Reinforcement Learning for Production-based Cognitive Models

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Decision making

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- How do we learn to make decisions in situations with recurring choices?

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  What should I choose first?
  What sequence of actions should I choose?
- In parsing, what interpretation should I pursue?

Parsing and decision making

The horse raced past the barn fell. $\rightsquigarrow$ Main Clause Int.

$\rightsquigarrow$ Reduced Rel. Int.

Production-system frameworks and decision making

- Production systems in cognitive sciences and psychology (Newell, 1973)
- Productions: conditionalized actions
  (actions that fire only if particular conditions are met)
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Can the agent acquire such production systems?

- Can the agent learn which decisions to make under which conditions?

  Fu and Anderson (2006), Sutton and Barto (2018, Ch. 14)

Acquisition of production systems

Can the agent acquire such production systems?

Our contribution: show how Reinforcement Learning (RL, Sutton and Barto 2018) methods can be combined with a production system (ACT-R) to learn sequential-choice behavior.

Explore two RL algorithms: tabular Q-learning and Deep Q-networks.

Road map

Learning goal-conditioned rules in lexical decision

Focus on a simple task: lexical decision (LD)

- participants see a string of letters on a screen
- if they think the string is a word, they press one key (`J`)
- if they think the string is not a word, they press a different key (`F`)
- after pressing the key, the next stimulus is presented

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- The model for LD tasks is simple, so good starting point
- But it is a component of more complex syntactic and semantic parsing models, so it is relevant when we scale up
- Not our focus:
  - fleshing out the model to capture major exp. results about LD
    (cf. Brasoveanu and Dotlačil 2020)
  - comparing it to previously proposed cognitive models of LD

Three LD tasks

We model three LD tasks of increasing length, hence difficulty:

- 1 stimulus: a word (elephant)
- 2 stimuli: a word (elephant) and a non-word
- 4 stimuli: a word (elephant), a non-word, another word (dog) and another non-word

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The model components are split between:

- declarative memory: stores the lexical knowledge of an English speaker
- procedural memory: stores production rules that enable the model to carry out the LD task

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Rule ordering and rule learning

The sequences of rule firings for the learned LD tasks:

- 1-stim: Rules [1 – 2] – 4
- 2-stim: Rules [1 – 2] – [1 – 3] – 4
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We let the Q-learning agent learn to successfully carry out these LD tasks. The agent gets a reward of:

1 if it reaches the final goal-state `done`

-0.15 for any intermediate rule firing, to encourage it to finish the task asap

0 (no penalty) if it chooses to wait and fire no rule

Preview of task and results

- The agent learns by trial and error how to properly order the rules and complete the LD tasks as efficiently as possible

- The actual number of steps, i.e., decision points, when the agent needs to select an action, is larger than the high-level sequences of rule firings discussed above

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- The actual number of steps, i.e., decision points, when the agent needs to select an action, is larger than the high-level sequences of rule firings discussed above

  - 1-stimulus task: 12 steps where the agent needs to decide whether to wait or to fire a specific rule

  - 2-stimuli task: 18 steps if task completed perfectly

  - 4-stimuli task: 34 steps if task completed perfectly

Preview of task and results (ctd.)

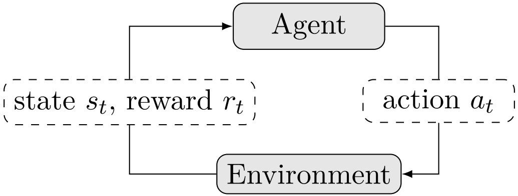
Why so many steps per task?

- Several points where agent should wait (retrieval, waiting for key press to complete, while encoding visual information)

The higher the number of steps, the harder the task is to learn:

- learning is faster and less noisy for shorter tasks (fewer stimuli)
- but the RL agents learn even the most complex 4-stimuli task fairly well (at least the tabular Q agent) ...
- ...they just 'learn' a lot of noise (incorrect rules) in the process also, particularly the neural-network agents

Markov Decision Processes (MDPs)



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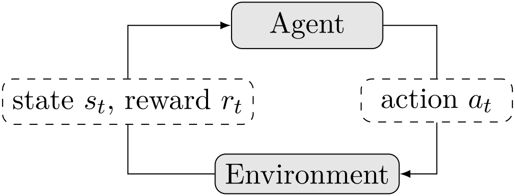

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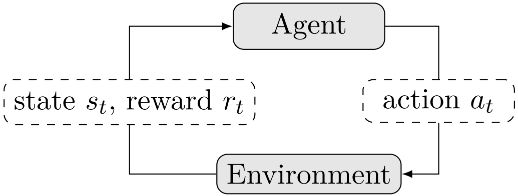

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- At every time step t: current state s_t provides all info relevant for the current action selection (Markov property)
- Environment passes to agent state s_t and reward signal r_t
- Agent observes s_t and r_t, and takes action a_t, which is passed from agent to environment; cycle continues at time step $t+1$

Markov Decision Processes (MDPs, ctd.)

- Agent's policy: complete specification of what action to take at any time step
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- Agent's goal: maximize cumulative reward over LD task
- Learning: agent learns (solves/optimizes the MDP) by updating its policy π to maximize cumulative reward

Discounted return and state-action values

The discounted return G at a time step $t < n$

$$G_t = r_{t+1} + \gamma r_{t+2} + \gamma^2 r_{t+3} \cdots + \gamma^{n-t-1} r_n$$

- sum of current reward and discounted future rewards until the final step n
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The (state-)action value function $Q_\pi(s, a)$

Q function provides expected discounted return when:

- starting in state s,
- performing action a,
- following the policy π until the end of the episode.

Tabular Q-learning

Estimating the Q function is one way to find an optimal policy

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- Q estimated based on experience (interactions between agent and environment)
- tabular Q learning: Q function $S \times A \to \mathbb{R}$ represented as look-up table storing estimated values of all state-action pairs
  - Q table initialized to 0
- at each time step t: update entry for (s_t, a_t) based on info agent gets from environment at next step
  - reward r_{t+1}
  - new state s_{t+1} (its value estimated from current Q table)

Q-learning for production selection

In our ACT-R model of LD tasks:

- agent: Q-value table guiding rule selection at every cognitive step

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In our ACT-R model of LD tasks:

- agent: Q-value table guiding rule selection at every cognitive step
- environment: cognitive state of ACT-R model/mind
- action space:
  - the 4 rules `retrieving`, `lexeme retrieved`, `no lexeme found` and `finished`
  - a special action `None`: the agent selects it when it prefers to wait for a new state

Reward structure

Rewards encourage the agent to finish the task asap & select fewest rules in the process:

- positive reward 1 when LD task is completed
- negative reward -0.15 for every rule other than `None`
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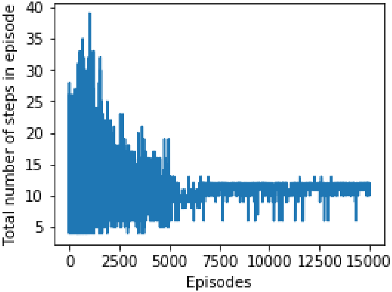
- at every step, negative temporal reward: time elapsed between immediately preceding and current step
  - negative temporal reward discourages agent from repeatedly selecting an action (`None`) and timing out task in small number of steps

One-stimulus task

- we simulate 15,000 episodes (LD tasks consisting of 1 stim only – the word ‘elephant’)



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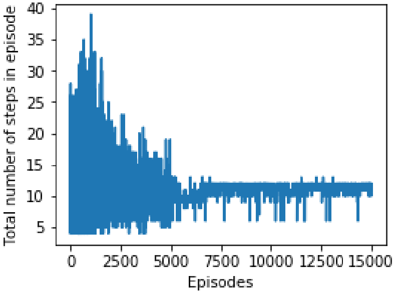

- agent learns to complete task perfectly in 12 steps after 5,000 episodes
- fewer steps when agent times out task, e.g., repeatedly selects action `None`

One-stimulus task: final Q-table

- Look only at states for which at least one rule has non-0 value – a total of 8 states
- For each state, identify rule with highest value

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- Last 2 state-action pairs:
  - correctly start the retrieval process as soon as the text is read off the virtual screen
  - correctly press the `J` key when retrieval is successful

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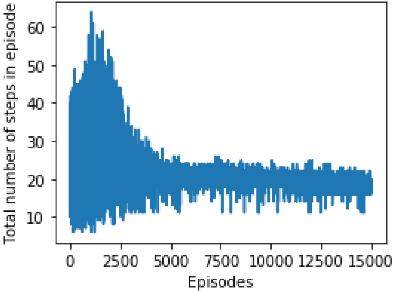
Thus: no need to hand-code goal states in rule preconditions.
(at least for tabular Q in this very simple task)

Two-stimuli task: final Q-table

- 15,000 episodes, task completed perfectly (18 steps) after 9,000 episodes



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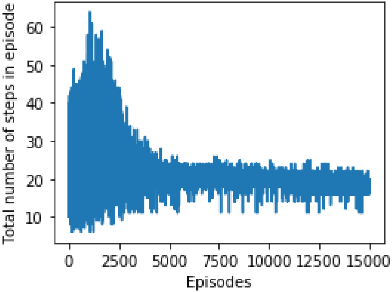

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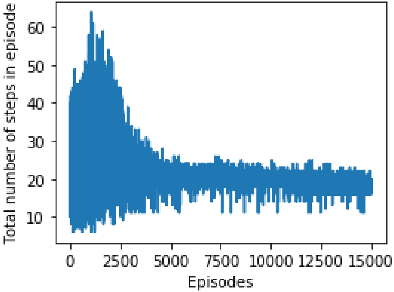

- Final Q-table: 13 states with non-0-value rules
- 4 states where the agent does nothing
  - waiting for retrieval process to complete
  - waiting for text to be read off the virtual screen

Two-stimuli task: final Q-table (ctd.)

- 4 states where agent fires `finished` correctly because text on the virtual screen is FINISHED

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- 4 states where agent fires `finished` correctly because text on the virtual screen is FINISHED
- 4 state-action pairs are exactly what we expect:
  - trigger `retrieving` as soon as text is read off virtual screen
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  - trigger `retrieving` as soon as text is read off virtual screen
  - trigger `lexeme retrieved` when retrieval process successful
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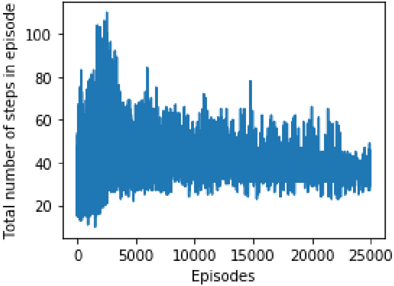
- 1 state-action pair that reflects trial-and-error learning process
  - state: previous stimulus not fully processed, but new stimulus already read off virtual screen
  - action: agent attempts to retrieve

Four-stimuli task: final Q-table

- 25,000 episodes, task completed fairly well after 22,000 episodes



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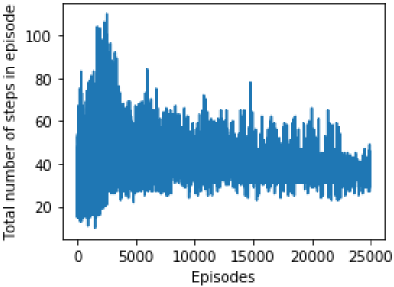

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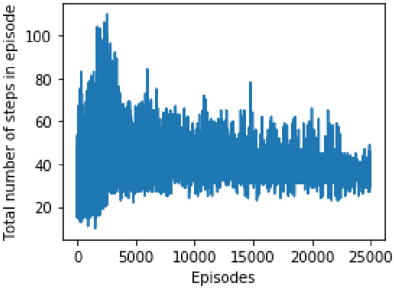

- Even after 25,000 episodes, agent still tries incorrect rules, waits for no good reason
- Final Q-table: 24 states with at least one non-0-value action
  - 18 are exactly what we expect
  - 6 reflect the noise in the trial-and-error learning process

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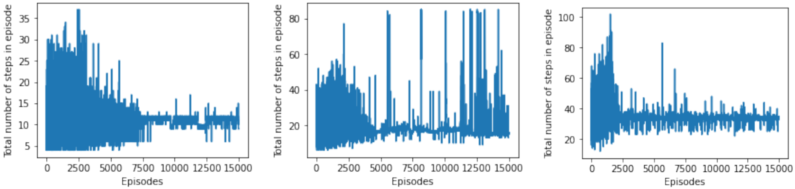
DQN: 1-stim | DQN: 2-stim | DQN: 4-stim



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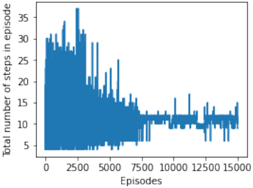
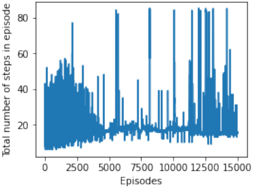


DQN: 2-stim



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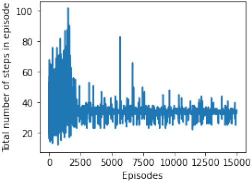

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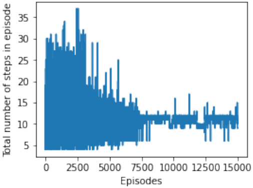

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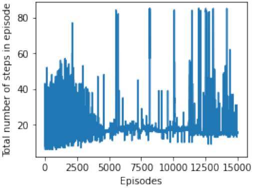

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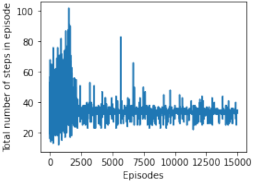

- DQN generalizes much more aggressively, which might be why it is good at the more difficult 4-stim task
- but even for 4-stim, it only partially learns when to trigger rules, and learns a lot more noise (incorrect rules) than tabular Q

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- what specifically in the human cognitive architecture enables us to learn from much fewer interactions?
- there are other RL algorithms, e.g., (Expected) Sarsa, policy-based approaches etc.; how do these algorithms perform on LD tasks?

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- the learnability problem for production-based cognitive models can be systematically formulated and computationally addressed as an RL problem

But this is merely a first inroad into a rich nexus of issues:

- what specifically in the human cognitive architecture enables us to learn from much fewer interactions?
- there are other RL algorithms, e.g., (Expected) Sarsa, policy-based approaches etc.; how do these algorithms perform on LD tasks?
- how do all these different RL algorithms perform on a variety of production-based cognitive models?

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