Feature-based learning increases the generalizability of predictive inferences

Bakkour Memory and Decision Lab

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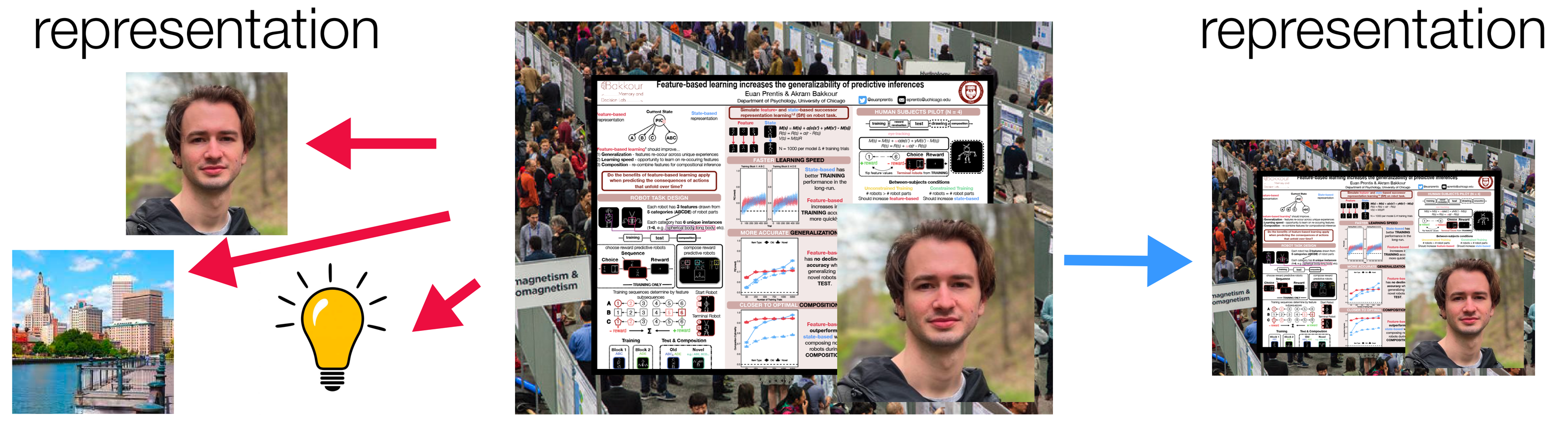
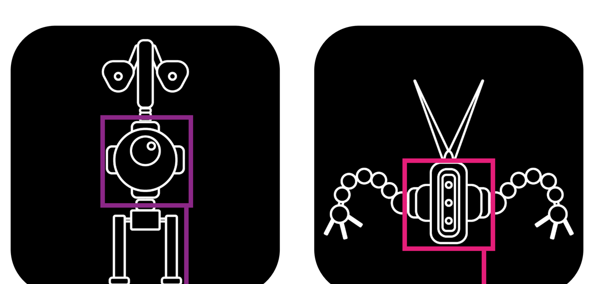
How can knowledge about the unfolding consequences of actions be generalized to new contexts?



Feature-based learning[1] should be better for...
1) **Learning speed** - opportunity to learn on re-occuring features
2) **Generalization** - features re-occur across unique experiences
3) **Composition** - re-combine features for compositional inference

ROBOT TASK DESIGN



Each robot has **3 features** drawn from **5 categories (ABCDE)** of robot parts

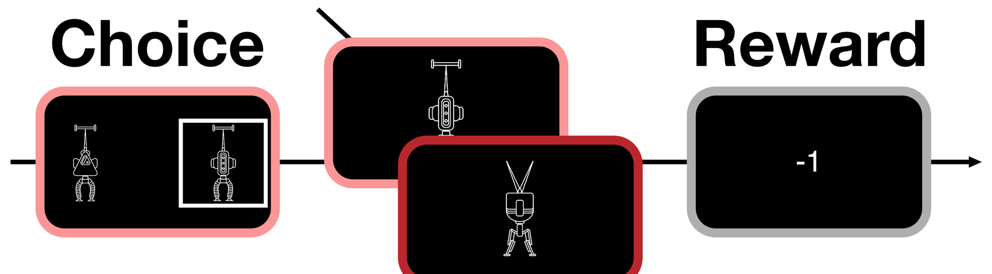
Each category has **6 unique instances** (**1-6**, e.g., spherical body, long body, etc).

training → test → composition

choose reward predictive robots

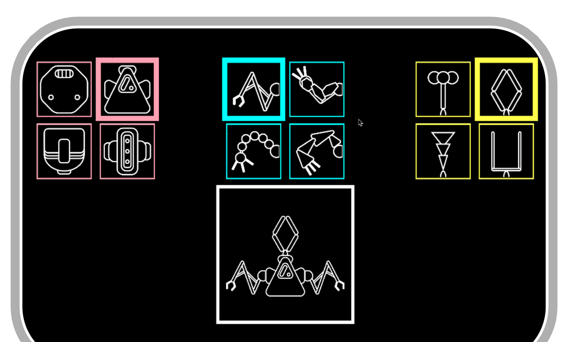
Sequence

Choice **Reward**



TRAINING ONLY

compose reward predictive robots



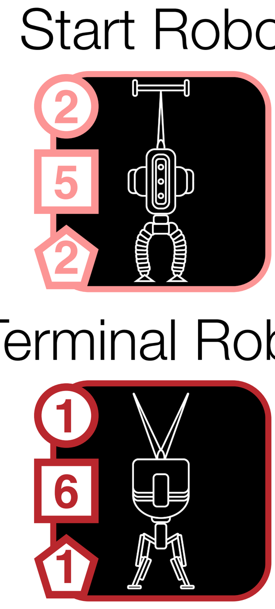
Training sequences determined by feature subsequences

A	1	2	3	4	5	6
B	1	2	3	4	5	6
C	1	2	3	4	5	6

−2 reward → −1 ← +1 reward

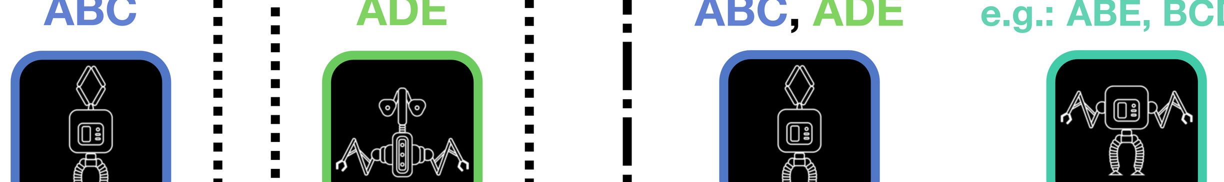
Start Robot

Terminal Robot

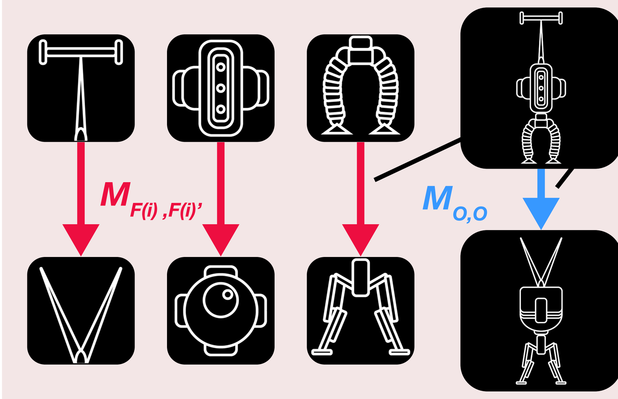


Training **Test & Composition**

Block 1	Block 2	Old	Novel
ABC	ADE	ABC, ADE	e.g.: ABE, BCD...



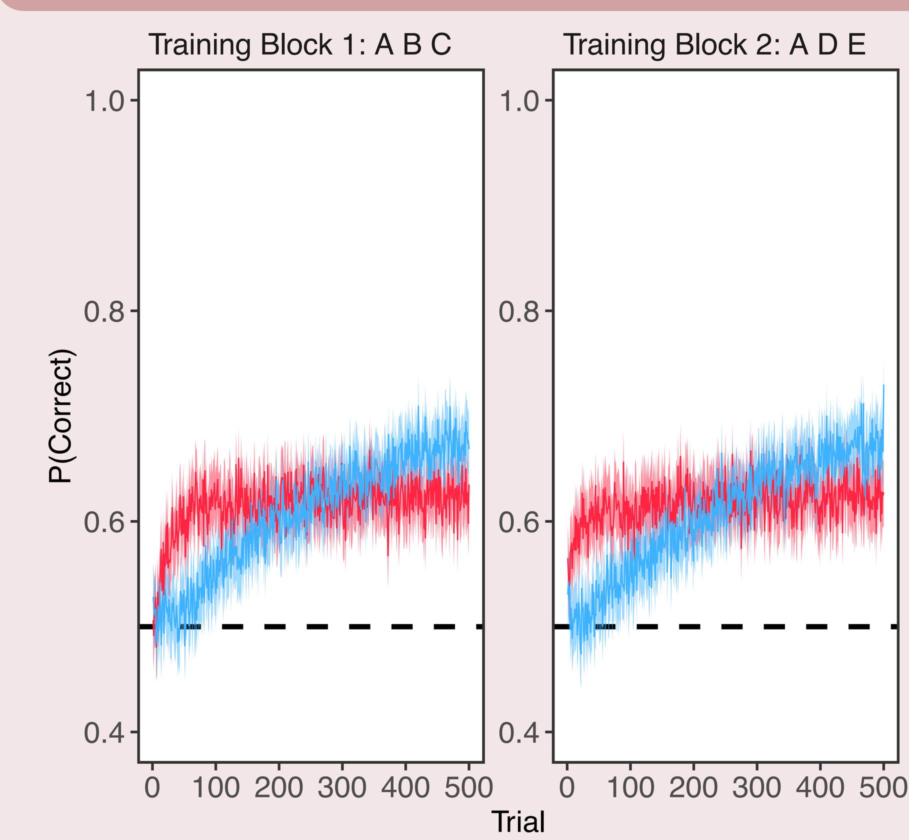
Simulate feature- and state-based successor representation learning[2,3] **(SR) on robot task.**



$$M_s = M_s + \alpha(e_{s'} + \gamma M_{s'} - M_s) \quad \text{(predictive)}$$
$$Q_s = Q_s + \alpha(r - Q_s) \quad \text{(reward)}$$
$$V_s = M_s Q_s \quad \text{(state value)}$$

N = 1000 per model & # training trials

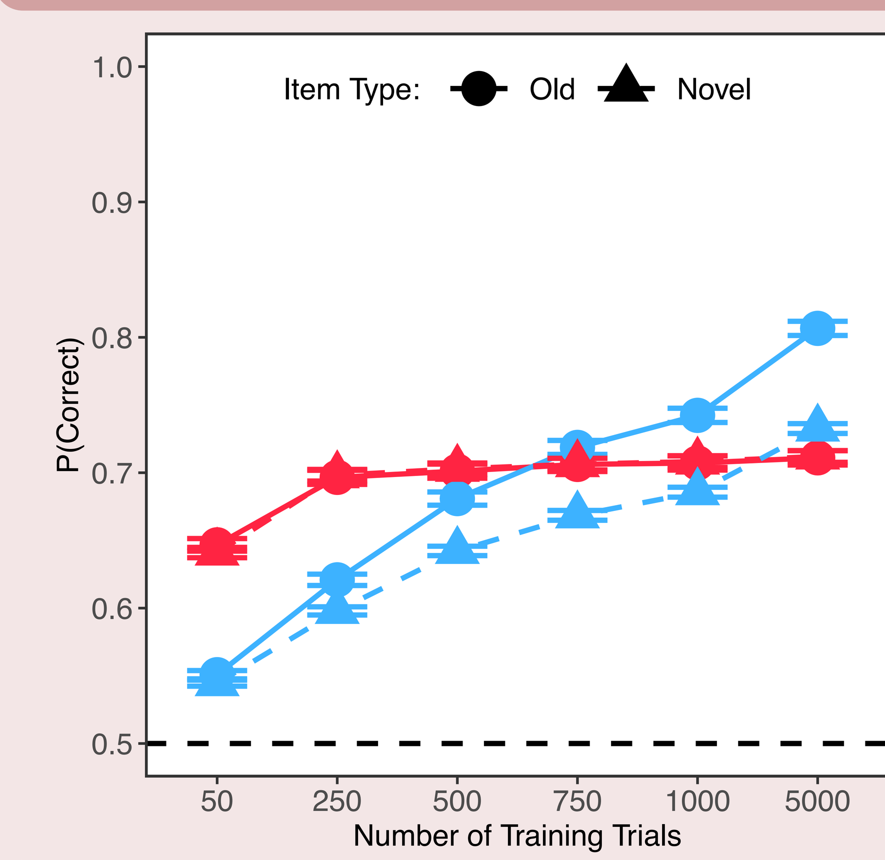
FASTER LEARNING SPEED



State-based has better **TRAINING** performance in the long-run.

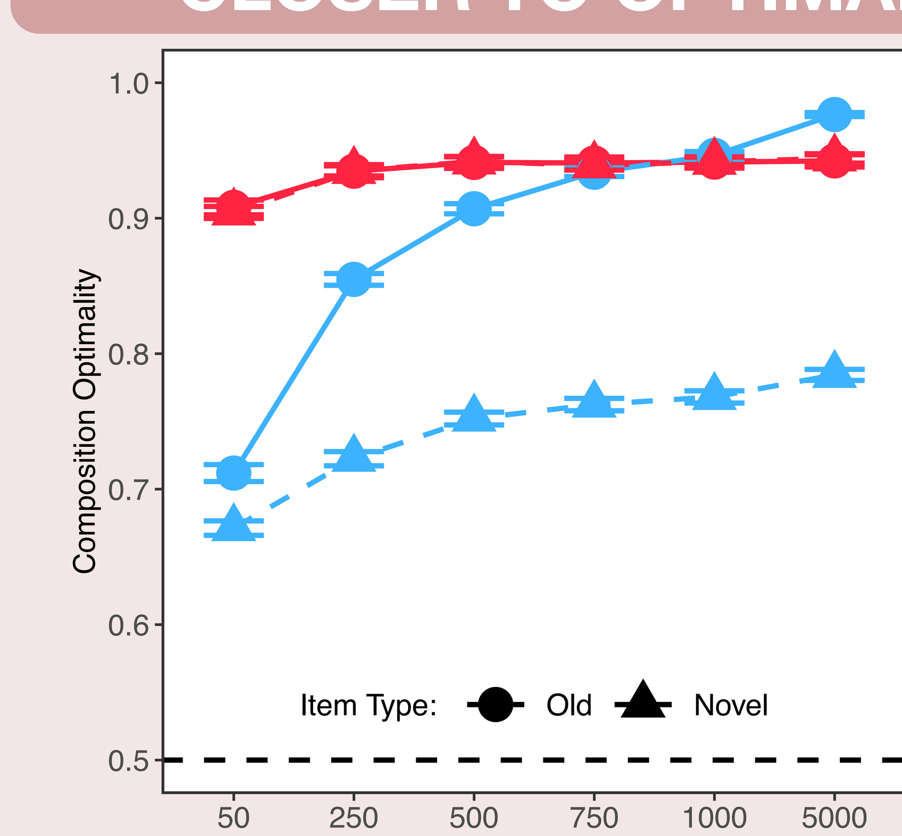
Feature-based increases in **TRAINING** accuracy more quickly.

MORE ACCURATE GENERALIZATION



Feature-based has **no decline in accuracy** when generalizing to novel robots at **TEST**.

CLOSER TO OPTIMAL COMPOSITION



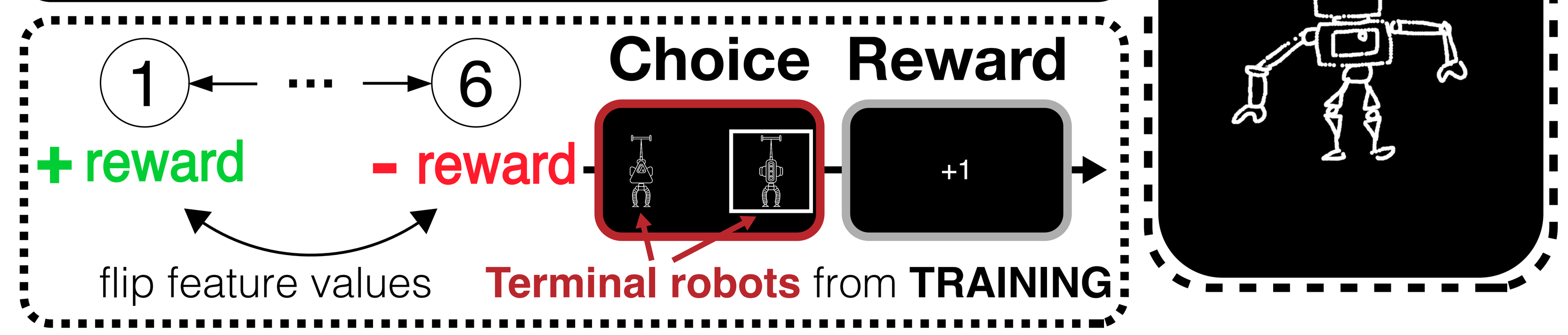
Feature-based outperforms state-based when composing novel robots during **COMPOSITION**.

HUMAN SUBJECTS PILOT (N = 4)

training → reward revaluation → test → drawing → composition

eye-tracking

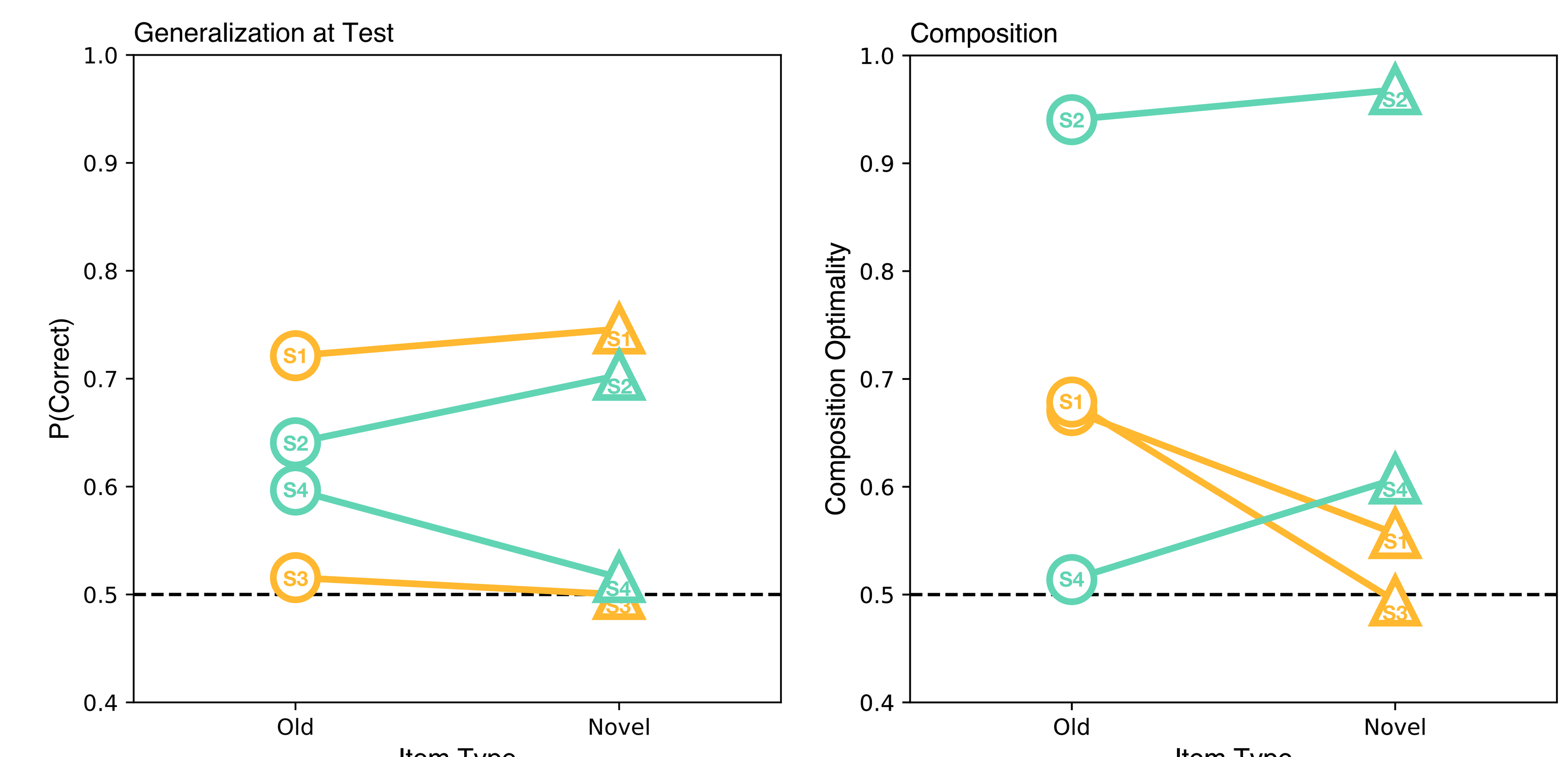
$$M_s = M_s + \omega\alpha(e_{s'} + \gamma M_{s'} - M_s)$$
$$Q_s = Q_s + \omega\alpha(r - Q_s)$$



Between-subjects conditions

Unconstrained Training	Constrained Training
# robots > # robot parts	# robots = # robot parts
Should increase **feature-based**	Should increase **state-based**

Subjects display ranging abilities to learn, generalize, and compose novel items.



each line = one subject

TAKE-HOME MESSAGE

Our simulations suggest that **feature-based learning**...
- May be **particularly useful in novel or volatile environments** where new knowledge must be rapidly acquired and re-used.
- Is **less accurate in the long-run**, so learning on abstract state representations in parallel will give the best of both worlds: generalization to the new and precision about the old.

REFERENCES

1) Farashahi, S., Rowe, K., Aslami, Z., Lee, D., & Soltani, A. (2017). Feature-based learning improves adaptability without compromising precision. Nature Communications, 8(1), 1768.
2) Dayan, P. (1993). Improving Generalisation for Temporal Difference Learning: The Successor Representation. 14.
3) Momennejad, I., Russek, E. M., Cheong, J. H., Botvinick, M. M., Daw, N. D., & Gershman, S. J. (2017). The successor representation in human reinforcement learning. Nature Human Behaviour, 1(9), 680–692.

POSTER LINK