Value-based Methods

Reinforcement Learning

October 5, 2021

MSU

Reminder: Q-learning

For transition (s, a, r, s'):

$$Q^*_{k+1}(s,a) \leftarrow Q^*_k(s,a) + \alpha_k \underbrace{\left(\overbrace{r + \gamma \max_{a'} Q^*_k(s',a')}^{\textbf{Bellman target}} - Q^*_k(s,a) \right)}_{\textbf{temporal difference}}$$

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Q-learning can learn Q^* from trial and error in *finite* MDPs: $|\mathcal{S}| \ll \infty, |\mathcal{A}| \ll \infty$

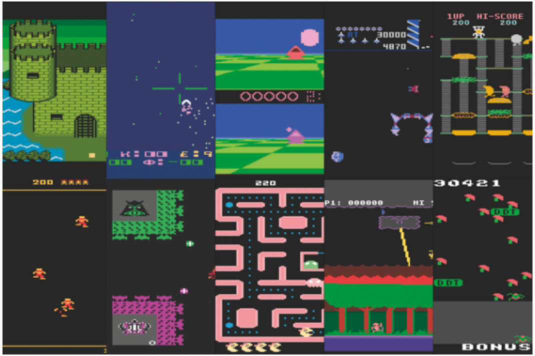
Important!

Q-learning is **off-policy**

Atari Games

Setup: ~~$|\mathcal{S}| \ll \infty$~~, $|\mathcal{A}| \ll \infty$

- 57 various games
- Only screen image as input.
- No game-specific features.
- Finite-state case... not quite finite.
- $|\mathcal{A}| \leqslant 18$



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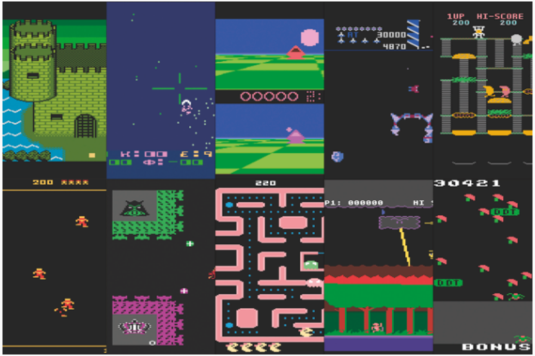

Approximate $Q^*(s, a)$ with neural network!

Is Atari game a MDP?

Practical notes: preprocessing

Action selection frequency:

- Framestack;
- Frameskip;
- MaxAndSkip;
- (sometimes) Sticky actions;

Atari-specific preprocessing:

- EpisodicLife;
- FireReset;

Standard tricks:

- Crop image;
- Rescale (often to 84x84);
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Reward preprocessing:

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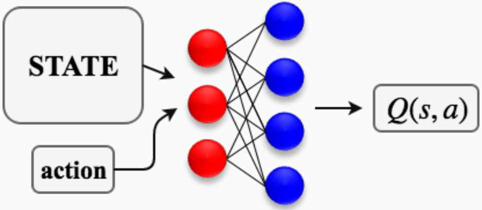
Important!

No hyperparameter tuning for each specific game!

Option 1



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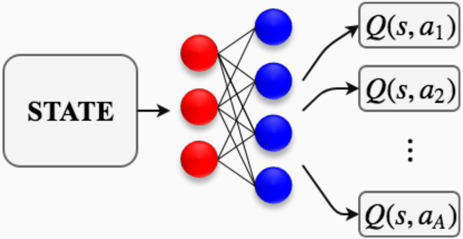

Deep Q-network

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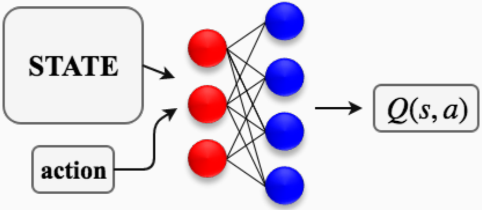
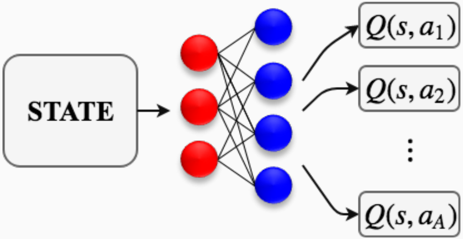


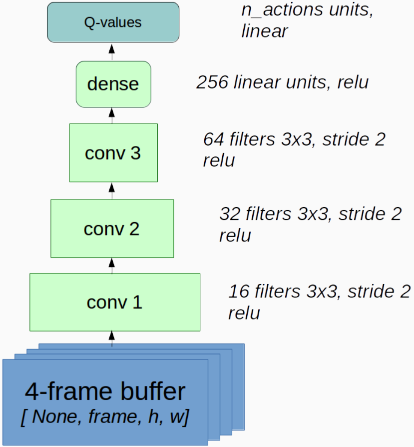
$\times$ $\underset{a}{\operatorname{argmax}}\, Q^*(s, a, \theta)$ — expensive!

Option 2



$\checkmark$ $\underset{a}{\operatorname{argmax}}\, Q^*(s, a, \theta)$ — one forward pass.

Deep Q-network: architecture



- 3-4 convolutional layers followed by 1-2 dense layers;
- stride > 1 for size reduction; linear layers still wide;

Think twice before using:

- × max pooling
- × batch normalization
- × dropout

Idea: Approximate Dynamic Programming

Consider the following **regression task**:

- s, a is input;
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$$y(s, a) := r(s, a) + \gamma \mathbb{E}_{s'} \max_{a'} Q^*(s', a', \theta_k)$$

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$$\frac{1}{2}\mathbb{E}_{(s,a,y)}(y - Q^*(s, a, \theta_{k+1}))^2 \to \min_{\theta_{k+1}}$$

Looking at the gradient

$$\nabla_\theta \frac{1}{2} \left(y - Q^*(s, a, \theta)\right)^2 =$$

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where $s' \sim p(s' \mid s,a)$.

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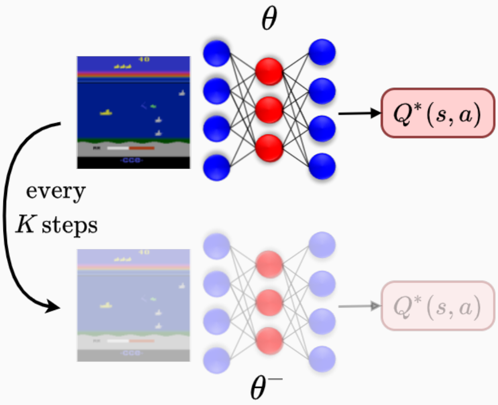

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- One SGD iteration
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- Till convergence
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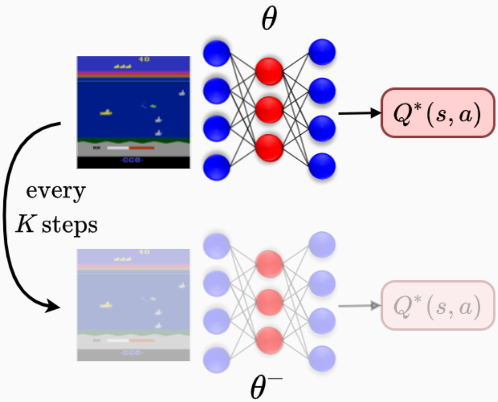
- ✓ ≈1000 SGD iterations
  - **a)** $\theta^- \leftarrow \theta$ every K SGD iterations
  - **b)** $\theta^- \leftarrow (1-\beta)\theta^- + \beta\theta$



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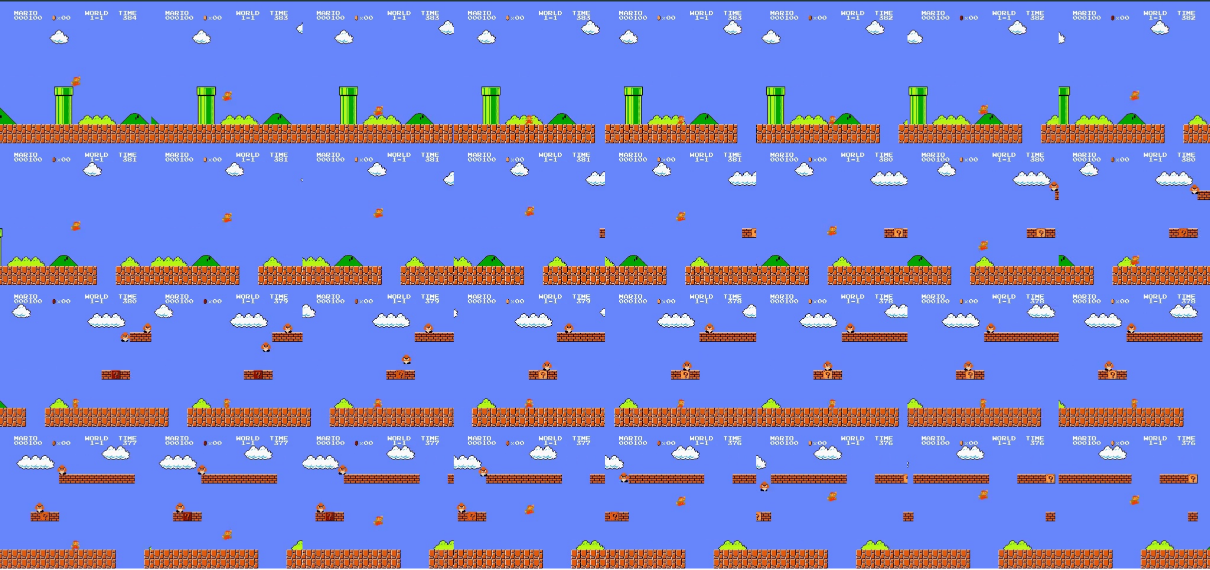
Sample Decorrelation



Experience Replay

Do we still need exploration?

Trial and error

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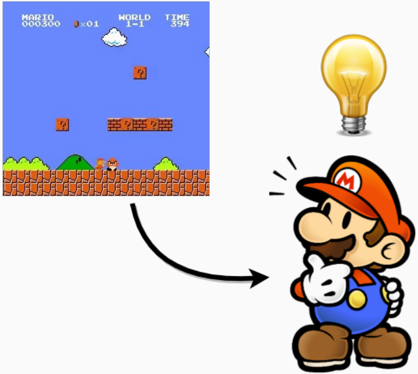

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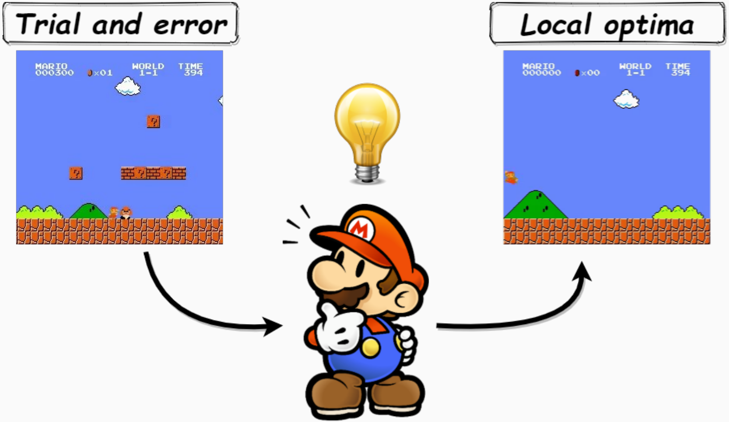

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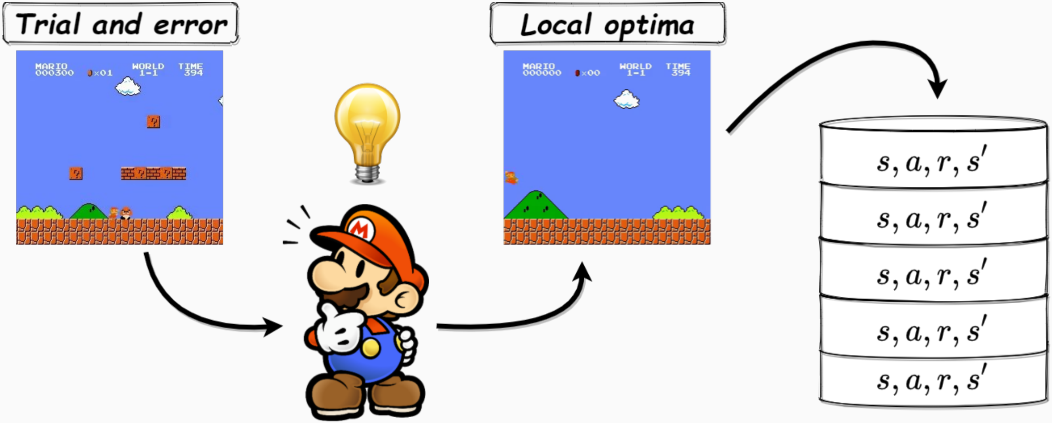

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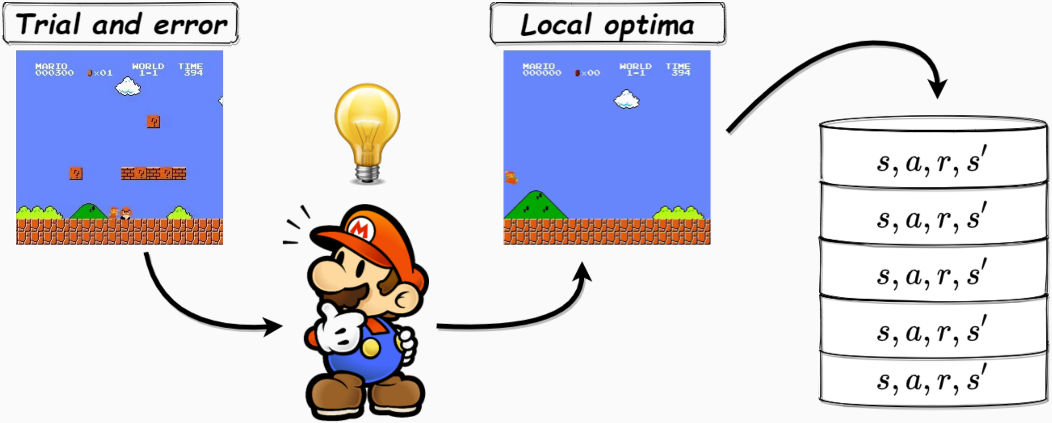

Important!

Diverse data is still required!

Full alrogithm

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Initialize $Q^*(s, a, \theta)$ arbitrarily, $\theta^- := \theta$, $\mathcal{D} = \varnothing$;

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- take action $a_k \sim \varepsilon$-greedy$(Q^*(s_k, a, \theta))$;
- observe $r_k, s_{k+1}, \mathrm{done}_{k+1}$, store $(s_k, a_k, r_k, s_{k+1}, \mathrm{done}_{k+1})$ in $\mathcal{D}$;

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- update target network: if $k \bmod K = 0$: $\theta^- \leftarrow \theta$

There is a lot to improve

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Decouple **action selection** and **action evaluation**:

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Action Evaluation: options

Name	**Networks**	**Targets**
Double Q-learning not really	Q_1^* Q_2^*	$y_1 = r + \gamma Q_?^*(s', \operatorname{argmax}_{a'} Q_?^*(s', a'))$

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Double DQN	Q^* Q_-^* — target network	$y = r + \gamma Q_-^*(s', \operatorname{argmax}_{a'} Q^*(s', a'))$
Twin DQN («Clipped Double DQN»)	Q_1^* Q_2^*	

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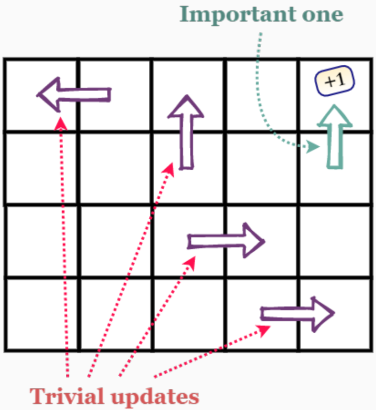
Prioritized Experience Replay



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Goal: propagate reinforcement from future to past

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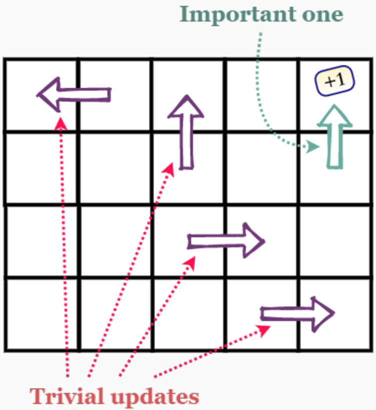

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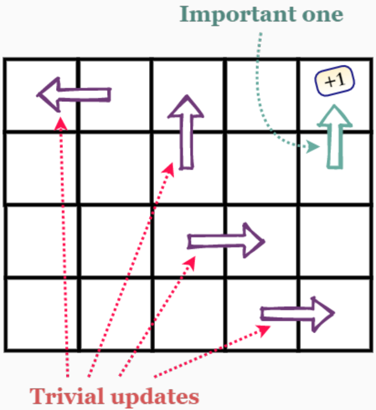

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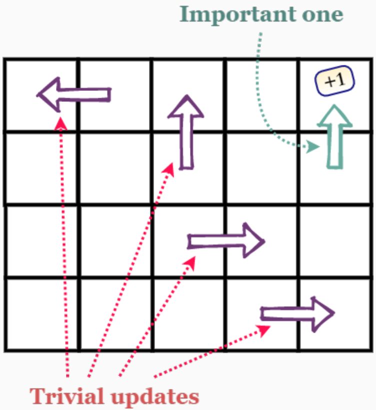

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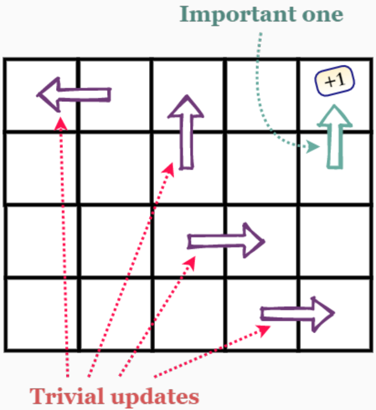

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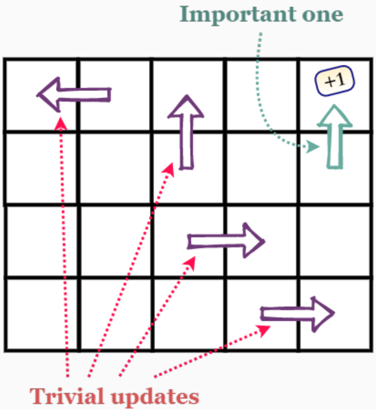

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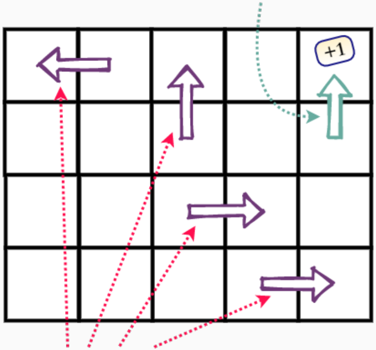

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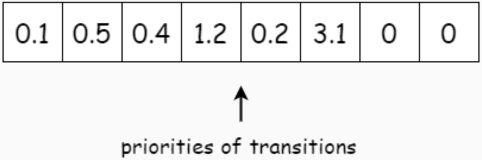
$$\mathbb{E}_{\mathbb{T}\sim \text{Uniform}} \text{Loss}(\mathbb{T}) \approx \mathbb{E}_{\mathbb{T}\sim P(\mathbb{T})} \left(\frac{1}{P(\mathbb{T})}\right)^{\beta(t)} \text{Loss}(\mathbb{T}),$$

where $\beta(t)$ anneals from 0 to 1.

Technical note: SumTree structure

Use **SumTree** structure:

- leaf nodes are sampling priorities



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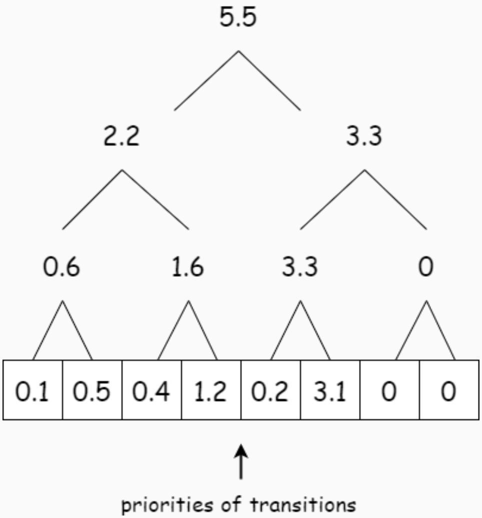

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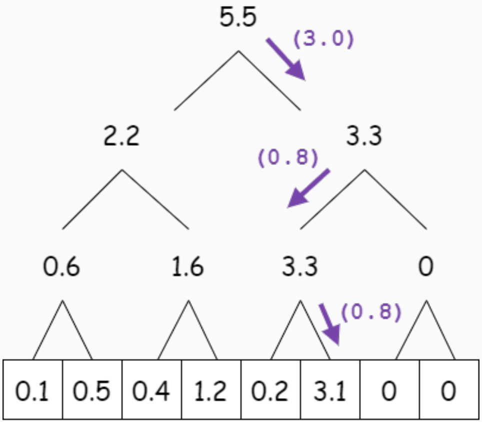

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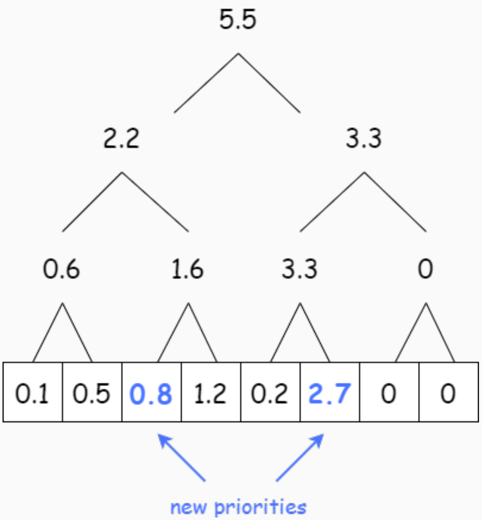

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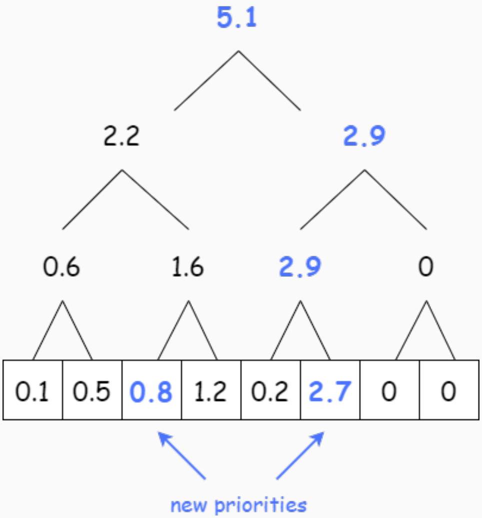

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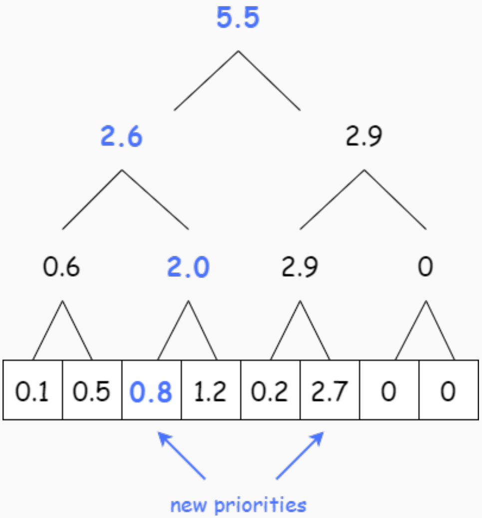

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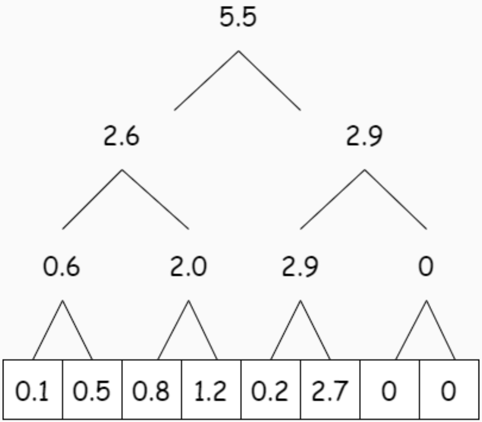

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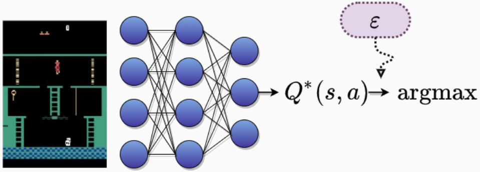
Complexity: $O(\log N)$, where N is buffer size.

Noisy Networks

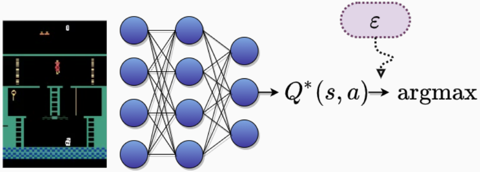


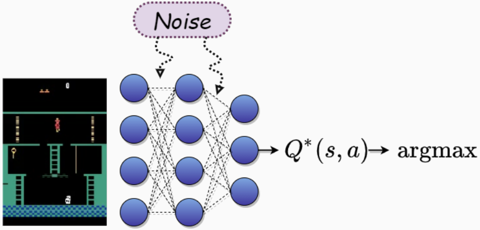
Problem: ε-greedy is naive

× inconvenient hyperparameter

× state-independent exploration

Noisy Networks





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Add noise to the network weights

$$w := \mu + \sigma\varepsilon, \quad \varepsilon \sim \mathcal{N}(0, 1)$$

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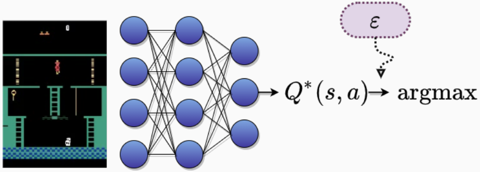

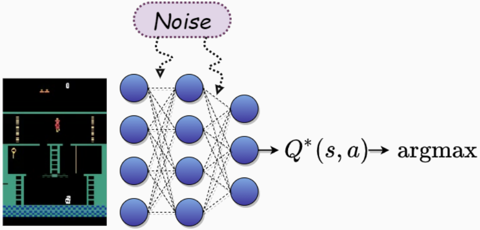

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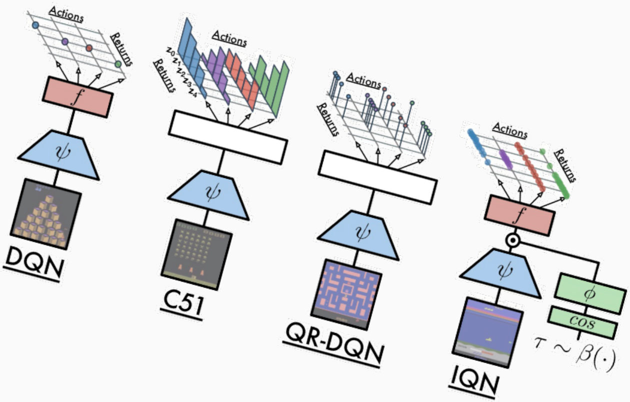
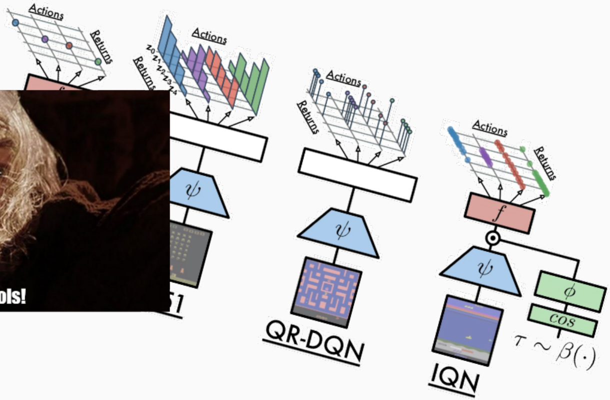
✓ no hyperparameters (initialization of σ?)

✓ state-dependent (not interpretable though)

× expensive in wall-clock time


Actions
Returns
f
ψ
DQN
Actions
z_0 z_1 z_2 z_3 z_4
Returns
ψ
C51
Actions
Returns
ψ
QR-DQN
Actions
Returns
f
ψ
ϕ
cos
$\tau \sim \beta(\cdot)$
IQN

Distributional RL



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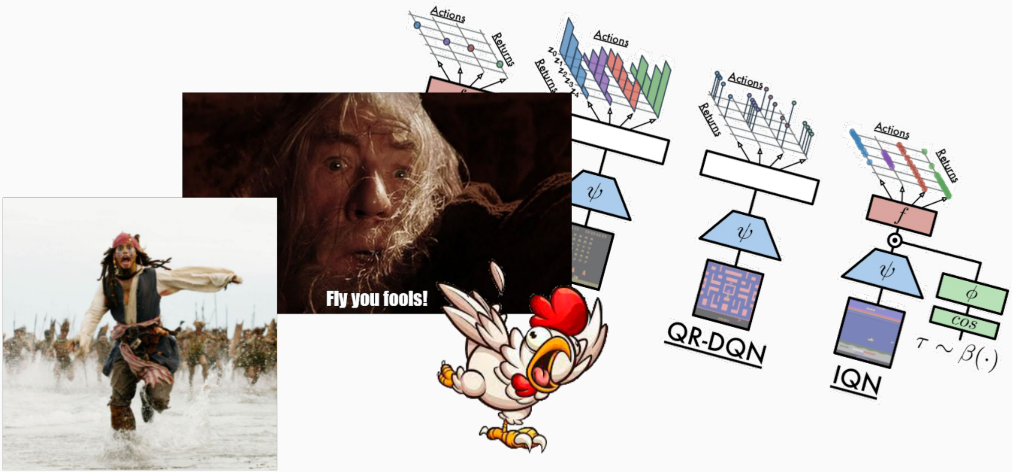

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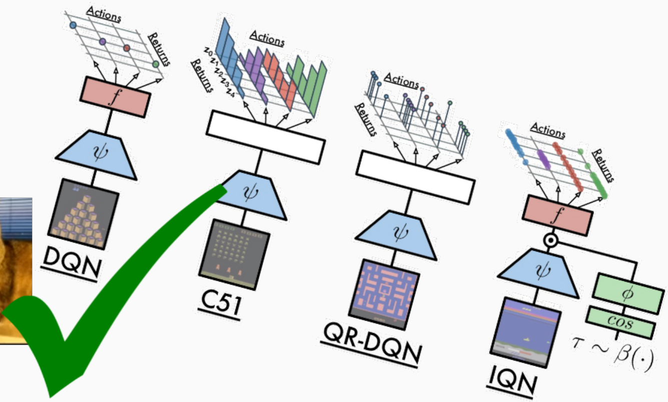

Dueling DQN

Problem: state value estimation requires knowledge about *all* actions

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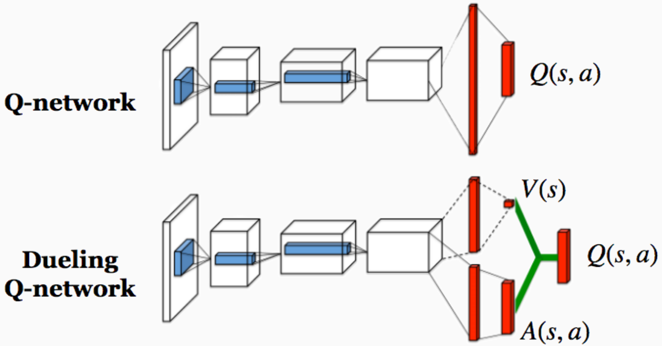
$$Q^*(s,a) := V^*(s) + \underbrace{A^*(s,a)}_{\text{not arbitrary}}$$



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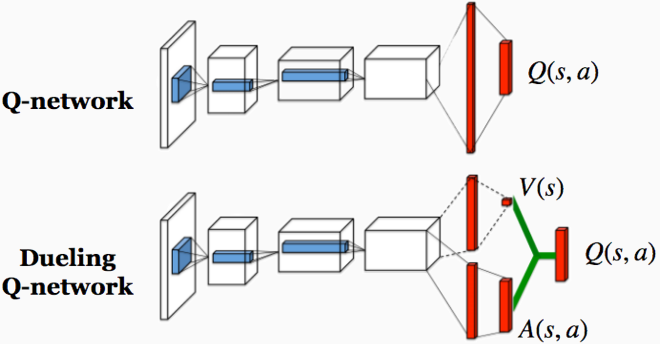
This introduces one **extra dimension of freedom**!



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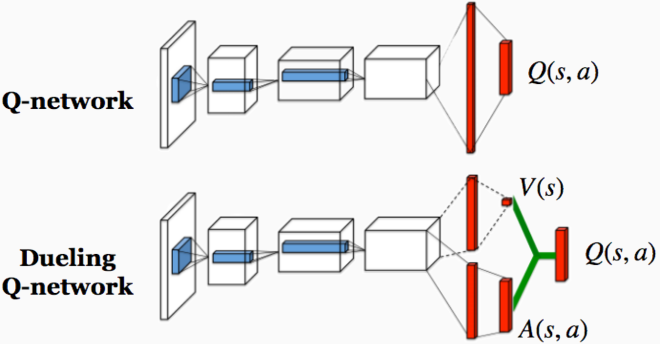
$$Q^*_\theta(s,a) := V^*_\theta(s) + A^*_\theta(s,a) - \underbrace{-\operatorname*{mean}_a A^*_\theta(s,a)}_{\text{theory: take max}}$$



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Problem: no access to full state description, only to **observations**:

$$o_t \sim p(o_t \mid s_t)$$

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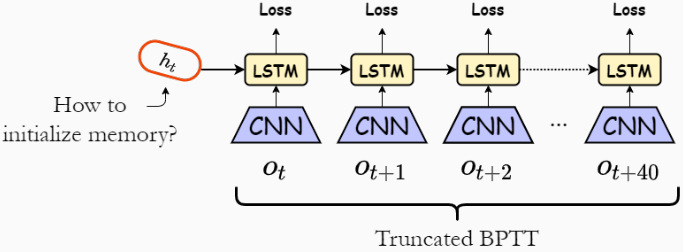

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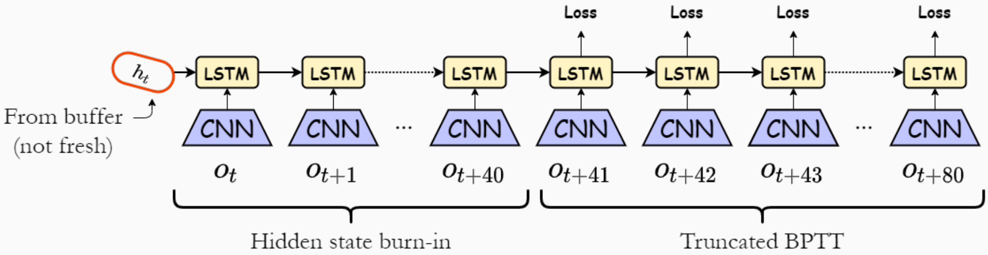

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Problem: delayed rewards + compounding error

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Important!

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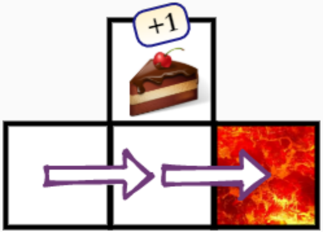

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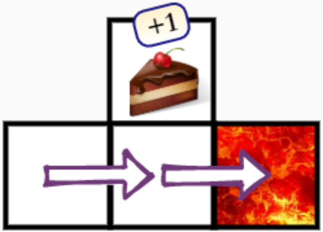

Implementation: just store in replay buffer

$$\left(s, \quad a, \quad \sum_{n=0}^{N-1} \gamma^n r^{(n)}, \quad s^{(N)}, \quad \bigvee_{n=1}^{N} \mathrm{done}_n\right)$$

Rainbow DQN
(2017)

- Double DQN
- Prioritized buffer
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- Noisy Nets
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\+ LSTM

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Agent 57 (2020)

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\+ Retrace

\+ Intrinsic motivation

\+ Meta-controller for hyperparameters

Literature

- Playing Atari with Deep Reinforcement Learning (2013);
- *For DQN modifications use links on previous slide*;