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

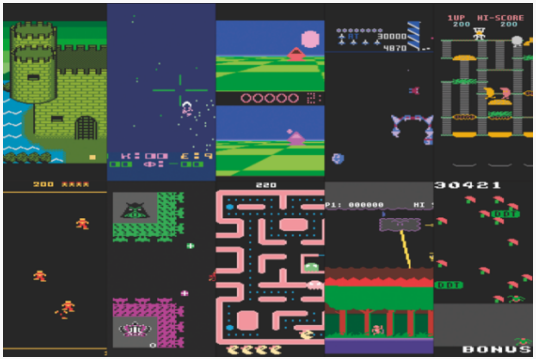
Important!

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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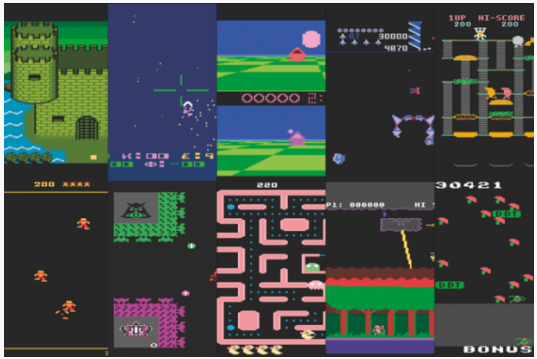
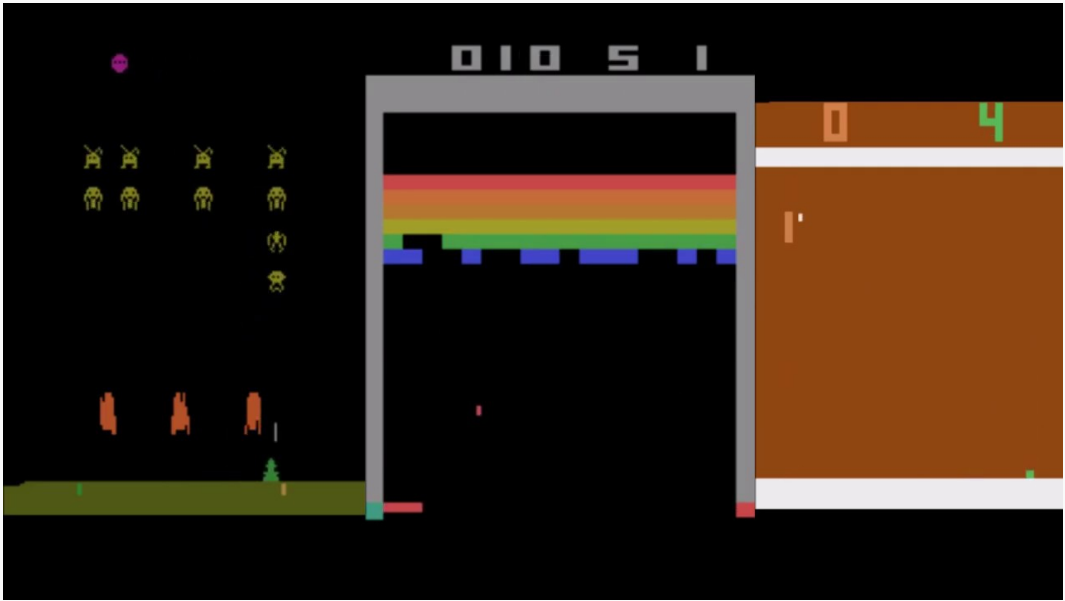


Approximate $Q^*(s, a)$ with neural network!

Is Atari game a MDP?



Practical notes: preprocessing

Action selection frequency:

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

Atari-specific preprocessing:

- EpisodicLife;
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Standard tricks:

- Crop image;
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(!) Clip reward to $\{-1, 0, 1\}$;

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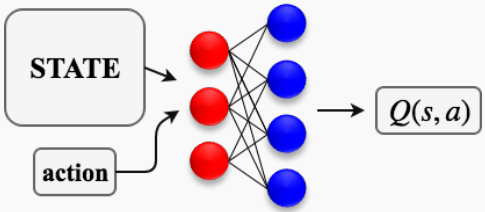
Important!

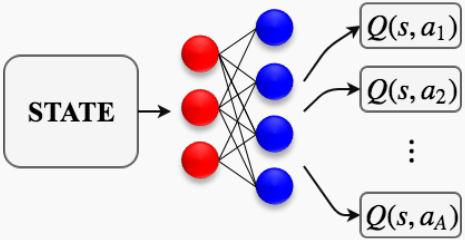
No hyperparameter tuning for each specific game!

Deep Q-network

Option 1



Option 2



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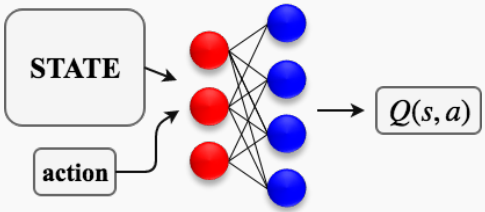
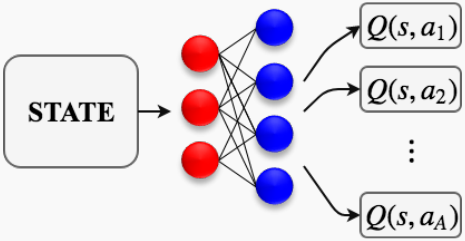


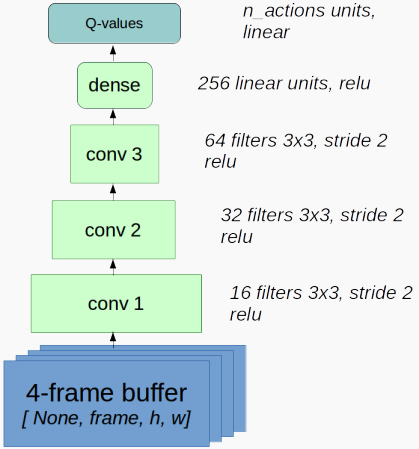
× $\underset{a}{\operatorname{argmax}}\, Q^*(s, a, \theta)$ — expensive!

Option 2



✓ $\underset{a}{\operatorname{argmax}}\, Q^*(s, a, \theta)$ — 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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Target network

For how long to solve one regression task?

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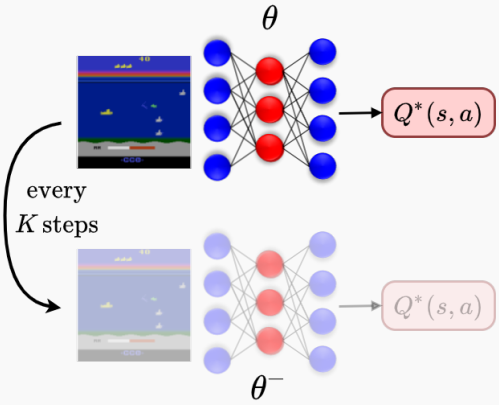

Store a copy of your old Q-network $Q^*(s, a, \theta^-)$

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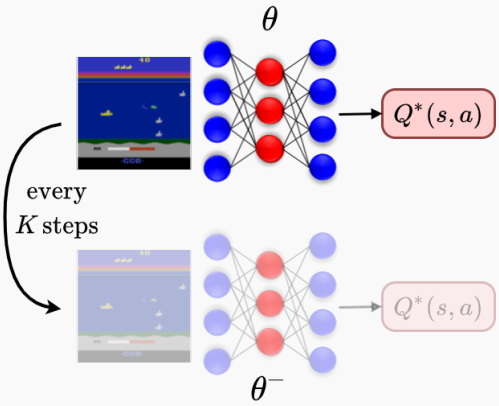
a) $\theta^- \leftarrow \theta$ every K SGD iterations

b) $\theta^- \leftarrow (1-\beta)\theta^- + \beta\theta$



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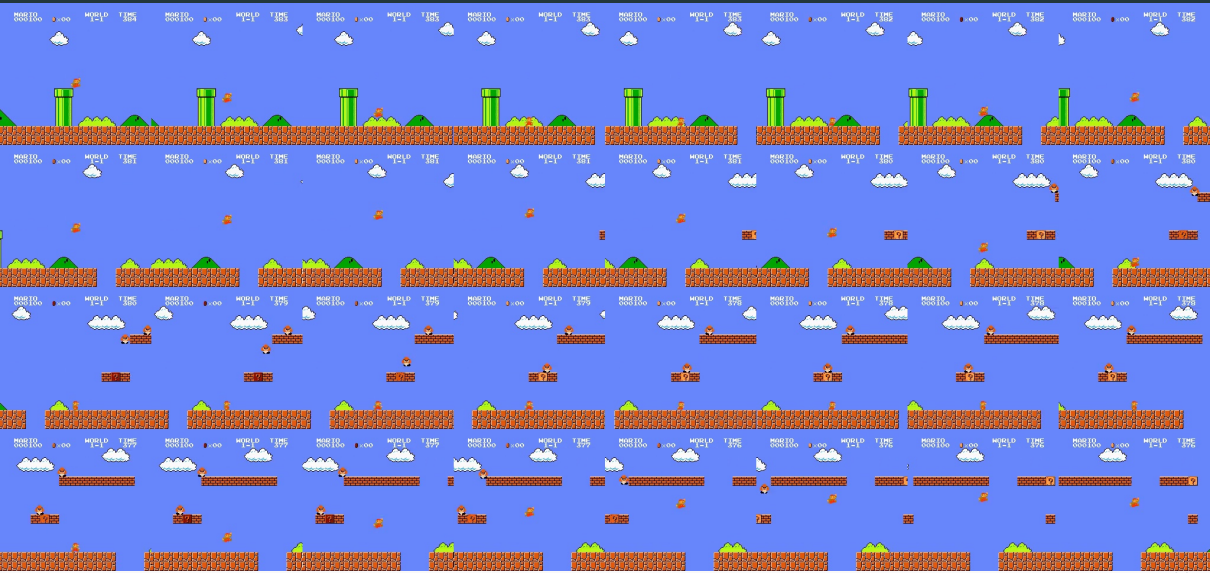
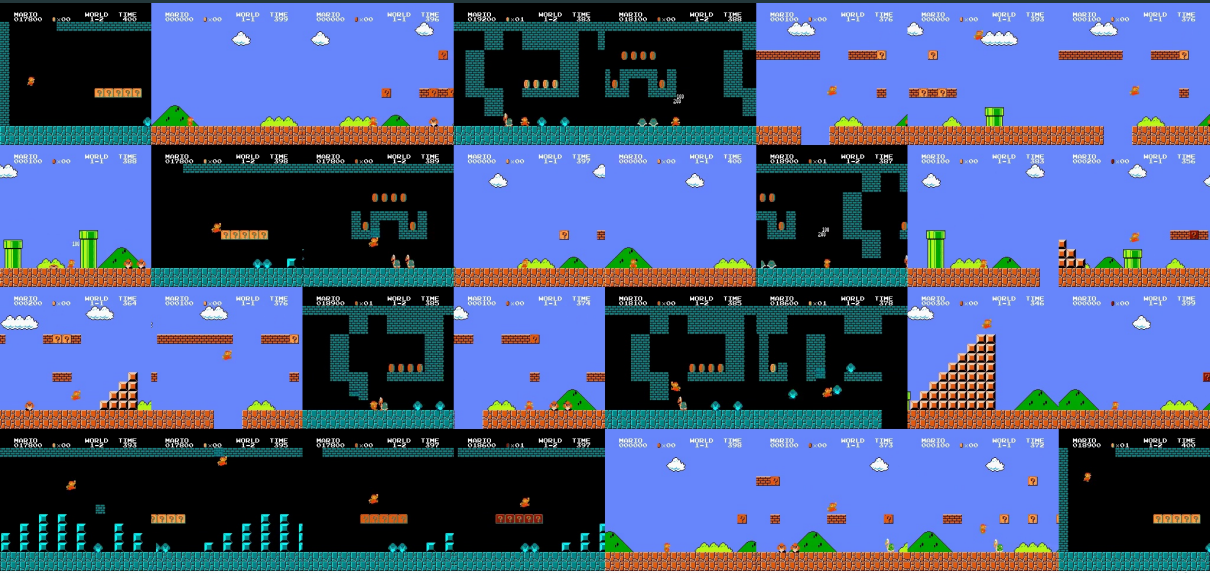
Sample Decorrelation



Experience Replay



Do we still need exploration?

Trial and error

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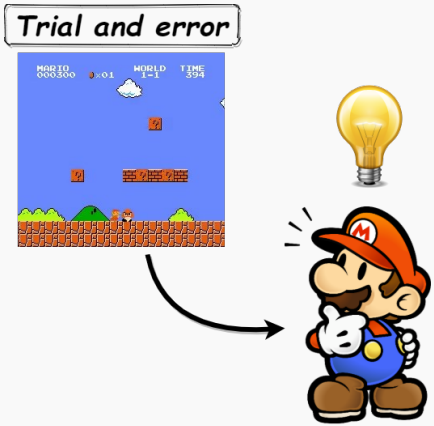

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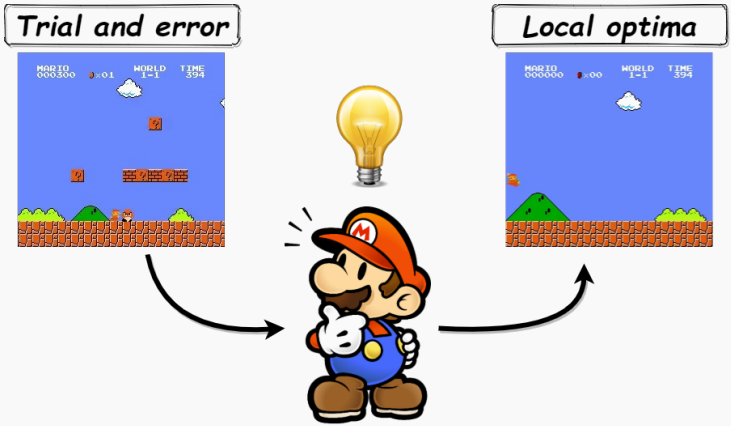

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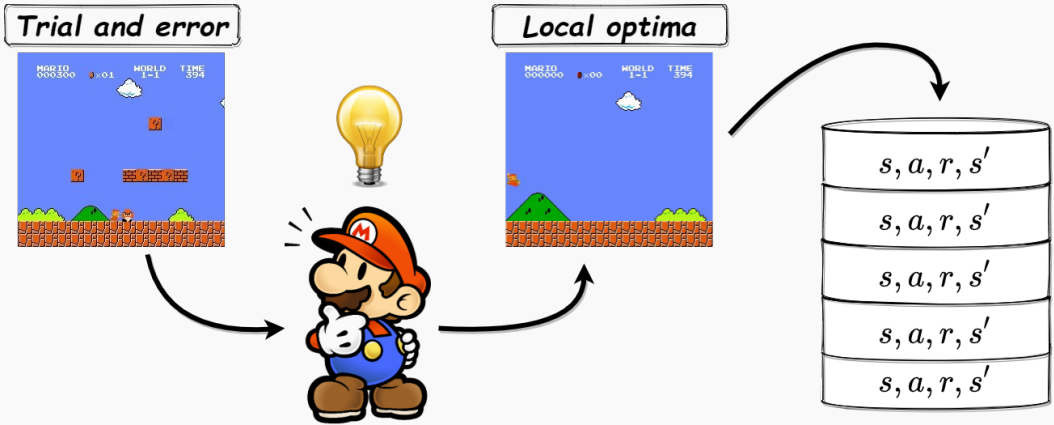

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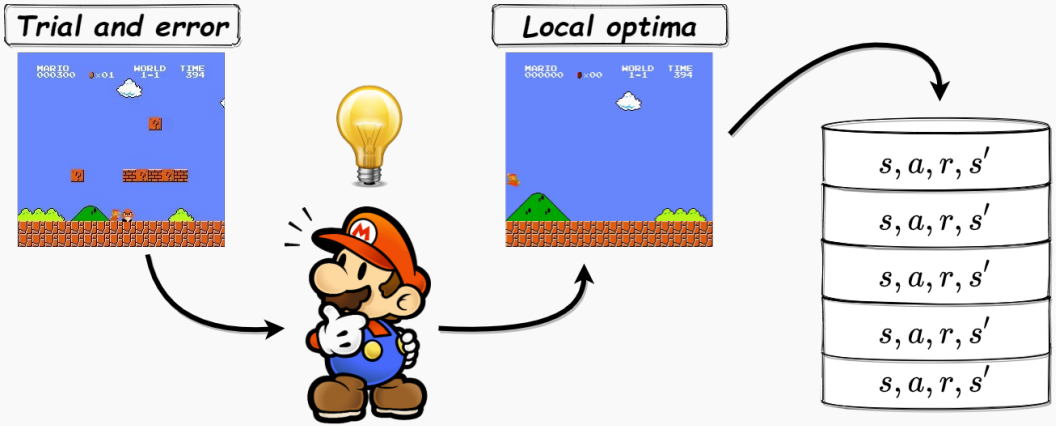

Important!

Diverse data is still required!

Full alrogithm

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

There is a lot to improve

Overestimation Bias and how to fight it

Problem: model often *overestimates* future reward.

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Action Evaluation: options

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

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Double DQN	Q^* Q_-^* — target network	

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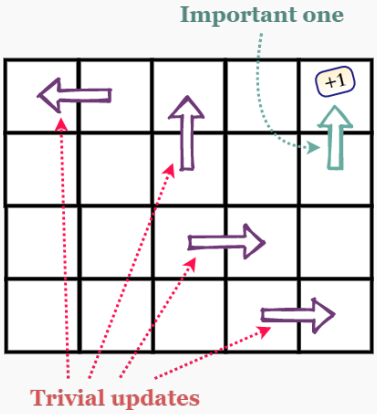
Prioritized Experience Replay



Problem: a lot of trivial updates.

Goal: propagate reinforcement from future to past

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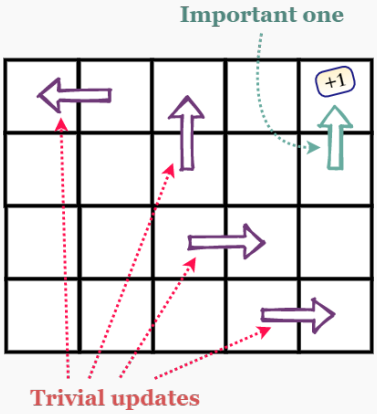

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Prioritized sampling from replay buffer:

$$\mathrm{P}(\mathbb{T}) \propto |y(\mathbb{T}) - Q^*(s, a, \theta)|^{\alpha}$$

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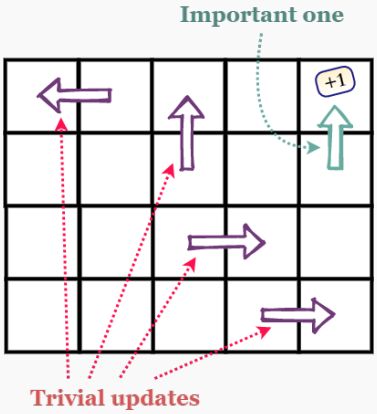

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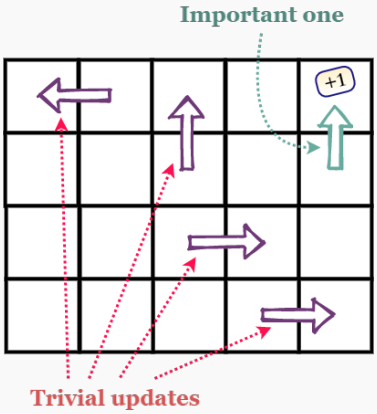
Goal: propagate reinforcement from future to past

Prioritized sampling from replay buffer:

$$P(\mathbb{T}) \propto |y(\mathbb{T}) - Q^*(s, a, \theta)|^{\alpha}$$

Issues?

Prioritized Experience Replay



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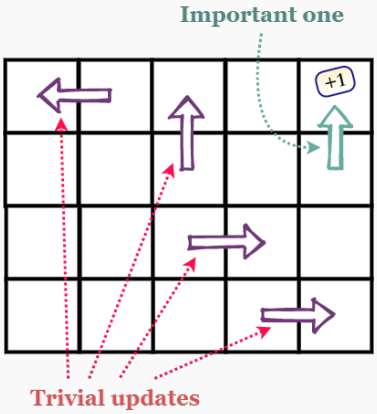

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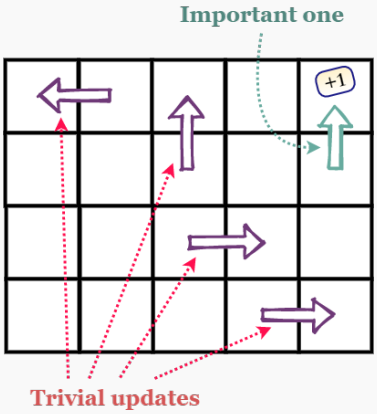

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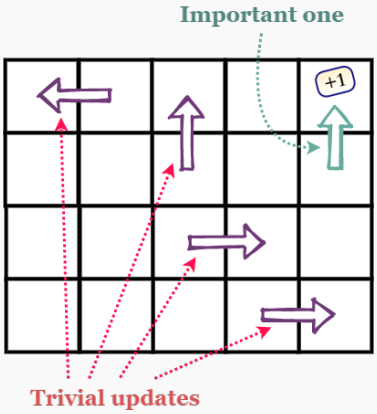

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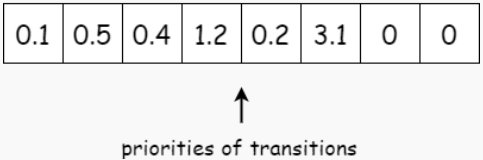
where $\beta(t)$ anneals from 0 to 1.

Technical note: SumTree structure

Use **SumTree** structure:

- leaf nodes are sampling priorities



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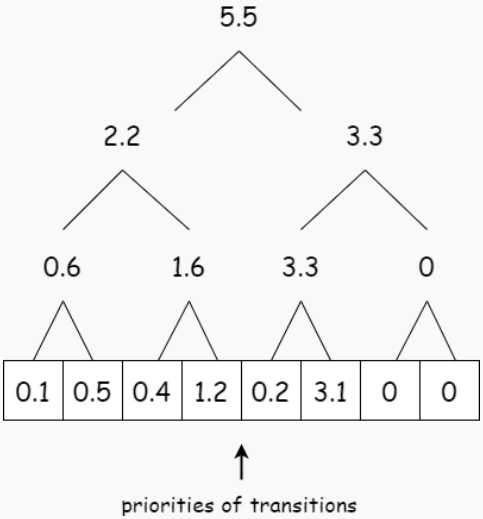

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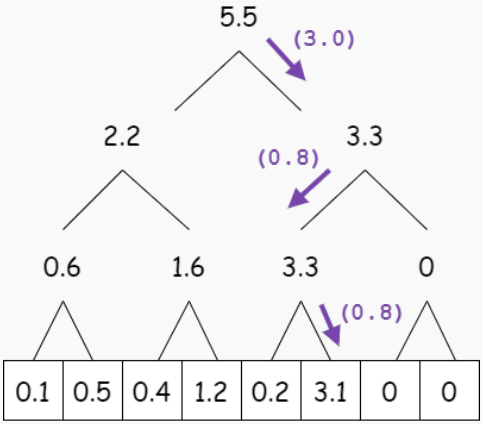

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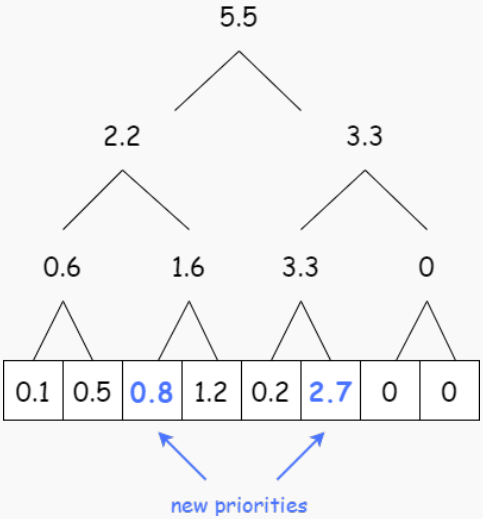

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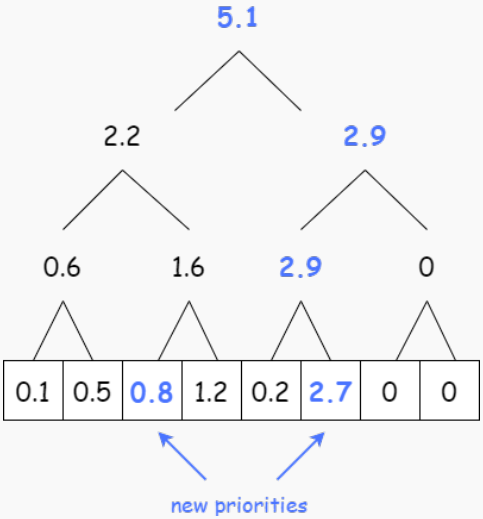

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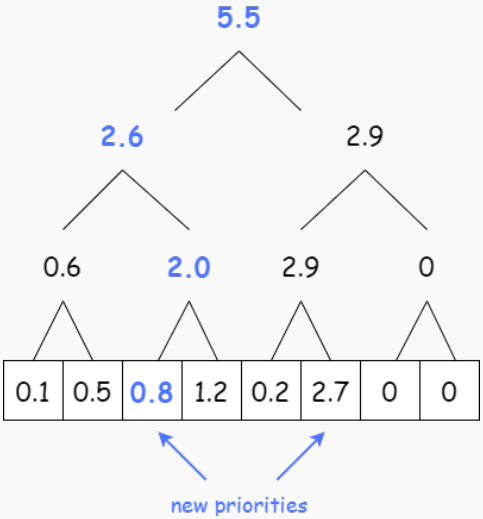

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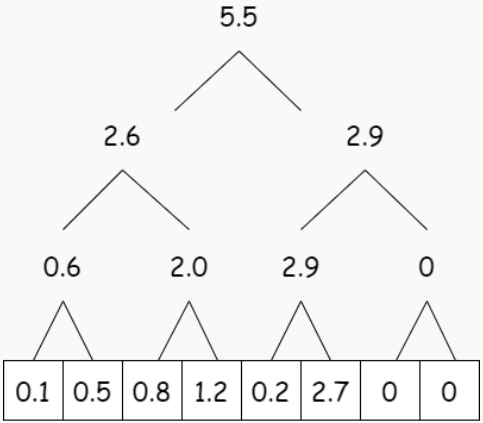

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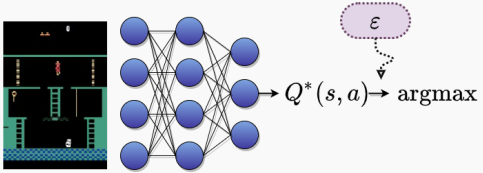
Complexity: $O(\log N)$, where N is buffer size.

Noisy Networks



Problem: ε-greedy is naive

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- × state-independent exploration

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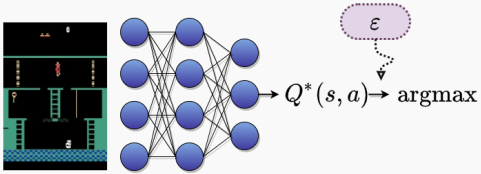

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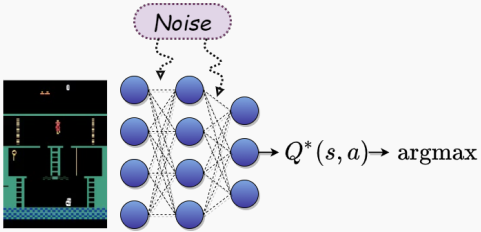

Add noise to the network weights

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

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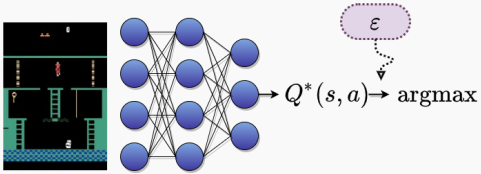

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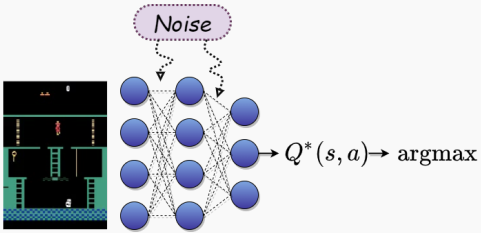

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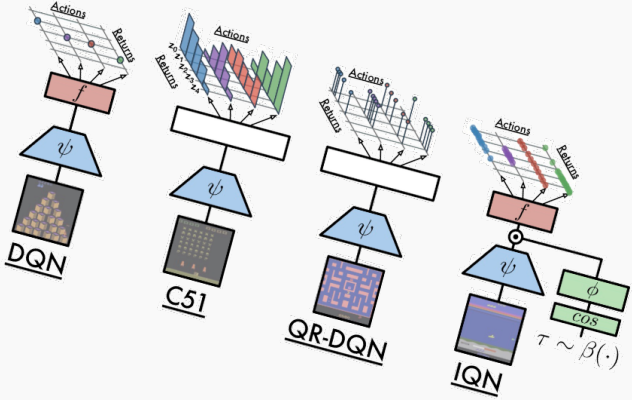
- ✓ no hyperparameters (initialization of σ?)
- ✓ state-dependent (not interpretable though)
- × expensive in wall-clock time

Distributional RL



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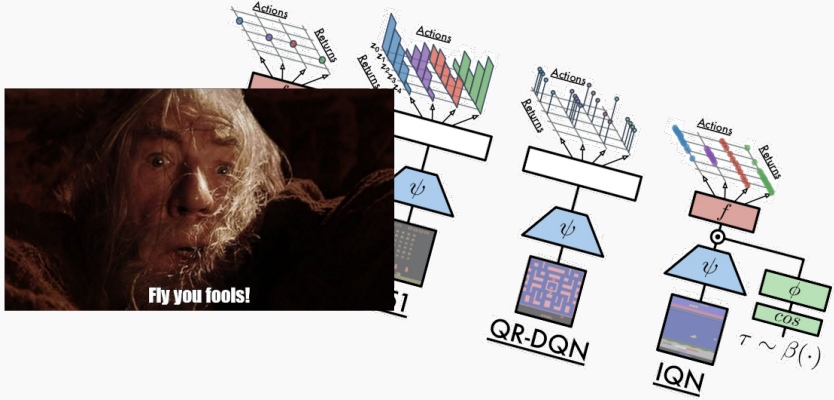

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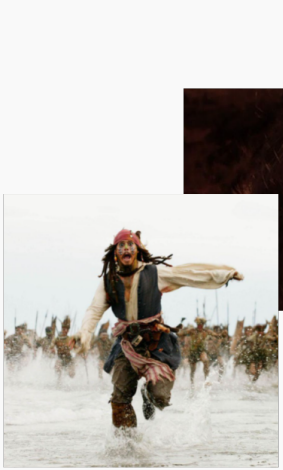

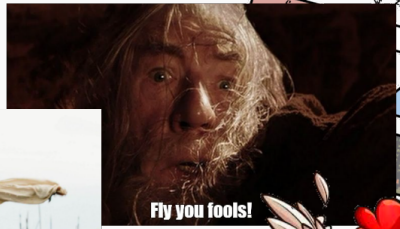

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Problem: state value estimation requires knowledge about *all* actions

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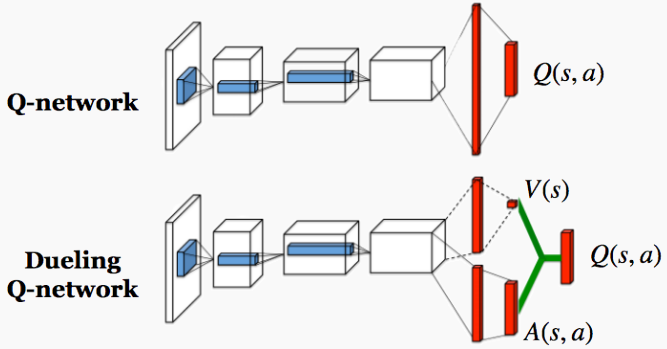

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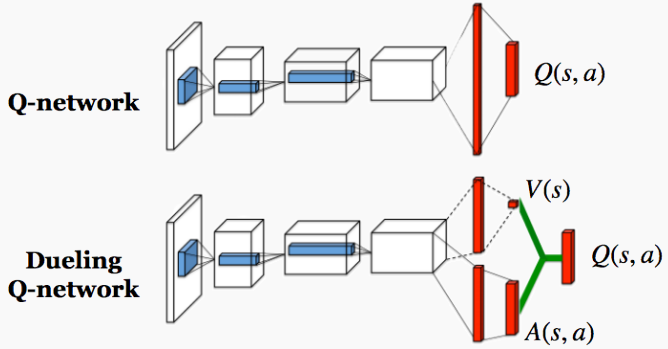
This introduces one **extra dimension of freedom**!



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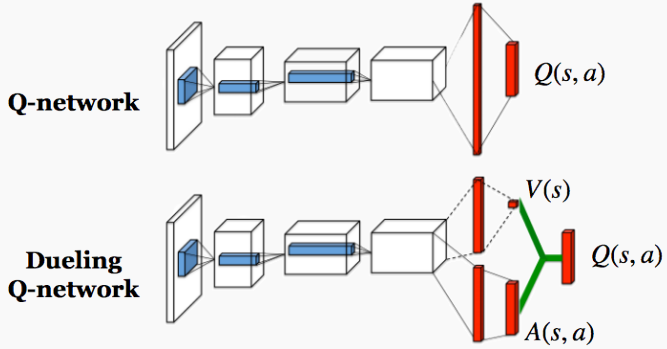
$$Q^*_\theta(s,a) := V^*_\theta(s) + A^*_\theta(s,a) - \underbrace{- \operatorname{mean}_a A^*_\theta(s,a)}_{\text{theory: take max}}$$



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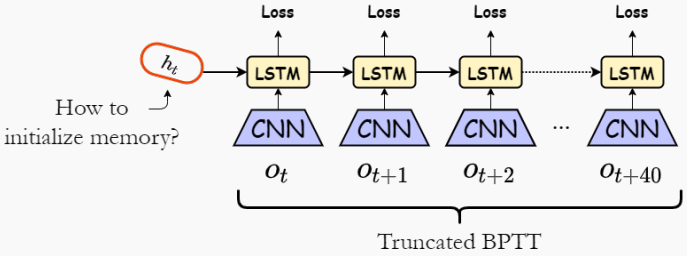

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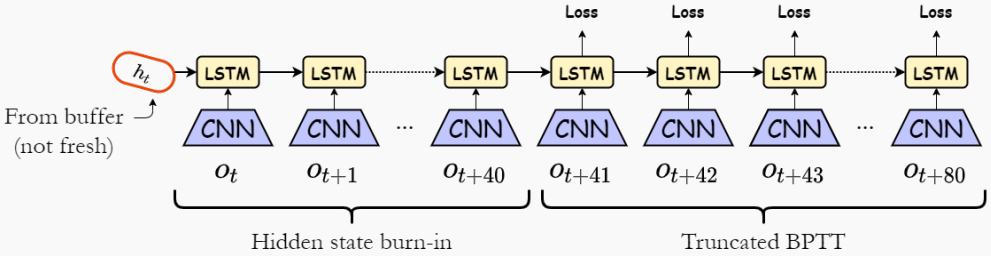

Multi-step DQN

Problem: delayed rewards + compounding error

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$$y := \underbrace{r + \gamma r' + \gamma^2 r'' + \dots}_{\approx \text{«optimal behavior»?}} + \gamma^N \max_{a^{(N)}} Q^*(s^{(N)}, a^{(N)})$$

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- ✓ can *significantly* help with this issue;
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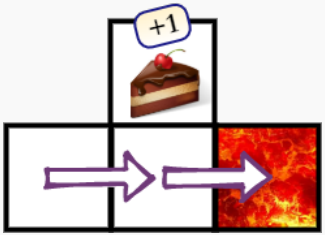

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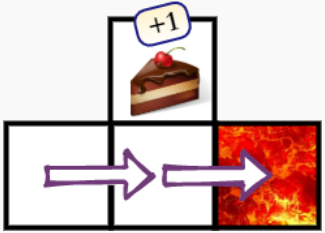

Implementation: just store in replay buffer

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

Frontiers

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(2017)

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- Prioritized buffer
- Multi-step DQN
- Noisy Nets
- Dueling DQN
- *Distributional RL*
  (next time)

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Agent 57
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- LSTM
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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*;