Learning predictive temporal structure under uncertainty

Poster 085.18

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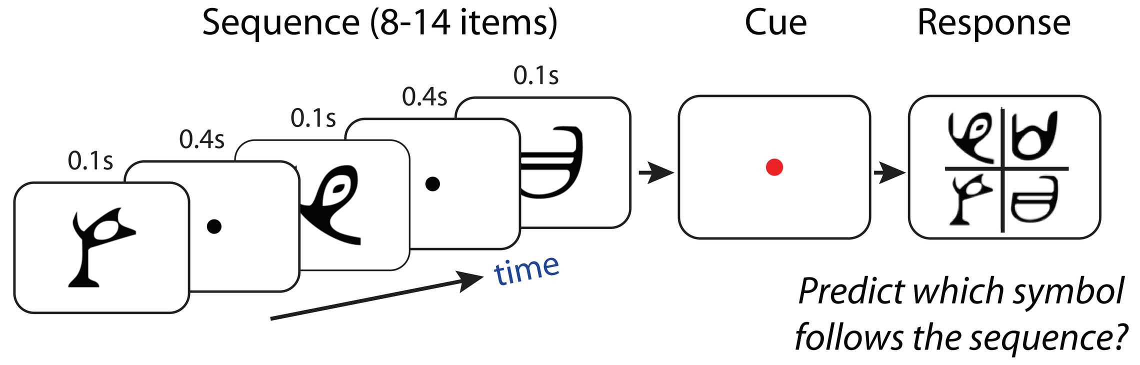
INTRODUCTION

Experience is thought to facilitate our ability to extract structures from streams of events. We have shown that extracting complex temporal regularities relates to individual decision strategy (matching vs maximization) (Wang et al., 2017).

Here we test whether this ability for learning predictive structures is maintained under uncertainty and whether it generalizes.

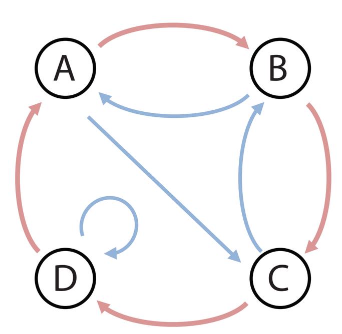
METHODS

Task



Sequences

We trained participants with sequences of symbols determined by first-order Markov models (i.e. level-1), where the symbol at time *i* is determined probabilistically by the immediately preceding symbol.



Level-1		Target A	Target B	Target C	Target D
Context	A		0.8	0.2	
	B	0.2		0.8	
	C		0.2		0.8
	D	0.8			0.2

Behavioural analysis

Performance index (PI):

We assessed human responses by quantifying how closely the probability distribution of participant responses matches the presented symbols.

$$PI(P_{resp}, P_{pres}) = \sum_i \min(P_{resp}(i), P_{pres}(i))$$

P_{resp}: Participants' response distribution for target i per context
P_{pres}: Presented distribution for target i per context

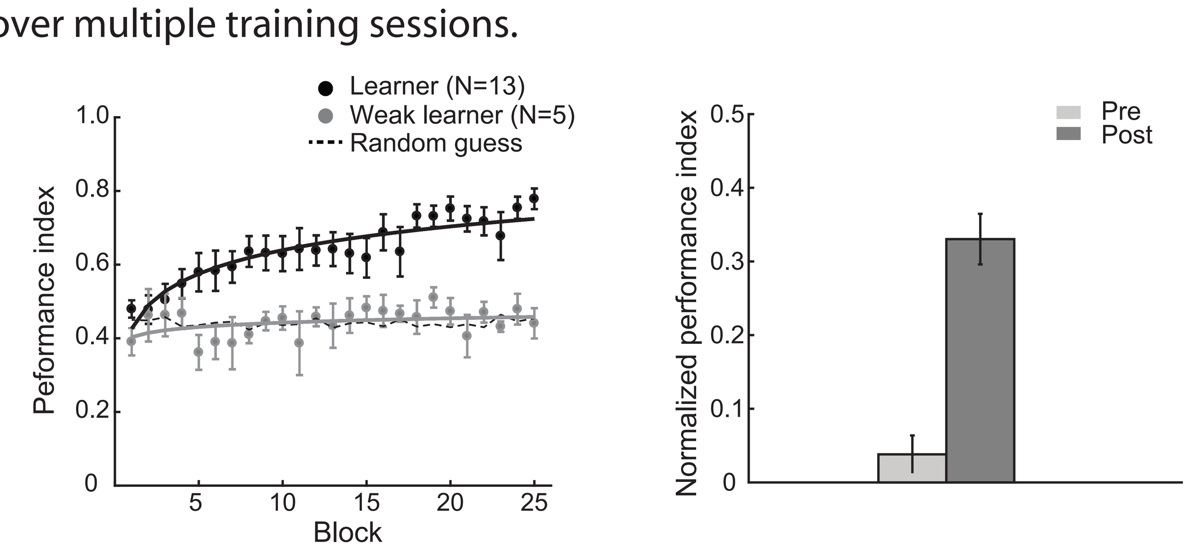
Strategy choice:

We computed a strategy index that indicates each observer's preference for responding using probability matching (i.e. match the exact sequence statistics) vs. maximization (i.e. predict the most probable outcome for each context).

RESULTS

Experiment 1: Baseline

❖ We first replicated the previous findings of learning temporal statistics, that is observers succeed in extracting regularities and making predictions over multiple training sessions.



Experiment 2: Learning under uncertainty

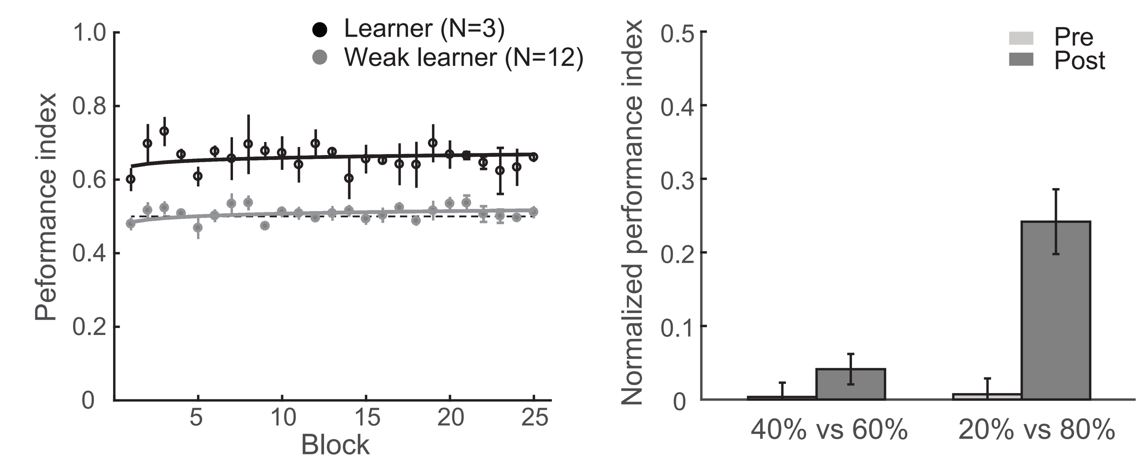
Experiment 2.1: Probability uncertainty

❖ We decreased the discriminability of symbol probabilities (i.e. changing the previous marginal probabilities from 80% vs. 20% to 60% vs.40%).

❖ Probability of occurrence was important for structure learning, and decreasing the probability contrast of the items compromised performance in the prediction task.

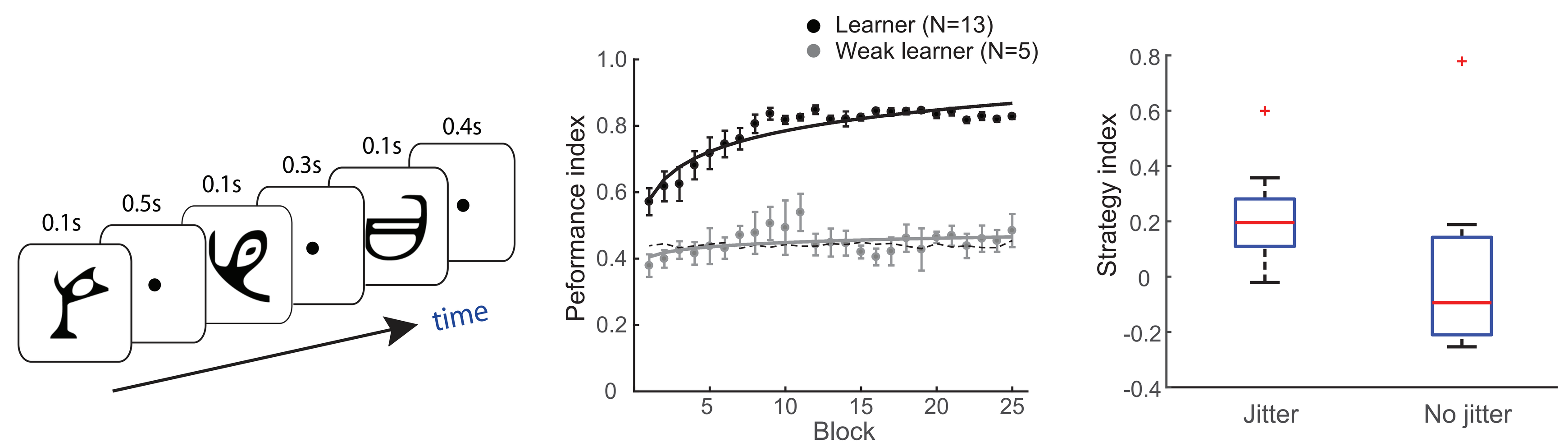
Conditional probability matrix

Level-1		Target A	Target B	Target C	Target D
Context	A		0.6	0.4	
	B	0.4		0.6	
	C		0.4		0.6
	D	0.6			0.4



Experiment 2.2: Uncertainty in stimulus presentation rate

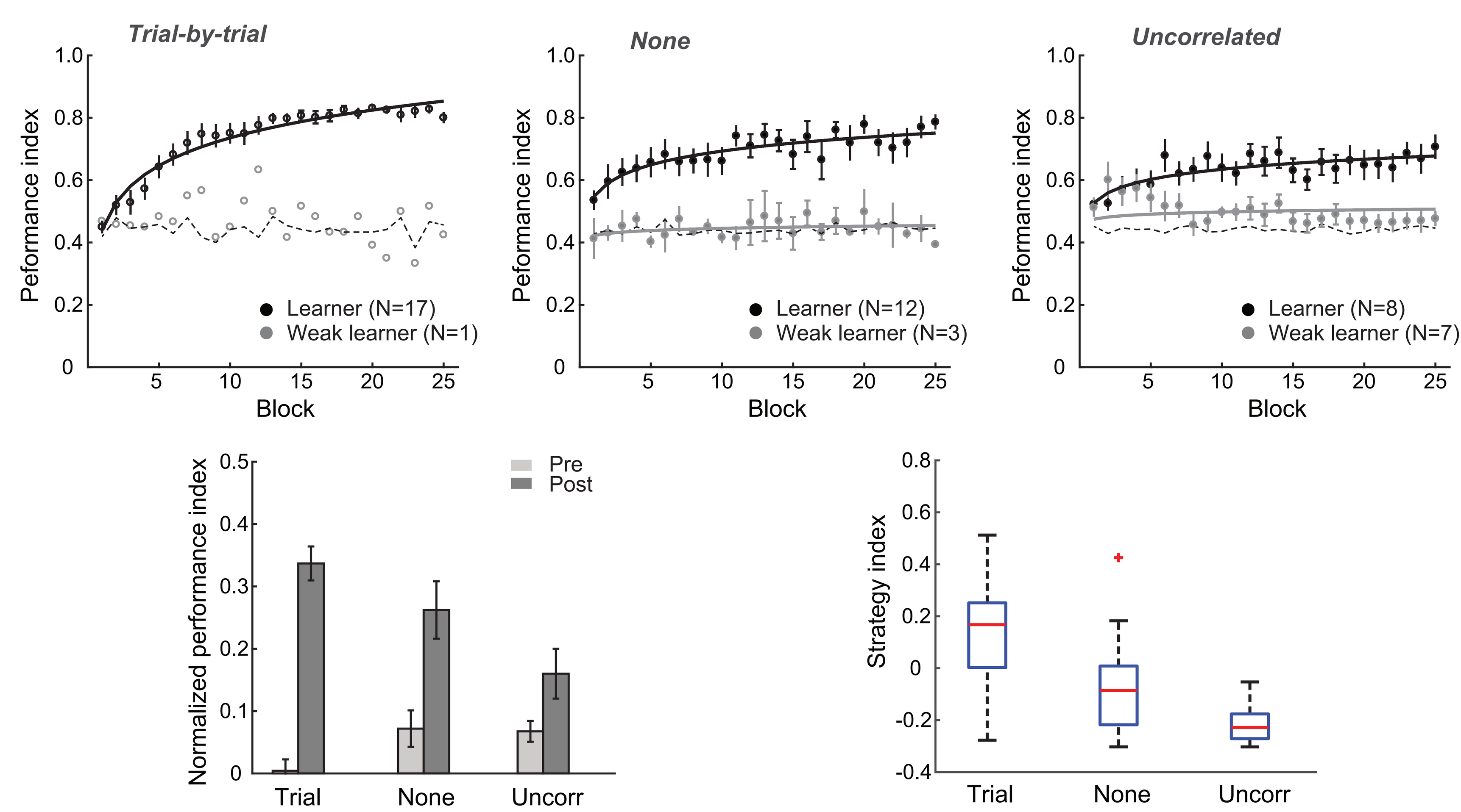
❖ Increasing uncertainty in stimulus presentation rate by temporal jittering did not impair observers' performance, but led observers to adopt a strategy closer to probability maximization.



Experiment 2.3: Feedback uncertainty

❖ Three groups of observers were provided with trial-by-trial feedback based on whichever symbol was correctly predicted by pre-defined sequences, no feedback and uncorrelated feedback, respectively.

❖ Feedback played an important role in predictive learning: Trial-by-trial feedback yielded a larger improvement of performance than no feedback, and encouraged participants to adopt a strategy closer to maximization. Providing uncorrelated feedback resulted in limited improvement.



Modelling feedback learning

To understand how predictive learning of statistics evolves under various uncertainty conditions (e.g. feedback) , we created a model which integrates chunk learning and reinforcement learning processes.

Sequence viewing

Observers extract statistics (level-0 and level-1) from blocks of sequences (chunk) during sequence viewing

for each symbol , $s_i (s_i \in S)$

chunks of a certain memory length n, $(s_{i-n+1}, s_{i-n+2}, \cdots, s_{i-1}, s_i)$

Internal learning is weighted by the probability of occurrence of each symbol (level-0) or adjacent pairs (level-1) over chunks

$$\text{Level 0: } A(s_j) = A'(s_j) + 1$$

$$\text{Level 1: } A(s_j | s_{j-1}) = A'(s_j | s_{j-1}) + 1$$

Feedback

Extenal learning is reinforced by feedback which is given for each human choice

Correct responses

$$B(s^r|s^c) = B'(s^r|s^c) + v$$
$$B(s^r) = B'(s^r) + v$$

v - intensity of feedback

Incorrect responses

$$B(s^r|s^c) = B'(s^r|s^c) - v \qquad B(s|s^c) = B'(s|s^c) + \frac{1}{3}v \quad (s \neq s^r)$$
$$B(s^r) = B'(s^r) - v \qquad B(s) = B'(s) + \frac{1}{3}v \quad (s \neq s^r)$$

Decision making

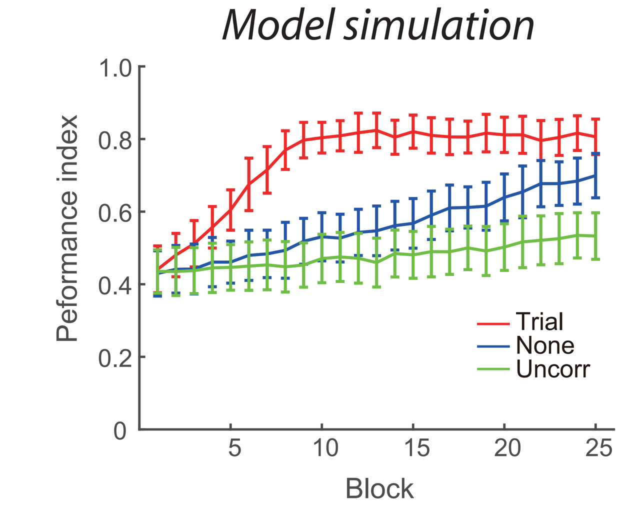
Observers update the models through the two learning processes and make the most probable choices

fitness I. $Q^A(s) = A(s) - A(s)$, $Q^A(s|s^c) = A - \bar{A}(s|s^c)$ II. $Q^B(s) = B(s) - \bar{B}(s)$, $Q^B(s|s^c) = B - \bar{B}(s|s^c)$

To update the protocol and make a choice *k - noise*

$$p(s|s^c) = \frac{(\exp(kQ^A(s|s^c)) + \exp(kQ^A(s))) + (\exp(kQ^B(s|s^c)) + \exp(kQ^B(s)))}{(\sum_{s\in S}\exp(kQ^A(s|s^c)) + \sum_{s\in S}\exp(kQ^A(s))) + (\sum_{s\in S}\exp(kQ^B(s|s^c)) + \sum_{s\in S}\exp(kQ^B(s)))}$$

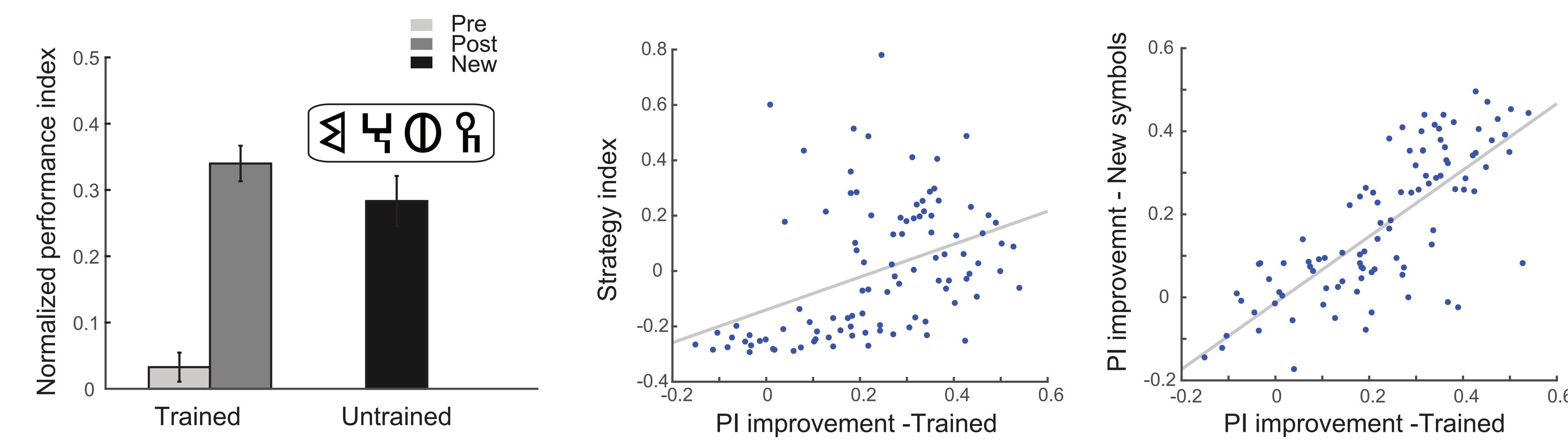
Model simulation



Experiment 3: Does learning transfer to novel symbols?

❖ After training, observers were tested with a new sequence of stimuli comprising four different symbols. It was shown that predictive learning of temporal statistics transferred fully to distinct new stimuli.

❖ Correlating individual strategies with learning and transfer performance showed that observers who adopted the maximization strategy showed improved performance and higher learning transfer.



SUMMARY

❖ We manipulated 'uncertainty' in the sequences in three respects: probability of symbol occurrence, stimulus presentation rate and feedback, and have demonstrated how learning changes under uncertainty.

❖ Our results suggest that adopting maximization reduces uncertainty when learning in variable environments. Further, maximization facilitates predictive learning and generalization.

REFERENCES

Wang, R., Shen, Y., Tino, P., Welchman A. E. & Kourtzi Z. (2017). Learning predictive statistics from temporal sequences: dynamics and strategies. *Journal of Vision*, 17(12):1, 1-16