# Habitual control of goal selection

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## Question

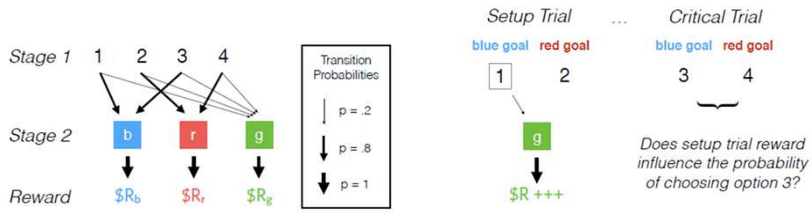
Decomposing tasks into hierarchical goals/subgoals allows for efficient decision making[1], but choosing goals via exhaustive model-based search is often intractable. How do people select goals efficiently?

## Hypothesis

Goal selection can be under model-free control. People will select goals/subgoals previously associated with reward, independent of the underlying causal structure.

## Experiment 1

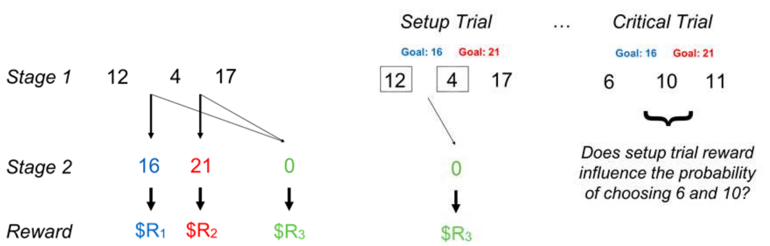
Participants performed a two-stage decision task[2]. On critical trials, they experienced a low-probability transition and received a reward; then, they were given the option of choosing a different action with the same goal. A system of model-free goal selection uniquely predicts an increase in that action.




**Result:** Participants were more likely to select the same-goal action after reward than after punishment.

## Experiment 2

Participants chose numbers which summed to one of two goal numbers. On critical trials, they experienced a low-probability transition and received a reward; then, they were presented with novel numbers. A system of model-free goal selection uniquely predicts an increase in selecting the numbers which sum to the previously selected goal.




**Result:** Participants were more likely to sum to the previously selected goal after reward than after punishment.

## Computational Model

We adopt the options framework[3] to model decision making in Experiment 1. Let $Q_o$ represent the value of choosing option $o$ (either "get blue" or "get red") in Stage 1. We simulate agents which use model-free learning to select an option:

$$Q_o = Q_o + \alpha(Reward - Q_o)$$

but model-based planning to choose primitive actions which complete the option. We simulate agents with or without our mechanism.

**Result:** Our behavioral results only emerge with the inclusion of model-free goal selection.

## Conclusions

**(1)** People exhibit model-free control of goal selection.

**(2)** This mechanism may support efficient goal-directed planning.

## References

1. Botvinick, M., & Weinstein, A. (2014). Model-based hierarchical reinforcement learning and human action control.

2. Gläscher, J., Daw, N., Dayan, P., & O'Doherty, J. P. (2010). States versus rewards: dissociable neural prediction error signals underlying model-based and model-free reinforcement learning.

3. Sutton, R. S., Precup, D., & Singh, S. (1999). Between MDPs and semi-MDPs: A framework for temporal abstraction in reinforcement learning.

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