knowledge is acquired by learning such rules. In neural-network accounts, active knowledge is represented in

rapidly changing neuronal-unit activations and long-term knowledge by excitatory and inhibitory synaptic connections between units, processing involves activation passing from one layer of units to another, and knowledge acquisition results from adjustment of connection weights and perhaps recruitment of new units into the network. The symbolic approach has been referred to as *rule use*, and the neural-network approach as *rule following* (Shultz & Takane, 2007).

Although this may seem to be a subtle distinction, there are important differences between the two viewpoints that have consistently guided research over the last few decades. The rule-use approach assumes that people have and use rules to guide their reasoning and behavior, affording the perfect generalization that symbolic rules may allow. Rule-use is consistent with the idea that human cognition

\* Corresponding author. Tel.: +1 514 398 6139.

E-mail addresses: [frederic.dandurand@gmail.com](mailto:frederic.dandurand@gmail.com) (F. Dandurand), [thomas.shultz@mcgill.ca](mailto:thomas.shultz@mcgill.ca) (T.R. Shultz).

is often quite regular. In contrast, the rule-following approach assumes that such regularities may be naturally approximated by neural networks that adapt to regularities in the environment. This affords more graded generalizations whose regularity approximates the extent to which the environment is consistently regular, with the possible advantage that both regularities and exceptions can be accommodated within the same neural network. In rule-use systems, exceptions are instead typically memorized, and represented separately from the rules themselves. Such differences are highlighted in precise computational models of psychological phenomena (Shultz, 2003).

The balance-scale task is interesting because it is representative of the many problems requiring integration of information across two separate quantitative dimensions and because it provides well-replicated results with an interesting stage progression.

Here we present a new computational model of balance-scale acquisition that addresses a recent criticism affecting many of the balance-scale computational models – ensuring that the final stage consists of a genuine, multiplicative torque rule and not a simpler rule based on addition (Quinlan, van der Maas, Jansen, Booij, & Rendell, 2007). After describing the balance-scale task and phenomena, we present our new computational model.

### 1.1. Balance-scale task and phenomena

The task presents several pegs positioned on a rigid beam at regular distances to the left and right of a fulcrum (Siegler, 1976). An experimenter places some identical weights on a peg on the left side and some number of identical weights on a peg on the right side of the beam. The participant is asked to predict which side of the scale will drop, or whether the scale will remain balanced, when the beam is released from its supports, usually a block placed under each end of the beam. Archimedes' principle of the lever describes a rule that yields a correct answer to all such problems: multiply the weight and distance from the fulcrum on each side and predict that the side with the larger product (or torque) to drop.

A neural-network simulation using the cascade-correlation (CC) algorithm (Shultz, Mareschal, & Schmidt, 1994) captured the four stages seen in children (Siegler, 1976): (1) predicting the side with more weights to descend, (2) when the weights are equal on both sides, also predicting the side with greater distance to descend, (3) predicting correctly when weight and distance cues both forecast the same result and performing at chance when these cues conflict, and (4) being correct on at least 80% of balance-scale problems.

### 1.2. Diagnosing stage 4

If performance at Stage 4 is diagnosed as being correct on 80% of balance-scale problems, some of which are difficult problems in which weight and distance cues conflict

with each other, then at least some computational models, both symbolic (Schmidt & Ling, 1996) and connectionist cascade-correlation networks (Shultz et al., 1994) reach Stage 4. But if Stage 4 is defined by possession of a genuine multiplicative torque rule, as opposed to say an addition rule, the modeling challenge remains open. Because many conflict problems can be solved by just adding weight and distance, documentation of a torque rule must be supported by success on problems that cannot alternately be solved by an addition rule (Boom, Hoijtink, & Kunnen, 2001; Quinlan, van der Maas, Jansen, Booij, & Rendell, 2007).

With five pegs and five weights, the problem size often used in simulations of the balance scale (Shultz et al., 1994), there are 625 total problems, of which only 200 are relatively difficult conflict problems in which weight and distance information, used alone, predict different outcomes. Only 52 of these conflict problems are torque problems that cannot be solved by mere addition; the other 148 are addition problems that can be solved by adding distance and weight on each side and comparing these sums.

An addition rule was routinely ignored in computational models of balance-scale development, whether symbolic (Schmidt & Ling, 1996) or connectionist (McClelland, 1989; Schapiro & McClelland, 2009; Shultz et al., 1994), just as it had been ignored in many older psychology experiments on the balance scale. But with evidence that at least some people use or follow a genuine torque rule, solving balance-scale problems that addition cannot solve (Boom, Hoijtink, & Kunnen, 2001; Quinlan, van der Maas, Jansen, Booij, & Rendell, 2007), it becomes important to test computational models for their ability to acquire and use a genuine torque rule.

This problem of accurately diagnosing a terminal stage does not arise in the many other developmental domains where constructive neural networks have been successfully applied: conservation (Shultz, 1998, 2006), seriation (Mareschal & Shultz, 1999), transitivity (Shultz & Vogel, 2004), integration of cues for moving objects (Buckingham & Shultz, 2000), shift learning (Sirois & Shultz, 1998), deictic pronouns (Oshima-Takane, Takane, & Shultz, 1999; Shultz, Buckingham, & Oshima-Takane, 1994), word stress (Shultz & Gerken, 2005), syllable boundaries (Shultz & Bale, 2006), morpho-phonology (Shultz, Berthiaume, & Dandurand, 2010), habituation of infant attention to auditory (Shultz & Bale, 2001, 2006) and visual (Shultz, 2011; Shultz & Cohen, 2004) information, false-belief (Berthiaume, Onishi, & Shultz, 2008; Berthiaume, Shultz, & Onishi, 2013; Evans, Berthiaume, & Shultz, 2010), and concept acquisition (Baetu & Shultz, 2010; Shultz, Thivierge, & Laurin, 2008).

Our experience teaching university students about psychological development on the balance scale suggests that those few students who spontaneously use the torque rule to solve balance problems admit that they learned this method in science classes, either in secondary school or college. When the remaining students are informed that

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