reinforcement learning

1

pavlov's dog

nervous system ←  → digestion

2

robot flipping pancakes

3

http://cs.stanford.edu/groups/littledog/

4

another example

- a child learning to walk:
  - tries out many different strategies
  - some do not work (**falling**), some seem to work (**staying up longer and longer**)
  - the **ones that do not work are discarded**
  - the **ones that work are tried again and again** until perfected or replaced by better strategies

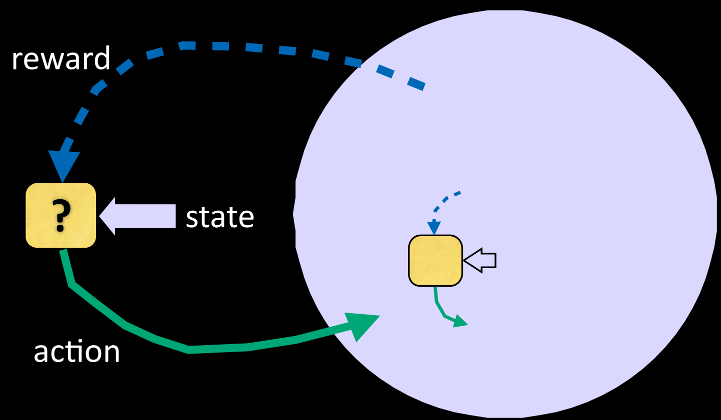
5

hovering... inverted!

Inverted autonomous helicopter flight via reinforcement learning, Andrew Y. Ng, Adam Coates, Mark Diel, Varun Ganapathi, Jamie Schulte, Ben Tse, Eric Berger and Eric Liang. In *International Symposium on Experimental Robotics*, 2004.
URL: http://heli.stanford.edu/

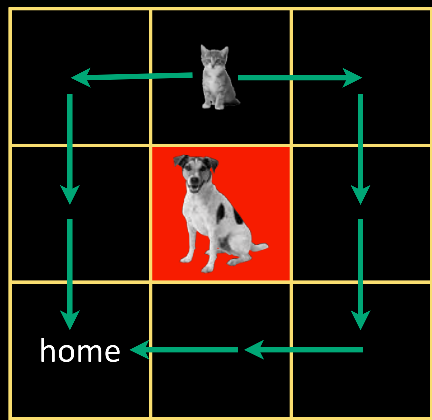
6

the problem



7

toy problem



8

state and action spaces

- size of these spaces can be quite large
- specifying the spaces is crucial in designing a good learning agent

5 integer values between 1 and 100: {22,44,12,67,9}

size of state space = 100 x 100 x 100 x 100 x 100

can quantise state space differently

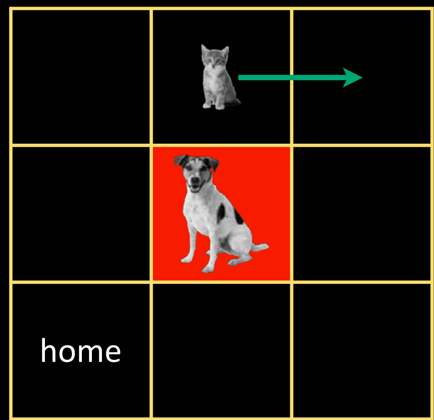
5 values belonging to 2 classes: {1, 2, 1, 2, 1}

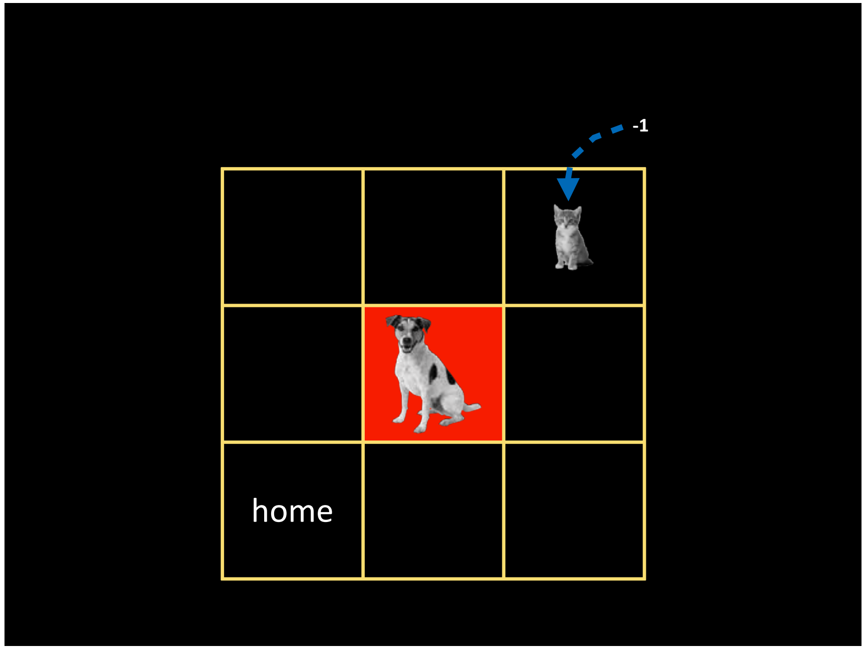
size of state space = 2 x 2 x 2 x 2 x 2

in the toy problem? 9

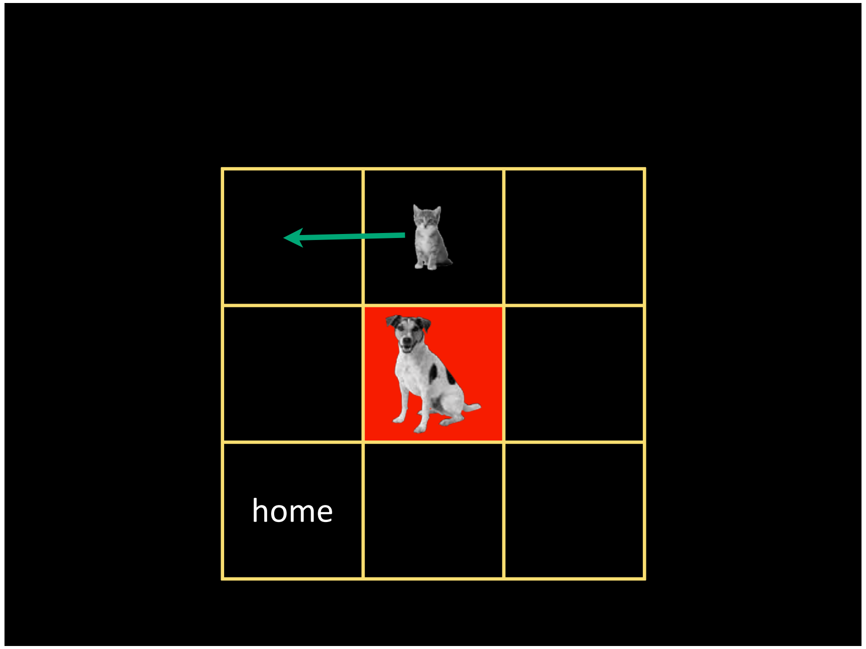
reward

taking an action in some state results in an **immediate reward** (can be negative)

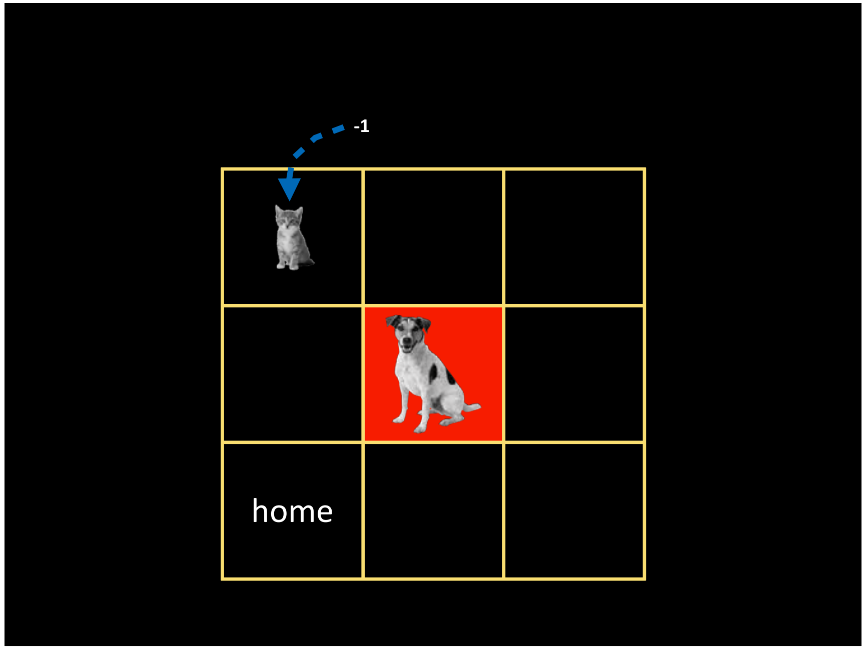



-1
home

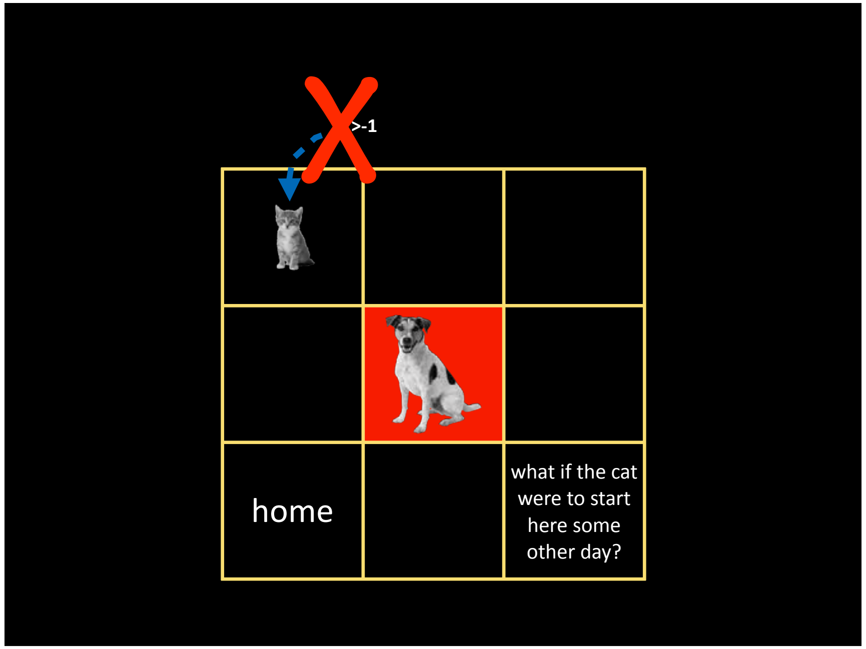
13


home

14


-1
home

15


>-1
home
what if the cat
were to start
here some
other day?

16

reward system should tell the agent:

what to achieve

rather than how to achieve

17

reward?

but agent has to choose an action based on **expected "long term" reward** (cumulative reward in the long run)

18

expected "long term" reward (cumulative reward in the long run)

?

19

task

episodic
(there is an **end**)

continual
(there is no **end**)

20

episodic

(there is an **end**)

agent taking **finite (say 5) steps** till the end...

should act based on the
average of the following

$$R_0 = r_1 + r_2 + r_3 + r_4 + r_5$$

continual

(there is no **end**)

agent can continue acting for **infinite steps in time...**

should **discount** future rewards and act based on the **average of the following**

$$R_0 = r_1 + \gamma r_2 + \gamma^2 r_3 + \gamma^3 r_4 + \gamma^4 r_5 + \ldots$$

discount

future reward is probably **more uncertain** than **immediate reward**

shortsighted?
ϒ=0

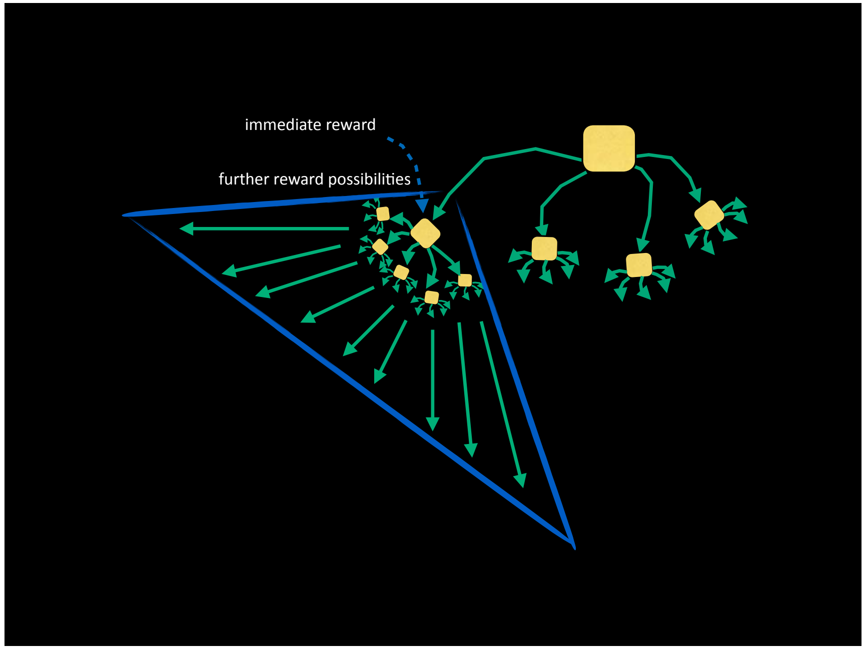
$0 \leq \gamma \leq 1$

farsighted?
ϒ=1

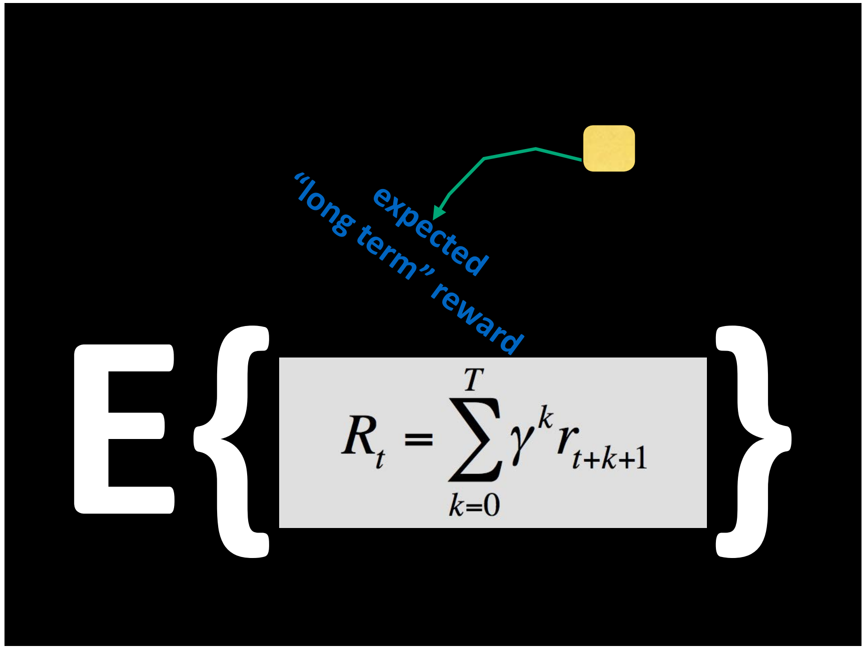
$$R_0 = r_1 + \gamma r_2 + \gamma^2 r_3 + \gamma^3 r_4 + \gamma^4 r_5 + \ldots$$

$$R_0 = \sum_{k=0}^{T} \gamma^k r_{k+1}$$

$$\mathbf{E}\left\{ R_t = \sum_{k=0}^{T} \gamma^k r_{t+k+1} \right\}$$



25



$$E\left\{ R_t = \sum_{k=0}^{T} \gamma^k r_{t+k+1} \right\}$$

26

but these expected rewards are

not known to agent

beforehand!

27

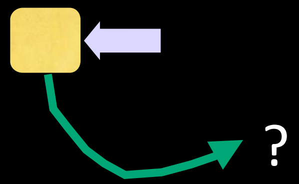
whether they are known or not, the agent has to act somehow!

how to act/action selection?

how to get to know/estimate?

28

action selection?



values of each possible action
in the current state?

expected reward for
carrying out the action is its **value**

but **what are these values?**

<<expected rewards are not known>>
<<actions based on expected rewards>>

these expected rewards **$E\{R_t\}$** are to be
estimated by agent
whilst acting!

Q

	a	b	c
1	2	0	1
2	3	0	-1
3	-5	6	2
4	2	3	1
.	.	.	.
.	.	.	.
.	.	.	.
n	7	8	7

agent maintains **values**
for actions within each state

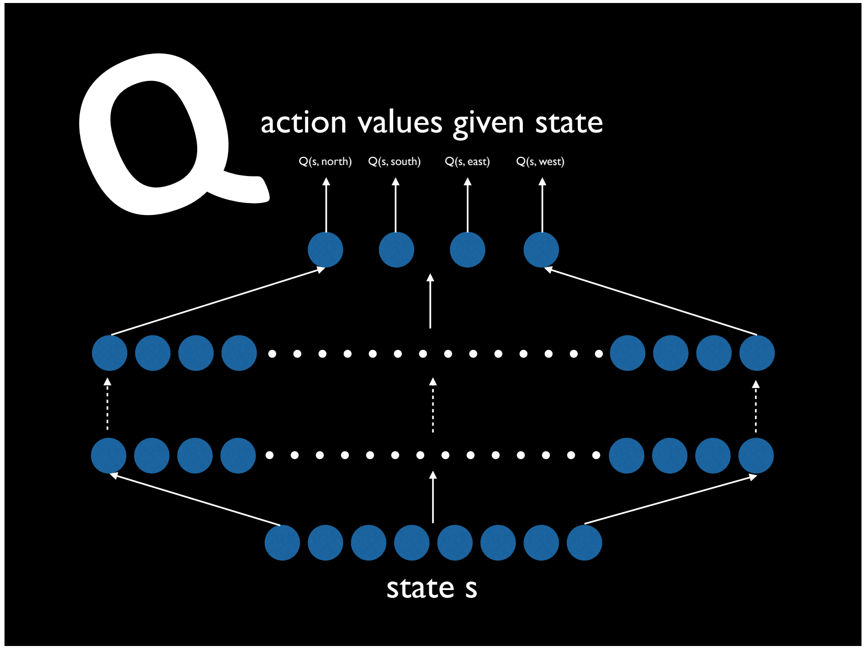
selects actions using these values based on a
“policy”

V

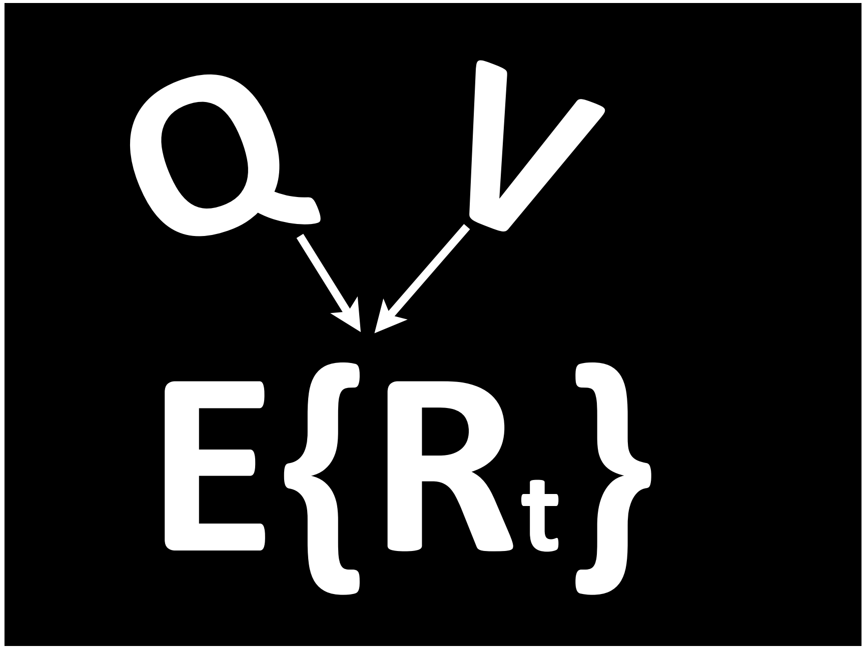
1	2
2	3
3	-5
4	2
.	.
.	.
.	.
n	7

agent **maintains state values**

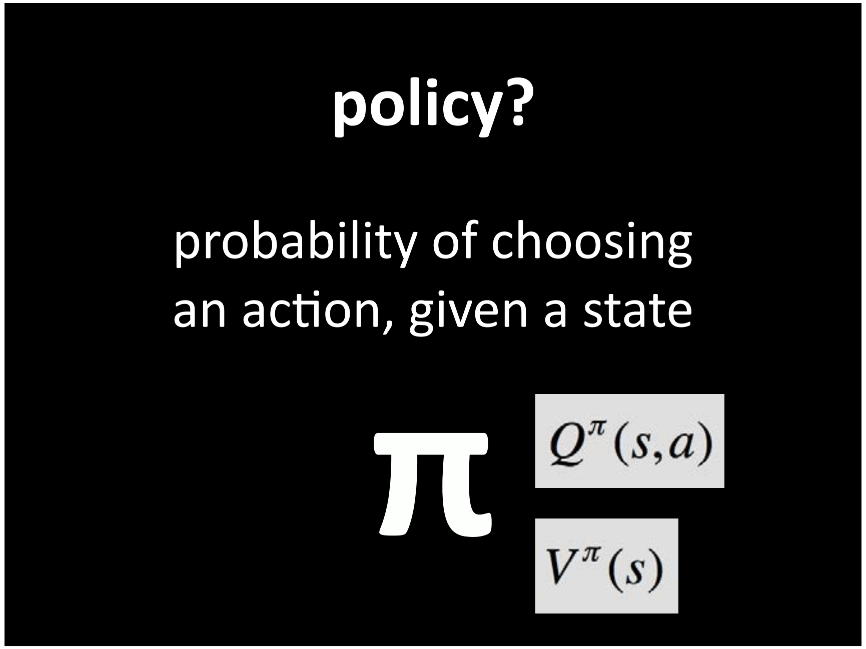
selects actions using these values based on a
“policy”


Q
action values given state
Q(s, north)
Q(s, south)
Q(s, east)
Q(s, west)
state s

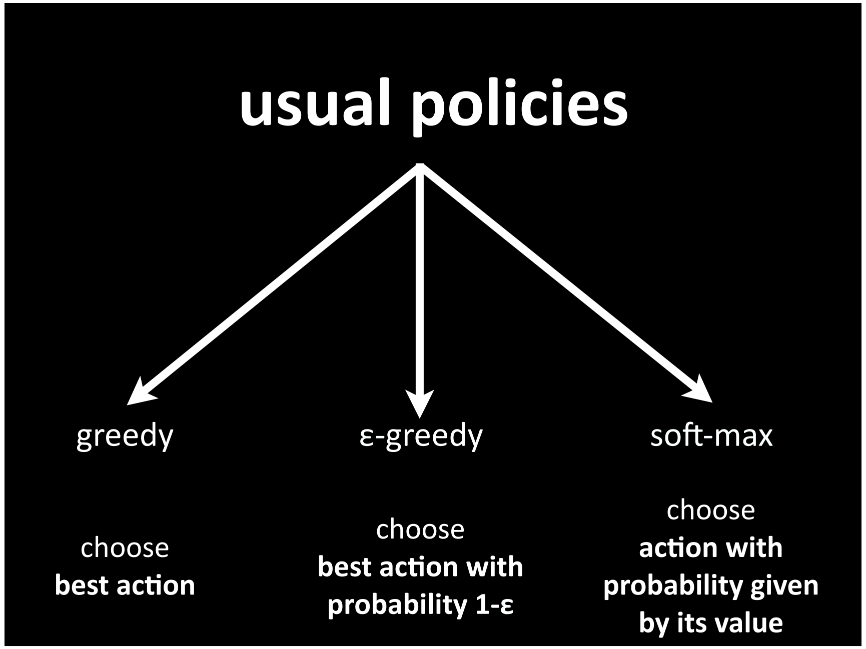
33


Q
V
E{R_t}

34


policy?
probability of choosing
an action, given a state
π
Q^π(s,a)
V^π(s)

35

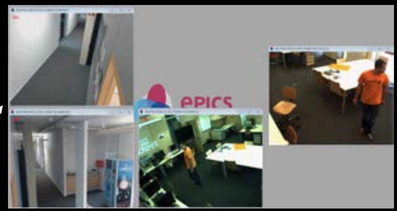

usual policies
greedy
ε-greedy
soft-max
choose
best action
choose
best action with
probability 1-ε
choose
action with
probability given
by its value

36

exploration vs. exploitation

policy = multi-armed bandit strategy

Yamaguchi先生, http://en.wikipedia.org/wiki/File:Las_Vegas_slot_machines.jpg

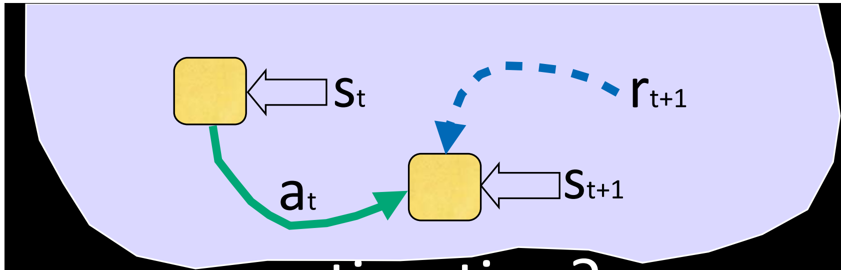


Learning to be different: Heterogeneity and efficiency in distributed smart camera networks, P. R. Lewis, L. Esterle, A. Chandra, B. Rinner, and X. Yao, In Proceedings of the IEEE Conference on Self-Adaptive and Self-Organizing Systems (SASO), IEEE, 2013.

Static, dynamic and adaptive heterogeneity in socio-economic distributed smart camera networks, P. R. Lewis, L. Esterle, A. Chandra, B. Rinner, J. Torresen, and X. Yao, ACM Transactions on Autonomous and Adaptive Systems (TAAS), ACM, 2015.

A/B Testing

37



estimation?

<<use currently visible rewards to update values of where you are coming from>>

the current state (or state-action pair) has an estimated value (say zero/random initially),

which can be **used together with r_{t+1} to update value of previous state (or state-action pair)**

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i.e.

fraction of (currently visible rewards - old value)

+

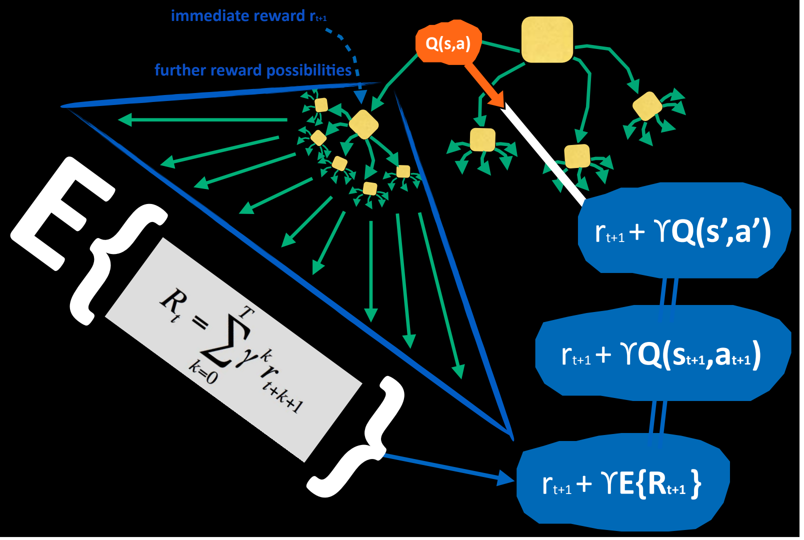
old value

↓

new value

(1-fraction) old value + fraction curr. vis. rewards

39



40

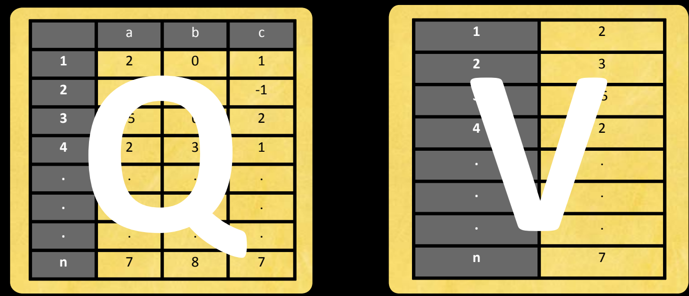
$$V(s) \leftarrow V(s) + \mu(r + \gamma V(s') - V(s))$$

e.g.

$$Q(s,a) \leftarrow Q(s,a) + \mu(r + \gamma Q(s',a') - Q(s,a))$$

41

e.g. **update**
a lookup table maintaing
expected rewards



42

$$Q(s,a) \leftarrow Q(s,a) + \mu(r + \gamma Q(s',a') - Q(s,a))$$

let's play with a version of the above update rule:

$$Q(s,a) \leftarrow Q(s,a) + \mu(r + \gamma \max_{a'} Q(s',a') - Q(s,a))$$

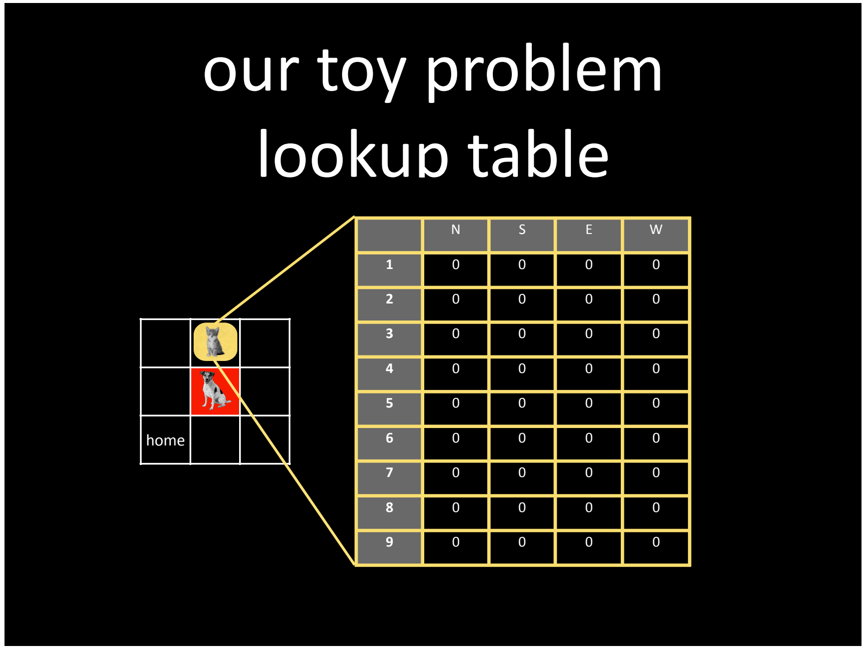
43

indicates a' to be the action with maximum value in next state s'

let's play with a version of the above update rule:

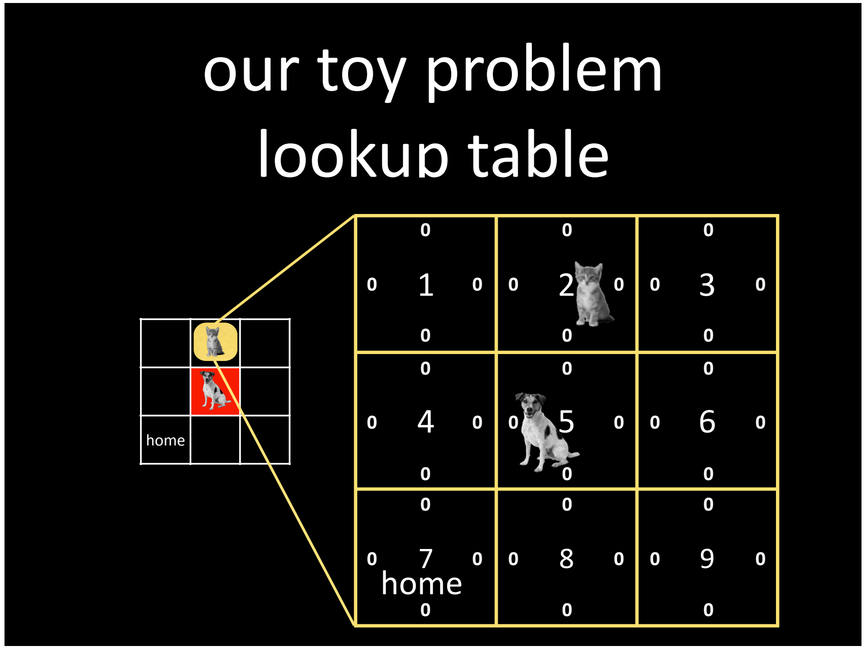
$$Q(s,a) \leftarrow Q(s,a) + \mu(r + \gamma \max_{a'} Q(s',a') - Q(s,a))$$

44

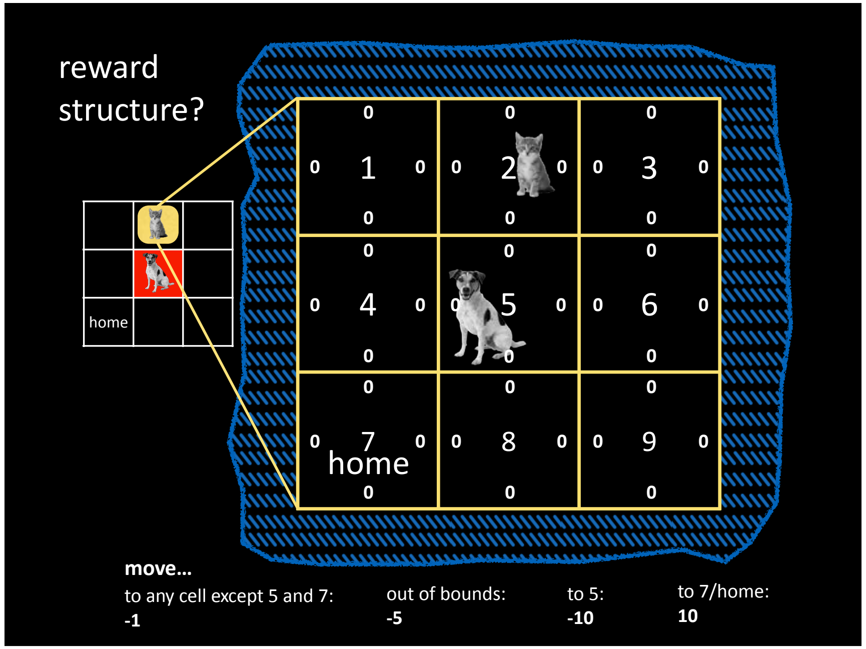

our toy problem
lookup table
home

	N	S	E	W
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0
5	0	0	0	0
6	0	0	0	0
7	0	0	0	0
8	0	0	0	0
9	0	0	0	0

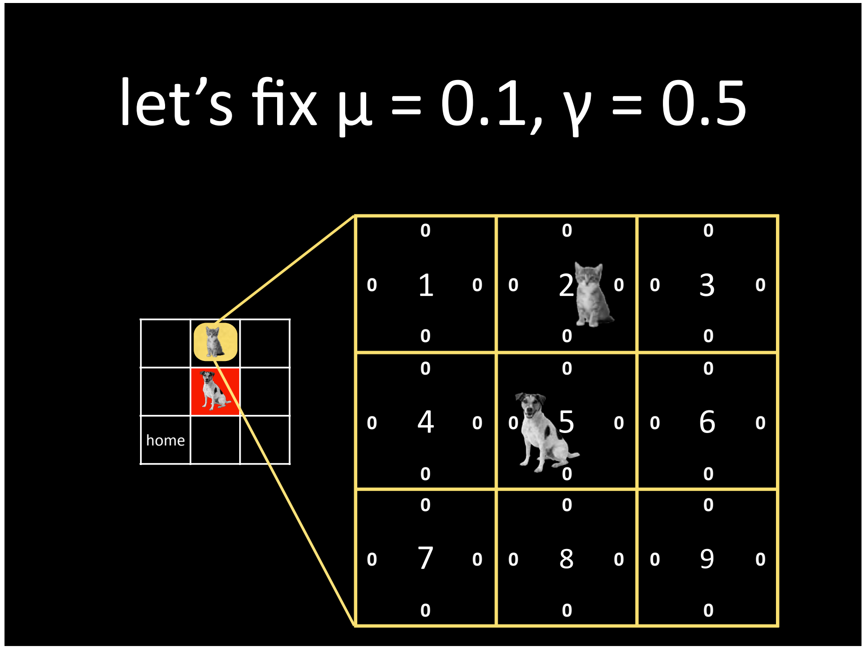
45


our toy problem
lookup table
home
1
2
3
4
5
6
7
home
8
9
0

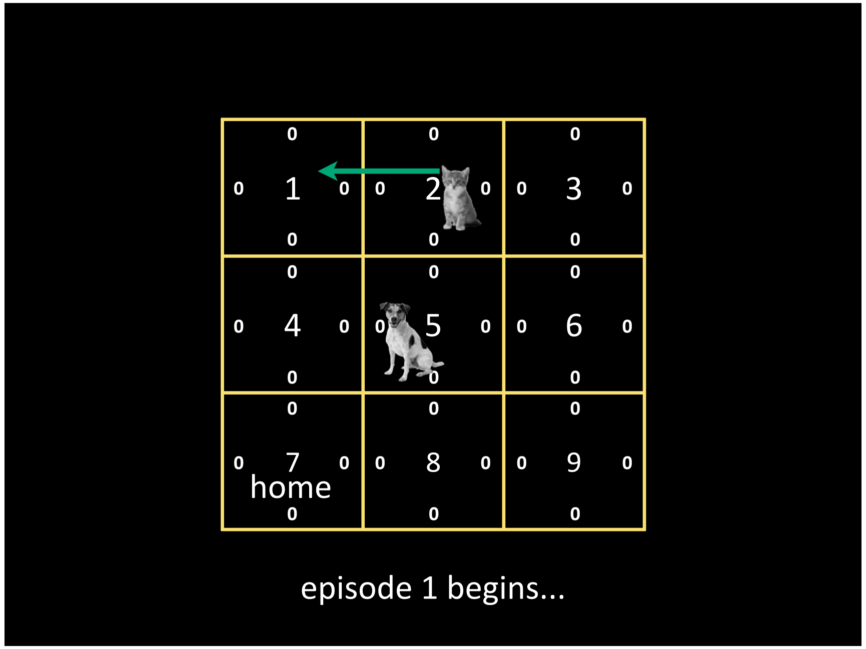
46


reward
structure?
home
1
2
3
4
5
6
7
home
8
9
0
move...
to any cell except 5 and 7:
-1
out of bounds:
-5
to 5:
-10
to 7/home:
10

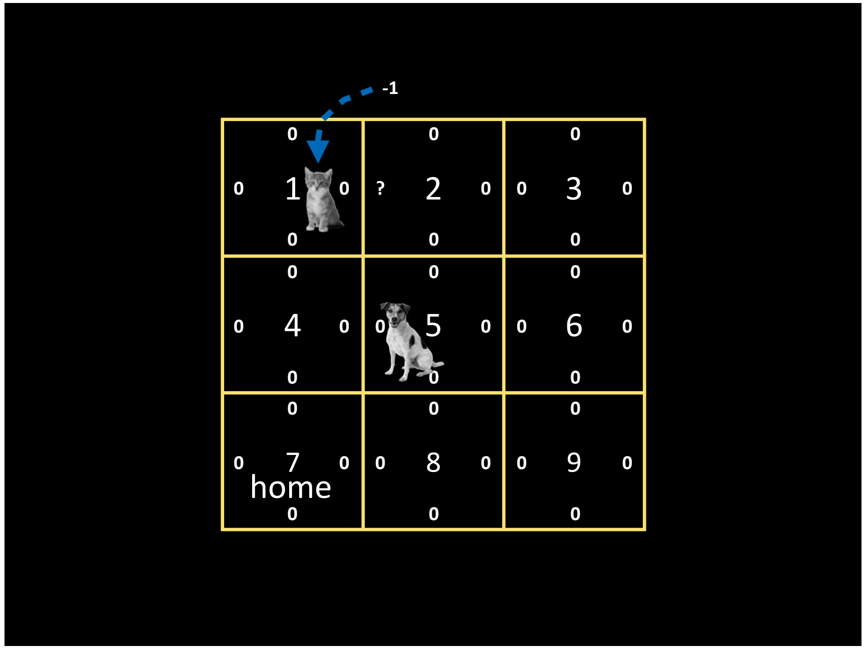
47


let's fix μ = 0.1, γ = 0.5
home
1
2
3
4
5
6
7
8
9
0

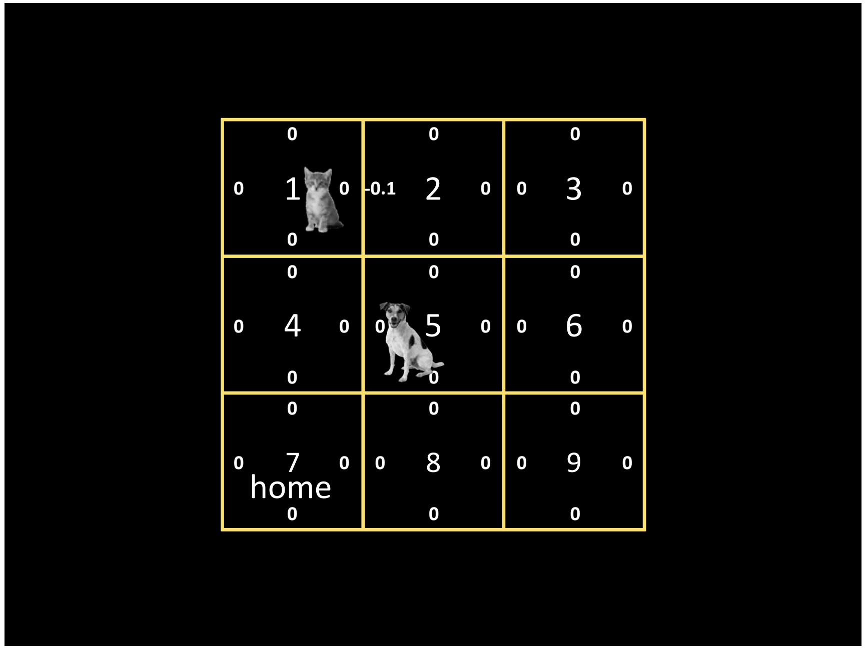
48


1
2
3
4
5
6
7
home
8
9
episode 1 begins...

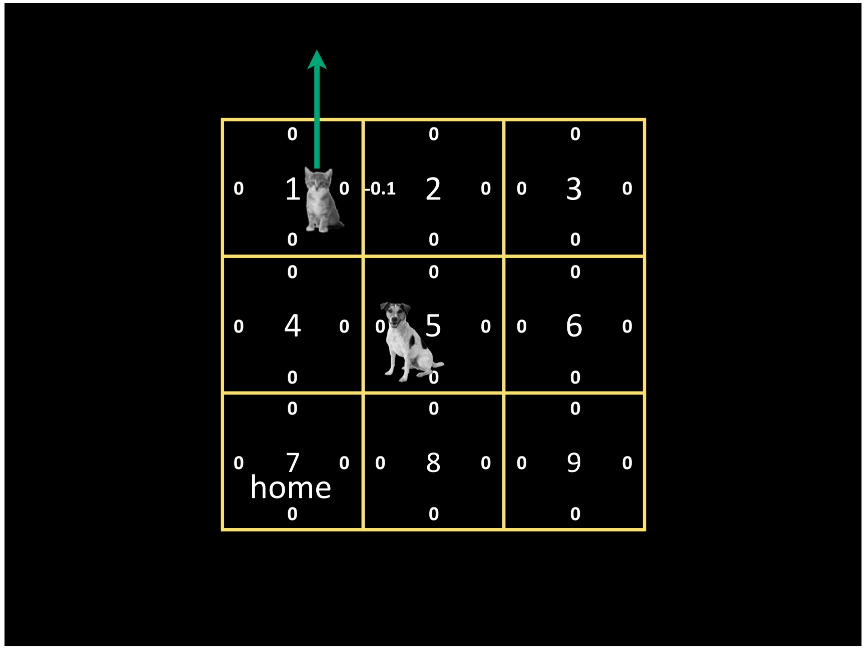
49


-1
1
?
2
3
4
5
6
7
home
8
9

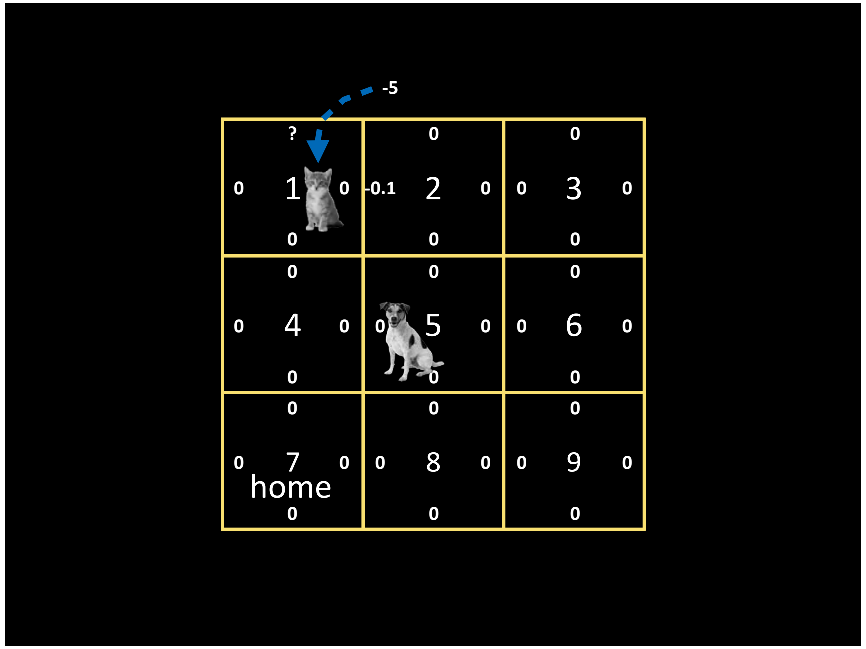
50


1
-0.1
2
3
4
5
6
7
home
8
9

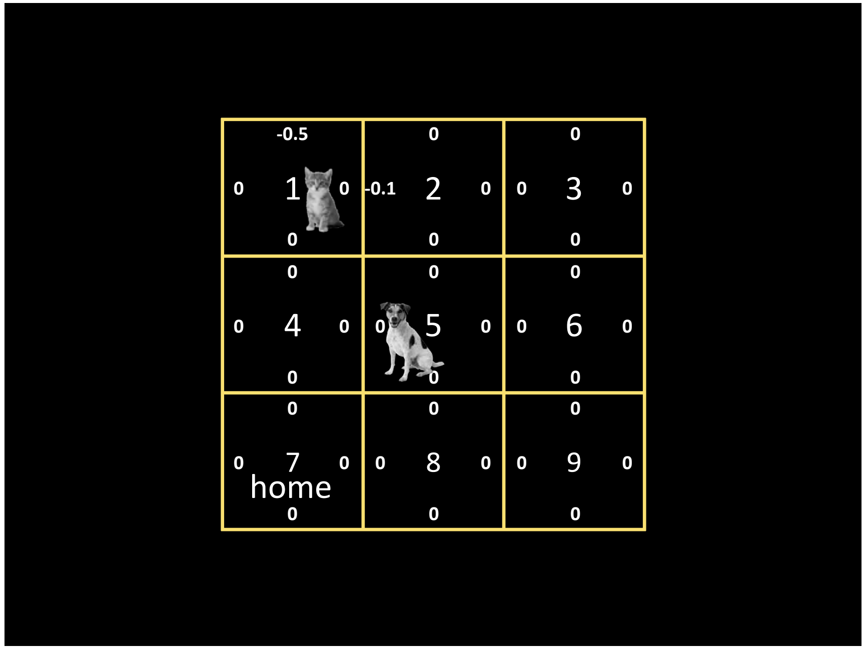
51


1
-0.1
2
3
4
5
6
7
home
8
9

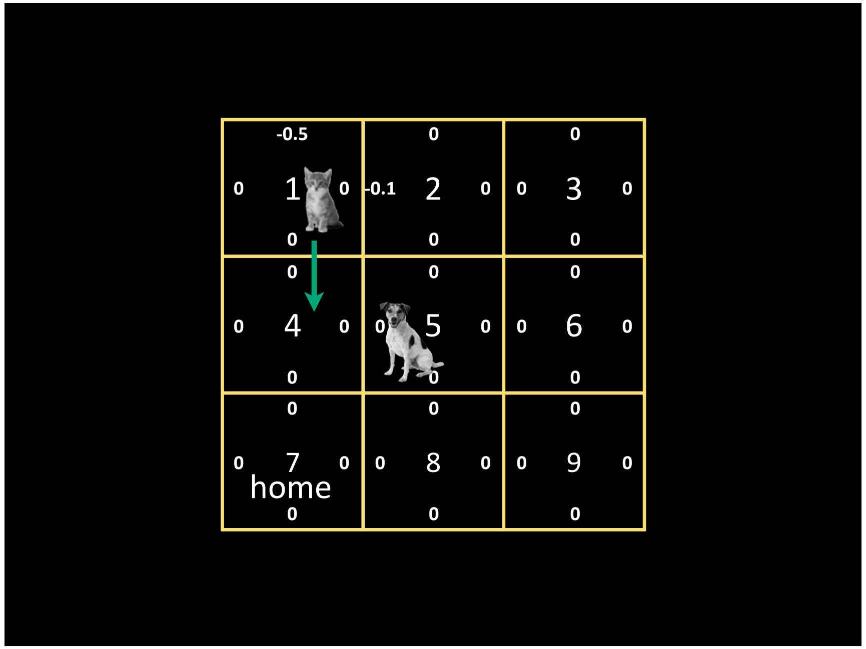
52


-5
?
1
-0.1
2
3
4
5
6
7
home
8
9

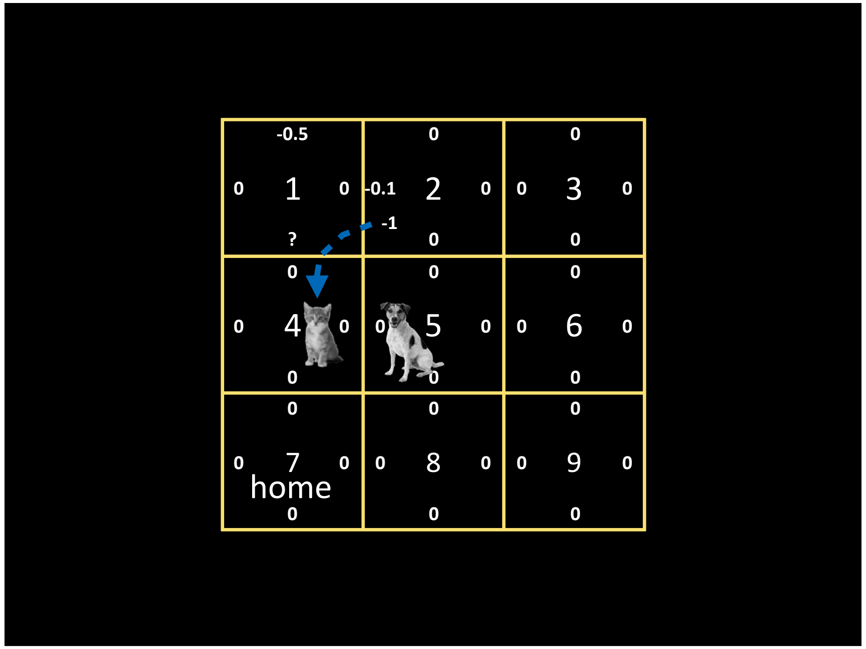
53


-0.5
1
-0.1
2
3
4
5
6
7
home
8
9

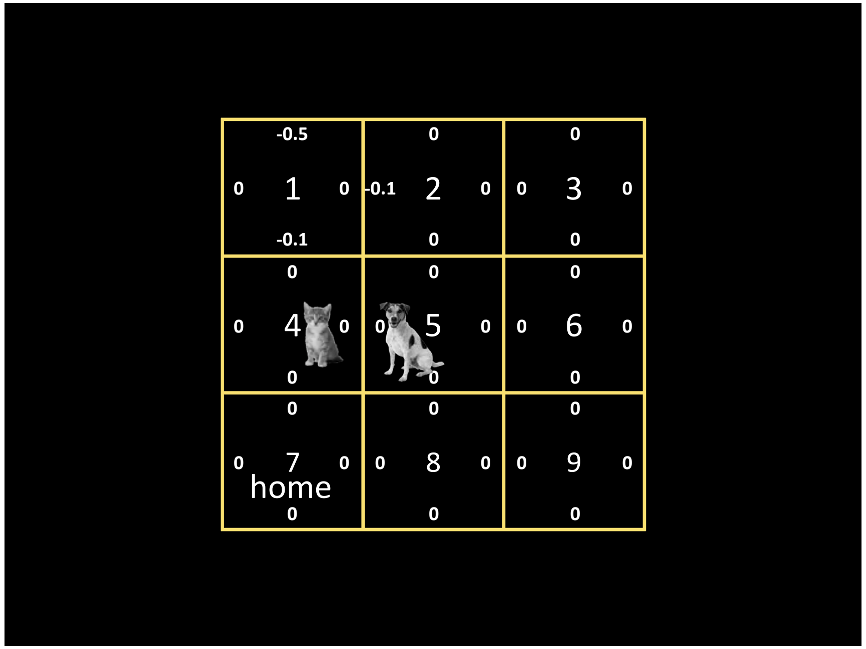
54


-0.5
1
-0.1
2
3
4
5
6
7
home
8
9

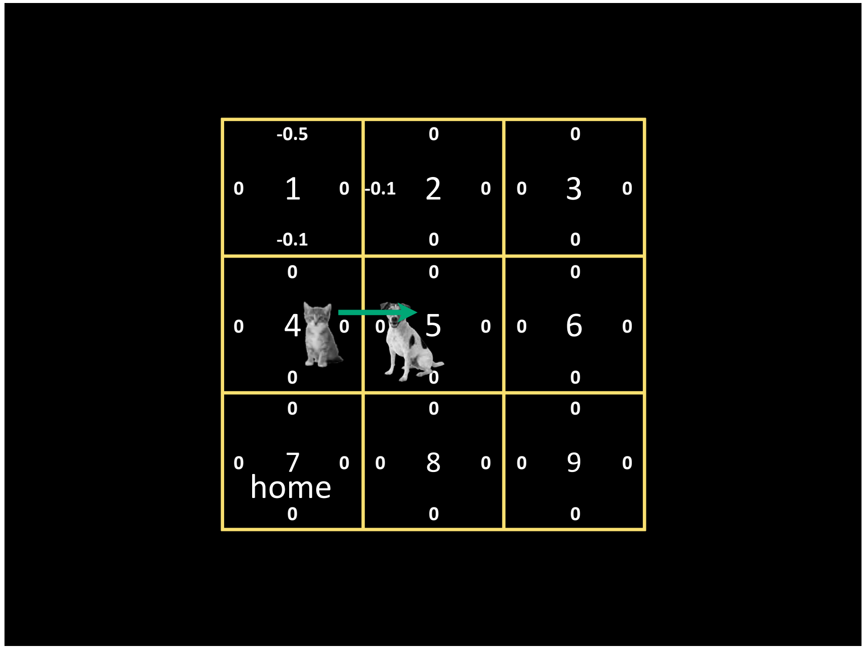
55


-0.5
1
-0.1
2
3
-1
?
4
5
6
7
home
8
9

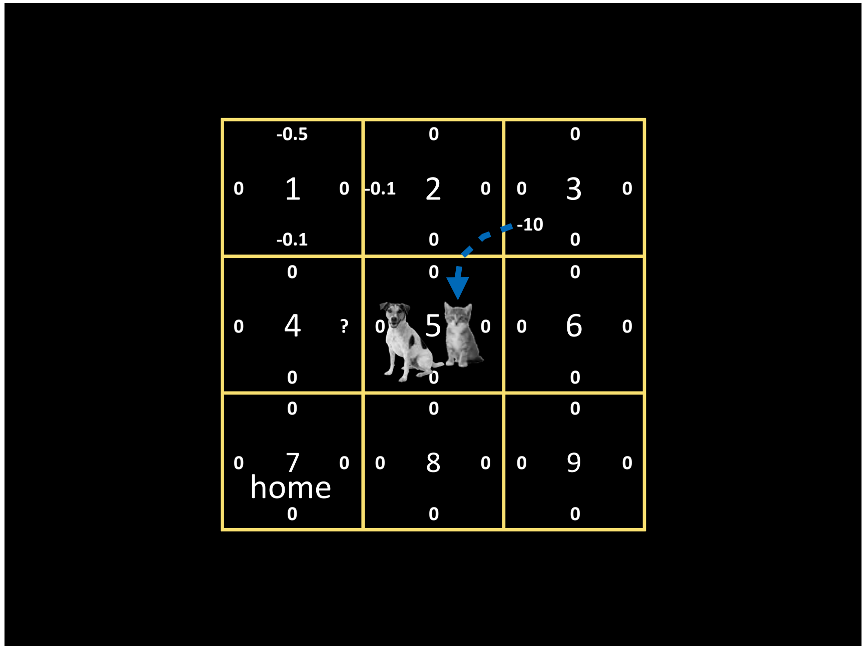
56


-0.5 0 0
0 1 0 -0.1 2 0 0 3 0
-0.1 0 0
0 0 0
0 4 0 0 5 0 0 6 0
0 0 0
0 0 0
0 7 0 0 8 0 0 9 0
home
0 0 0

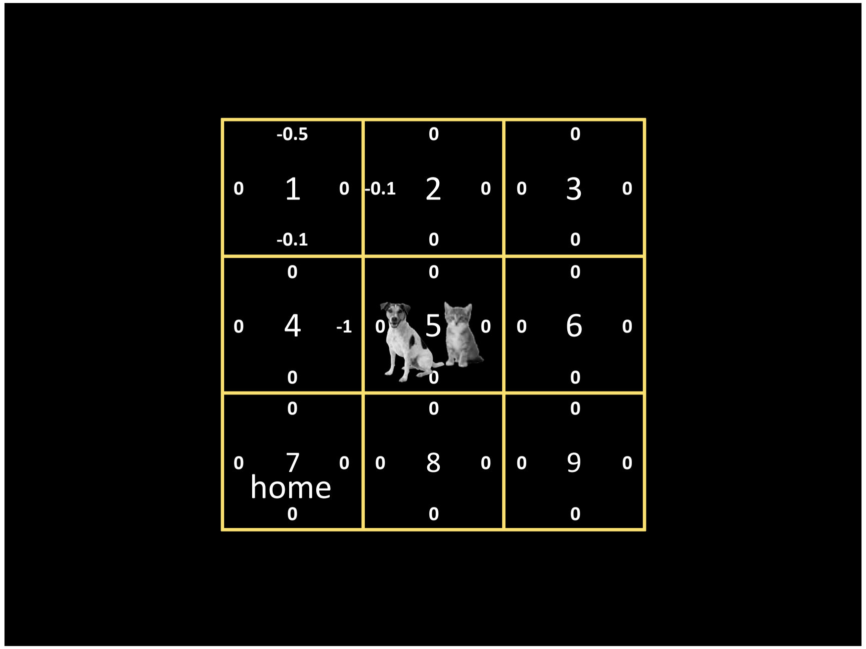
57


-0.5 0 0
0 1 0 -0.1 2 0 0 3 0
-0.1 0 0
0 0 0
0 4 0 0 5 0 0 6 0
0 0 0
0 0 0
0 7 0 0 8 0 0 9 0
home
0 0 0

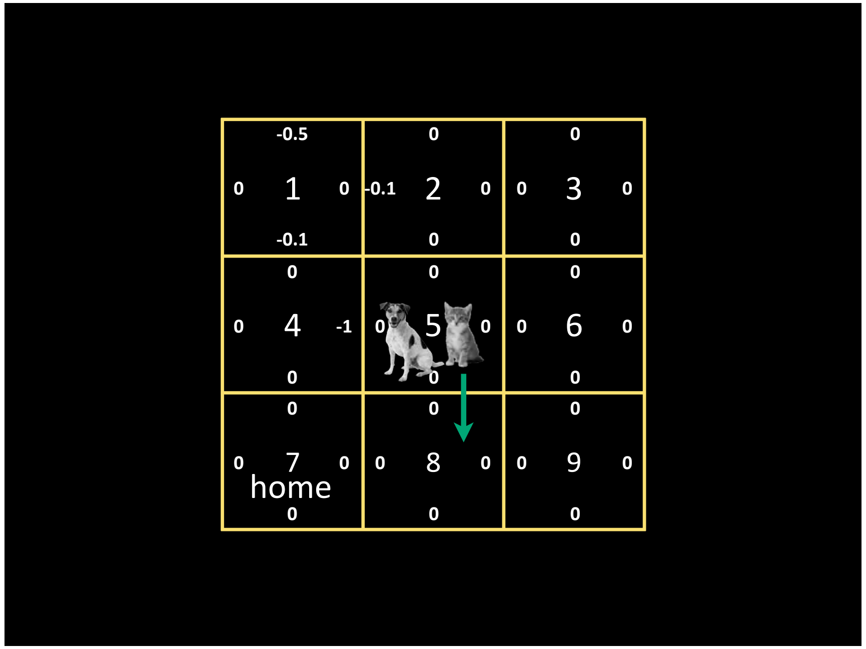
58


-0.5 0 0
0 1 0 -0.1 2 0 0 3 0
-0.1 0 -10 0
0 0 0
0 4 ? 0 5 0 0 6 0
0 0 0
0 0 0
0 7 0 0 8 0 0 9 0
home
0 0 0

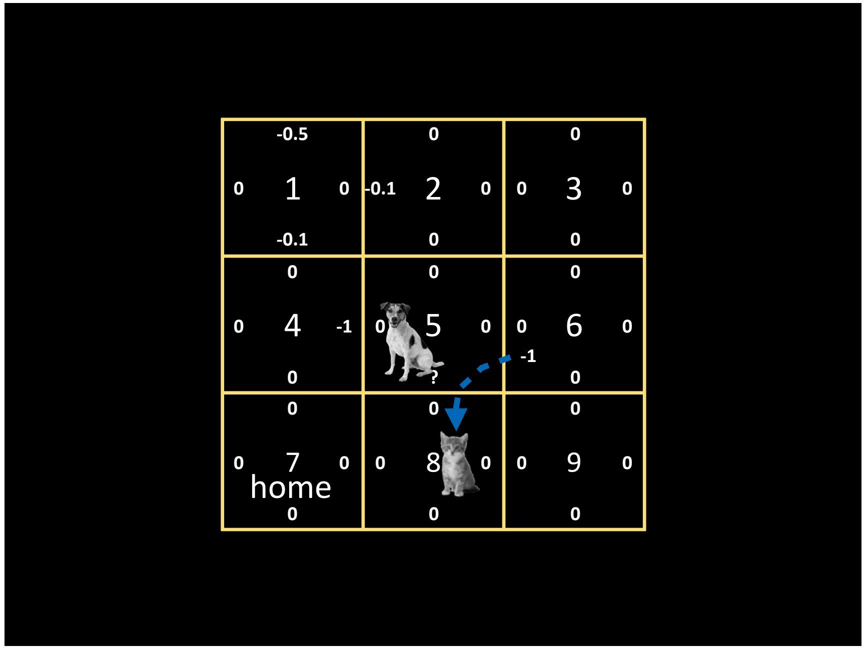
59


-0.5 0 0
0 1 0 -0.1 2 0 0 3 0
-0.1 0 0
0 0 0
0 4 -1 0 5 0 0 6 0
0 0 0
0 0 0
0 7 0 0 8 0 0 9 0
home
0 0 0

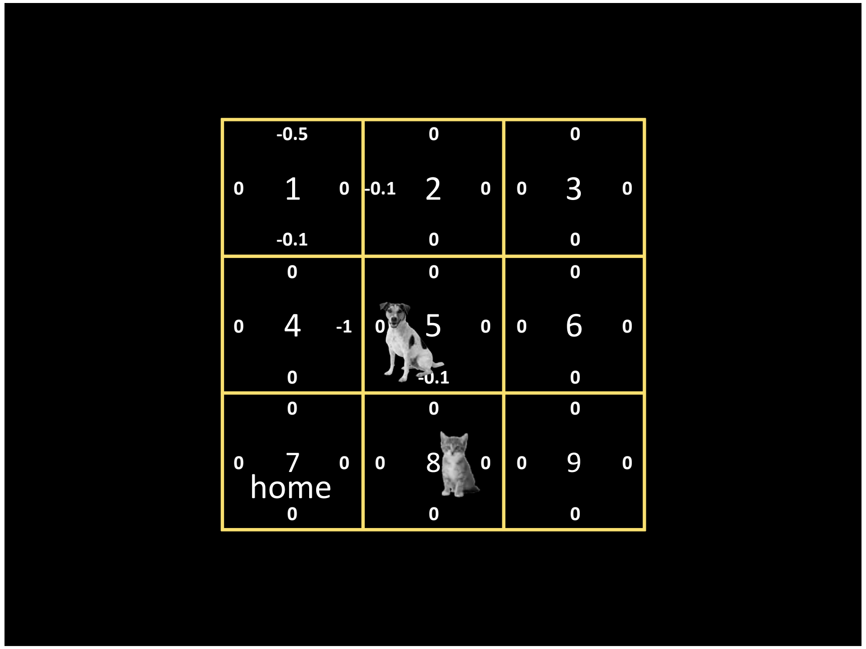
60


-0.5
0
0
0 1 0
-0.1 2 0
0 3 0
-0.1
0
0
0
0
0
0 4 -1
0 5 0
0 6 0
0
0
0
0
0
0
0 7 0
home
0 8 0
0 9 0
0
0
0

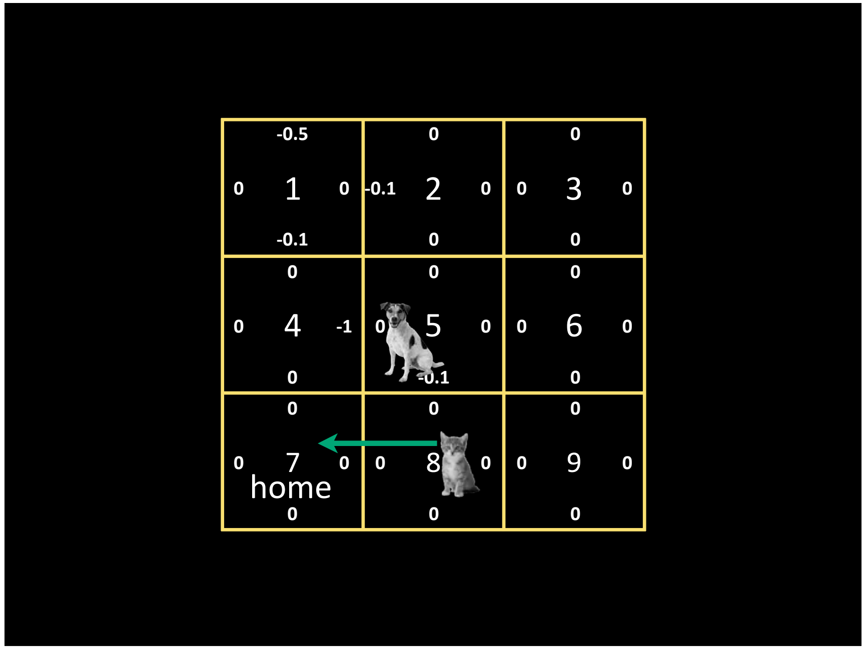
61


-0.5
0
0
0 1 0
-0.1 2 0
0 3 0
-0.1
0
0
0
0
0
0 4 -1
0 5 0
0 6 0
-1
0
?
0
0
0
0
0 7 0
home
0 8 0
0 9 0
0
0
0

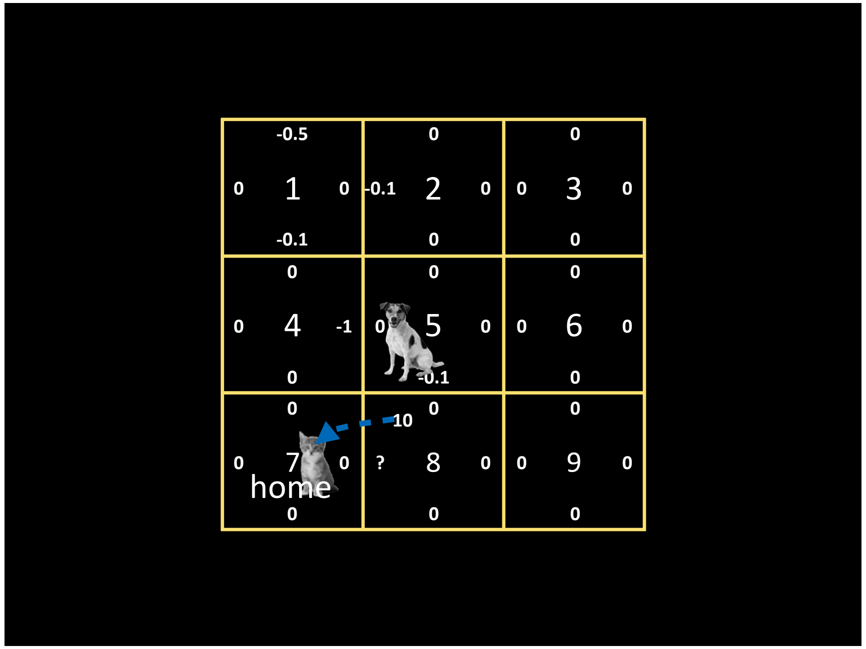
62

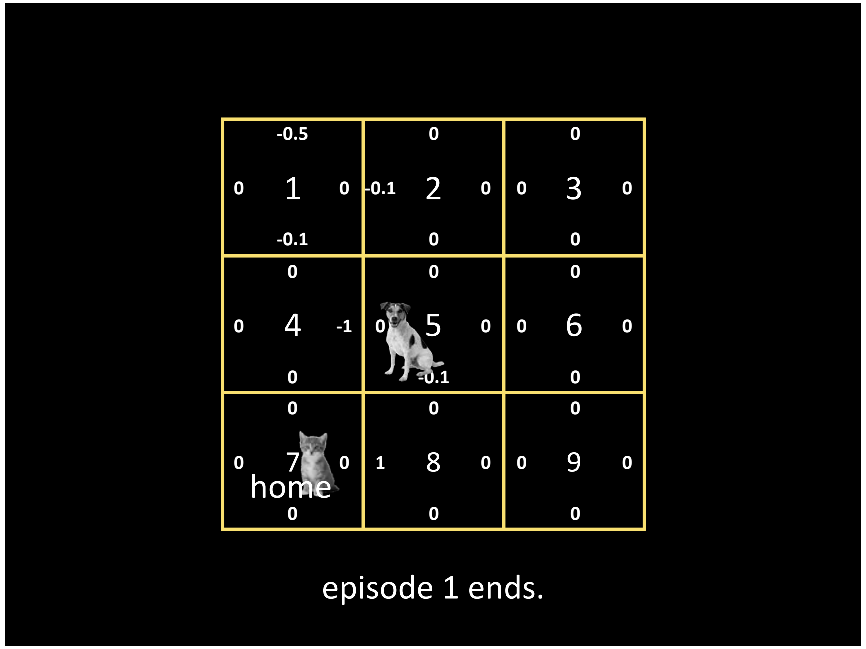

-0.5
0
0
0 1 0
-0.1 2 0
0 3 0
-0.1
0
0
0
0
0
0 4 -1
0 5 0
0 6 0
0
-0.1
0
0
0
0
0 7 0
home
0 8 0
0 9 0
0
0
0

63


-0.5
0
0
0 1 0
-0.1 2 0
0 3 0
-0.1
0
0
0
0
0
0 4 -1
0 5 0
0 6 0
0
-0.1
0
0
0
0
0 7 0
home
0 8 0
0 9 0
0
0
0

64

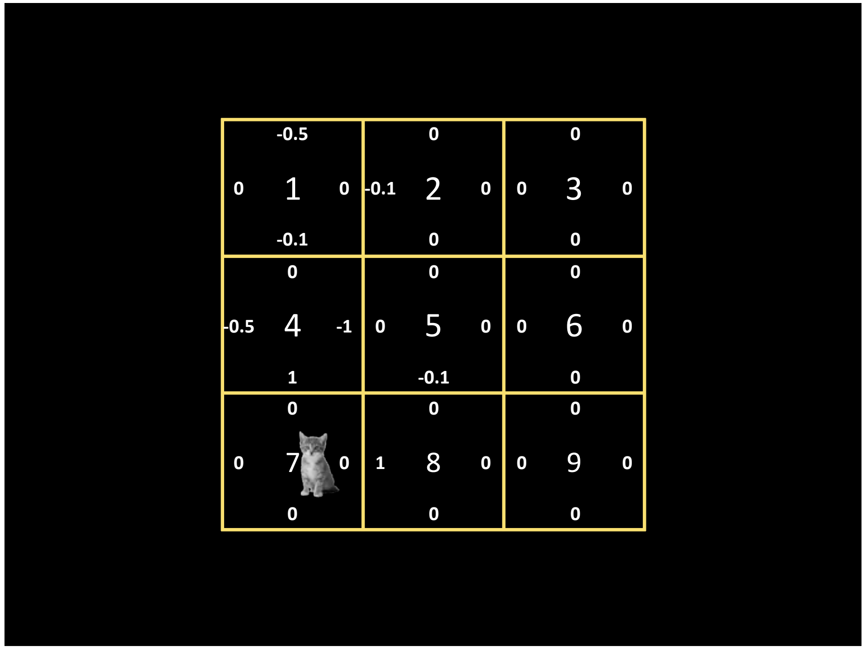




let's work out the next episode, starting at state 4

go WEST and then SOUTH

how does the table change?

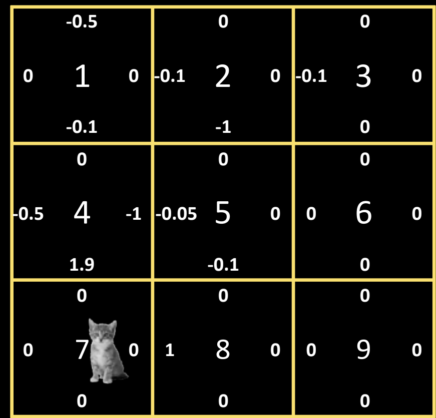


and the next episode, starting at state 3

go WEST -> SOUTH -> WEST -> SOUTH

how does the table change?

69



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what we just saw was some episodes of **Q-learning**

value updates based on **optimal policy**:
value of **best next action**

off-policy learning

71

SARSA-learning?

value updates based on **used policy**:
value of **the actual next action**

on-policy learning

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73

mountain car...

74

pole balancing...

Pole balancing in reality: http://www.youtube.com/watch?v=Lt-KLtkDlh8

75

human level game control

- **pixel** input
- **18 joystick/button positions** output
- **change in game score** as feedback
- **convolutional net representing Q**
- **backpropagation** for training!

Human-level control through deep reinforcement learning,
Mnih et. al., Nature 518, Feb 2015
http://www.nature.com/nature/journal/v518/n7540/full/nature14236.html

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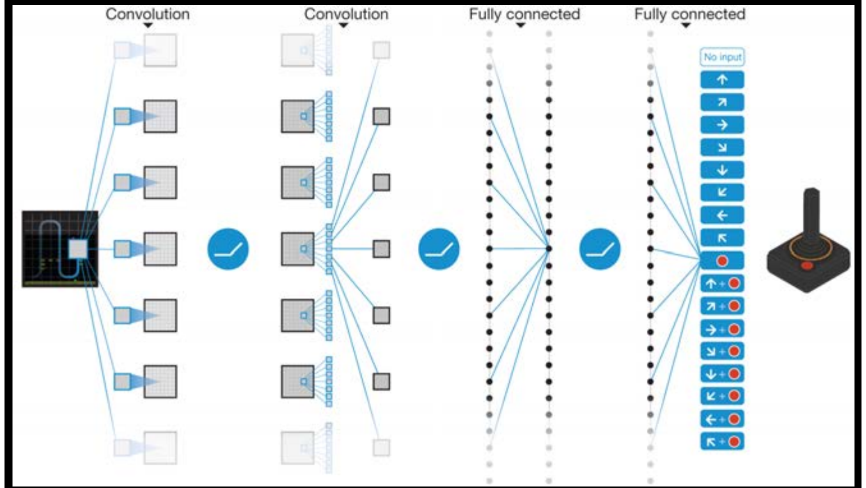
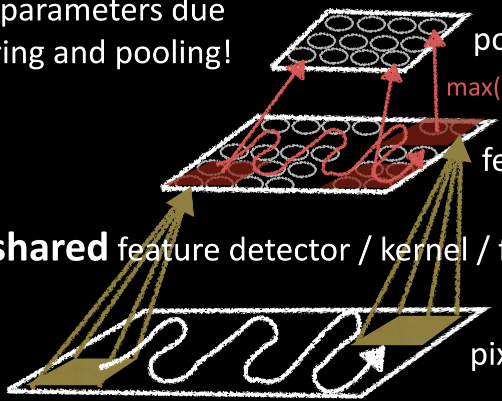
neural network



convolution, weight sharing, and pooling

fewer parameters due to sharing and pooling!



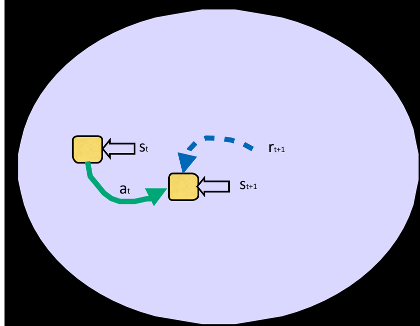
backpropagation?

What is the **target** against which to minimise error?

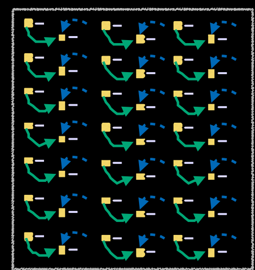
$$\mathcal{L}(w) = \mathbb{E}\left[\left(\underbrace{r + \gamma \max_{a'} Q(s', a', w)}_{\text{target}} - Q(s, a, w)\right)^2\right]$$

$$\frac{\partial \mathcal{L}(w)}{\partial w} = \mathbb{E}\left[\left(r + \gamma \max_{a'} Q(s', a', w) - Q(s, a, w)\right) \frac{\partial Q(s, a, w)}{\partial w}\right]$$

experience replay



save current transition
(s, a, r, s') in memory
every time step



randomly sample a set of (s, a, r, s') from memory for training Q network **(instead of learning from current state transition) every step**

= i.i.d + learn from the past

freezing target Q

moving target => **oscillations**

freeze

$$\mathcal{L}(w) = \mathbb{E}\left[\left(\underbrace{r + \gamma \max_{a'} Q(s', a', w)}_{\text{target}} - Q(s, a, w)\right)^2\right]$$

stabilise learning by **fixing target**, moving it every now and then

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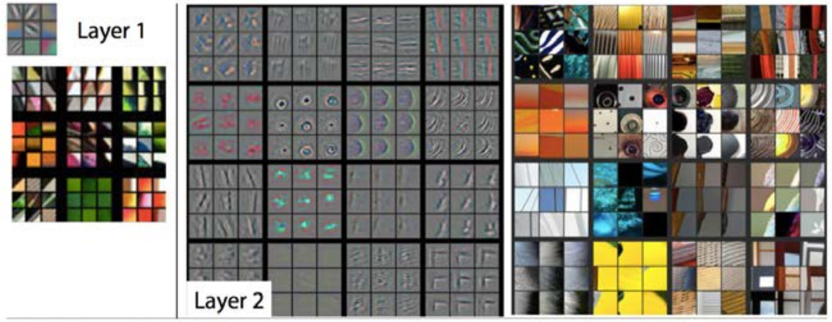
what does a deep neural network do?



corners & edge/color conjunctions

reverse **projections** of neuron outputs in pixel space

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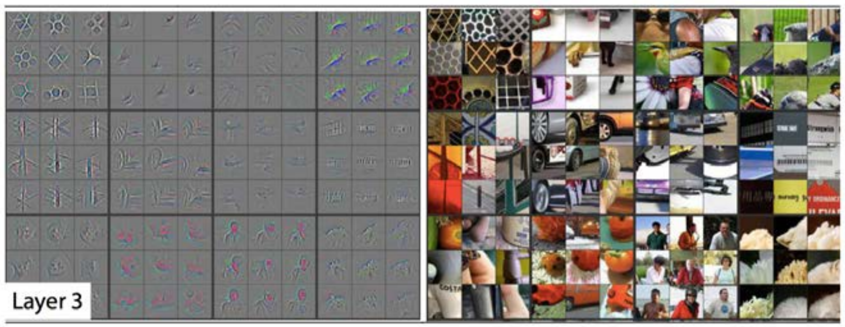

similar textures

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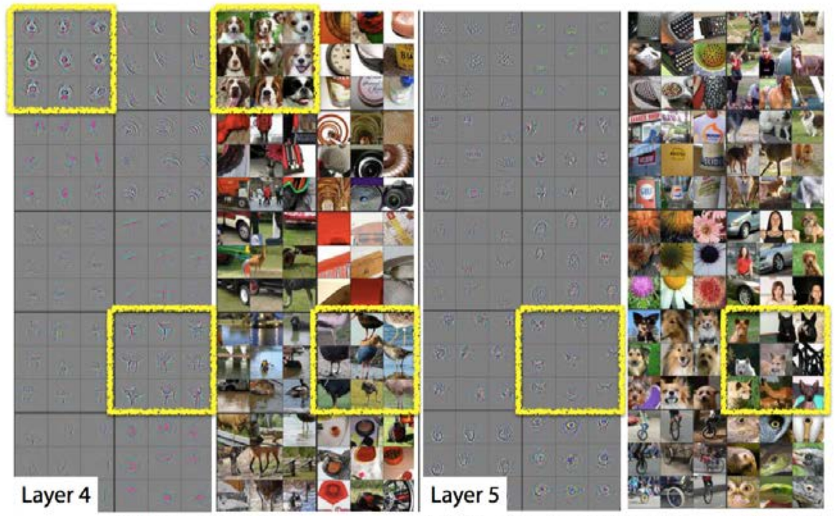

Object parts (dog face & bird legs)

Entire object with pose variation (dogs)

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compositional features

compositional problem solving

multiplication (circuit design)

<— composed of adding numbers

<— composed of adding bits

```
       output: x.y
─────multiply─────
───adding nums───
───adding bits───
     input: x and y
```

human knowledge organisation

find roots of a linear expression

<— composed of setting expression to zero and solving linear equations

<— composed of rearranging terms

```
             output: x = -2
─────(find roots of x+2)─────
─────(set x+2=0)─(solve)─────
──────────────(rearrange)────
       input: x, +, 2, =, 0
```

deep layers make representation of knowledge and processes happen with **fewer neurons**!

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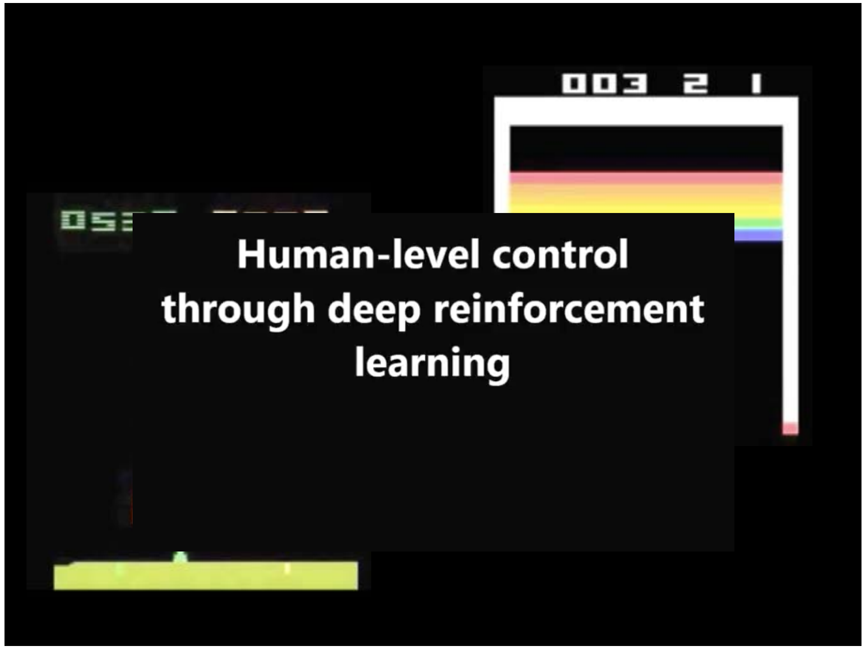

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code for you to play with...

tabular approaches:
http://jamh-web.appspot.com/download.htm#Reinforcement_Learning:

deep learning approach:
Environment: http://www.arcadelearningenvironment.org/
Code: https://sites.google.com/a/deepmind.com/dqn/

please do e-mail for questions, and if you want to work on reinforcement learning research projects:
arjun.chandra@gmail.com / chandra@ifi.uio.no

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coyote learning what not to do...

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