

Analysis of reaction time during pattern learning

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Outline

- 1 Introduction
 - Hick's Law
 - SRT Task
- 2 Previous work
 - Methods
 - Results
- 3 Work in Progress
 - Distinct probabilities
 - Hypothesis

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Equiprobable choices

- Simple choices are faster than complex ones
- What matters is the number of possibilities η
- Reaction time increases logarithmically with η

$$T = b \cdot \log_2(\eta + 1)$$

Unequal probabilities

- Can be generalized using the Entropy H
- Reaction time increases linearly with H

$$T = bH$$

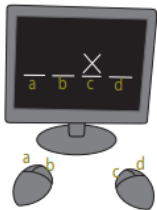
$$H = \sum_i^{\eta} p_i \log_2 \left(\frac{1}{p_i} + 1 \right)$$

Problems

- There is no upper bound for reaction time
- It takes no account of the learning process

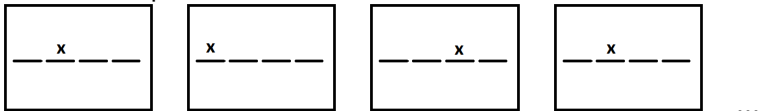
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The reaction time is the time between the marking on the screen and the pressing of the correct button.

If we let a sequence be fixed as $S=213$, the first events would be:

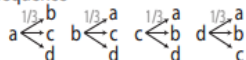


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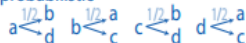
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- Testing sigmoidal fits to compare with Hick's linear
- Using simple sequences to see learning

random sequence



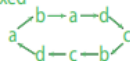
complex probabilistic



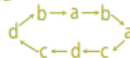
simple probabilistic



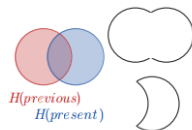
complex fixed



simple fixed



very simple fixed



joint entropy

$$H(\text{previous} \cup \text{present}) = -\sum_x p(x_{-1}, x_0) \log_2[p(x_{-1}, x_0)]$$

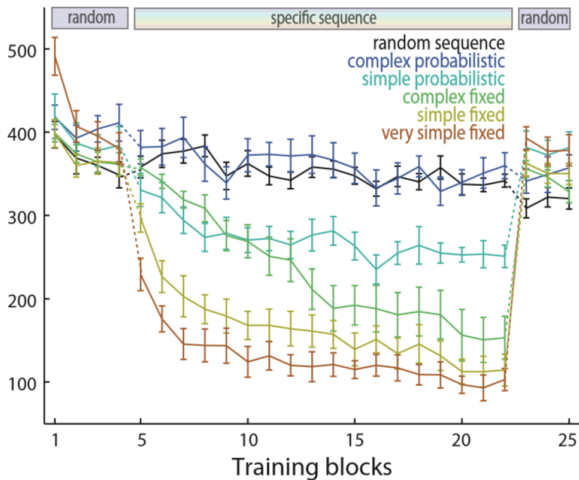
conditional entropy

$$H(\text{present} | \text{previous}) = -\sum_x p(x_{-1}, x_0) \log_2[p(x_0|x_{-1})]$$

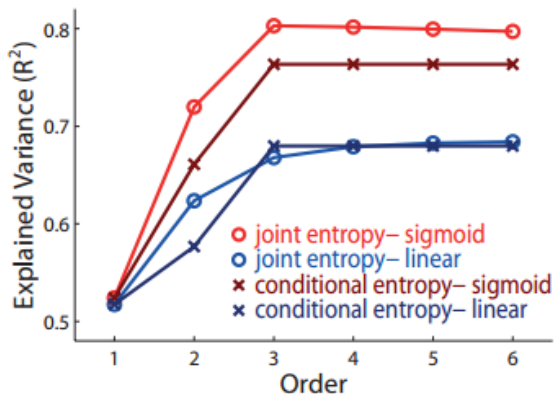
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Learning



Sigmoidal fits better



What is missing

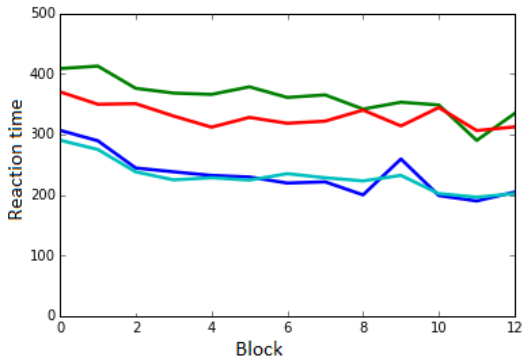
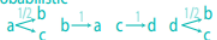
- The sigmoidal entropy fit explains the variance, but still doesn't explain the learning process.
- Is reaction time the same on events with distinct probabilities from the same source?

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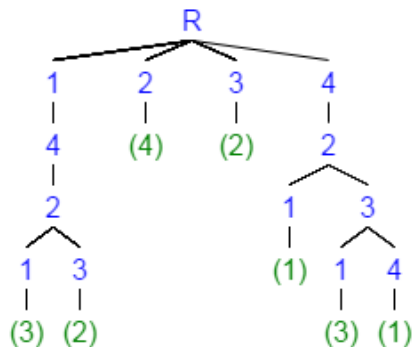
Simple probabilistic sequence

simple probabilistic



- Reaction time strongly differs throughout same sequence's distinct events
- Can we use context trees? Will depth explain reaction time?

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Results

- Will depth explain reaction time?

Results

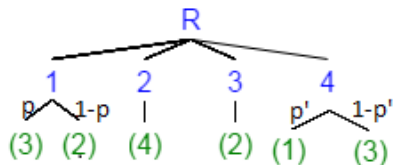
- Will depth explain reaction time? Not at all.

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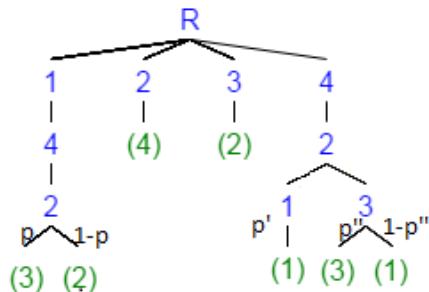
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- We may use context trees, but subject-made (Rissanen)
- The tree should be updated during learning

Early Learning



Late Learning

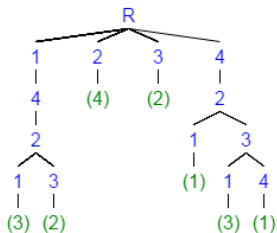


To analyze

- The probabilities of the roots could explain intra-sequence variance (?)

Problems




- Upper levels must be considered



Problems

- Upper levels must be considered
- Learning rate changes with subject

References

-  Rissanen, J., A universal data compression system, IEEE Trans. Inform. Theory 29, Number 5, 656–664, 1983.
-  Pavão R, Saviotto JP, Sato JR, Xavier GF, Helene AF. Entropy and probability measures describe sequence learning performance
-  Shannon, C. (1948) A mathematical theory of communication. Bel I System Tech. J. 27, 379–423.