Model-Based and Model-Free Decision-Making

Neural Modelling 2023

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Outline

- Model-based and model-free control
- Dyna
- Hippocampal replay
- Exploration
- Assignment: part 1
- Assignment: part 2
- Questions

Model-based and model-free control

Model-based control

- Learns a model of the environment
- Performs prospective evaluation (planning)

Pros:

- Reflective; affords behavioural flexibility

Cons:

- Expensive; slow

Model-free control

- Learns and stores expected outcomes associated with each state-action pair

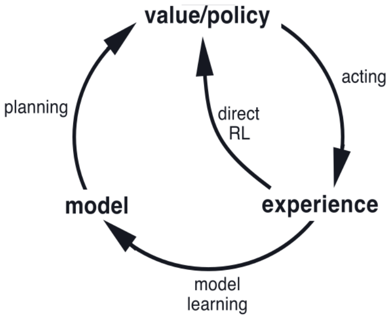
Pros:

- Reflexive; fast
- Computationally cheap

Cons:

- Stubborn; inflexible

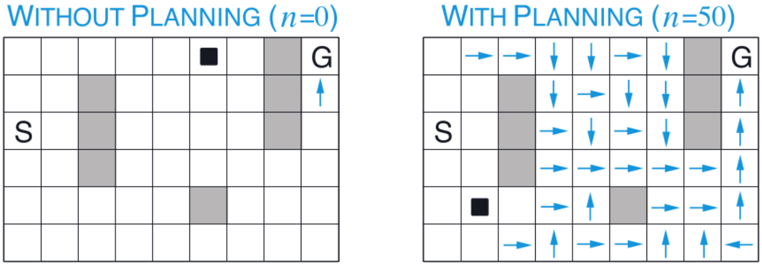
Dyna



Sutton (1990)

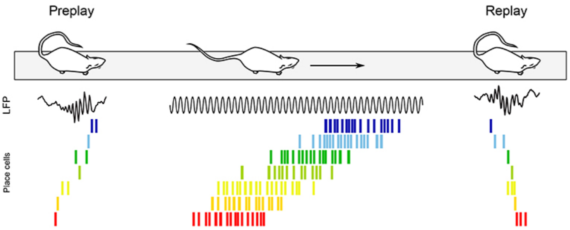
- DYNA is an integrated architecture
- Combines a *reflexive* MF policy and a *reflective* MB system
- MB system is used offline to provide additional training for MF values

Dyna



- Agent discovers online prediction erros (e.g., a goal)
- Model inversion (planning) to additionally train MF values

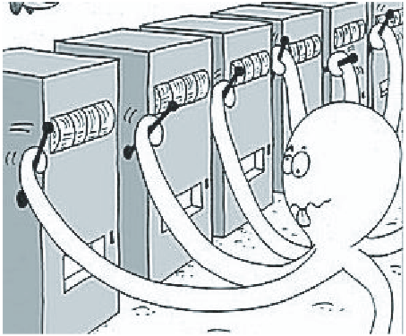
Hippocampal replay



Drieu et al. (2019); Diba et al. (2007)

- Reinstatement of behaviourally-relevant neural activity during periods of quiet wakefullness and sleep [offline periods] (M. A. Wilson et al., 1993)
- The order of the replayed experiences is highly specific
- Forward replay seems to be predictive of the subsequent animal choices (Pfeiffer et al., 2013); reverse replay is highly sensitive to reward (Ambrose et al., 2016)

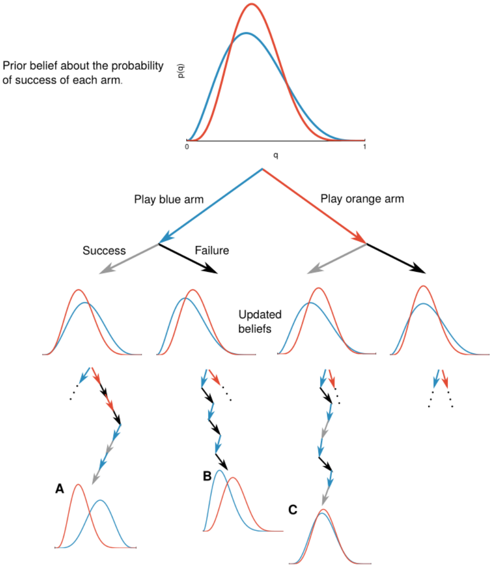
Exploration



Source: link

- Multi-arm bandit is the classic problem for studying the exploration-exploitation tradeoff
- The objective is to maximise discounted expected reward
- Payoff probabilities are unknown
- One of the few problems for which an optimal solution is possible to compute: the Gittins index (Gittins, 1979)
- Some animals explore near-optimally (Krebs et al., 1978)

Exploration



- Optimal exploration amounts to performing optimal control in belief space
- Belief spaces are continuous so forget about tractability in most problems more complex that simple bandits
- Good approximations exist, such as for instance BAMCP (Guez et al., 2012)

Exploration

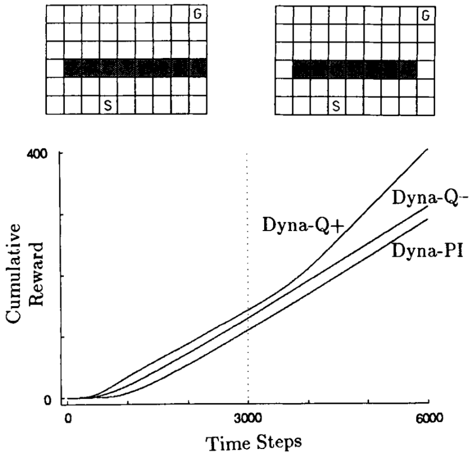
- Undirected
  - ϵ-gredy
  - Softmax (Boltzmann)
- Directed, 'optimism in the face of uncertainty'
  - upper confidence bound (Auer, 2002)

$$a = \arg\max_a \left[Q_t(s,a) + c\sqrt{\frac{\log N(s)}{N(s,a)}} \right]$$

Exploration bonus

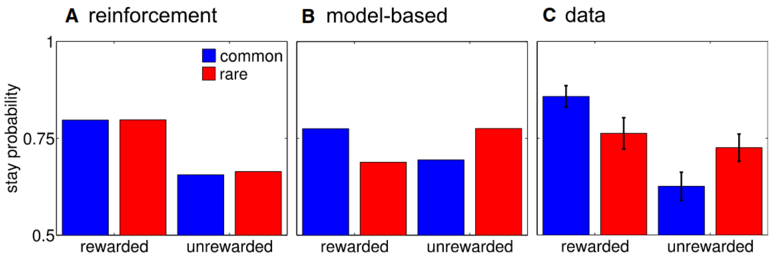
Sometimes humans' and other animals' exploration is random (undirected) (Daw, O'Doherty, et al., 2006), sometimes directed (R. C. Wilson et al., 2021)

Assignment: part 1



- One of the original intensions of Dyna was to improve exploration efficiency
- By incorporating an exploration bonus into the planning updates, uncertainty can propagate to distal states and therefore encourage exploration
- Your task is to reproduce this figure; focus only on Dyna-$Q+$ and Dyna-Q-

Assignment: part 2



- The iconic RL task (Daw, Gershman, et al., 2011) to probe the relative contributions of MB and MF control to subjects' choices
- In this part of the assignment, your task is to reproduce the above figure

Questions?

- You will find the assignment and all the necessary details in my github repository:

  https://github.com/geoant1/GTC_Neural_Modelling_Tutorial

- For part 1 the code is already written for you; the task is to fill in the missing implementation
- For part 2 you have to write most of the code yourself