Deep Q-Learning

Reinforcement Learning

September 29, 2020

MSU

Atari Games

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

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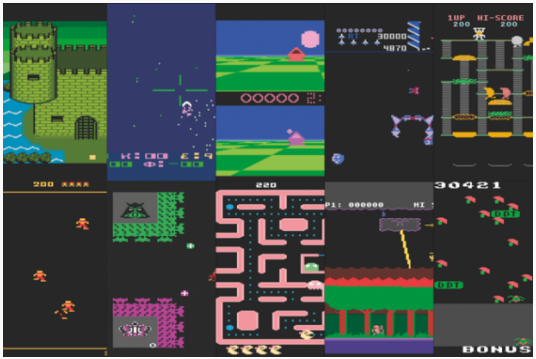
- 57 various games
- Only screen image as input.
- No game-specific features.
- Finite-state case... not quite finite.
- $|\mathcal{A}| \leqslant 18$



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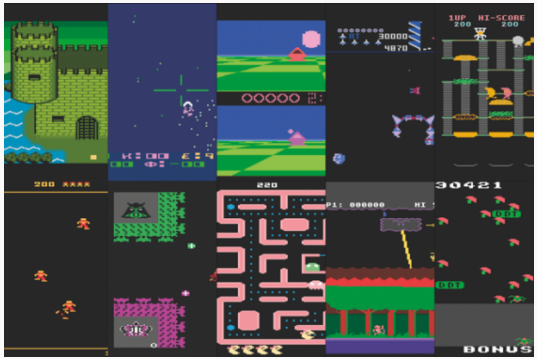
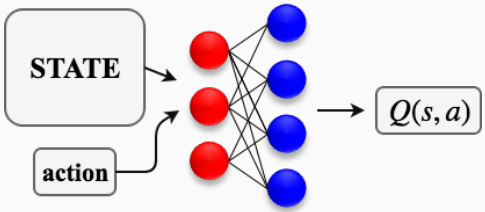


Approximate $Q^*(s, a)$ with neural network!

Deep Q-network

Option 1



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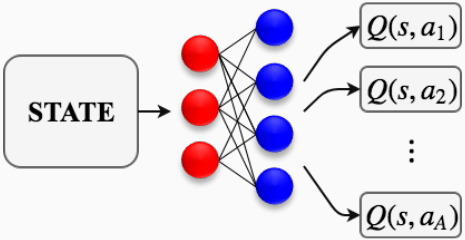

Deep Q-network

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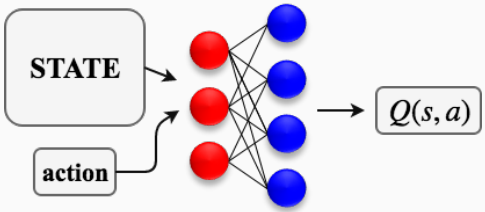
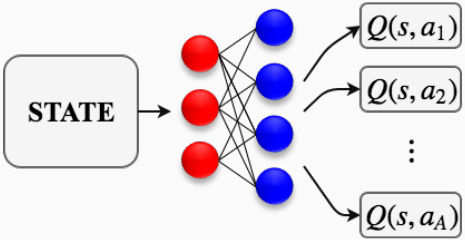


× $\underset{a}{\operatorname{argmax}}\, Q^*(s, a, \theta)$ — expensive!

Option 2



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

Intuition: Q-learning as gradient descent

Consider *tabular* parametric family:

$$Q^*(s, a, \theta) := \theta_{s,a}$$

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Consider the following **regression task**:

- s, a is input;
- $y \in \mathbb{R}$ is target:

$$y(s, a) := r + \gamma \max_{a'} Q^*(s', a', \theta_k)$$

where $r = r(s, a), s' \sim p(s' \mid s, a)$;

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

Solving Bellman equations: deep version

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

What solution is optimal?

$$Q^*(s, a, \theta^*_{k+1}) =$$

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$$= \underbrace{r(s, a) + \gamma \mathbb{E}_{s' \sim p(s'|s,a)} \max_{a'} Q^*(s', a', \theta_k)}_{\text{value iteration update}}$$

Target network

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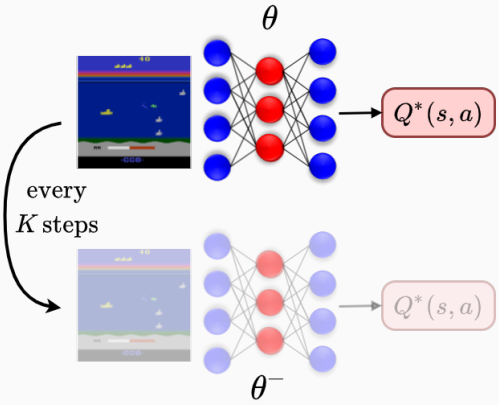

Store a copy of your old Q-network $Q^*(s, a, \theta^-)$

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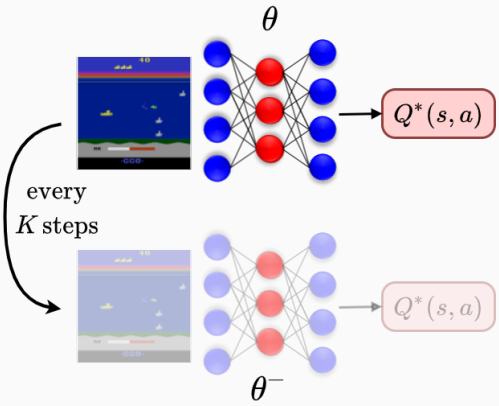
a) $\theta^- \leftarrow \theta$ every K SGD iterations

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



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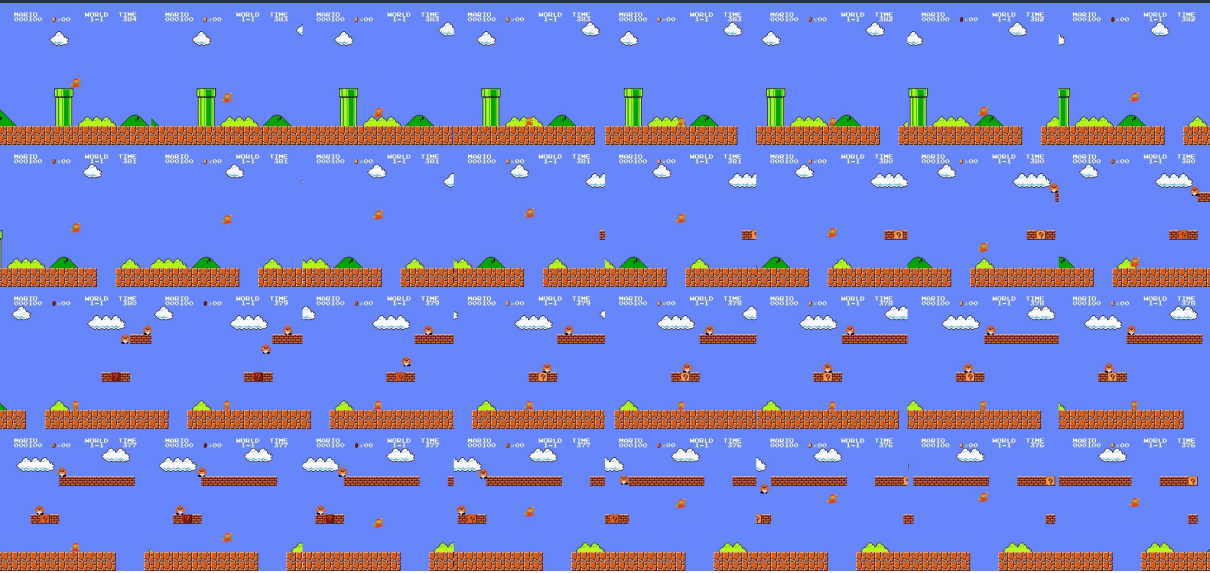
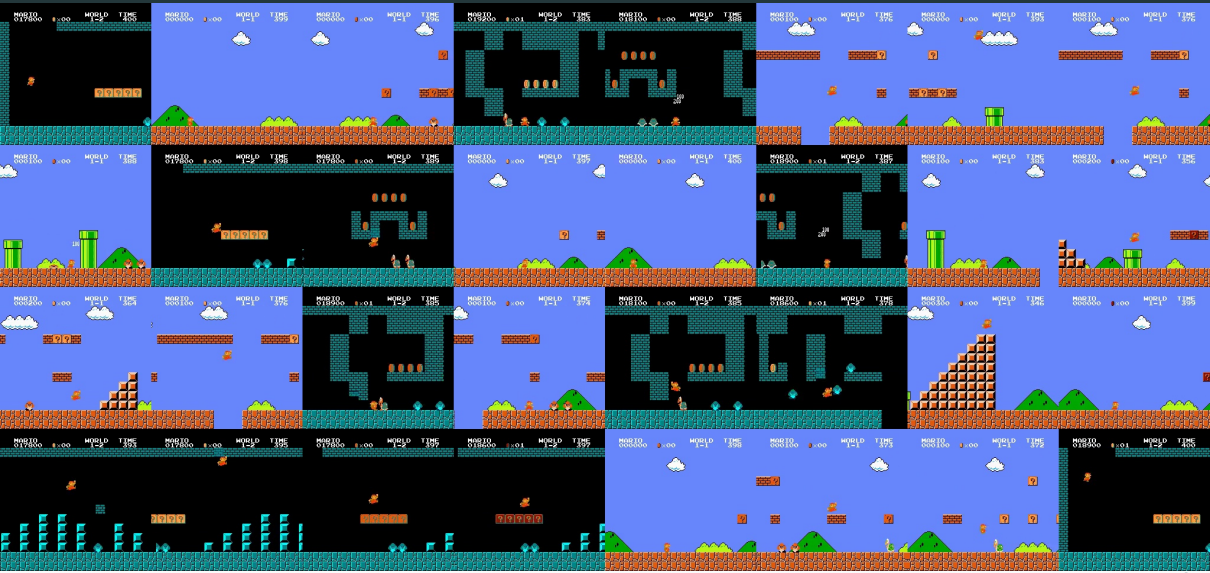
Sample Decorrelation



Experience Replay



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observe s_0;

for $k = 0, 1, 2 \ldots$

- 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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- perform a step of gradient descent:

$$\theta \leftarrow \theta - \frac{\alpha}{B} \sum_{\mathbb{T}} \nabla_\theta \left(Q^*(s, a, \theta) - y(\mathbb{T}) \right)^2$$

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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

$$\max_{a'}(Q^*(s', a', \theta) + \underbrace{\varepsilon(s', a')}_{\text{approximation error or luck}})$$

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

$$\max_{a'} Q^*(s', a') = \overbrace{Q^*(s', \underbrace{\operatorname{argmax}_{a'} Q^*(s', a')}_{\text{action selection}})}^{\text{action evaluation}}$$

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Action Evaluation: options

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

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

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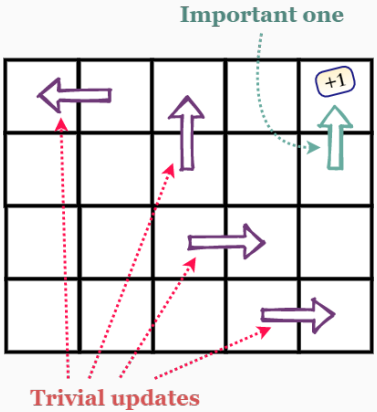
Prioritized Experience Replay



Problem: a lot of trivial updates.

Goal: propagate reinforcement from future to past

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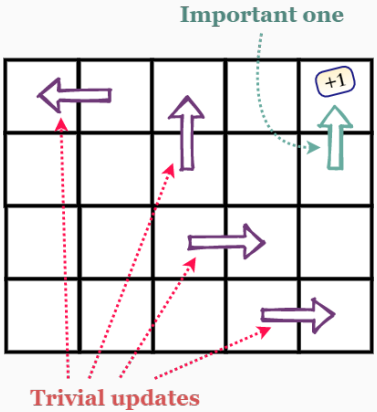

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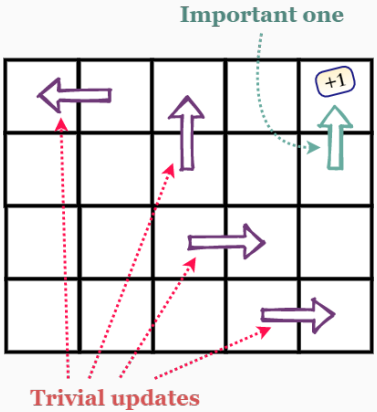

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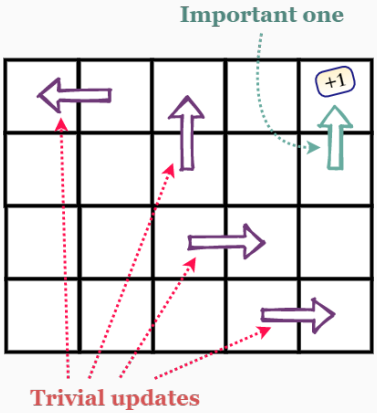

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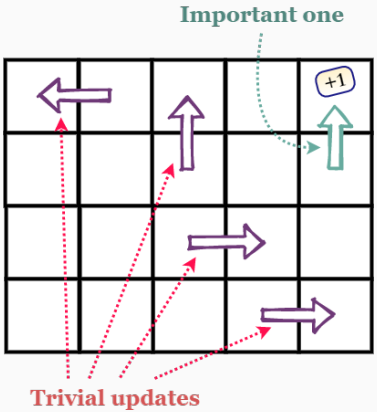

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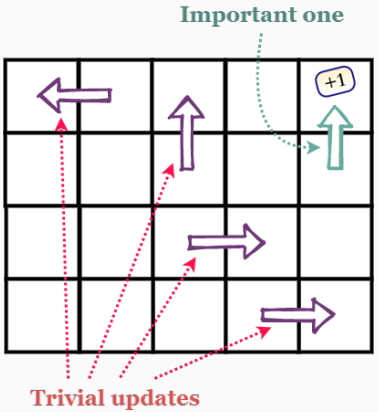

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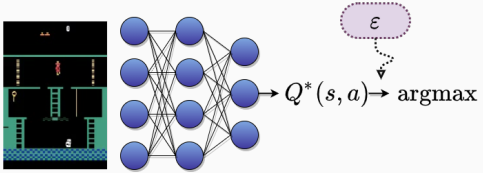
Noisy Networks



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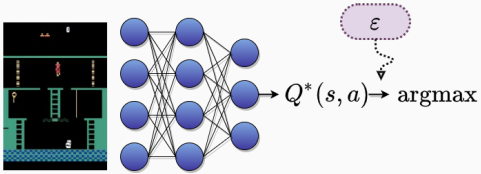

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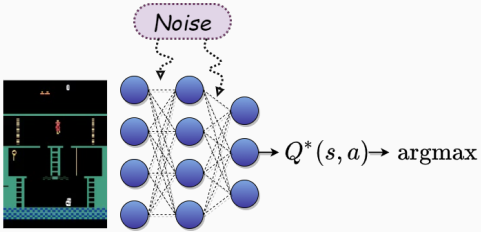
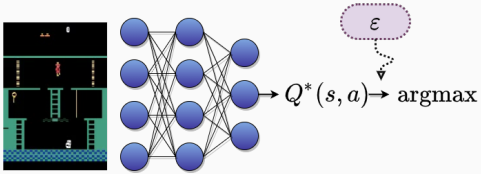
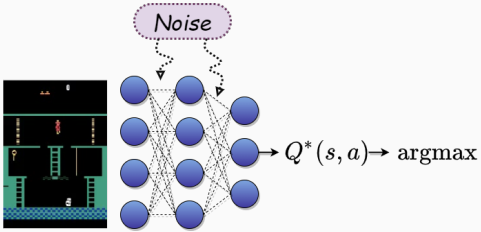


Add noise to the network weights

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

Noisy Networks





Problem: ε-greedy is naive

- × inconvenient hyperparameter
- × state-independent exploration

Add noise to the network weights

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

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

More modifications!

Dueling DQN

Problem: state value estimation

More modifications!

Dueling DQN

Problem: state value estimation

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

More modifications!

Dueling DQN

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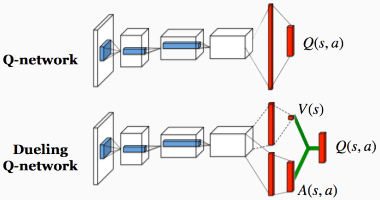

Dueling DQN

Problem: state value estimation

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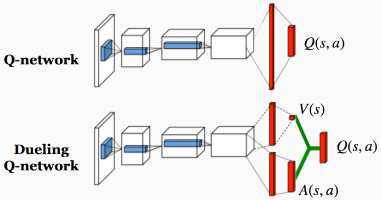

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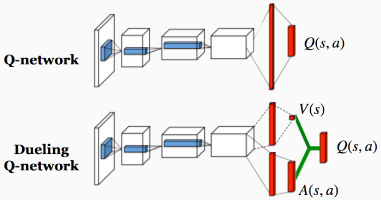

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Partial Observability

Problem: no access to full state description

More modifications!

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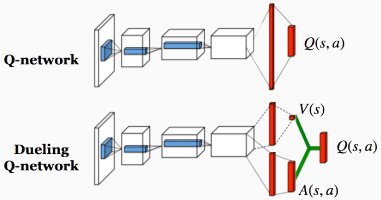

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Partial Observability

Problem: no access to full state description

Theory: see PoMDP; **Practice:** LSTM

More modifications!

Dueling DQN

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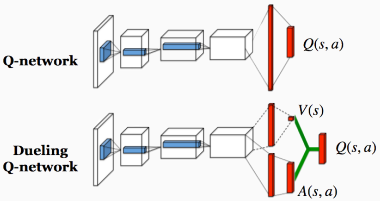

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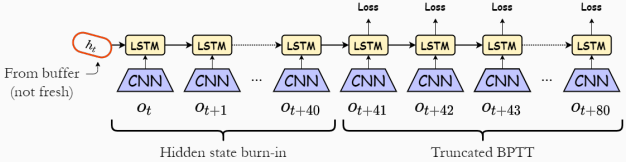

More modifications!

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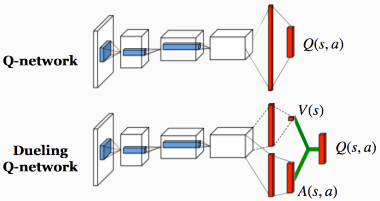

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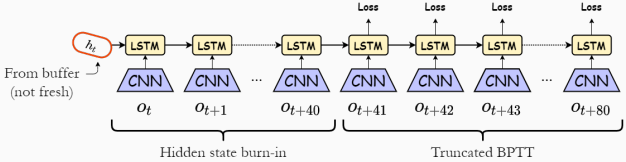

Multi-step DQN

Problem: delayed rewards + compounding error

More modifications!

Dueling DQN

Problem: state value estimation

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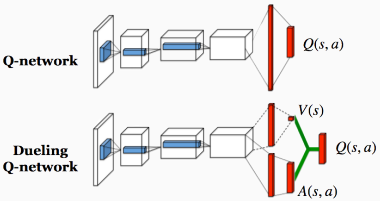

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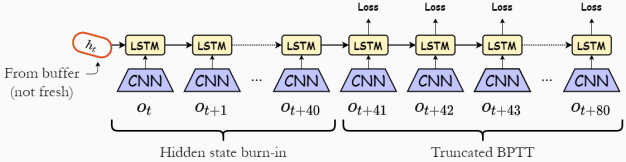

Multi-step DQN

Problem: delayed rewards + compounding error

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

Frontiers

Rainbow DQN
(2017)

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

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R2D2
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\+ LSTM

\+ Massive parallelization

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- Prioritized buffer
- Multi-step DQN

\+ LSTM

\+ Massive parallelization

Agent 57
(2020)

- Double DQN
- Prioritized buffer
- Multi-step DQN
- LSTM
- Massive parallelization

\+ Retrace

\+ Intrinsic motivation

\+ Meta-controller for hyperparameters

Literature

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

  Pictures from Berkeley CS 188 | Introduction to Artificial Intelligence;