Reinforcement Learning in Games

Ege Can Özer

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- More focus on the algorithm

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  - Exploitation vs exploration
  - Many problems DL perspective

Outline

- Reinforcement Learning to Play Mario [LYY12]
- High-level Reinforcement Learning in Strategy Games [AmS10]
- Temporal Difference Learning and TD-Gammon [Tes95]
- Playing Atari with Reinforcement Learning [MKS13]

} 4 articles

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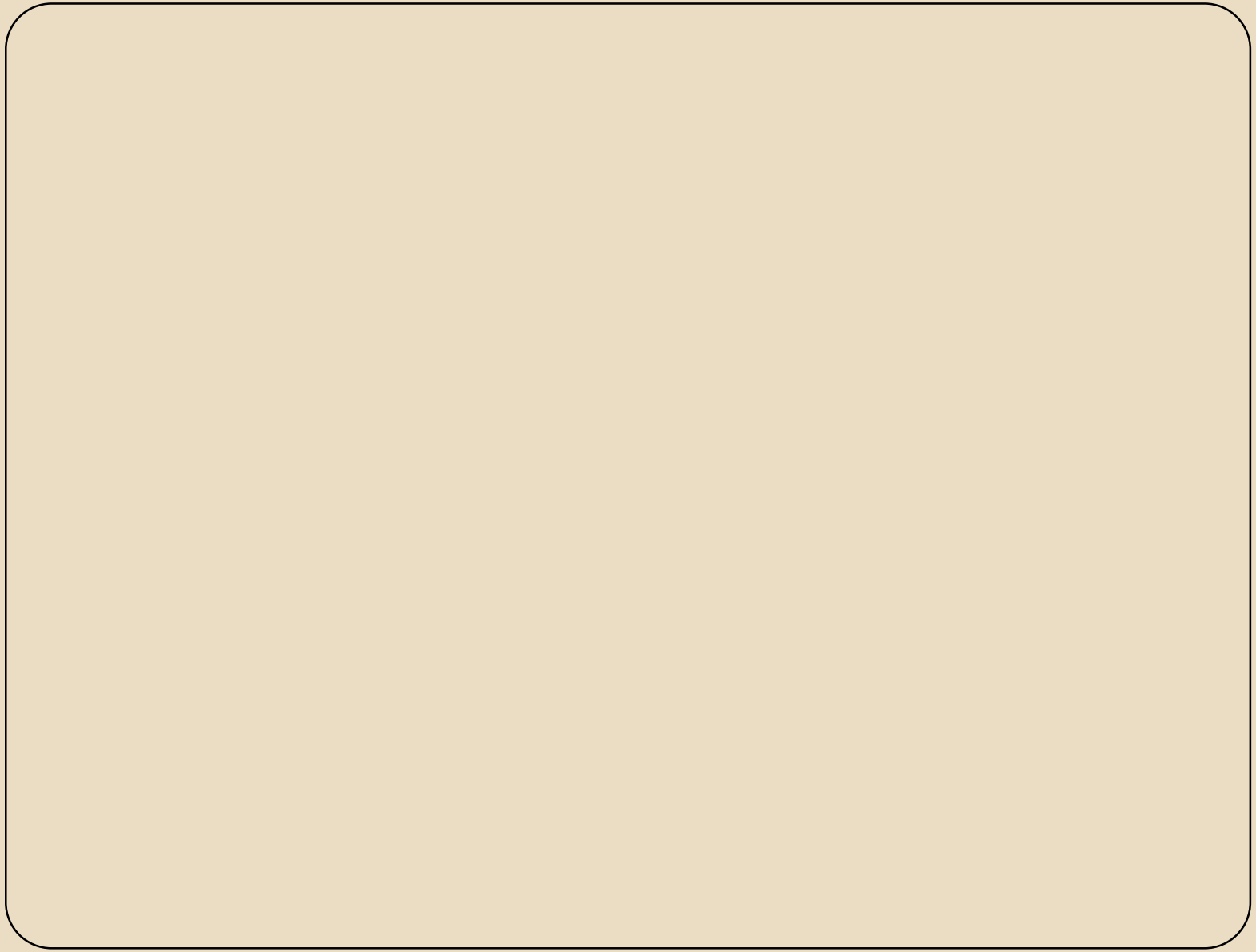
- Mario AI Framework
  - Used to both train and test the system
- Fast convergence and decent results
  - 5000 iterations, 90% win probability

$$Q(s_t, a_t) \leftarrow (1 - a_{s,a})Q(s_t, a_t) + a_{s,a}(r + \gamma max(Q(s_{t+1}, a_{t+1})))$$



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Q-table

Initialized with a
uniform distribution

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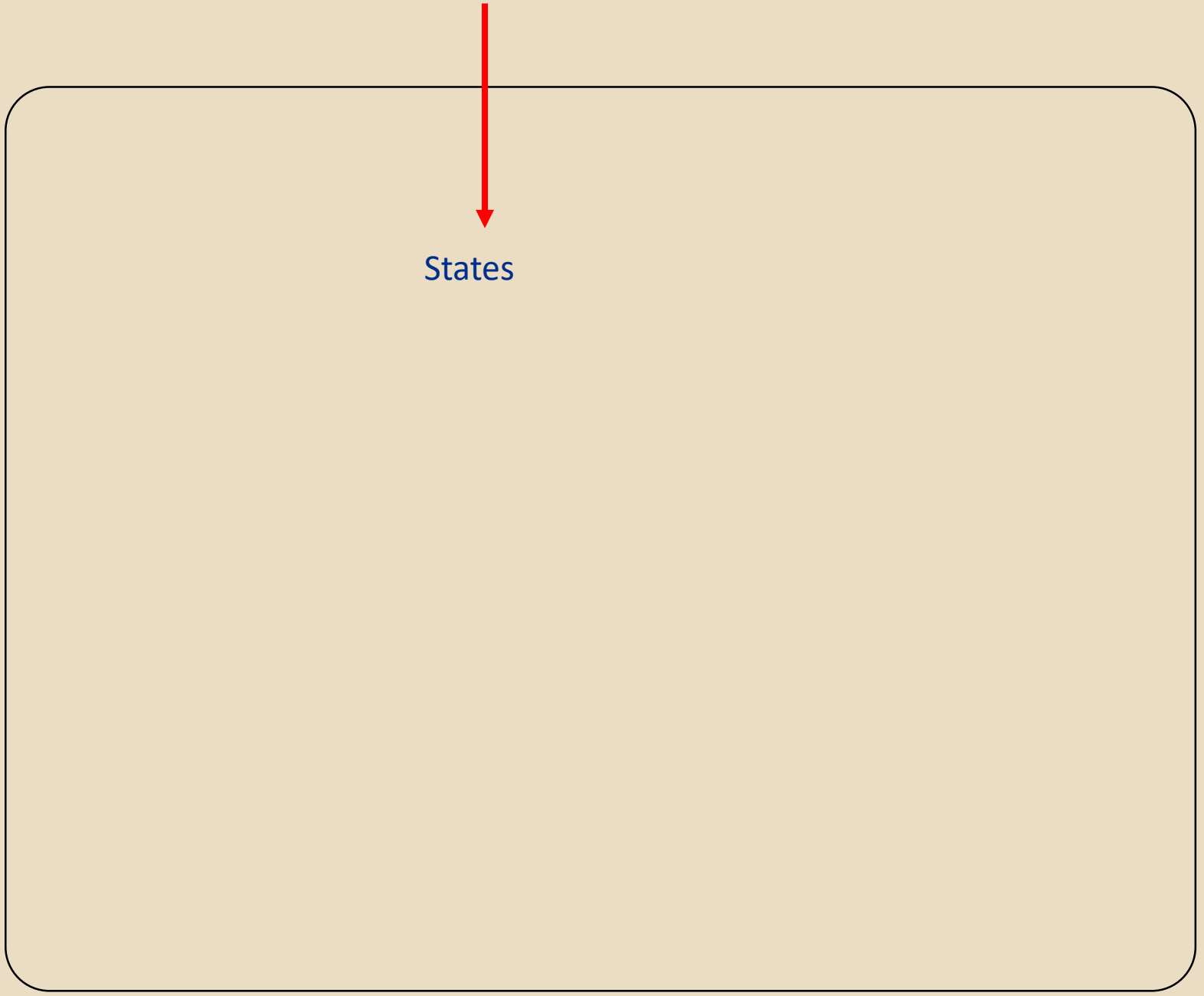

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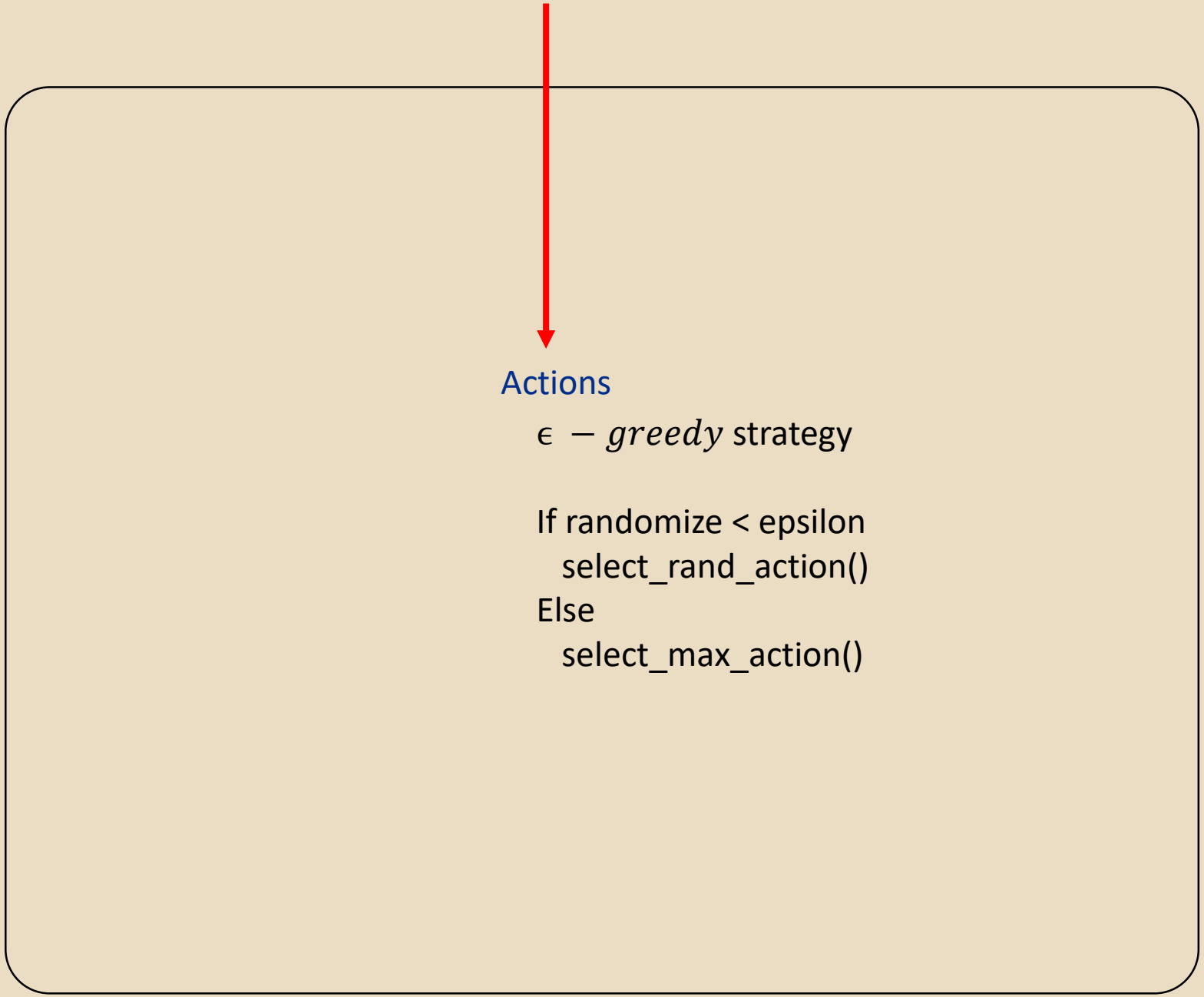

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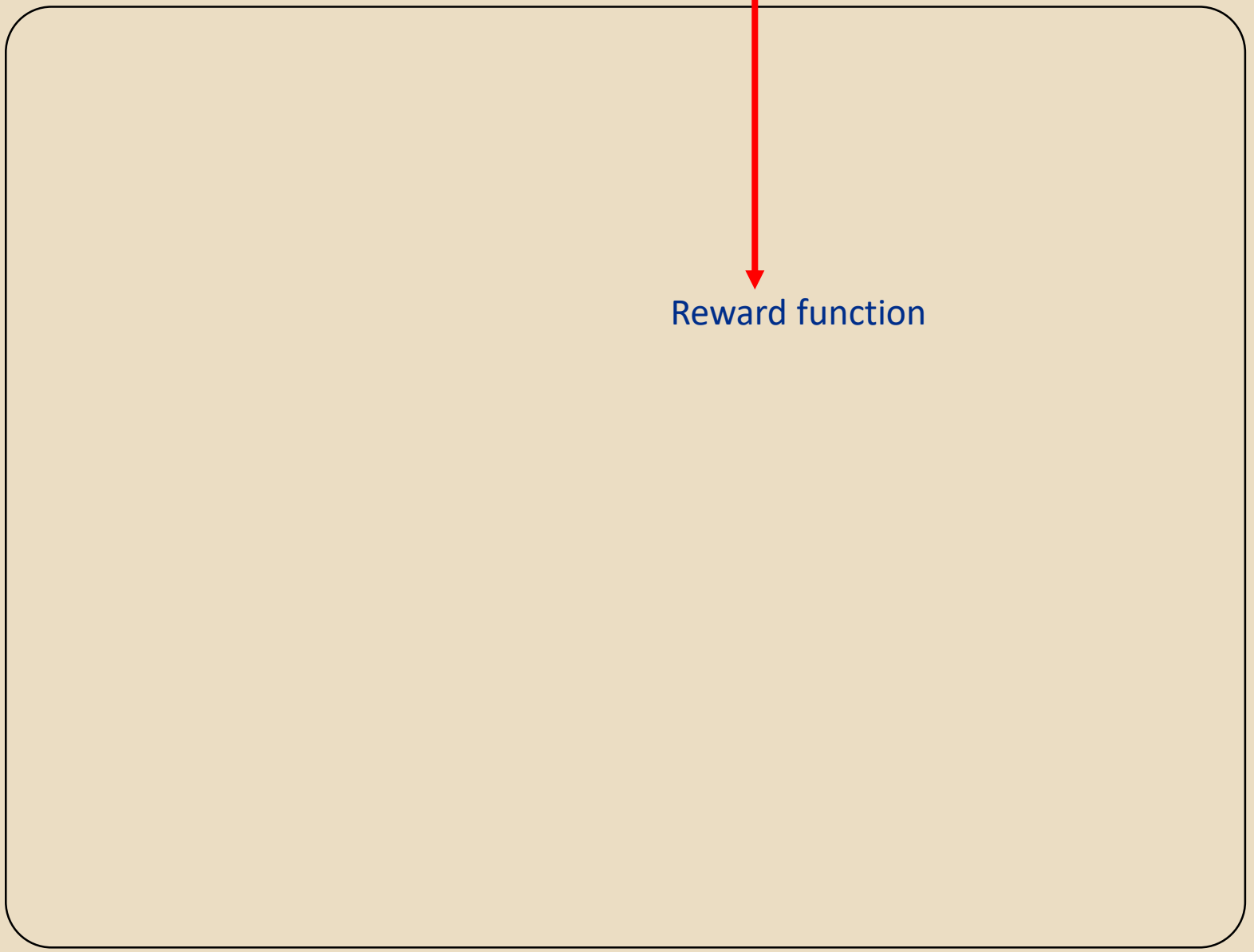

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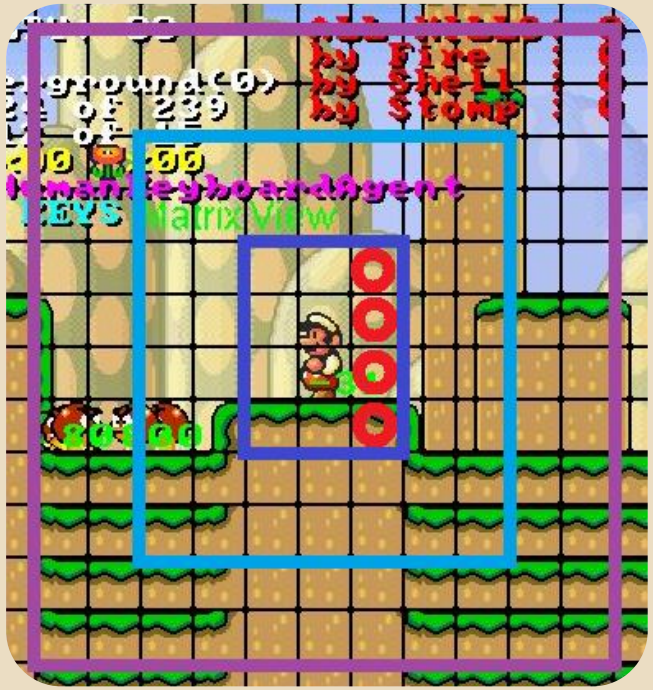
Learning rate

How fast learning converges

$$Q(s_t, a_t) \leftarrow (1 - a_{s,a})Q(s_t, a_t) + a_{s,a}(r + \gamma max(Q(s_{t+1}, a_{t+1})))$$

Discount factor

How much future state is taken into account



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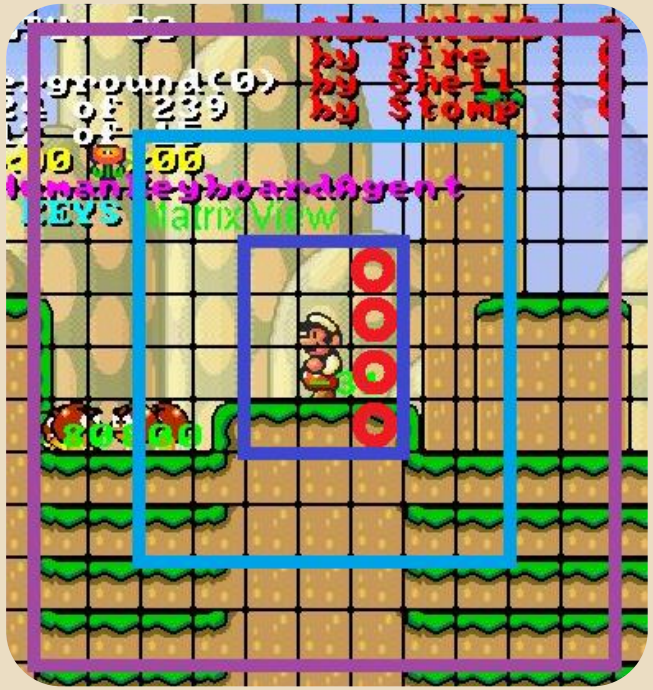
Using Mario AI framework
those variables defined



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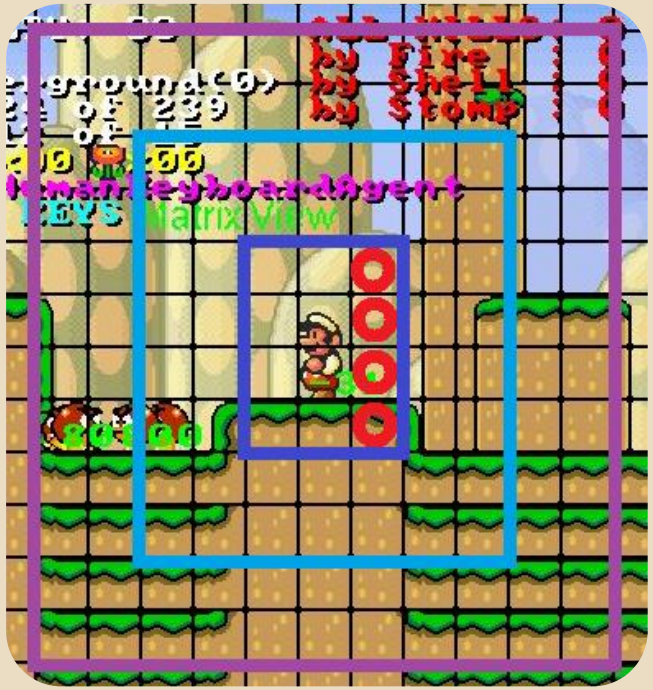
- States



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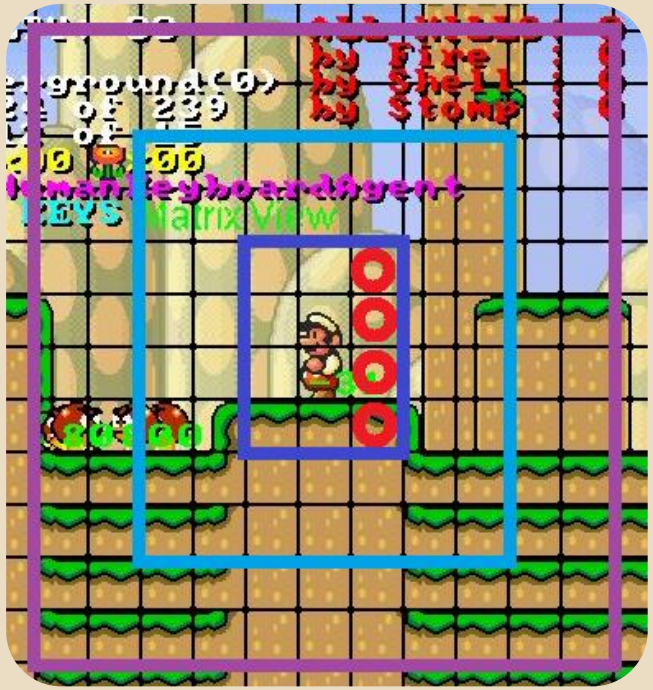
- Mario mode: 0 – small, 1 – big, 2-fire
- If on ground: 0 or 1
- If can jump: 0 or 1
- If stuck: 0 or 1
- Nearby, midrange, far enemies
- If enemies killed by stomp: 0 or 1

...

A state needs **39 bits** to encode



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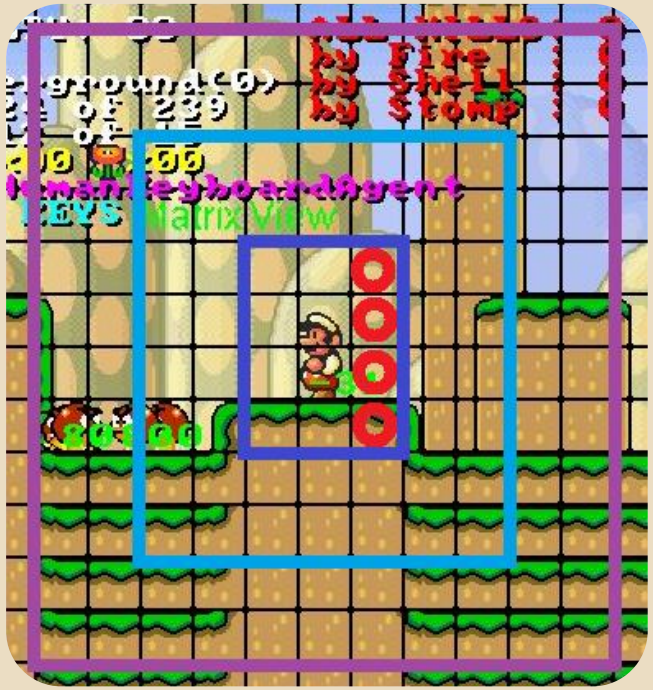

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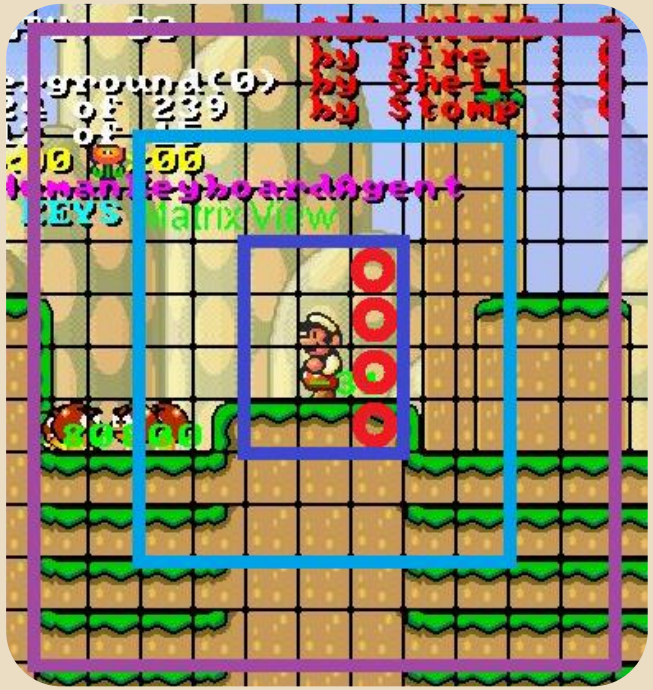
Mario performs one of 12 actions

{LEFT, RIGHT, STAY} X
{JUMP, NOT_JUMP} X
{SPEED/FIRE, NOSPEED} X



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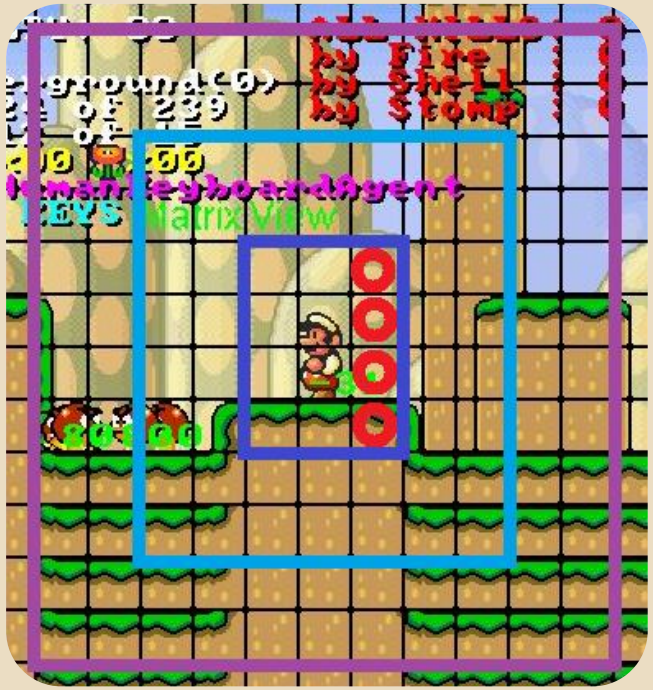
- Reward function



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- States
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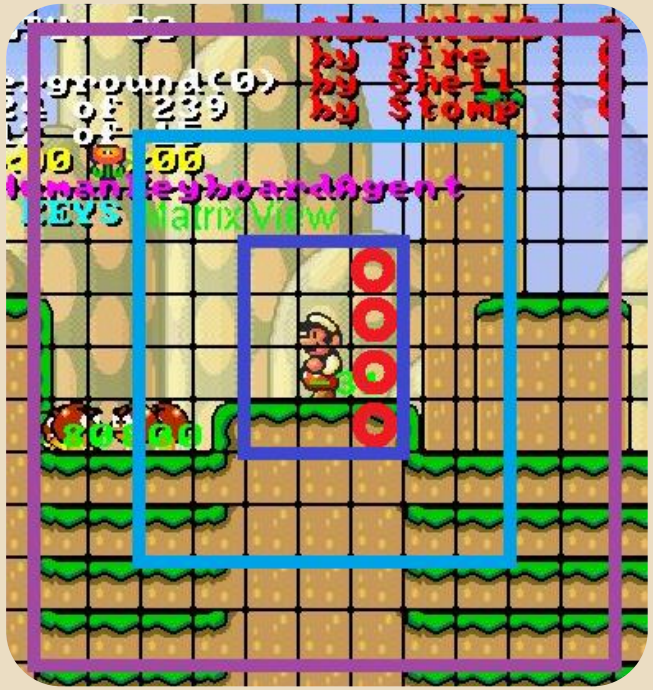
- Reward function

- Positive reward
  - Moving forward, jump on higher platforms
    - Reward decreases when there is an enemy nearby
  - Killing enemies
- Negative reward
  - Colliding with enemies
  - Being stuck



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- States
- Actions
- Reward function
- Decreasing learning rate
- Discount factor

$$a(s_t, a_t) = \frac{a_0}{\#\ of\ times\ a_t\ performed\ in\ s_t}$$

After several experiments
optimum values are selected

Reinforcement Learning to Play Mario [LYY12]

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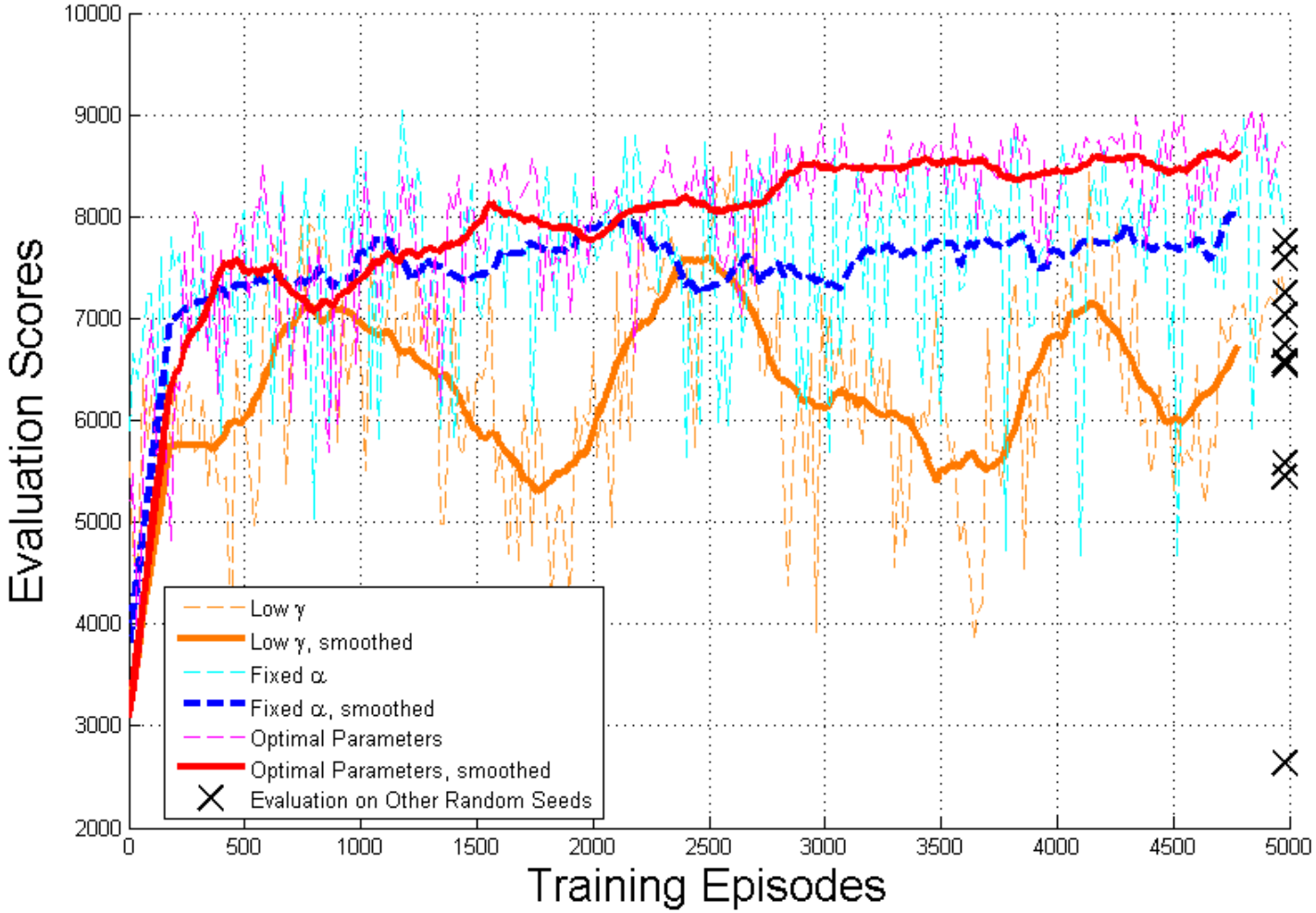
- Four measures
  - Composite score
  - Winning probability
  - % of Monster killed
  - Time spent



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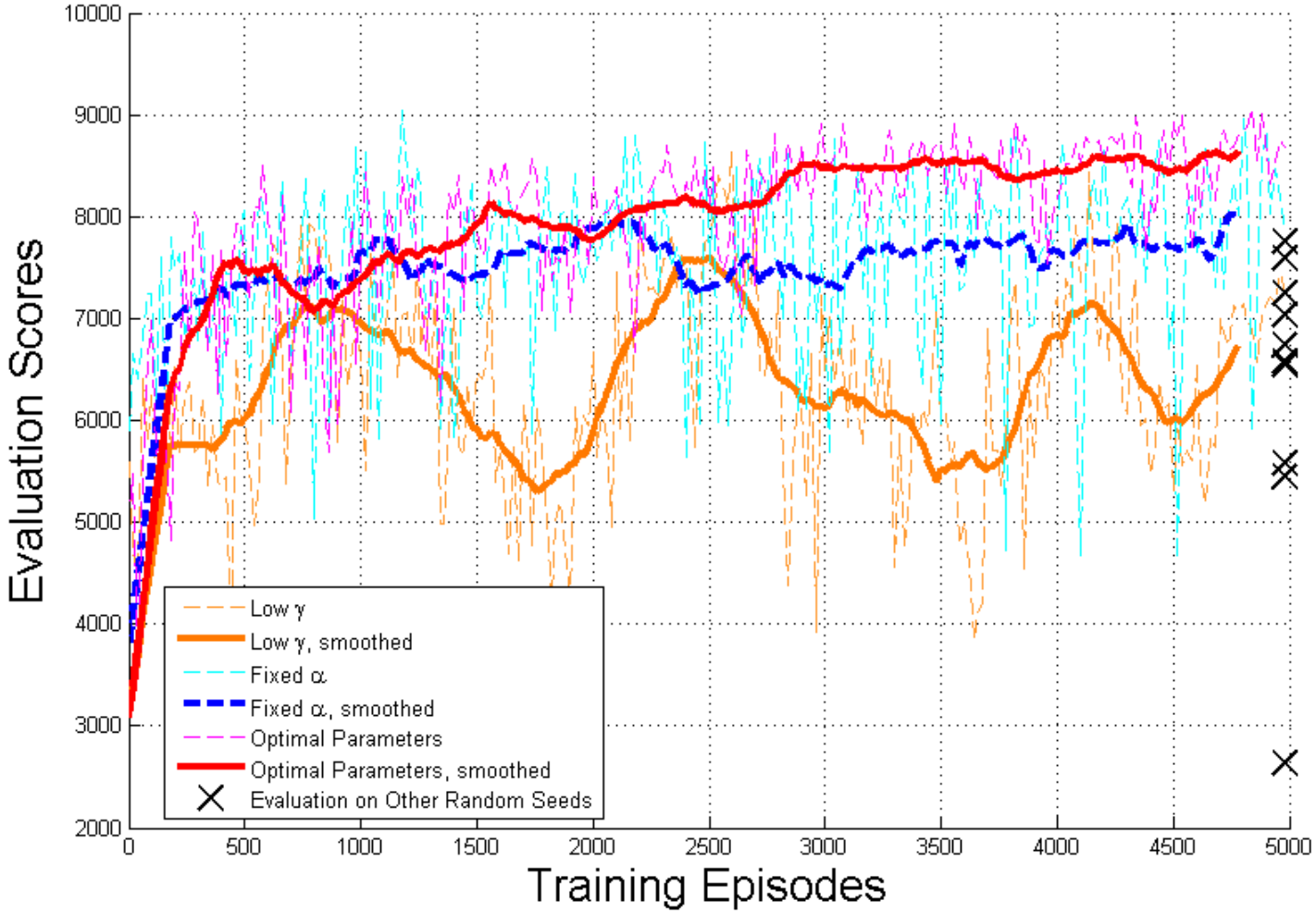
- Four measures
  - Composite score
    - Win status
    - Kills in total
    - Distance passed
    - Time spent in frames



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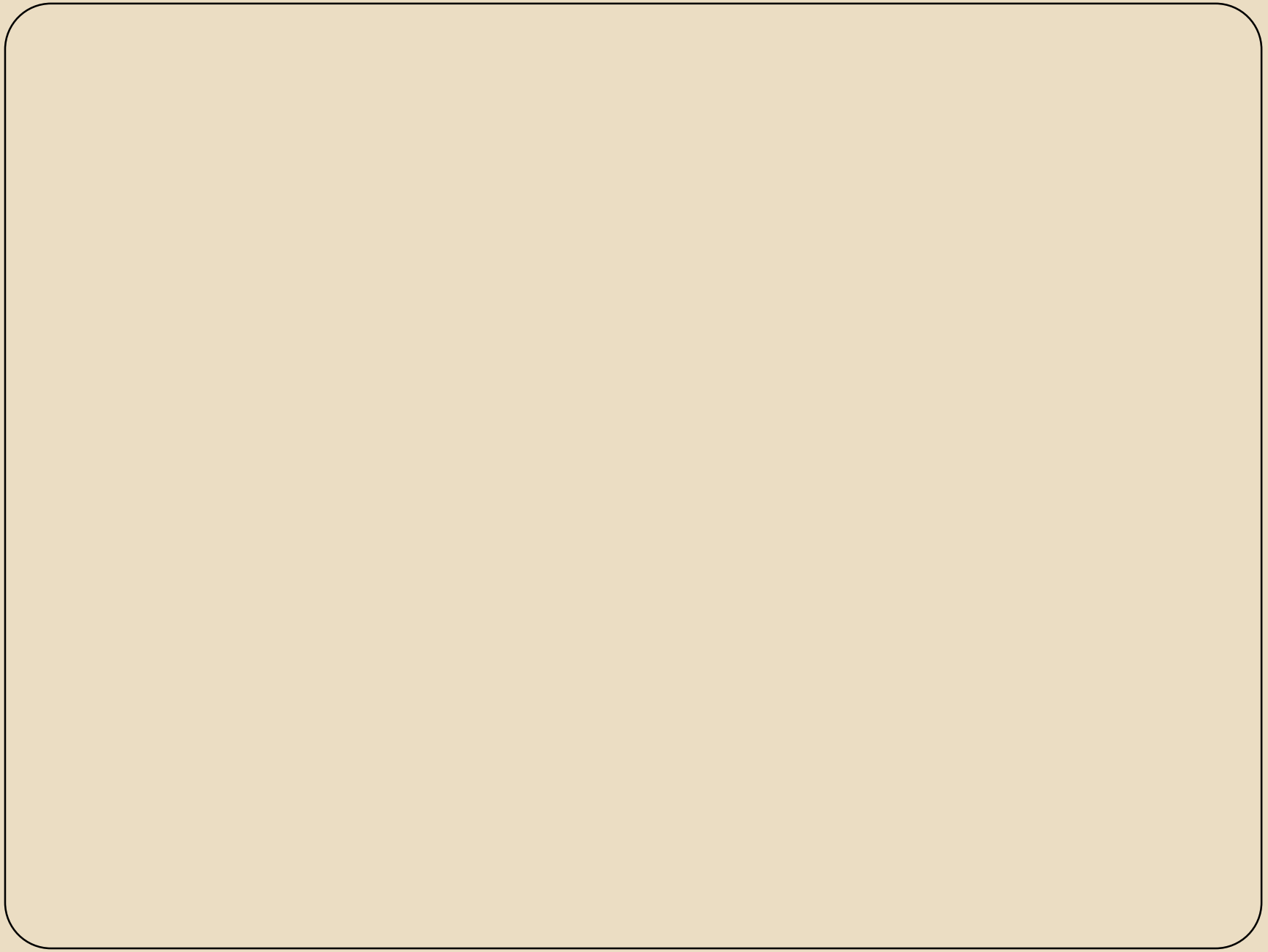
  - Focus only on high-level RL learning and abstraction of the game environment!

- State space



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- 4 state features, in total 81 possible states

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  - Population difference
  - Land diff.
  - Military power diff.
  - Remaining land

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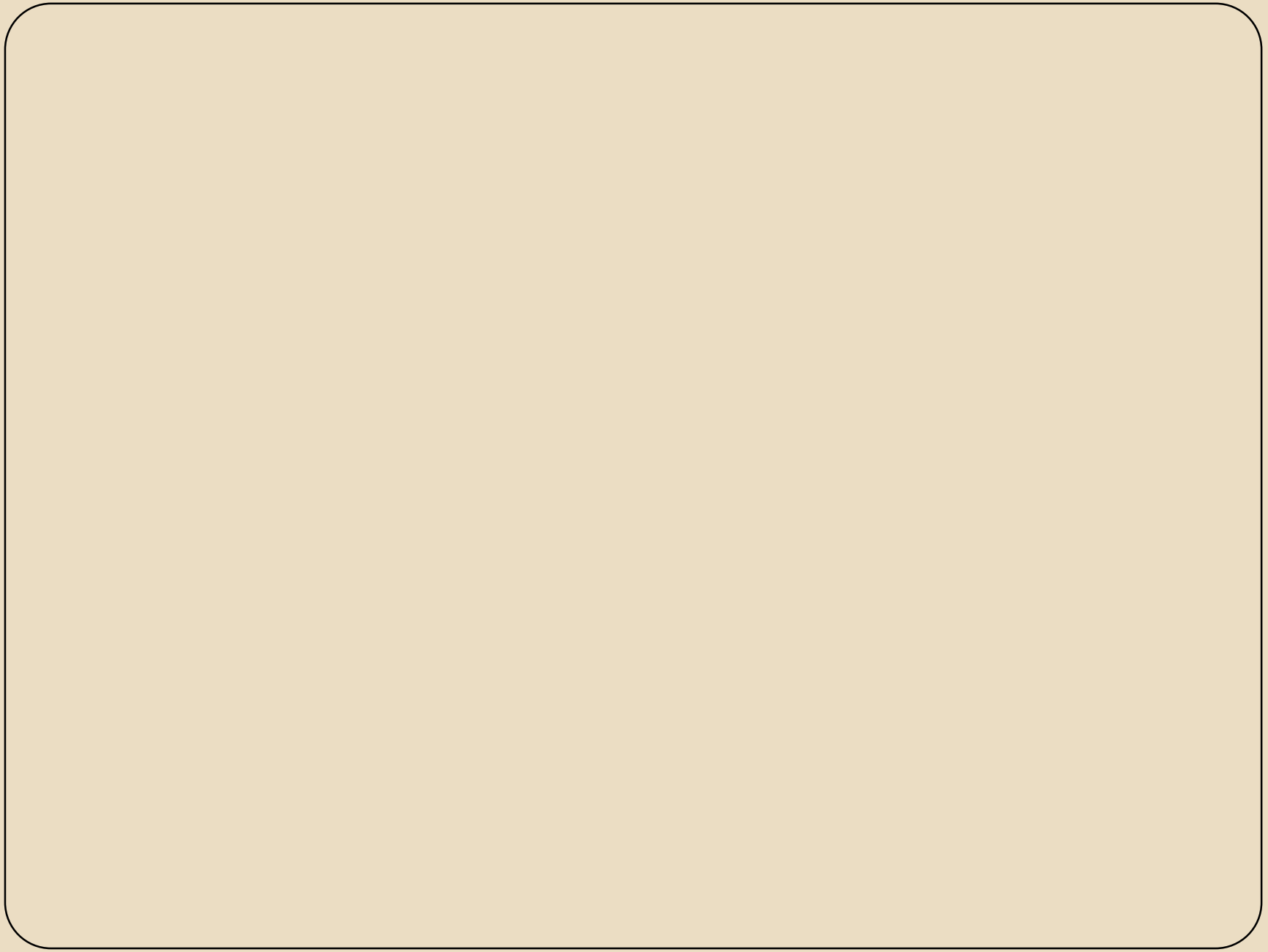
All common and provided by game

$$f_i = \begin{cases} 2, & if\ diff > \mathbf{10} \\ 1, & if\ -\mathbf{10} < diff < \mathbf{10} \\ 0, & if\ diff < -\mathbf{10} \end{cases}$$

- State space
- Action space



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  - Covers all 8 possible leader traits

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  - For example
    - Washington is Financial and Organized

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- Reward model

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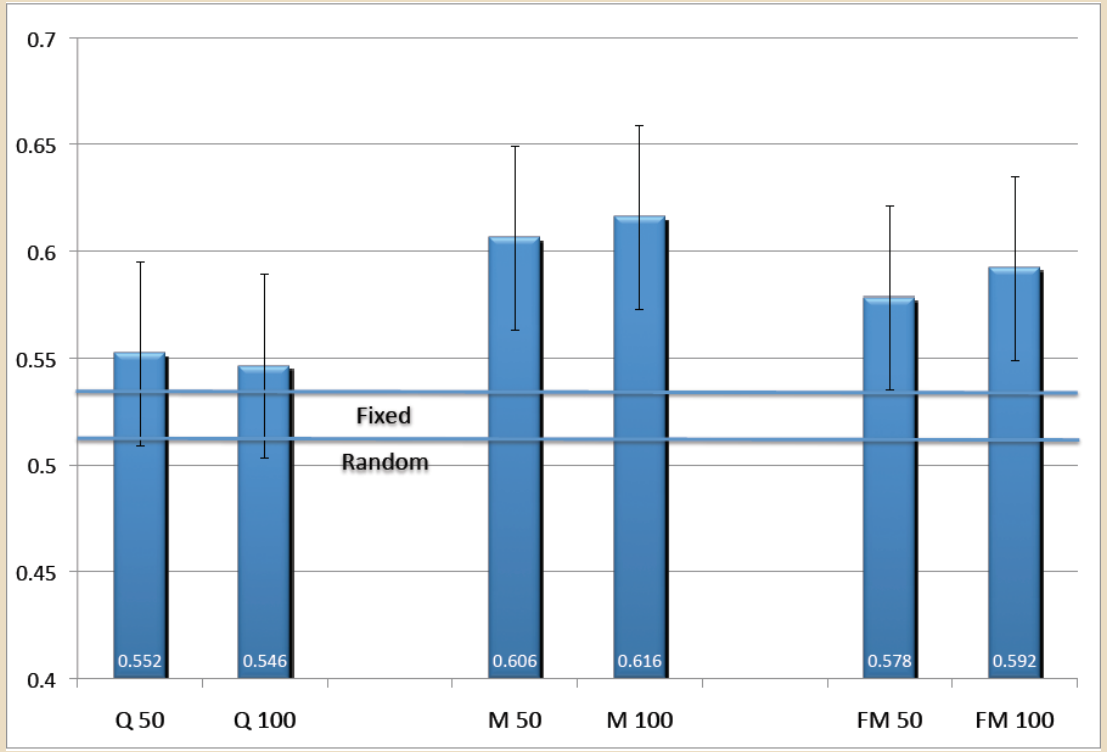
- Still possible to lose the game while having high score

High-level Reinforcement Learning in Strategy Games [AmS10]



versus

Fredrick

- Organized
- Philosophical

Washington

- Expansive
- Charismatic

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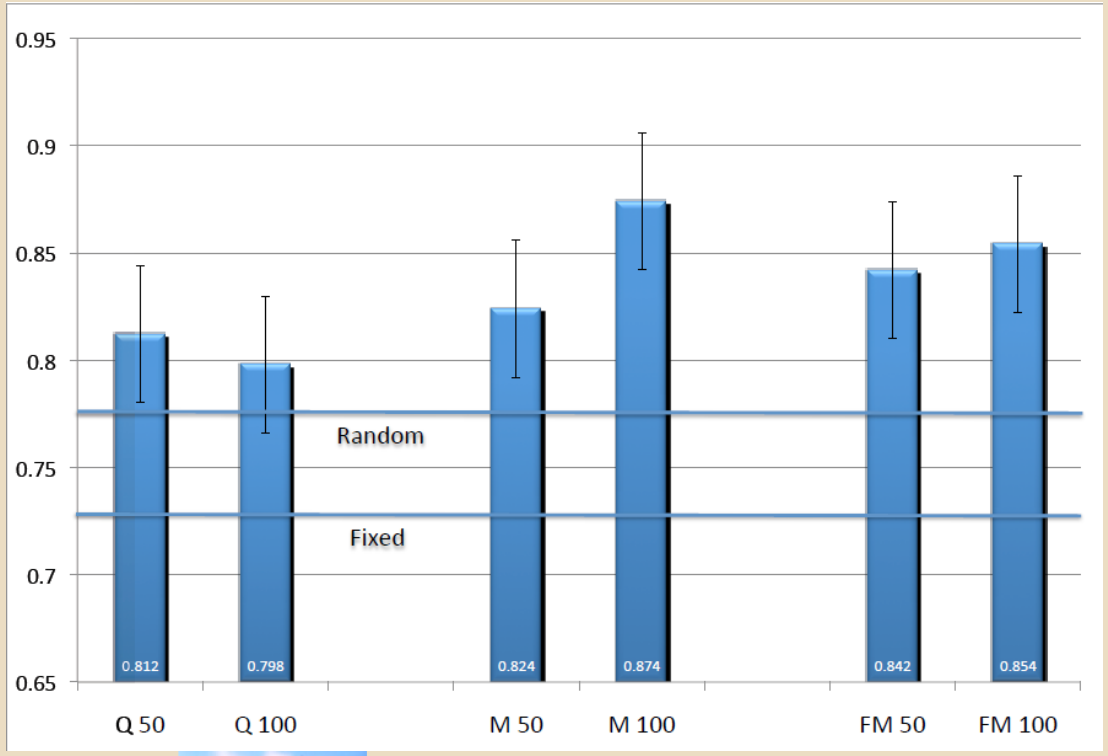

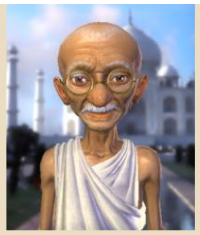

versus

Gandhi

- Spiritual
- Philosophical

Genghis Khan

- Aggressive
- Imperialistic

Temporal Difference Learning and TD-Gammon [Tes95]

- $TD(\lambda)$ algorithm and NN
- Helped set the groundwork for many advancements made
- Referenced in both Atari and AlphaGo papers

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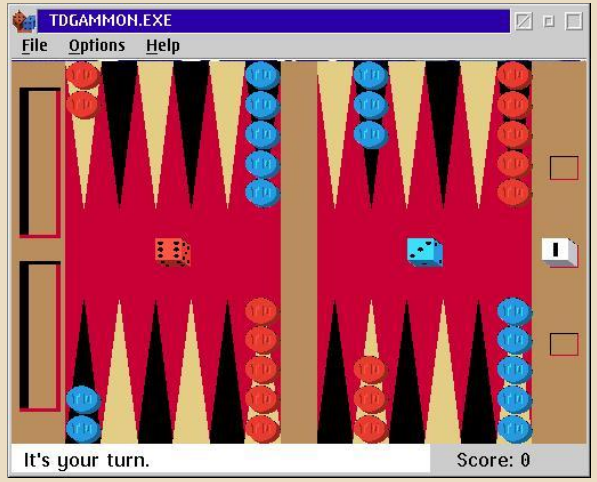

Temporal Difference Learning and TD-Gammon [Tes95]

- Backgammon playing agent
- First successful NN & RL approach
  - $TD(\lambda)$ algorithm and NN
  - Helped set the groundwork for many advancements made
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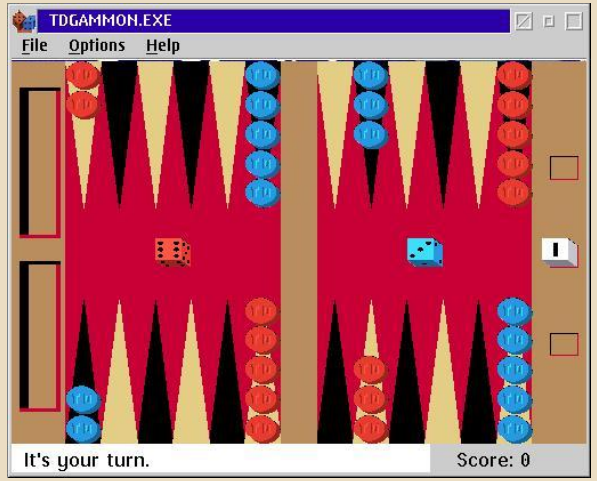

  - 10^{20}

Temporal Difference Learning and TD-Gammon [Tes95]

- $TTDD\ \lambda\ \lambda\ \lambda$ algorithm and NN
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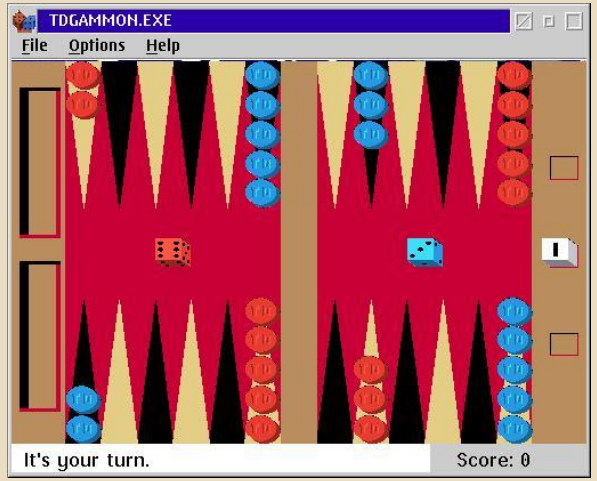

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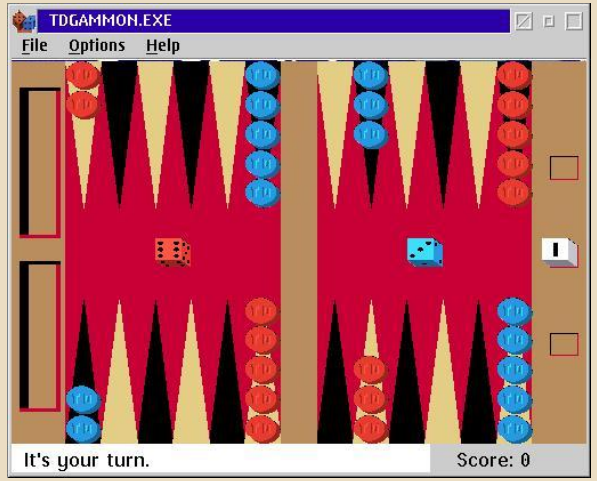

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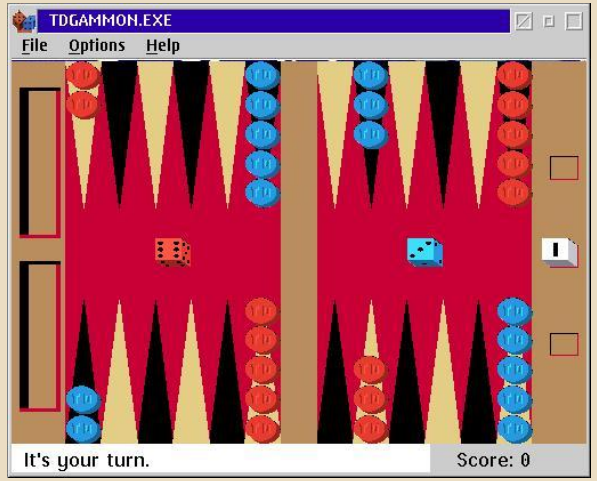

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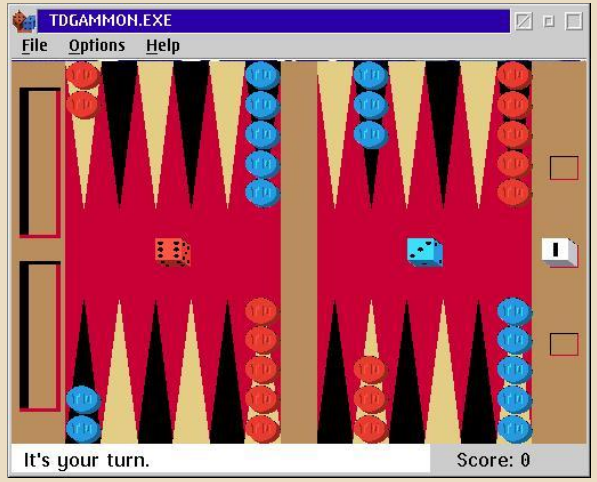
- Other approaches did not work well
  - 10^{20}



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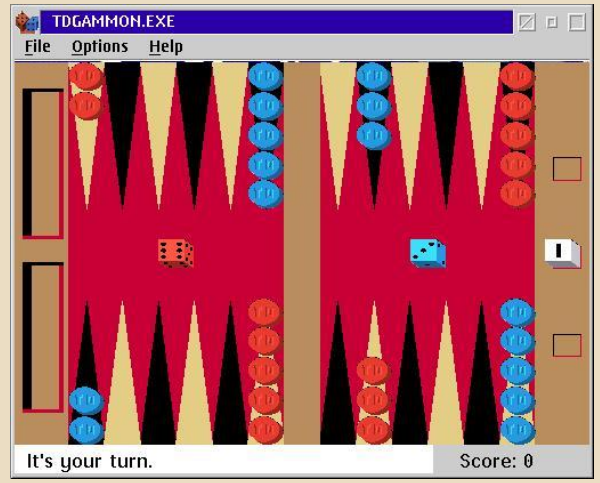

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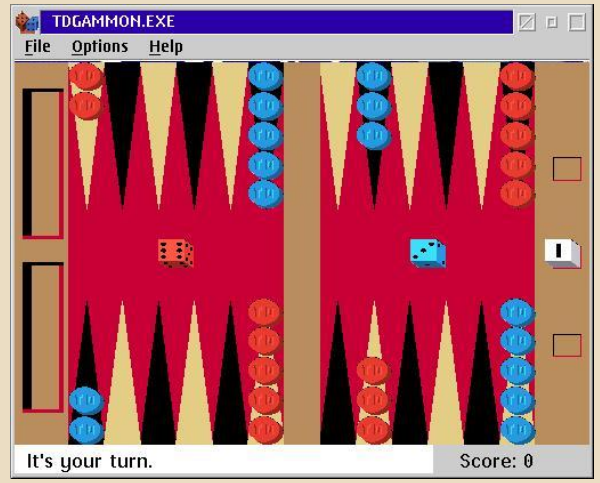
    - High branching ratio: 21 possible dice combinations
  - 10^{20}



Temporal Difference Learning and TD-Gammon [Tes95]

- 10 20 10 10 20 20 10 20
- $TTDD$ λ λ λ algorithm and NN
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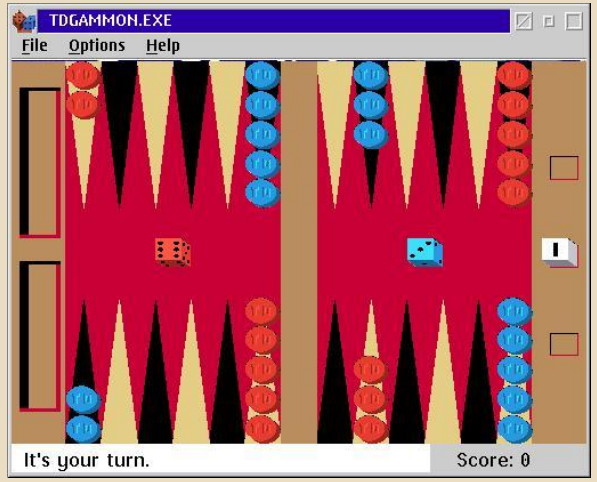
  - Brute-force not feasible
    - High branching ratio: 21 possible dice combinations
  - Huge search space ≈ 10^{20}
  - 10^{20}



Temporal Difference Learning and TD-Gammon [Tes95]

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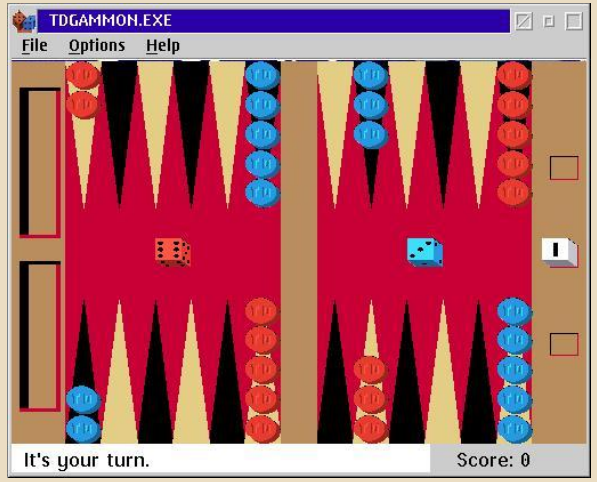
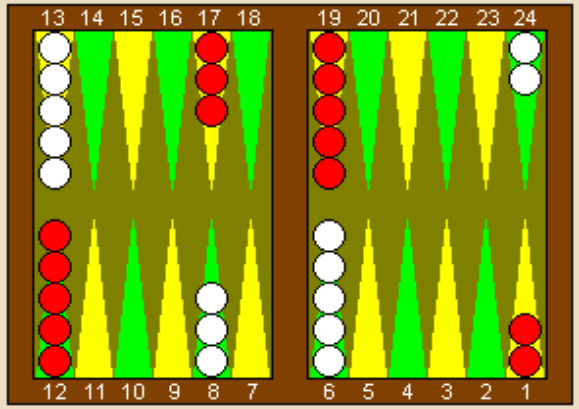
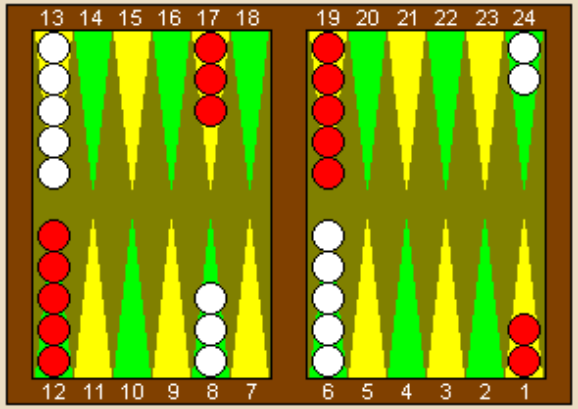
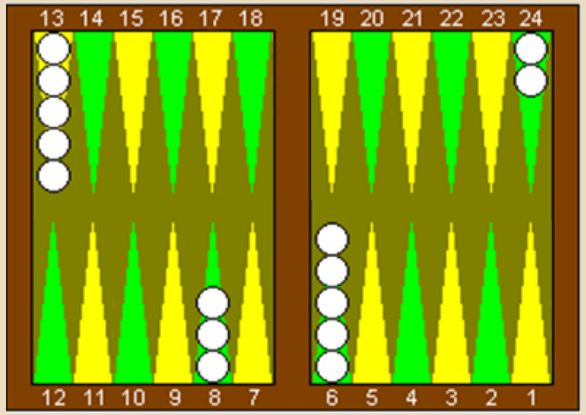
  - Referenced in both Atari and AlphaGo papers
- Other approaches did not work well
  - Brute-force not feasible
    - High branching ratio: 21 possible dice combinations
  - Supervised method, hand-crafted features achieved only high-intermediate level
  - 10^{20}



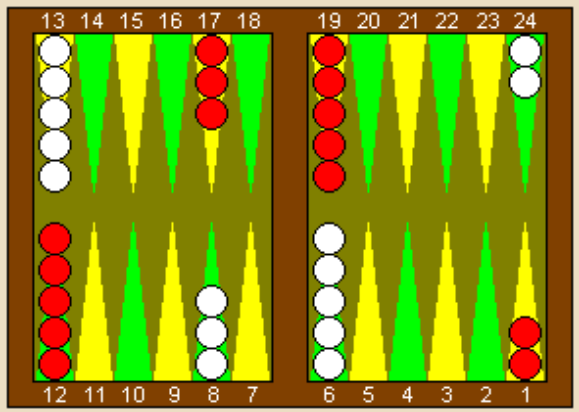

13 14 15 16 17 18
19 20 21 22 23 24
12 11 10 9 8 7
6 5 4 3 2 1

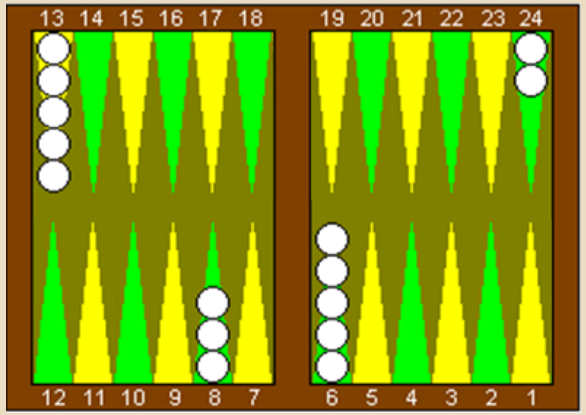
Only one side



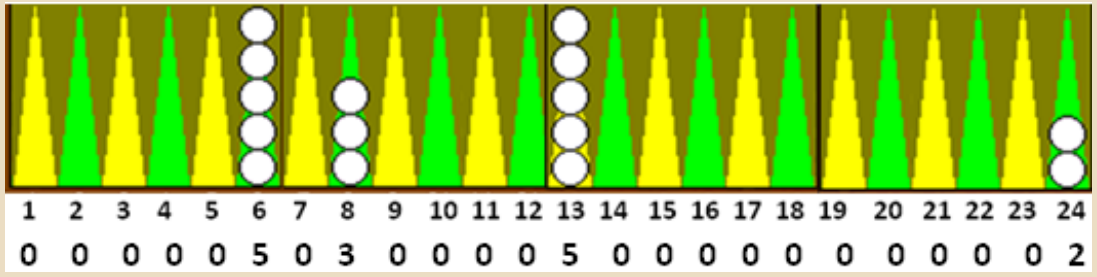


Only one side



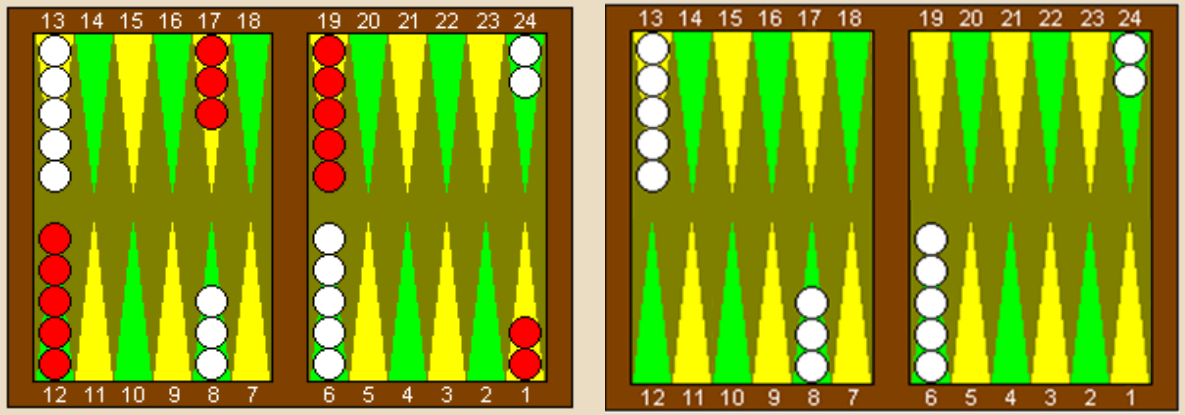


Checkers position as feature vectors

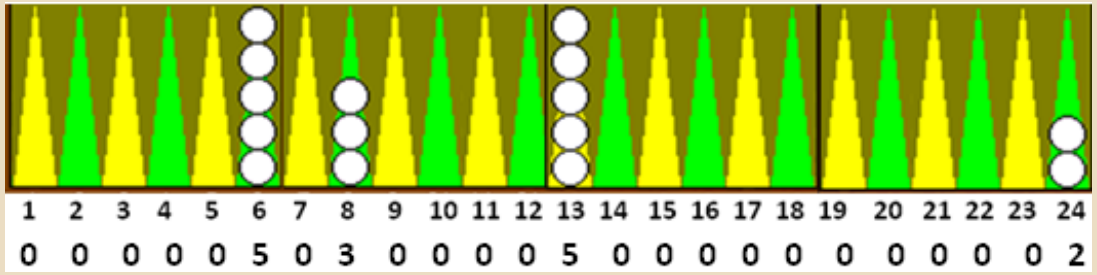


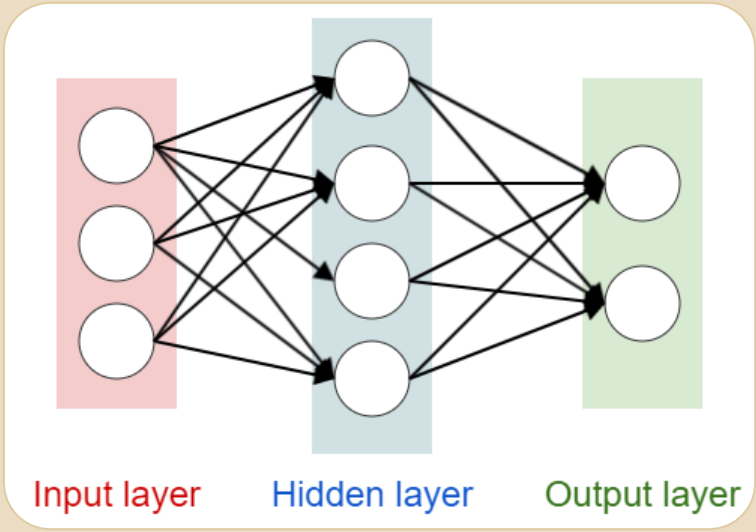
1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
0	0	0	0	0	5	0	3	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	2

Only one side

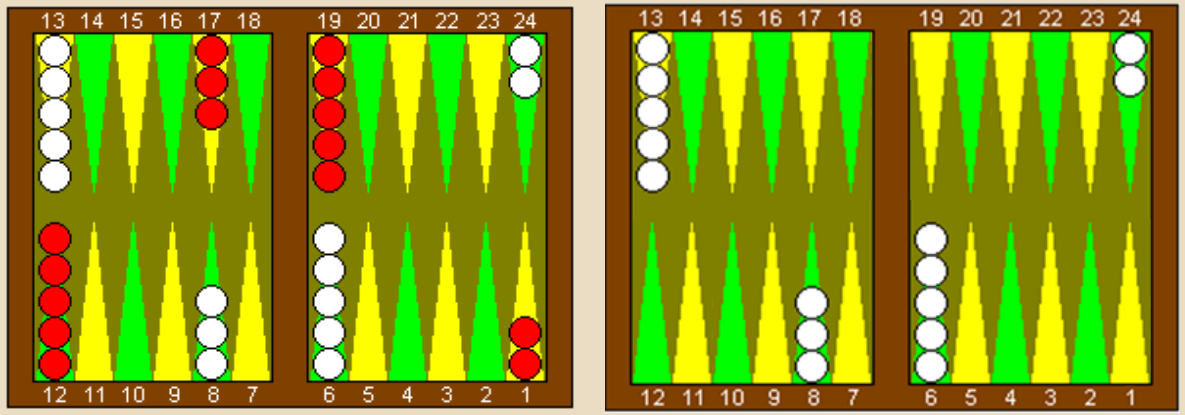


Checkers position as feature vectors





Only one side



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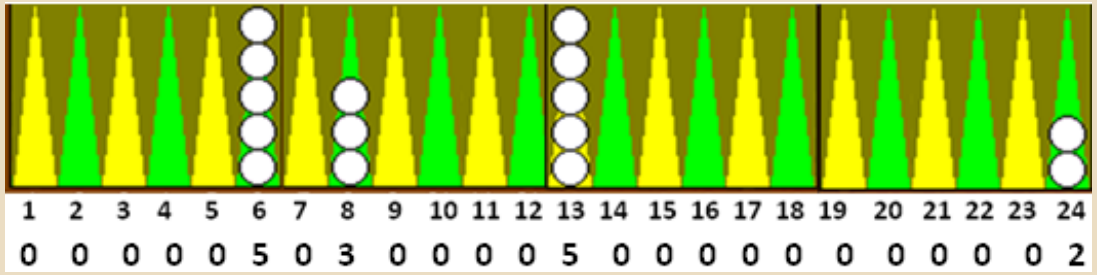
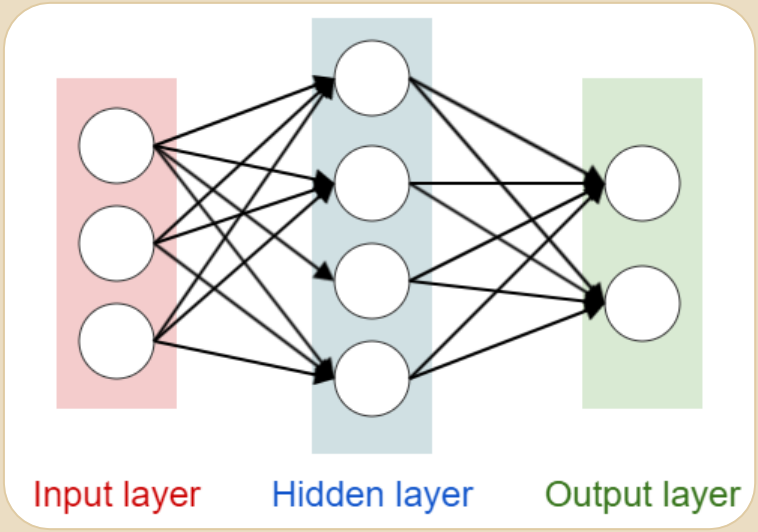
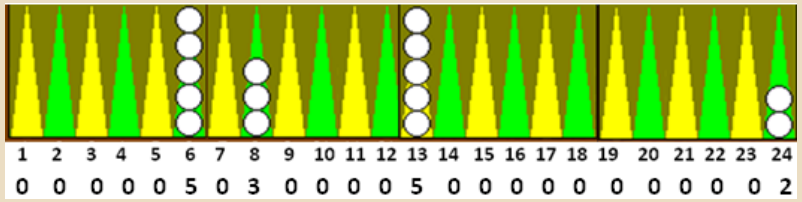
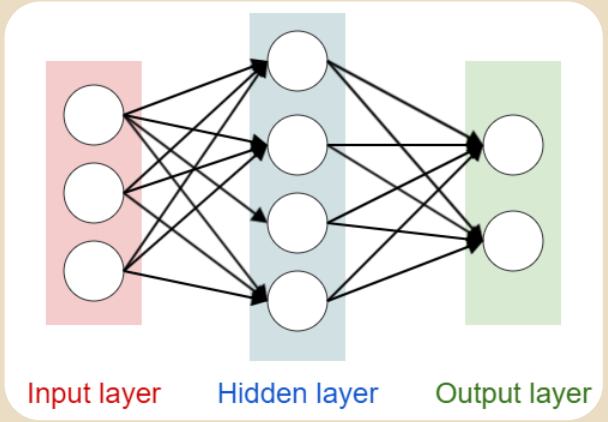


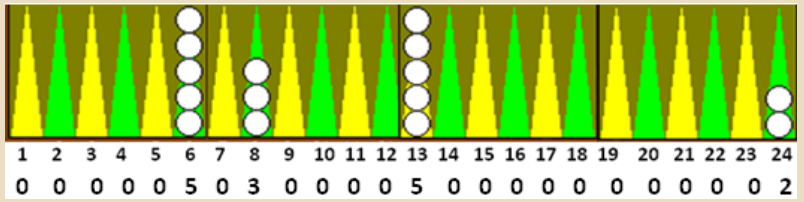


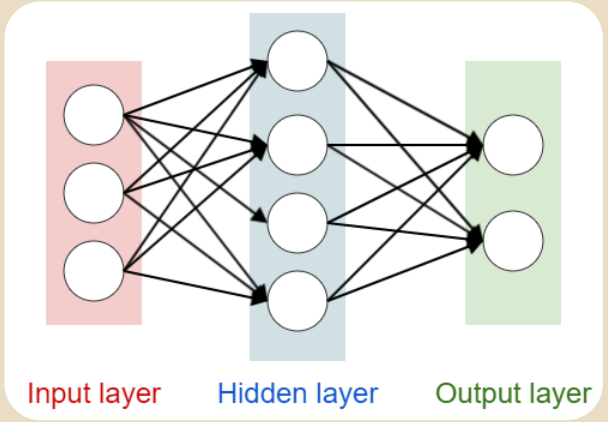
White	Normal
Red	Gammon





- Pr(White wins)
- Pr(White gammons)
- Pr(Red wins)
- Pr(Red gammons)





- Pr(White wins)
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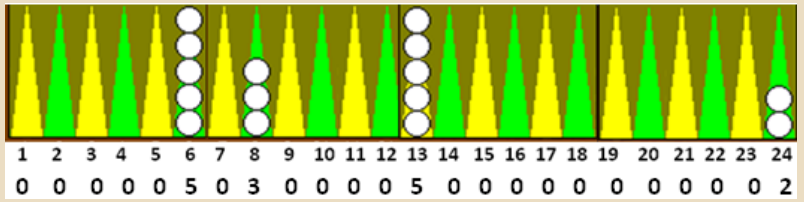
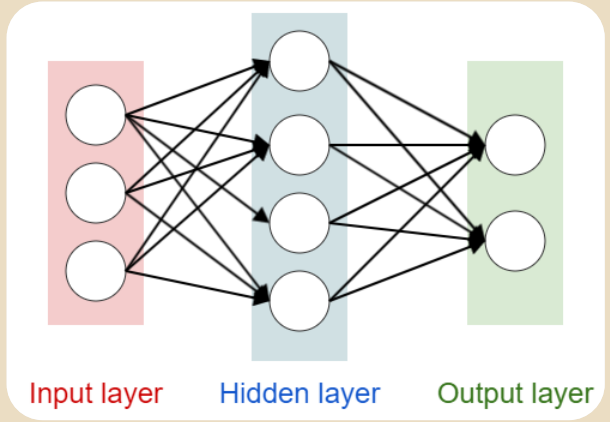
- Pr(Red wins)
- Pr(Red gammons)

- After each turn, each weight in NN gets updated according to $\mathrm{TD}(\lambda)$:

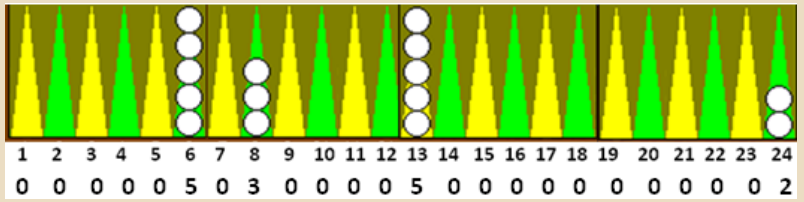


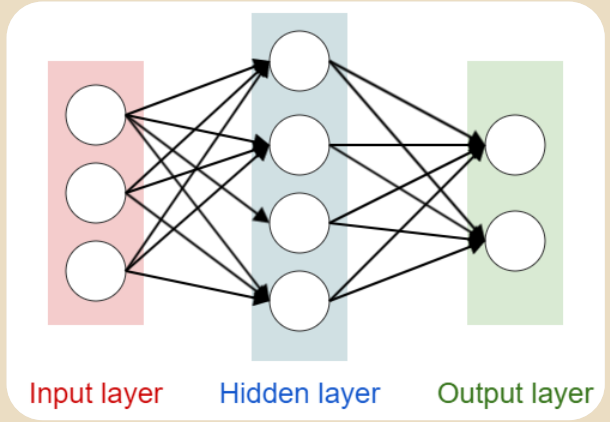


- Pr(White wins)
- Pr(White gammons)
- Pr(Red wins)
- Pr(Red gammons)

- After each turn, each weight in NN gets updated according to $\mathrm{TD}(\lambda)$:

$$w_{t+1} - w_t = \alpha(Y_{t+1} - Y_t) \sum_{k=1}^{t} \lambda^{t-k} \nabla_w Y_k$$





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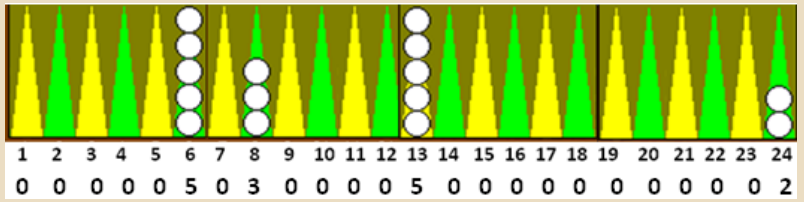
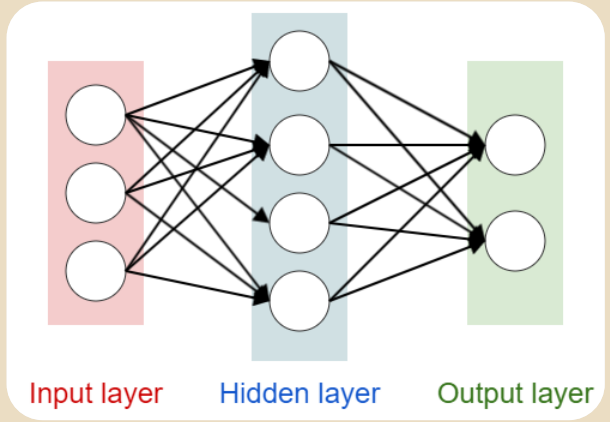
to change the weight from its value on the previous turn





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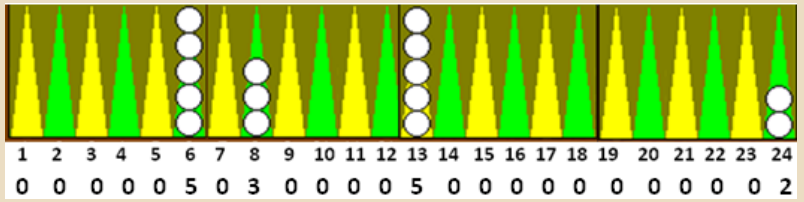
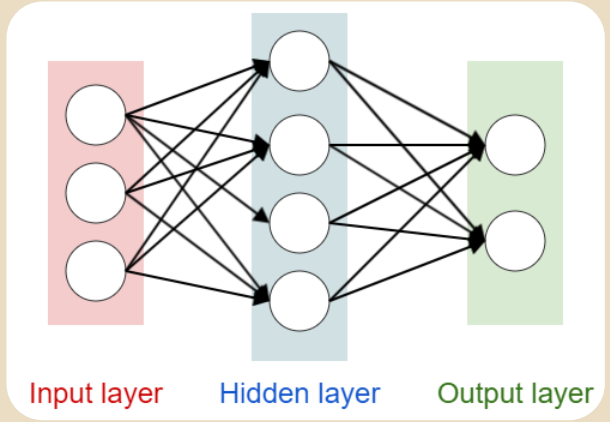
The difference between current and previous turn's board evaluations





- Pr(White wins)
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- Pr(Red gammons)

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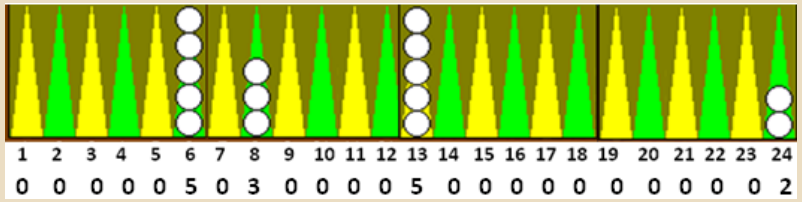
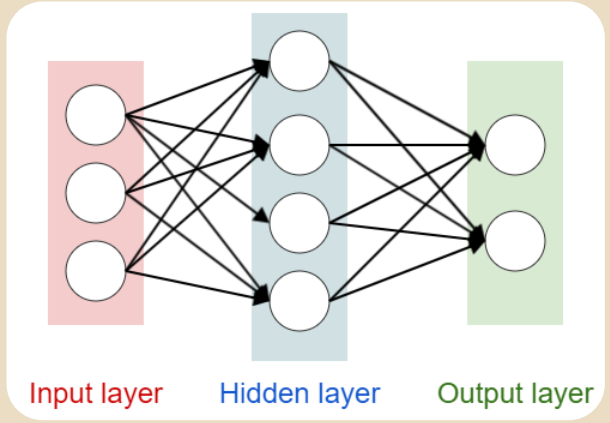
Learning rate





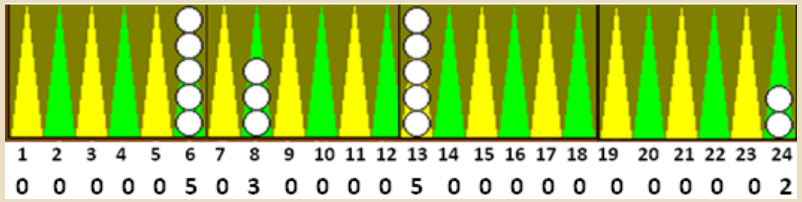
- Pr(White wins)
- Pr(White gammons)
- Pr(Red wins)
- Pr(Red gammons)

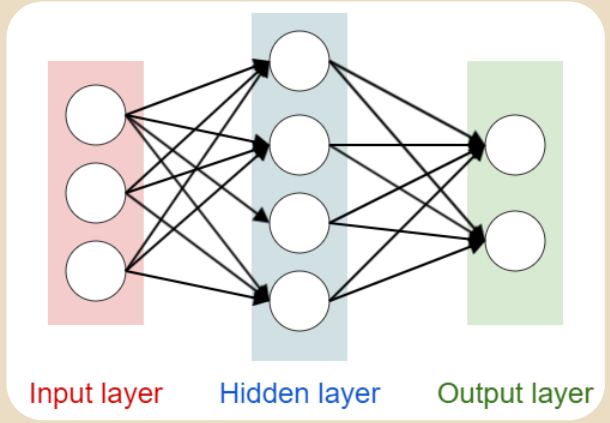
- After each turn, each weight in NN gets updated according to $\mathrm{TD}(\lambda)$:

$$w_{t+1} - w_t = \alpha(Y_{t+1} - Y_t) \sum_{k=1}^{t} \lambda^{t-k} \nabla_w Y_k$$

Controls the decay of older estimates.

If => 0
Corrects only the previous turn's estimate
If => 1
Attempts to correct all previous turns



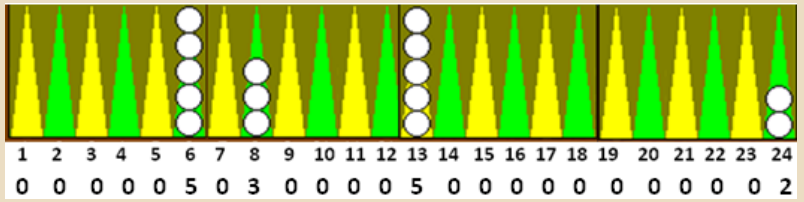


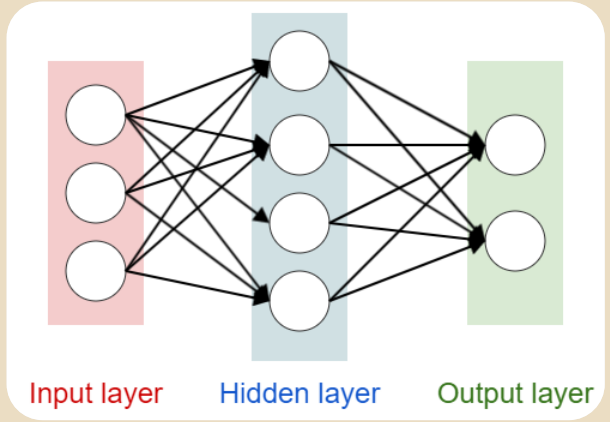
- Pr(White wins)
- Pr(White gammons)
- Pr(Red wins)
- Pr(Red gammons)

- After each turn, each weight in NN gets updated according to $\mathrm{TD}(\lambda)$:

$$w_{t+1} - w_t = \alpha(Y_{t+1} - Y_t) \sum_{k=1}^{t} \lambda^{t-k} \nabla_w Y_k$$

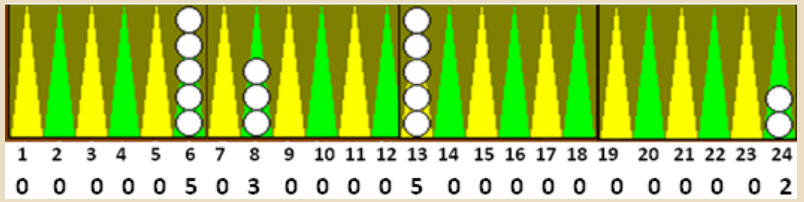
The gradient of NN output w.r.t to weights

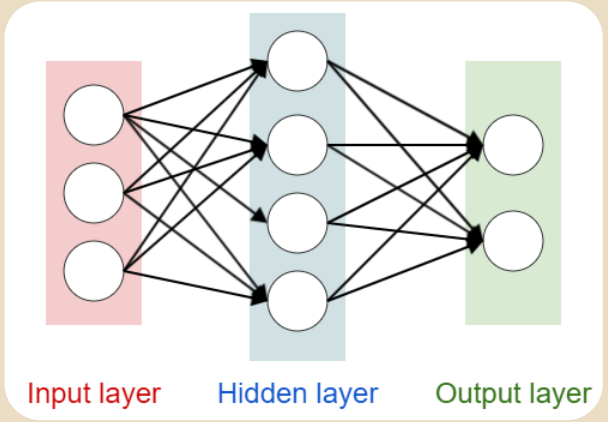




- Pr(White wins)
- Pr(White gammons)
- Pr(Red wins)
- Pr(Red gammons)

- After each turn, each weight in NN gets updated according to $\mathrm{TD}(\lambda)$:
- First chooses any legal move





- Pr(White wins)
- Pr(White gammons)
- Pr(Red wins)
- Pr(Red gammons)

- After each turn, each weight in NN gets updated according to $\mathrm{TD}(\lambda)$:
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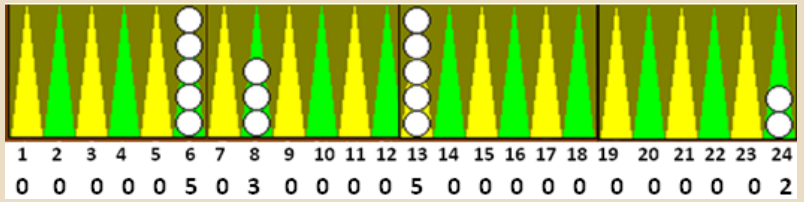
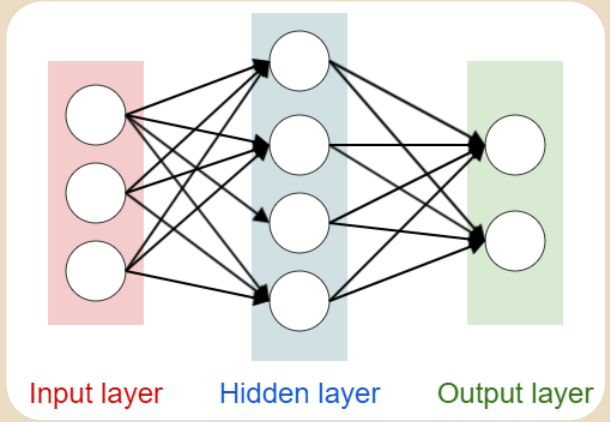
  - After NN weights updated (backpropagation), picks the maximum weighted corresponding move.





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- After each turn, each weight in NN gets updated according to $\mathrm{TD}(\lambda)$:
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  - After NN weights updated (backpropagation), picks the maximum weighted corresponding move.
- Self-training scheme and stochastic environment of the game improves the NN

Temporal Difference Learning and TD-Gammon [Tes95]

Program	Training Games	Opponents	Results
TDG 1.0	300,000	Robertie, Davis, Magriel	-13 pts/51 games (-0.25 ppg)
TDG 2.0	800,000	Goulding, Woolsey, Snellings, Russell, Sylvester	-7 pts/38 games (-0.18 ppg)
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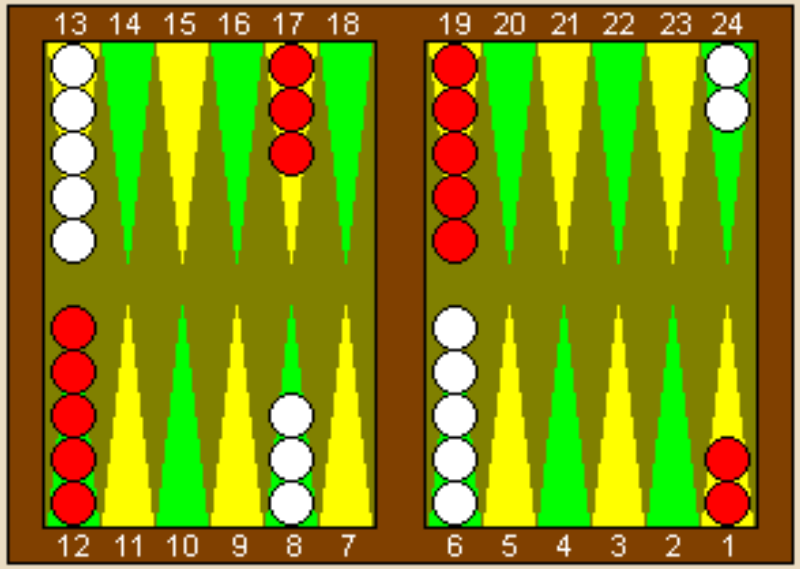
Addition!

Later in TDG 3.0 using 160 hidden nodes and a selective 3-ply search, managed to beat Kazaros +6pts /20 games

Temporal Difference Learning and TD-Gammon [Tes95]



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Move	Estimate	Rollout
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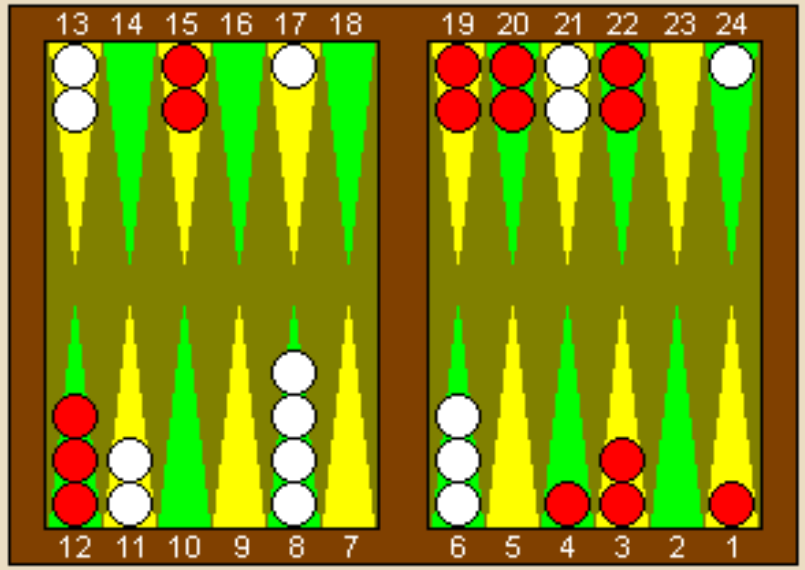

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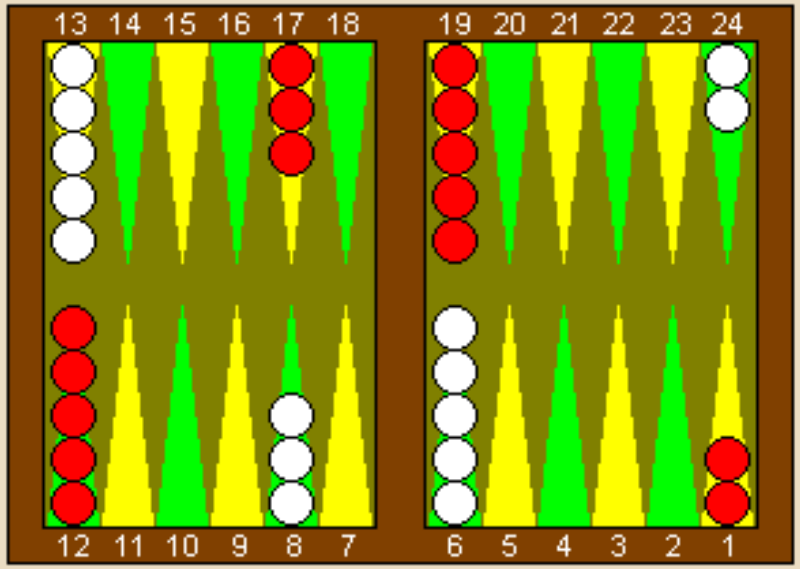

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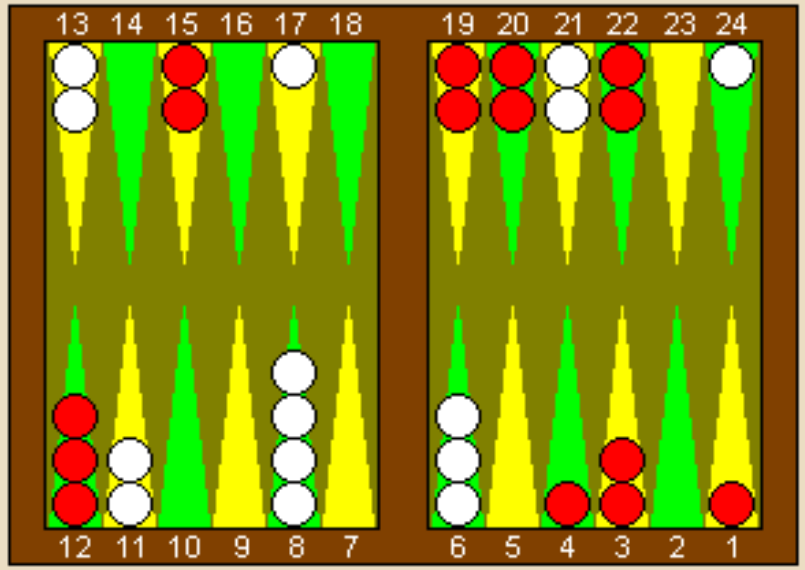

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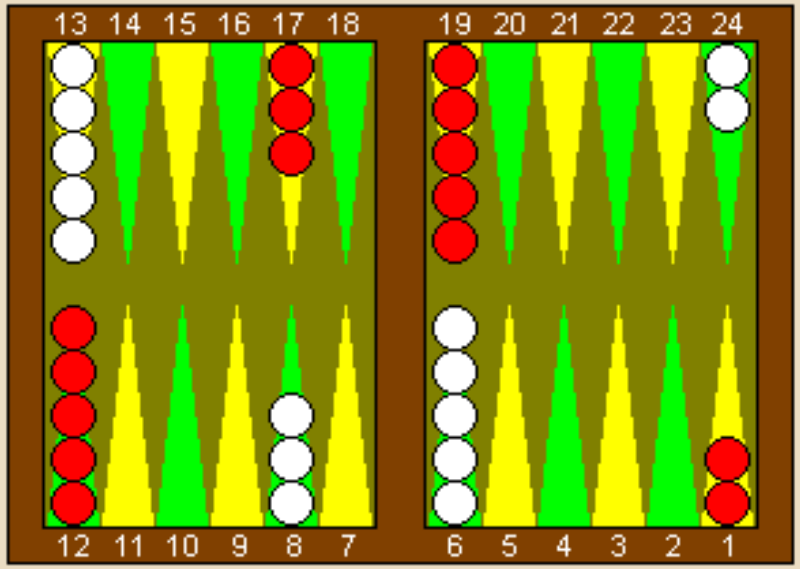

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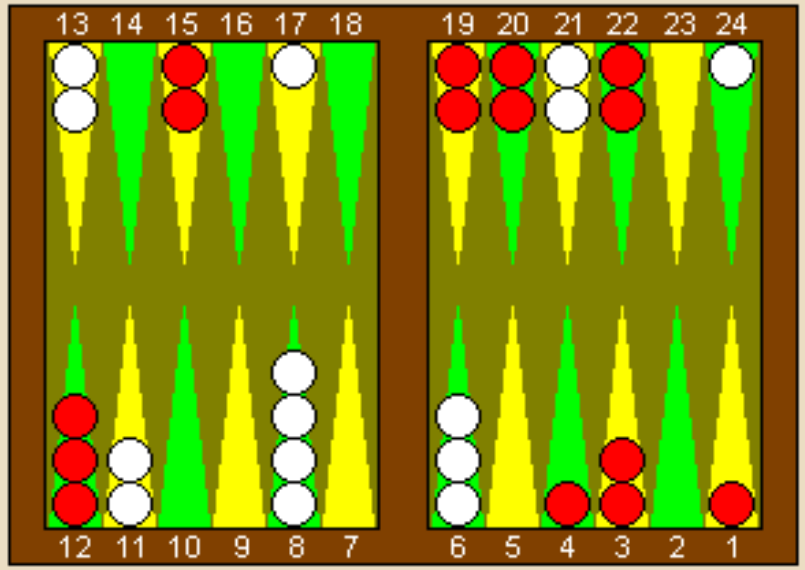

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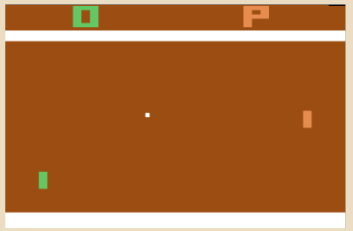

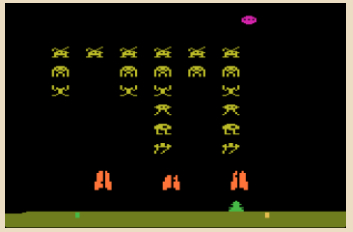

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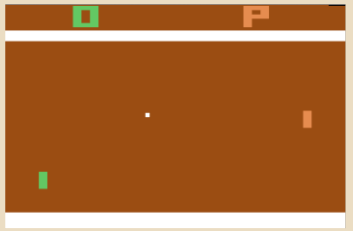

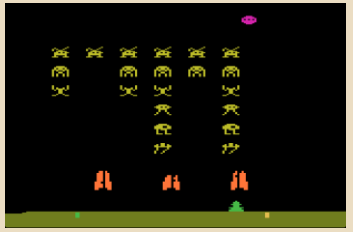

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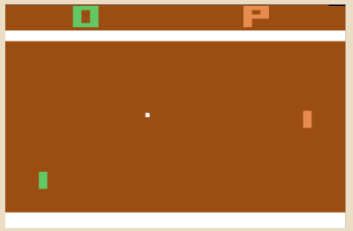

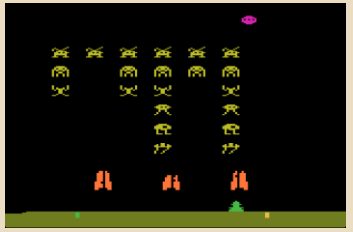

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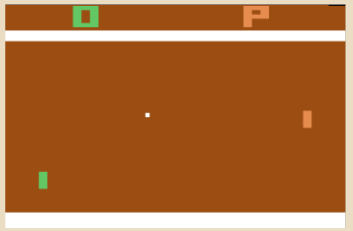

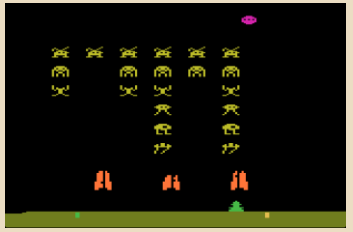

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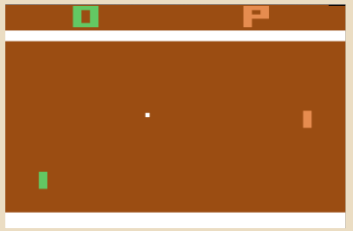

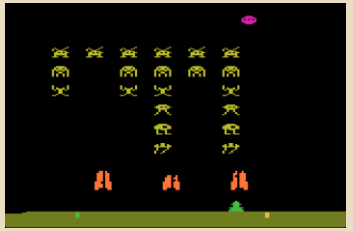

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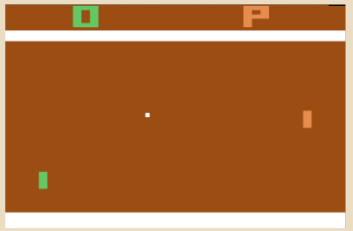
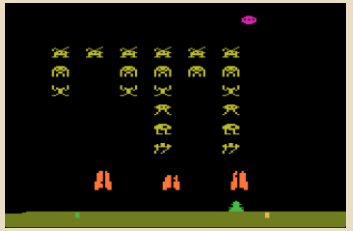
  - Randomly sample previous transition = smooth the distribution





Algorithm 1 Deep Q-learning with Experience Replay

Initialize replay memory $\mathcal{D}$ to capacity N
Initialize action-value function Q with random weights
for episode $= 1, M$ **do**
  Initialise sequence $s_1 = \{x_1\}$ and preprocessed sequenced $\phi_1 = \phi(s_1)$
  for $t = 1, T$ **do**
    With probability ϵ select a random action a_t
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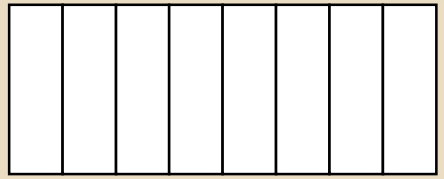
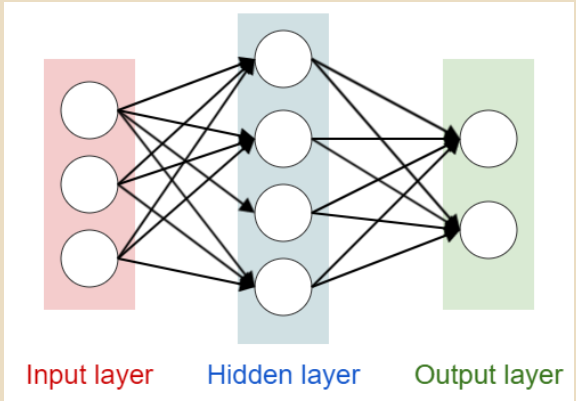
Replay memory





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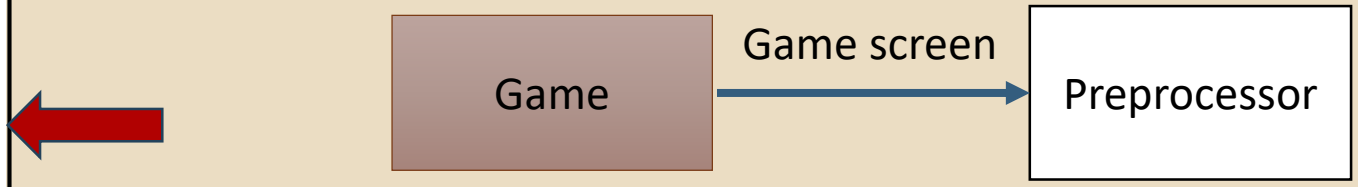

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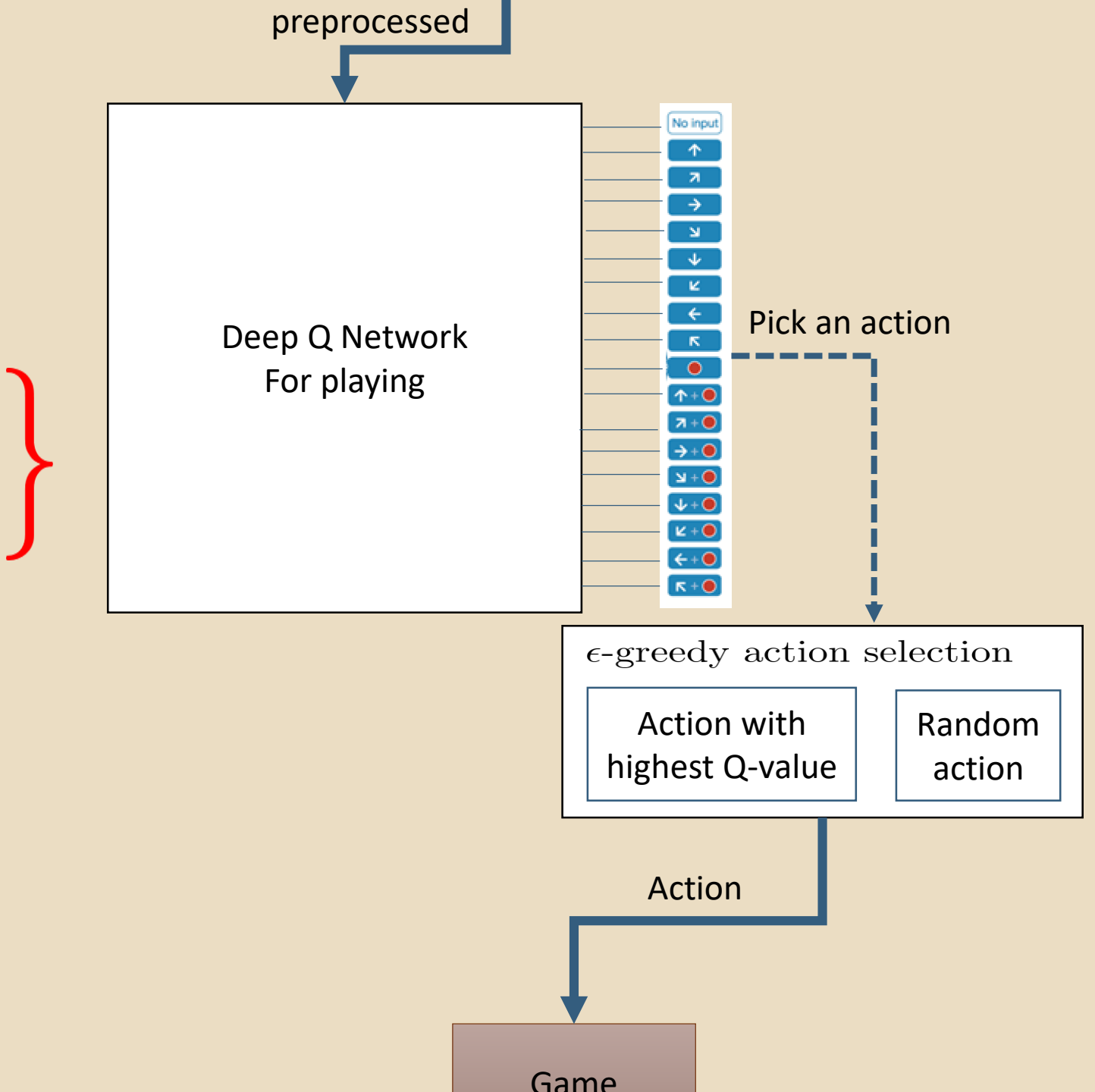

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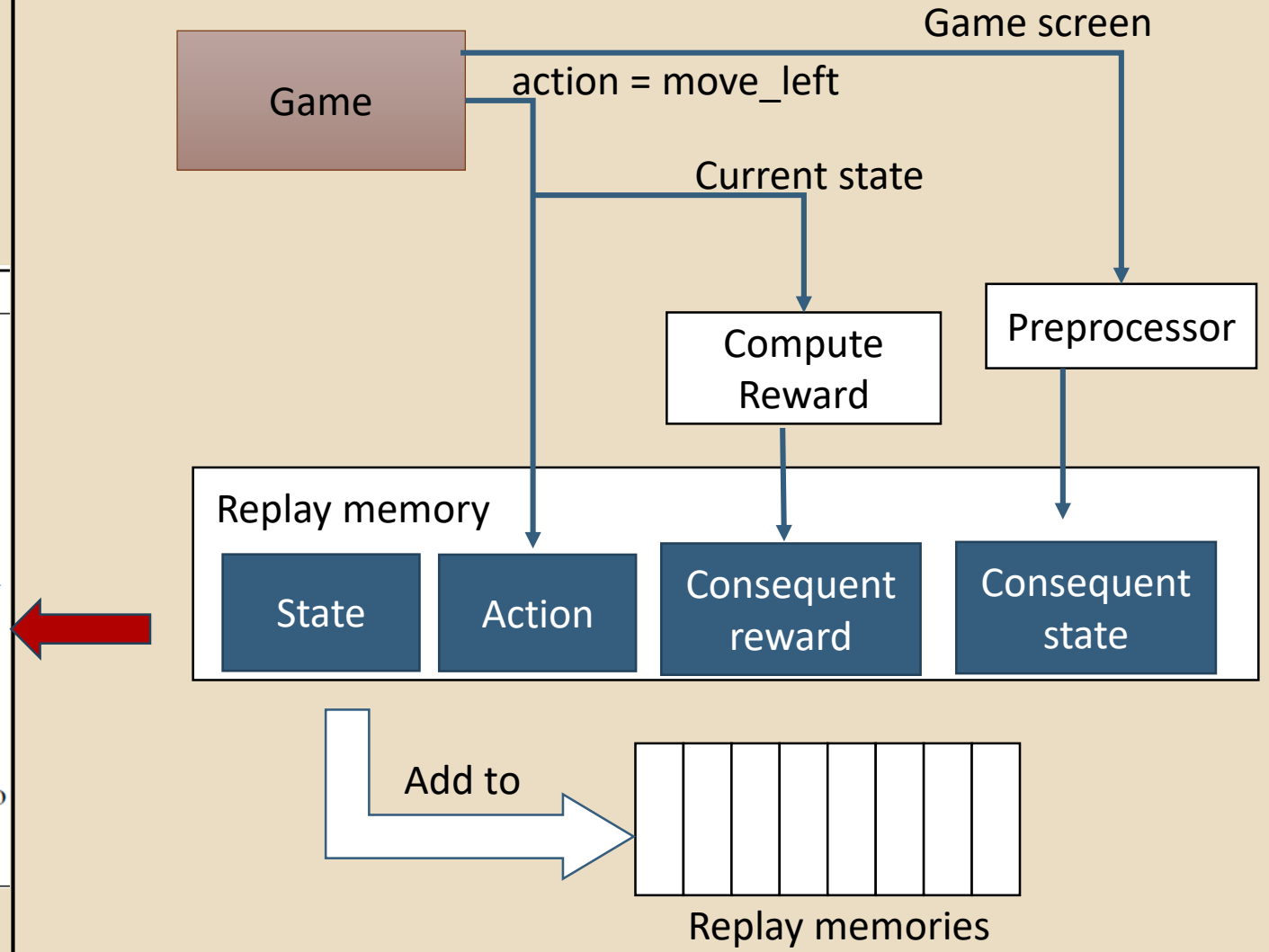

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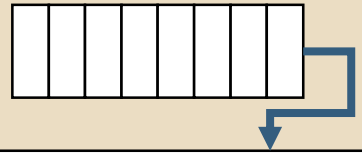
end for

For each replay memory «j»



Replay memory

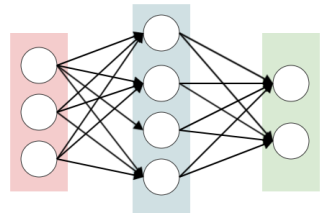
State | Action | Consequent reward | Consequent state

Smooth training distribution

If terminal memory -> current reward
Otherwise; update w.r.t. Max Q value of A

Compute loss
and Update network

Gradient descent



Playing Atari with Reinforcement Learning [MKS13]

	B. Rider	Breakout	Enduro	Pong	Q*bert	Seaquest	S. Invaders
Random	354	1.2	0	−20.4	157	110	179
Sarsa [3]	996	5.2	129	−19	614	665	271
Contingency [4]	1743	6	159	−17	960	723	268
DQN	**4092**	**168**	**470**	**20**	**1952**	**1705**	**581**
Human	7456	31	368	−3	18900	28010	3690

Average total reward

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Average total reward

HNeat Best [8]	3616	52	106	19	1800	920	**1720**
DQN Best	**5184**	**225**	**661**	**21**	**4500**	**1740**	1075

Neuro-evolution approach comparison

Conclusion

- Summary
- Some problems in articles
  - Evaluation
  - Why did TD-Gammon work? [PoB97]
- What to expect next?
  - Faster, stronger, less HW requirements
  - Sandbox learning

Thank you for listening!

Questions?

References

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