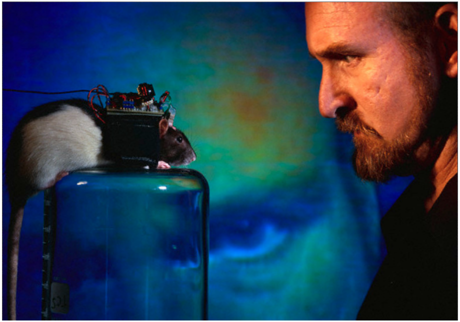
CS325 Artificial Intelligence
Ch. 21 – Reinforcement Learning

Cengiz Günay, Emory Univ.

Spring 2013

Rats!



Fundooprofessor

- Rat put in a cage with lever.
- Each lever press sends a signal to rat's brain, to the **reward center**.

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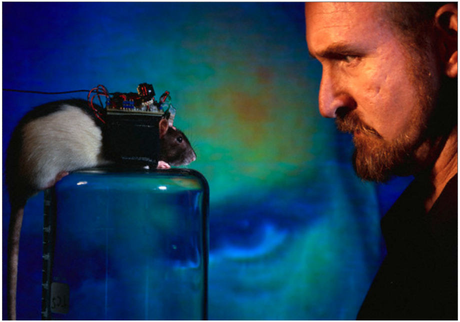

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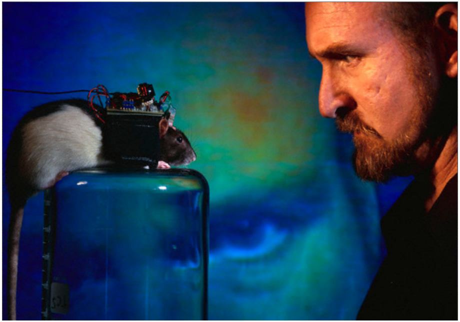

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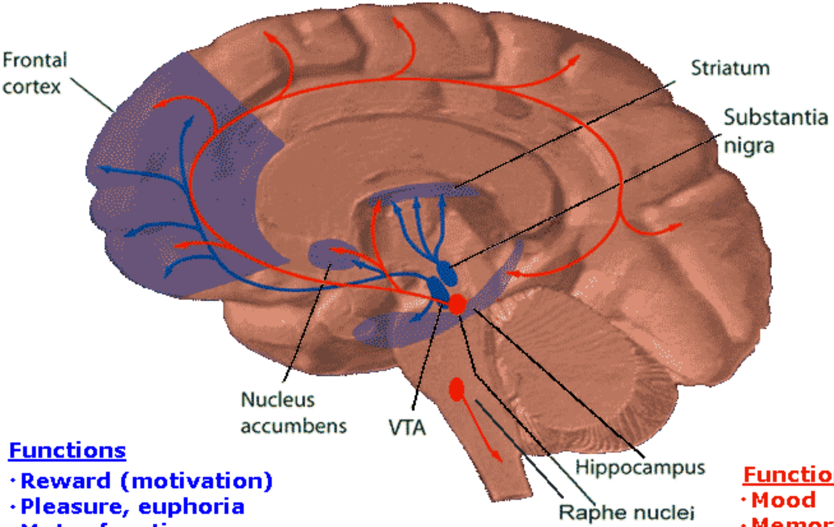
- Rat put in a cage with lever.
- Each lever press sends a signal to rat's brain, to the **reward center**.
- Rat presses lever continously until . . . it dies because it stops eating and drinking.

Dopamine Pathways

Serotonin Pathways



Functions
- Reward (motivation)
- Pleasure, euphoria
- Motor function (fine tuning)
- Compulsion
- Perseveration

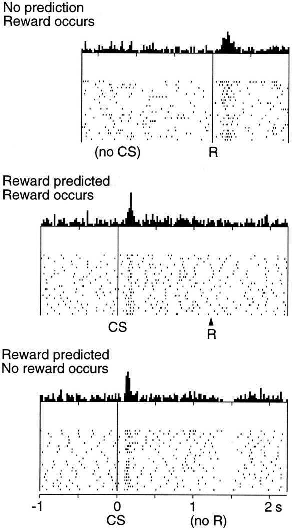
Functions
- Mood
- Memory processing
- Sleep
- Cognition

Wikipedia.org

Dopamine Neurons Respond to Novelty

sciencemuseum.org.uk

Schultz et al. (1997)



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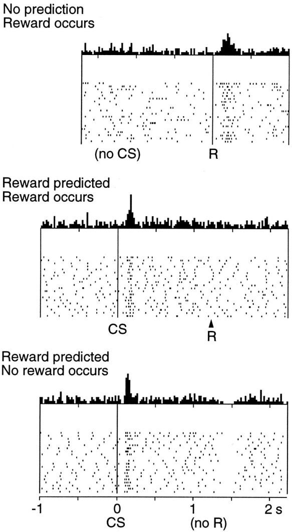
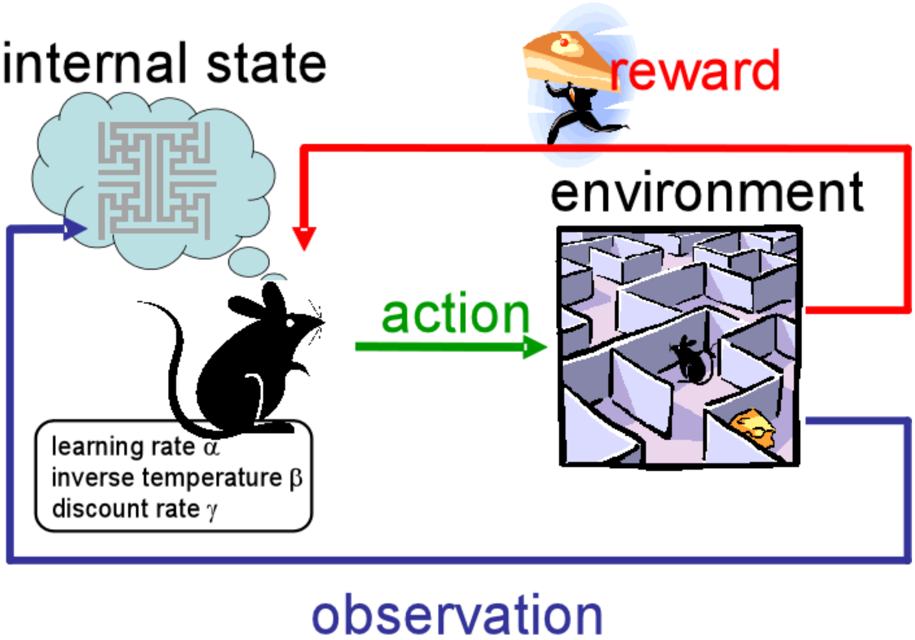
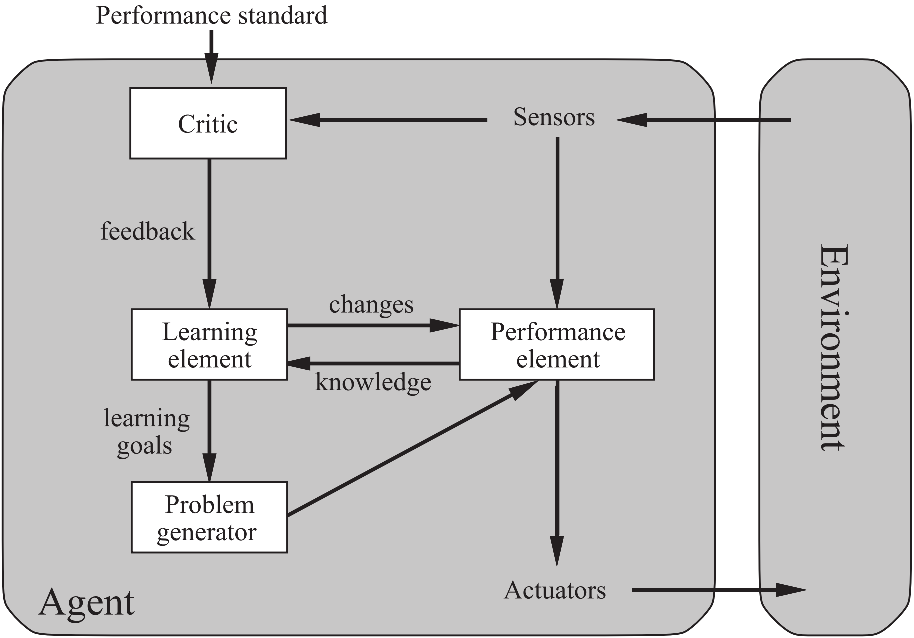


It turns out:
Novelty detection = **Temporal Difference** rule in Reinforcement Learning
(Sutton and Barto, 1981)


internal state
reward
environment
action
learning rate α
inverse temperature β
discount rate γ
observation


Performance standard
Critic
Sensors
feedback
changes
Learning element
Performance element
knowledge
learning goals
Problem generator
Actuators
Agent
Environment

Entry/Exit Surveys

Exit survey: Planning Under Uncertainty

- Why can't we use a regular MDP for partially-observable situations?
- Give an example where you think MDPs would help you solve a problem in your daily life.

Entry survey: Reinforcement Learning (0.25 points of final grade)

- In a partially-observable scenario, can reinforcement be used to learn MDP rewards?
- How can we improve MDP by using the plan-execute cycle?

Blindfolded MDPs: Enter Reinforcement Learning

	1	2	3	4
a				G
b				
c	S			

What if the agent does not know anything about:

- where walls are
- where goals/penalties are

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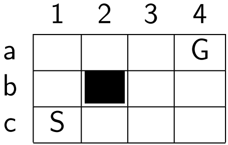

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Can we use the plan-execute cycle?

- Explore first
- Update world state based on reward/reinforcement

⇒ **Reinforcement Learning** (see Scholarpedia article)

Where Does Reinforcement Learning Fit?

Machine learning so far:

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Unsupervised learning: find regularities in input data, x

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Which is it?

S	U	R	
			Speech recognition: connect sounds to transcripts
			Star data: find groupings from spectral emissions
			Rat presses lever: gets reward based on certain conditions
			Elevator controller: multiple elevators, minimize wait time

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But, Wasn't That What Markov Decision Processes Were?

- Find optimal policy to maximize reward:

$$\pi(s) = \arg\max_{\pi} E\left[\sum_{t=0}^{\infty} \gamma^t R(s, \pi(s), s')\right],$$

with reward at state: $R(s)$, or from action, $R(s, a, s')$.

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- **Assumes we know $R(s)$ and $P(s'|s, a)$**

Blindfolded Agent Must Learn From Rewards

Don't know $R(s)$ or $P(s'|s, a)$. What to do?

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Agent types:

	knows	learns	uses
Utility agent	P	$R \to U$	U
Q-learning (RL)		$Q(s, a)$	Q
Reflex		$\pi(s)$	

Video: Backgammon and Choppers

How Much to Learn?

1. Passive RL: Simple Case
   - Keep policy $\pi(s)$ fixed, learn others
   - Always do same actions, and learn utilities
   - Examples:
     - public transit commute
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    - Keep policy $\pi(s)$ fixed, learn others
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    - Examples:
        - public transit commute
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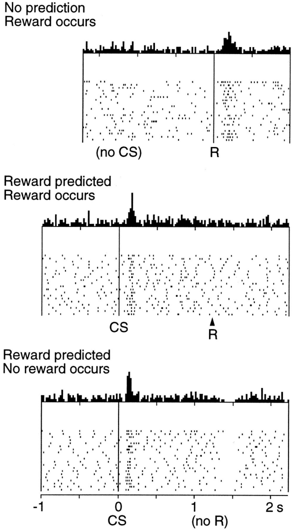
2. Active RL
    - Learn policy at the same time
    - Help explore better by changing policy
    - Example: drive own car

RL in Practise: Temporal Difference (TD) Rule

Animals use derivative:



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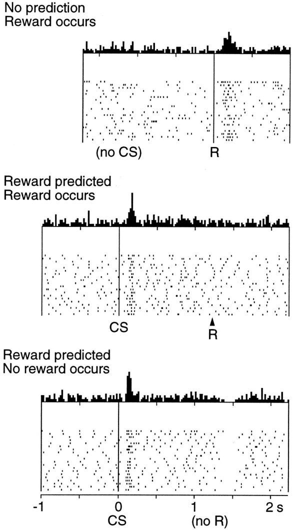

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TD rule:

Use derivative when going $s \to s'$:

$$V(s) \leftarrow V(s) + \alpha \left(R(s) + \gamma V(s') - V(s) \right)$$

where:

- α is the **learning rate**, and
- γ is the discount factor.

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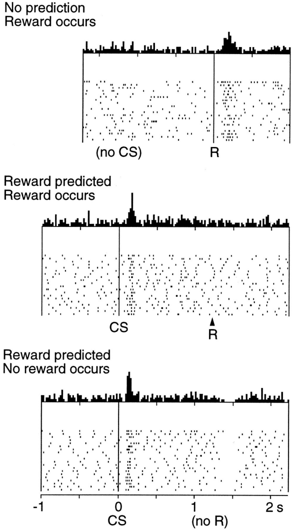

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It's even simpler than before!

Passive RL: Simple Case

	1	2	3	4
a				$+1$
b		■		-1
c	S			

- Keep same policy
- That is, follow same path and update values, $V(s)$

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$$\alpha = \frac{1}{N(s) + 1}$$

like in **simulated annealing**.

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Passive RL: Simple Case (2)

	1	2	3	4
a	$\rightarrow$	$\rightarrow$	$\rightarrow$	$+1$
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$$
\begin{aligned}
V(s) &\leftarrow V(s) + \Delta \\
\Delta &= \frac{1}{N(s)+1}\left(R(s) + \gamma V(s') - V(s)\right)
\end{aligned}
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For simplicity, $\gamma = 1$.

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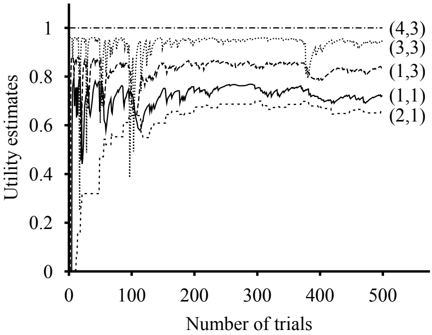
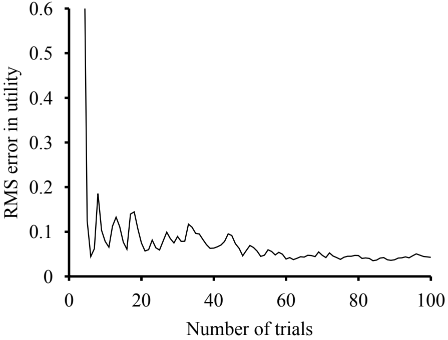
- Convergence time?

Passive RL: Problems?





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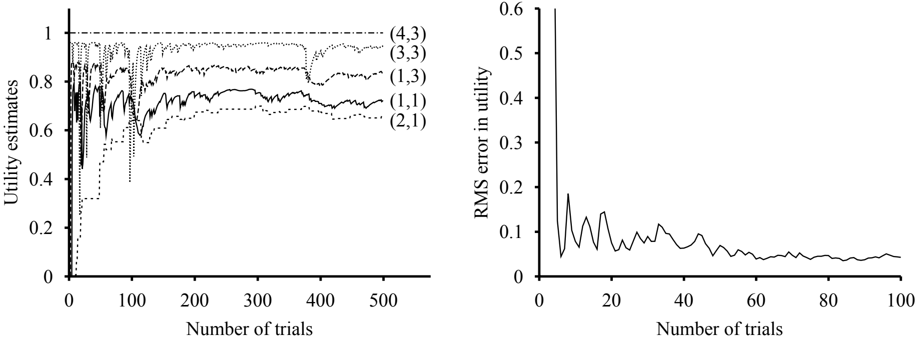

- Limited by constant policy?
- Fewer visited states cause poor estimate?

Active RL: Example

- Greedy algorithm
- After updating $V(s)$ and $N(s)$, **recalculate policy $\pi(s)$**

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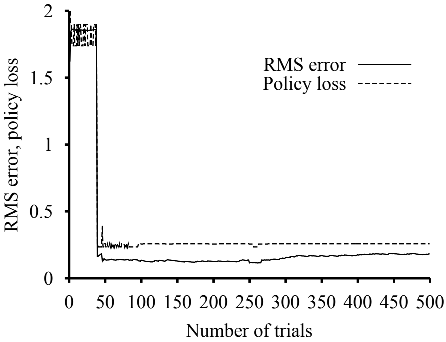

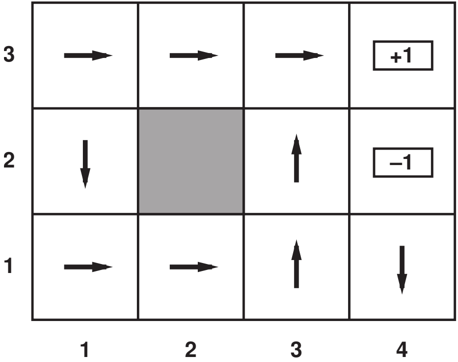

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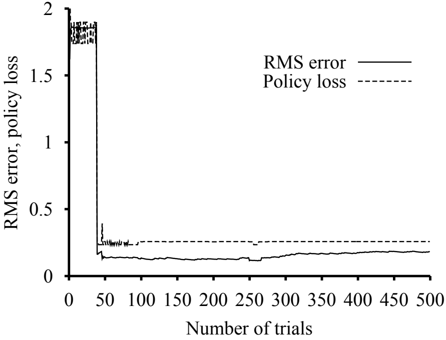

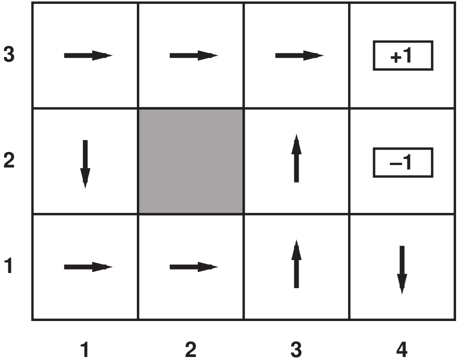

- Greedy algorithm cannot find optimal policy $\Rightarrow$ needs more exploration

How to Improve Active RL?

Source of errors:

Reason for error:	sampling	policy
V too low		
V too high		
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Exploration vs. Exploitation:

- We can't do without it
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Exploration vs. Exploitation:

- We can't do without it
- We can't live with too much of it

Exploration:

- Minimize it, use random moves?

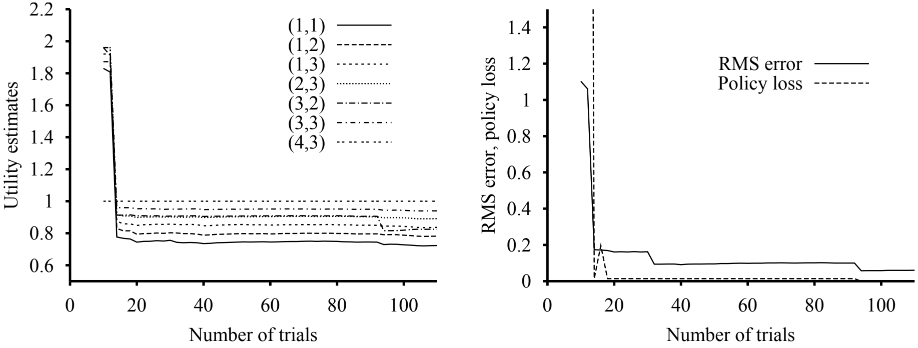
Exploring Agent

	1	2	3	4
a	+1	+1	+1	+1
b	+1		+1	+1
c	S	+1	+1	+1

- Initialize all $V(s) = +R$ (e.g., +1)
- Until $N(s)$>e; exploration threshold
- Then use $V(s)$

- Wait until built confidence

Exploring Agent Does Much Better



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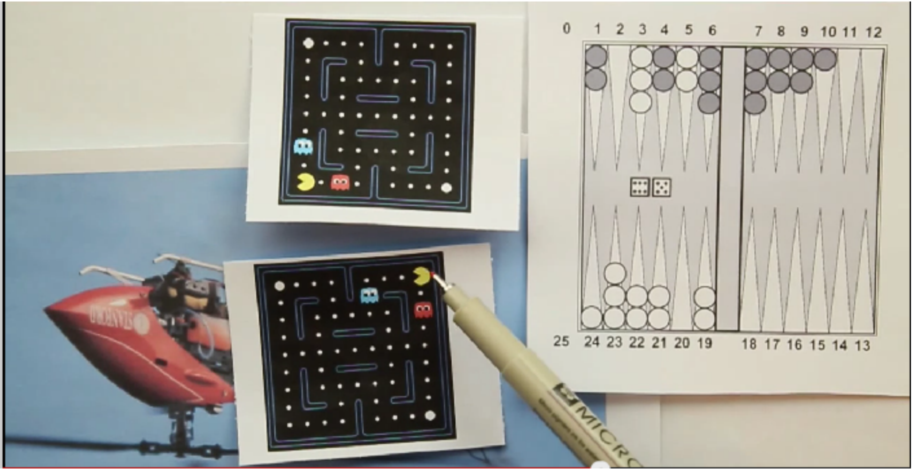
- State of the art, but also has problems with dimensionality

Q-Learning in Real World Problems



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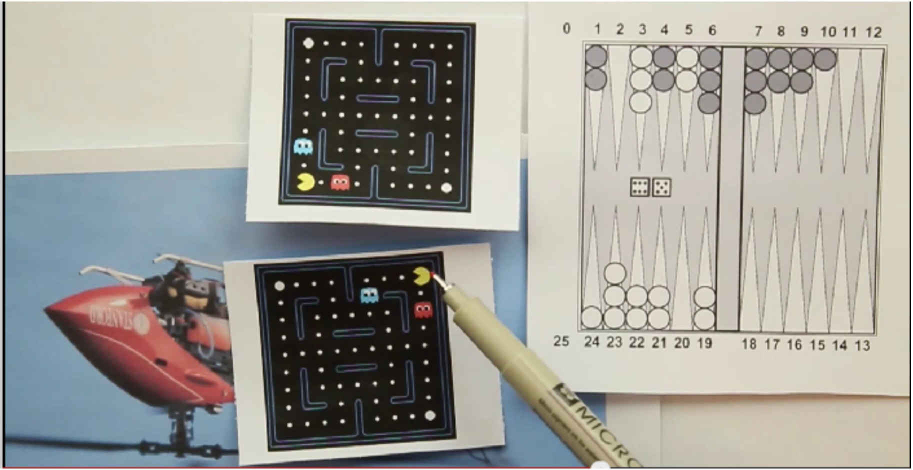

- Translate problem space to feature space: $s = [f_1, \ldots, f_m]$