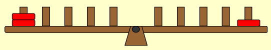
Computational Modelling of Variability in the Balance Scale Task



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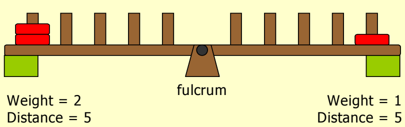
Overview

- The balance scale task
- Variability
- The computational study of variability
- Simulations
- Results
- Conclusions

The Balance Scale Task

- Problem-solving and reasoning
- Will the scale tip right, tip left, or balance?

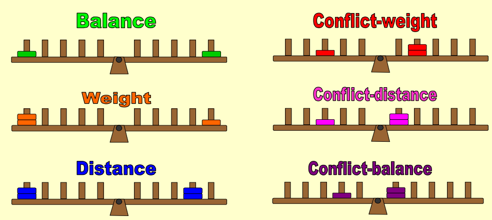
(Inhelder and Piaget, 1958)



Torque = Weight x Distance

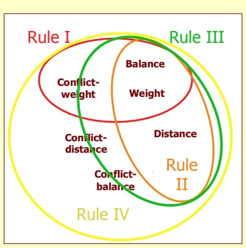
Assessing performance

- Use **six** different types of balance scale problem:



Balance scale behaviour

- Behaviour is characterised in terms of rules

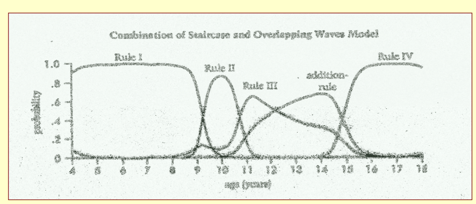


- Siegler's four core rules
- More rules:

Rule I
Smallest Distance Down *(SDD)*
Rule II
Qualitative Proportionality *(QP)*
Rule III
Addition *(Add)*
Rule IV

Developmental profile

- Model of distribution of rules over age



From Jansen and van der Maas (2002)

Variability

- Differences or fluctuations in behaviour or strategy

"Substantial variability is present during learning, even on tasks like the balance scale where most children use systematic rules before and after learning experiences…"

(Siegler and Chen, 1998, p303)

- Variability can be found both across individuals, and within the behaviour of a single individual
- A high degree of **variability** has been found around rule III

Why study variability?

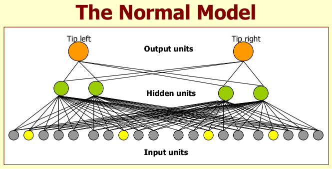
- Within a single individual, increased variability presages the onset of developmental transitions
- Variability across individuals of the same age provides insight into general and specific intelligence
- Variations from the normal pathway are found in disorders

Computational study of variability

- Changes to the model and the environment

(McClelland, 1989)

The Normal Model



- **Number of hidden units**
- **Number of hidden layers**
- **Number of output units**
- **Input encoding**
- **Learning rate**
- **Slope of transfer function**

Environment

	Prob type freq	Training set freq.
B	25	125
W	100	500
D	100	100
CW	88	88
CD	88	88
CB	24	24
WD	200	200

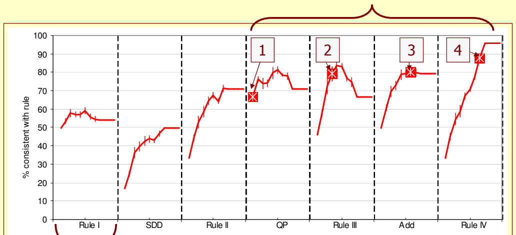
- **Proportion of problem types**
- **Restrict problem range**

Simulations

1. **Computational resources**
   - Number of layers
   - Number of hidden units
2. **Environment**
   - Limited range of problem types
   - Change frequency of problem types
3. **Learning rate**
4. **Case study**

The Normal Model

Transitions



Training epochs

Increasing complexity

Multi-Layer Models

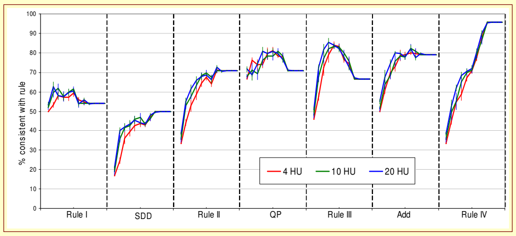
1HL: QP → R3 → Add → R4

2HL: QP → Add → R4

3HL: QP → R4

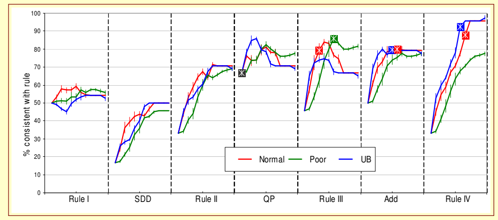
Extra Hidden Units

- Developmental profile for 1HL network



Changes to the Environment

- Restricted pattern set (Poor)
- Unbiased – no extra weight and balance problems (UB)
- Developmental profile for 1HL network:

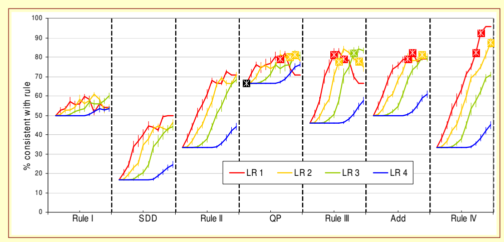


- Increasing the number of layers can improve performance on the restricted pattern set

Implementing delay

- Individual differences in developmental disorders are sometimes characterised in terms of *delay* – i.e Down's syndrome
- Obvious way to implement *delay* is to reduce the learning rate (lr)
- Reduced lr by 4 decrements
  For example, [**0.1:** 0.08, 0.06,0.04, 0.02]
- How does lr affect the transitions the system exhibits?

Reducing the learning rate



- Roughly parallel shifts for all metrics from left to right
- Development slows down
- Poorer behavioural discriminability

Delay and LR

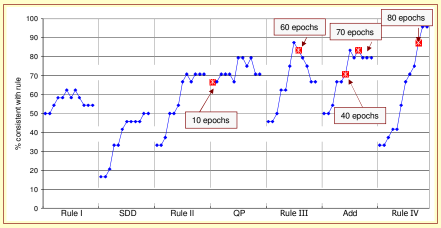
- *Developmental disorders:* performance asymptotes at lower level of complexity
- Models may "catch up" with extra training
- LR not a good sole candidate for explaining delay in disorders

Inter-individual variability

- Variability occurs during the development of individual children
- Risk of averaging across individuals
- Development can also include regression to less sophisticated rules

Case Study

- Single model run with 1HL (*lr = 0.008)*



Transitions: QP ⟶ Add ⟶ R3 ⟶ Add ⟶ R4

Conclusions

- Study of variability is important for both the normative profile of development and disorders
- Structure of the system and the environment can affect the sequence of transitions made during learning
- For the individual, progressive transitions and regressions are important in model's learning

End of Talk

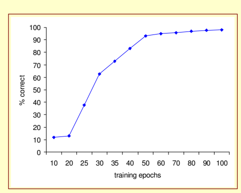
Thank you for listening

Further Details

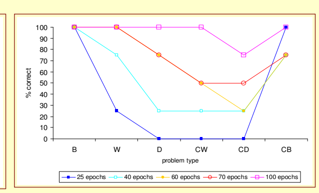
Simulation Details

- Epoch monitoring points:
  [10, 20, 25, 30, 35, 40, 50, 60 70, 80, 90, 100]
- LRs: 1HL = 0.01   2HL = 0.02   3HL = 0.2
- Multi-layer simulations run with same lr
  - 3HL: 200 epochs (R4 at 140 epochs+)
  - 4HL: 1000 epochs (R4 at 650 epochs+)

Case Study: Learning Profile



Training



Performance on problem types

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