

A Shallow Dive in Deep Reinforcement Learning - pt. 1 : Tabular & Q-Learning

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Speakers

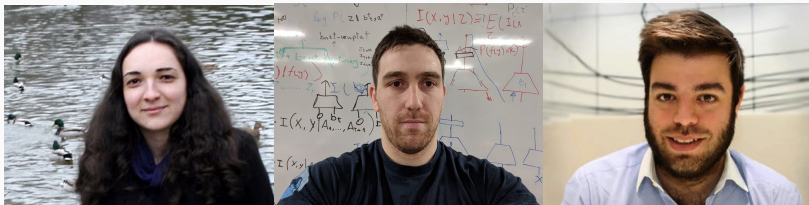


Figure 1: Diana Borsa, Bilal Piot, Pierre Richemond

RL in one minute !

- Reinforcement learning = **adaptive, extreme trial-and-error**
- Goal = solve sequential decision problems.
- To quote Remi Munos (head of DeepMind Paris), 'a child doesn't learn to ride a bicycle by solving equations; they try, fall, learn a bit and try again'
- Deep RL = **RL** combined with **deep** neural networks
- RL takes into account new, recent experience ; in that sense it goes beyond the standard supervised vs. unsupervised learning paradigm, and enables machine learning on an **evolving dataset**.
- There are way too many references to quote, but a great and just updated starting point is the classic book **[Sutton and Barto, 2018]**.

Examples of RL - Successes & use cases

- Flying stunt with a helicopter
- More generally, robotics control
- Potentially, self-driving cars
- Superhuman performance in board games (Backgammon, Chess, Go) **just from rules**
- Control of a power station with a view of reducing energy consumption
- Trade the financial markets
- Learn to play video games better than humans **just from pixels and score** - see video.

RL can be seen as a form of supervised, optimal **control**.

Chronology

- 1984 Rich Sutton's thesis
- 1989 Q-learning (Watkins)
- 1991 REINFORCE (Williams & Peng)
- 2006 Monte-Carlo Tree Search (Szepesvari)
- 2009 David Silver's Ph.D. thesis [Silver, 2009]
- 2013 Deep Q-Networks
- 2015 DQN scales - *Nature* paper
- 2016 Actor critic + deep networks
- 2017 Soft Q-learning = soft actor-critic ; AlphaGo Zero

Key algorithms are 25+ years old
(*but trained at scale only now*)

Key basic concepts

- Environment
- Agent
- State
- Action
- Next state
- Reward

The reward is the most important

- A reward R_t is a scalar feedback signal
- Indicates how well the agent is doing at step t
- The agent's job is ALWAYS to maximize cumulative reward
- The *reward hypothesis* posits *all goals* can be described by the maximisation of the *expected cumulative reward*
- A philosophical debate...

Examples of rewards

- Helicopter : + reward for going higher and following trajectory ; - reward for crashing
- Chess or Go : no reward for most moves (sparse signal), +1 for winning the game, -1 for losing
- Manage an investment portfolio : reward is the change in dollar market value of the portfolio
- Humanoid robot walk : +something for forward motion, -1 for falling over
- Atari : reward is the change in score in your emulator

Sometimes the reward is exogeneous (imposed by the world you're in), sometimes it's designed-engineered by the algorithm creator.

Sequential Decision Making

- Goal : **select actions** in order to **maximise total future reward**
- Actions may have long term consequences
- Rewards may be delayed
- It may be better to practice delayed gratification, and sacrifice immediate reward for the longer-term gain.

Agent and environment : the RL loop.

At each step t , the agent

- Executes action A_t
- Receives observation O_t
- Receives scalar reward R_t

The environment then:

- Receives action A_t
- Emits observation O_{t+1}
- Emits scalar reward R_{t+1}

Then, t is incremented (at environment step).

History, transitions, and state

- The **history** is the sequence of transitions.
- A **transition** is a triplet state, action, reward
- This represents the sensorimotor stream of a robot, or (embodied) agent
- The history can be written as $H_t = O_1, R_1, A_1, \dots, A_{t-1}, O_t, R_t$
- **State is the information used to determine what happens next**
- State is a function of history : $S_t = f(H_t)$
- Examples : Chess, Atari, Humanoid robot walk

Definition : a state is *Markov* iff

$$\mathbb{P}[S_{t+1}|(S_1, \dots, S_t)] = \mathbb{P}[S_{t+1}|S_t]$$

- ie 'the future is independent of the past, given the present'
- ie 'all of the history is contained in the current state'
- ie 'the state is a sufficient statistic of the future'
- ie 'we are memory-less'

We can *markovianize* (sic) the state by adding more information to it
- for instance, the last few frames in a video game so as to be able to infer speed and momentum.

To summarize till now

- Given a certain **environment** (game abstraction), an **agent** (player) selects between **actions** a available to her, and in doing so, collects a **reward** r and moves from **state** s to state s' .
- The agent's objective is to pick actions and build a trajectory so as to **maximize the sum of their rewards**.
- Rewards and states are not known in advance.

The discount factor γ

- We modify the definition of returns :

$$\sum_i r_i \rightarrow \sum_i \gamma^i \cdot r_i$$

- Constant γ is known as a *discount factor* that controls how far in the future we want to look
- γ is here to make the math work; better to build first intuitions without
- In practice it's an important parameter, slightly less than 1, that can be (carefully) tuned for performance.

Major components of an RL agent

An RL agent may include one or more of these components :

- **Policy** : agent's behaviour or function
- **Value function** : how good is each state of action
- **Model** : agent's representation of the environment

- The **policy** is the agent's behaviour.
- It is a map (function) from state to action, or a distribution over actions given states.
- This means:
- Deterministic policy: $a = \pi(s)$
- Stochastic policy: $\pi(a|s) = \mathbb{P}[A_t = a|S_t = s]$.

A policy fully defines the behaviour of an agent, and it only depends on the current state (not the history). Hence policies are *stationary*, that is, time-independent.

- A **value function** is a prediction of future reward.
- It is used to evaluate the goodness/badness of states
- And therefore to select between actions !
- Example:

$$V_{\pi}(s) = \mathbb{E}[r_{t+1} + r_{t+2} + \dots | S_t = s]$$

- A **model** predicts what the environment will do next. (Can you say 'imagination' ?)
- \mathcal{P} **predicts the next state**
- \mathcal{R} predicts the next (immediate) reward.

RL Agent Taxonomy : categorizing RL agents

There are many possible ways (hence algorithms) to do RL !

- Value-based : value function ; no policy
- Policy-based : policy ; no value function
- **Actor-critic** : policy **and** value function, together.

In this course (pt. 1), we will focus on value-based methods.

Another possible distinction is model-based versus model-free :

- Model-free : policy and/or value function; but no model
- Model based: policy and/or value function; model

In this course we will focus on model-free methods.

Exploration vs Exploitation

- RL is like trial-and-error; recall that rewards and states are not known in advance.
- The agent should discover a good policy from experiencing the environment. Doing so should be accomplished without sacrificing too much reward along the way !
- Exploration finds more information about the environment
- Exploitation exploits known information to maximise reward
- It is important to do both, in a **balanced** way
- If always following the same policy, some states may never be visited = high possibility of being stuck with a suboptimal policy in stochastic environments.
- Examples : restaurant selection, natural resources mining, game playing

Markov Reward Processes

- Markov chains are underpinning the transition dynamics in the states of our environment.
- **Markov Rewards Processes** are Markov chains with rewards attached !
- Think of it as collecting a string of rewards r_i associated with the states s_i taken via the (random) walk on the chain.
- Note that in RL the whole point is for the walk not to be random anymore.
- The **n-step return** $R_n = \sum_{i=1}^n r_i$ is just the sum of n rewards collected.
- It is a random quantity whose expectation (the *expected return*) we'd like to maximise ; mathematically, RL is cast as an **optimisation** problem.

Markov Decision Processes

- MDPs are Markov Decision Processes
- They are Markov Rewards Processes where now actions are informing randomly the next state you're in, i.e., MRPs with decisions.
- So every state s_i becomes a couple of a state and action (s_i, a_i) .
- Because of the introduction of those actions, the maximisation on previous slide becomes an active maximisation process
- That is, RL is also an control problem - finding the best policy, in order to optimise the future¹.

¹The flipside of this is *prediction*, that is, evaluate the future given a specific policy.

MDPs, illustrated

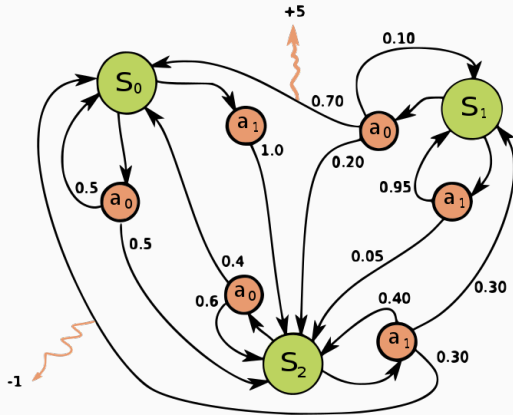


Figure 2: Toy MDP example with three states and two actions per states. Note transition probabilities and attached scalar rewards.

Why all this ?

Because we are Markov, we will only ever be interested in two states: the one we are coming from (s) and the one we are going to (s'). We can discard anything that comes before s . There are only two indices here, so matrices (rather than more general d -dimensional tensors) will be all we need. Notation-wise :

- $T(s, a, s')$ will be the *transition dynamics*, or probability to go to state s' after having taken action a in state s .
- $R(s, a, s')$ will be the reward associated with going to from state s to s' when taking action a .

Markov Decision Processes are the typical formulation used for reinforcement learning problems in the literature.

- V numbers are known as the state-value functions.
- They depend on policy π , so we often denote them by $V_\pi(s)$.
- They indicate **how good a given state is** (the long-term value of a state s) for a player following the policy π :

$$V_\pi(s) = \mathbb{E}_\pi \left[\sum_{i=0}^{\infty} \gamma^i \cdot r_{t+i} \mid S_t = s \right]$$

- i.e. the *expected cumulative return* from starting in state s , and following policy π thereafter.

Q and V : Q

- Q (for quality !) numbers go one step beyond, and are **action-value** functions (shorthand for action-state-value functions).
- These numbers contain more information than the $V(s)$ above.
- They indicate how good it is, in state s , to *first take action a* before continuing to follow policy π for all other next actions.
- They are denoted by $Q_\pi(s, a)$:

$$Q_\pi(s, a) = \mathbb{E}_\pi \left[\sum_{i=0}^{\infty} \gamma^i \cdot r_{t+i} \mid S_t = s, A_t = a \right]$$

- i.e. the *expected cumulative return* from starting in state s , taking first action a , and then following policy π thereafter.

Q and V redux : * optimality

- In general, these numbers depend on the policy we use to choose our actions. A given chess position is not as good if played by me (π_1) or by Kasparov (π_2) !
- The optimal Q and V numbers, i.e. the ones that would be attainable by a perfect controller or player π^* , are denoted by a star :

$$V^*(s) = V_{\pi^*}(s) = \max_{\pi} V_{\pi}(s)$$

- Similarly we define

$$Q^*(s, a) = Q_{\pi^*}(s, a) = \max_{\pi} Q_{\pi}(s, a)$$

.

Discounted formulae - Recap

$$R_t = r_{t+1} + \gamma r_{t+2} + \gamma^2 r_{t+3} \dots + \gamma^{T-t+1} r_T + \dots = \sum_{k=0}^{\infty} \gamma^k r_{t+k+1}$$

$$\forall s \in S \quad V^\pi(s) = E^\pi \left[\sum_{t=0}^{\infty} \gamma^t r(s_t, a_t) \mid s_0 = s \right]$$

$$\forall s \in S, a \in A \quad Q^\pi(s, a) = E^\pi \left[\sum_{t=0}^{\infty} \gamma^t r(s_t, a_t) \mid s_0 = s, a_0 = a \right]$$

$$V^\pi(s) = E^\pi \left[r(s, a) + \gamma \sum_{t=0}^{\infty} \gamma^t r(s_{t+1}, a_{t+1}) \mid s_0 = s, a \sim \pi(a|s) \right]$$

$$Q^\pi(s, a) = E^\pi \left[r(s, a) + \gamma \sum_{t=0}^{\infty} \gamma^t r(s_{t+1}) \mid s_0 = s, a_0 = a \right]$$

$$\forall s \in S \quad V^\pi(s) = \sum_a \pi(s, a) Q^\pi(s|a) = Q^\pi(s, \pi(s))$$

Policy evaluation and policy improvement

A policy is greedy wrt action-value functions Q if

$$\pi(s) \in \operatorname{argmax}_a Q^\pi(s, a)$$

Policy improvement theorem : if π' is greedy w.r.t Q^π , then $\pi' \geq \pi$.

Optimality theorem : if π is greedy w.r.t its own Q-function Q^π , then π is optimal.

Hence we can alternate between *policy evaluation* and *policy improvement* ($\pi \leftarrow \text{greedy}(Q)$) steps, and hope to converge to an optimum both in π^* and V^* .

Learn $Q^\pi(s, a)$ via sampling:

- Random choice of starting state s
- Random choice of an action a (exploration starts)
- Follow policy π and observe gain R_t
- Do that 'infinitely many' times, and average $Q^\pi(s, a) = E^\pi [R_t]$
- Perform policy improvement: $\pi(s) = \operatorname{argmax}_{a \in A} Q^\pi(s, a)$

Problem = this is a high-variance method.

In the deterministic case:

$$\begin{aligned} V(s_t) &= r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \gamma^3 r_{t+3} + \dots \\ &= r_t + \gamma V(s_{t+1}) \end{aligned}$$

In practice,

$$\delta_t = [r_t + \gamma V(s_{t+1})] - V(s_t) \neq 0$$

The *TD-error* is nonzero in practice (and we usually build algorithms via attempting to minimize it).

Widrow-Hoff like update rule.

$$V^{t+1}(s_t) \leftarrow V^t(s_t) + \alpha (r_t + \gamma V^t(s_{t+1}) - V^t(s_t))$$

(α is a learning rate, $V(s_t)$ is a target). This rule is used for **bootstrapping** - meaning, producing new estimates from existing estimates (a guess from another guess). For more details than the timespan of this course allows, on how exactly information propagates from terminal states, see for instance <https://mpatacchiola.github.io/blog/2017/01/29/dissecting-reinforcement-learning-3.html>.

SARSA (on-policy) vs Q-learning (off-policy)

These are the two main algorithms we will implement in the practical session. Notice how the targets (in red) differ, as an expectation vs. a max over successor actions:

SARSA update:

$$Q^{t+1}(s_t, a_t) \leftarrow Q^t(s_t, a_t) + \alpha (r_t + \gamma Q^t(s_{t+1}, a_{t+1}) - Q^t(s_t, a_t))$$

Q-learning update:

$$Q^{t+1}(s_t, a_t) \leftarrow Q^t(s_t, a_t) + \alpha \left(r_t + \gamma \max_b Q^t(s_{t+1}, b) - Q^t(s_t, a_t) \right)$$

Qs and Vs redux : * optimality, 2

- If we knew the optimal V numbers perfectly (through a *critic* or *value function iteration*) and we had a model of our world, we could act greedily towards choosing which state to go to.
- If we knew the Q^* numbers perfectly for each action, we would be in even better shape (why ?).
- The goal of value-function based RL is to **determine and act according to those Q^* numbers**.
- So we choose to do Q-learning : we will learn the optimal action-values $Q^*(s, a)$.

The Bellman Equation

- The Bellman equation is possibly the most important equation in all of reinforcement learning.
- It's a **time consistency property** for optimal value functions. It applies to either Q or V , and tells us how to do our neural network training.
- At optimality we get (easy to prove just by expanding the expectation sum one step forward) :

$$Q^*(s, a) = \sum_{s'} T(s, a, s') \left[R(s, a, s') + \gamma \max_{a'} Q^*(s', a') \right]$$

- Notice we have $Q^*(s, \cdot)$ on the **left**, but $Q^*(s', \cdot)$ on the **right** !

Bellman Equation : intuition

- In the case where we are looking back at past, realized transitions, we can simply set $T(s, a, s') = 1$ for the only one transition that has actually happened, and 0 elsewhere.
- This allows us to give an ex-post, intuitive decomposition of the Bellman equation in two parts:
- A horizontal (time axis) part: for the actual action taken a_{actual} ,

$$Q^*(s, a_{actual}) = r(s, a_{actual}) + \gamma V^*(s')$$

- A vertical (optimal action) part:

$$V^*(s') = \max_a Q^*(s', a)$$

- Taken together this is the classic form

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

.

ϵ -greedy : exploitation vs exploration, redux

Making sure we are not stuck in a suboptimal policy. In general (99% of the times) we will use $\arg \max Q(s, a)$ as an implicit policy.

However:

- Simplest idea for ensuring continual exploration
- All m actions are tried with non-zero probability
- We pick a small number ϵ before running the algorithm.
- With probability $1 - \epsilon$, choose the greedy action
- With probability ϵ , choose an action at random.
- $\pi(a|s) = \frac{\epsilon}{m} + (1 - \epsilon)\delta_{a=\arg\max Q(s, a^*)}$

We can show theoretically that this leads to policy improvement.

Theoretical Q-learning in 1 slide.

Q-learning is **learning the numbers that enable us to act**.

- The target policy π is greedy.
- If now we are being ϵ -greedy, everything simplifies and we get the Q-learning target $R_{t+1} + \max_{a'} Q(s_{t+1}, a')$
- As such, we update $Q(s, a)$ in the *direction* of the target :

$$Q_{t+1}(s_t, a_t) \leftarrow Q_t(s_t, a_t) + \alpha(R + \max_{a'} Q_t(s_{t+1}, a') - Q_t(s, a))$$

(with α a given learning rate)

Theorem

As we take more iterations, tabular Q-learning control converges to the optimal action-value function, $Q(s, a) \rightarrow Q^(s, a)$.*

Proof methods almost always invoke the Banach fixed point theorem by showing the Q- (Bellman) operator is a contraction - that is, its Lipschitz constant is < 1 .

Theorem

Assume a tabular, finite horizon, episodic MDP with number of states S , number of actions A , time horizon H , and number of time-steps T . Then, there exists an optimistic modification (exploration bonus) to the value iteration algorithm that achieves a provably optimal regret bound of $O(\sqrt{HSAT})$ with high probability.

The proof is highly technical [Gheshlaghi Azar et al., 2017], and makes extensive use of concentration inequalities (Azuma-Hoeffding, Bernstein-Freedman).

Description of our theoretical, tabular algorithm

We will train in *episodes* as follows.

- Initialize $Q(s, a)$ for each s, a arbitrarily, and $Q(\text{terminalstate}, \cdot) = 0$.
- For each episode, repeat :
 - Initialize S
 - Repeat (for each step of episode:)
 - Choose A from S using ϵ -greedy policy derived from Q
 - Take action A , observe R, S'
 - $Q_{t+1}(S, A) \leftarrow Q_t(S, A) + \alpha(R + \max_a Q_t(S', a) - Q_t(S, A))$
 - $S \leftarrow S'$

In practice : Tabular vs function approximation

First problem : there is a potential infinity of screenshots s . We will hence not be able to implement $Q(s, a)$ as a lookup table, but rather, will resort to using a neural network for *generalization*.

- Tabular : nice theoretical guarantees and regret bounds, but intractable...
- Function approximation : may or may not converge... but works, at scale !

In general we use **neural networks** for function approximation and we **stabilize** learning using a various set of RL-specific tricks (not just NN tricks).

- We refer to the weights of our NN as θ , so we get $Q_\theta(s, a)$.

Atari Example

Our canonical example. The rules of the game are unknown, and we want to learn directly from interactive game-play. We pick actions on joystick, see resulting pixels and scores.

- Environment = emulator
- States = stacks of 84x84x3 pixels & score (!).
- Notion of transition between states : from one screenshot to another.
- Actions = joystick button presses
- Rewards = changes in score



Figure 3: Screenshots from five Atari 2600 Games: (*Left-to-right*) Pong, Breakout, Space Invaders, Seaquest, Beam Rider. Taken from [Mnih et al., 2013].

Atari - DQN Architecture

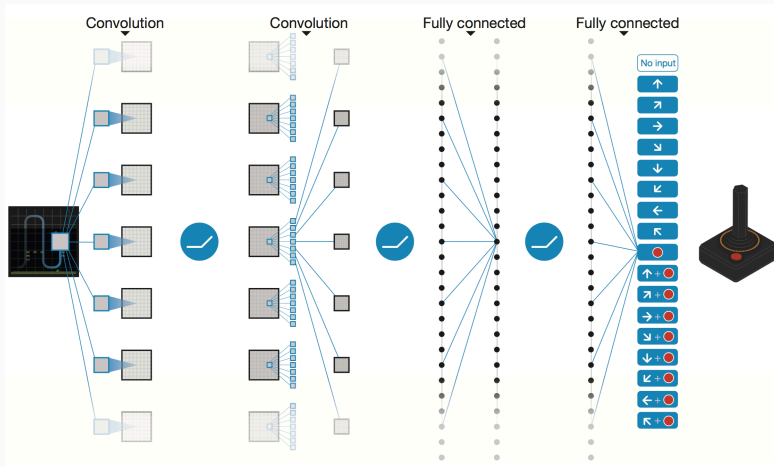


Figure 4: Architecture for the DQN. Input s is stacked frames, output is an 18-element action-value vector $Q_{\theta}(s, a)$. Taken from [Mnih et al., 2015].

- To learn, we will keep track of a table of 18 potential numbers (one per Atari action) for each state/screenshot.
- We will initialize the Q 's randomly and then interact with the environment by playing, collecting rewards and observations, and placing them into a memory : an *experience replay* buffer.
- Then we will use the Bellman equation to get our network to output better and better estimates for the Q^* .
- As we do this we will also continue playing to get better experiential data, by following the (implicit, greedy) policy given by those new Q values.

Convolutional architectures

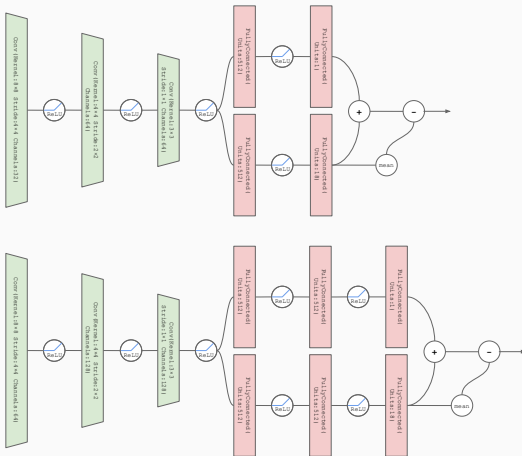


Figure 5: Two typical convolutional architectures for training Atari games. Note the shallow networks with at most 6 layers. Taken from [Pohlen et al., 2018].

Bootstrapping : an ansatz

- Bootstrapping = **wishful thinking** - 'what if we were already at optimality ?'
- The Bellman equation is not valid before we reached a perfect policy ; we are going to pretend it is.
- So instead of pretending the difference between the left side and the right side of the equation (the *Bellman residual*) is zero, we will **take its square as a loss function** and iteratively minimize it, to 0, via gradient descent :

$$L_i(\theta_i) = \mathbb{E}_{\underbrace{(s, a, r, s') \sim U(D)}_{\text{randomly sampled transitions}}} \left[\underbrace{\left(r + \max_{a'} Q(s', a', \theta_i) - Q(s, a, \theta_i) \right)^2}_{\text{target value } y_i} \right]$$

Bootstrapping : action-vector view

- In this case, we can repeatedly *pick a realized past transition* (s, a, r, s') and do the following :
- If we pass the destination screenshot s' to the network, we will get an estimate for the value of the state by just computing the action-vector $Q^*(s', a)$ and taking its maximum. We add the effective reward we got on our way there, and make a note of this total (a good proxy estimate of $V^*(s') + r(s, a)$).
- The Bellman equation says that when applying our network to the original screenshot, picking only the value in the action-vector that matches the actual chosen action, should return that very number.
- Hence, we can enforce that by now **training the network** (using standard supervised learning methods !) *to return that target value*.
- We will do that, and then move to another transition (s, a, r, s') and repeat in batches.

Bootstrapping : action-vector view

- Our RL setting and specifically the Bellman equation enabled us to determine target values our neural network should aim to return.
- Viewed in this way, RL is a second-level algorithm or **meta-algorithm** that sits on top of supervised learning.
- It is therefore not surprising it needs to be **stabilized** even more !
- You can see that this principle of Q-learning will work with different types of neural networks.
- There will be interplay between neural architecture (**deep**) and reinforcement algorithm (**RL**).

Two stabilizing tricks

- First stabilizing trick is to **shuffle** transitions (randomize their order in time) in our replay buffer²;
- Otherwise, consecutive updates are too correlated in time (as opposed to the SGD IID assumption), and the network diverges.
- Second trick is to use **two** networks : one for $Q(s')$ prediction, another one for $Q(s)$ training. This also stabilizes training by preventing a negative feedback loop where the network chases its own tail (reduce correlations between target and predicted Q-values).
- These two methods are called *experience replay* and *target network freezing* by [Mnih et al., 2015].

²Is this what dreams are made of ? There is clear **neuroscientific evidence** for replay in the brain, modulated by dopamine as a vector of surprise.

Description of the practical deep Q-learning algorithm

Algorithm 1 DQN algorithm with neural function approximation.

Initialize replay memory D to capacity N

Initialize action-value network Q with random weights θ

Initialize target action-value network \hat{Q} with weights $\theta^- = \theta$

for episode 1, M **do**

 Initialize sequence with s_1

for $t = 1, T$ **do**

 With probability ϵ , select a random action a_t

 Otherwise select $a_t = \arg \max_a Q(\phi(s_t), a; \theta)$

 Execute action a_t in the emulator

 Observe reward r_t and image s_{t+1}

 Store experience (s_t, a_t, r_t, s_{t+1}) in D

 Sample random minibatch of (s_j, a_j, r_j, s_{j+1}) from D

 Set $y_j = \begin{cases} r_j & \text{if episode terminates step } j + 1 \\ r_j + \max_{a'} \hat{Q}(\phi_{j+1}, a'; \theta^-) & \text{otherwise} \end{cases}$

 Perform a gradient descent step on $(y_j - Q(s_j, a_j; \theta))^2$

 w.r.t. network weights θ (SGD, RMSProp, ADAM ?)

 Every C steps, reset $\hat{Q} = Q$

DQN : Results

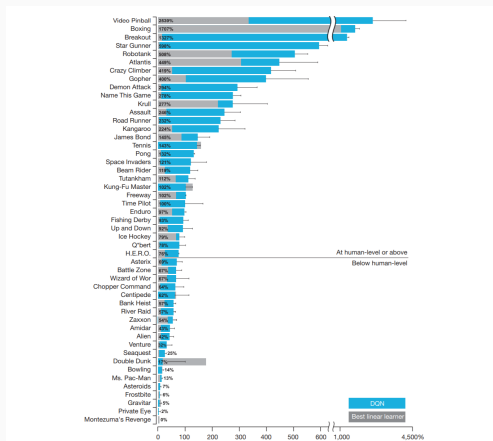


Figure 6: Performance on Atari games, normalized w.r.t. human professional games tester. DQN fares better on twitchy, reactive games than on planning-oriented ones. Training takes \sim a day per game on a modern GPU [Stooke and Abbeel, 2018]. Taken from [Mnih et al., 2015].

DQN : Monitoring convergence

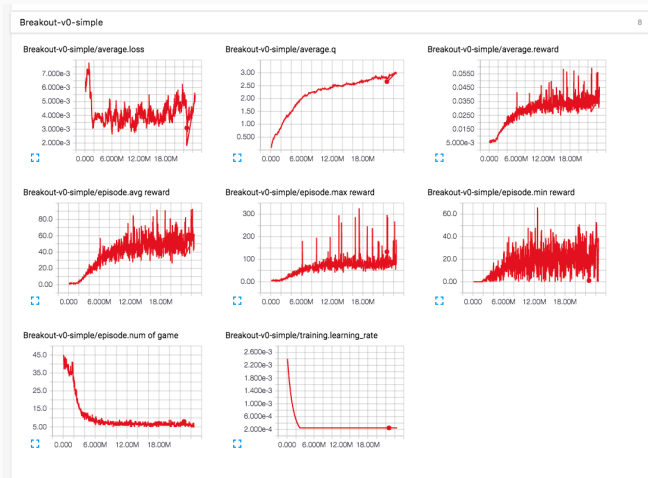


Figure 7: Deep RL convergence is much harder in practice than simple supervised learning - hence need to monitor indicators like reward & episode statistics with TensorBoard.

Some DQN extensions - sample efficiency & performance

- **Double DQN** [van Hasselt et al., 2015] decouples action selection and evaluation, between both current and target networks, so as to avoid propagating the max of estimation noise - which makes the network overestimate action-values (upward bias).
- **Duelling DQN** [Wang et al., 2015] attempt to separate the learning of a baseline state value, and the relative advantage of taking each action in that state (centered on zero, ergo variance reduction).
- **Prioritized Experience Replay** [Schaul et al., 2015] replays 'surprising' transitions (those with a high Bellman residual error) much more often, in order to learn faster.
- **NoisyNets for exploration** [Fortunato et al., 2017] look to learn the variance of the exploration noise automatically, rather than relying on a preset ϵ -greedy annealing schedule.

Combining improvements : RAINBOW agent performance

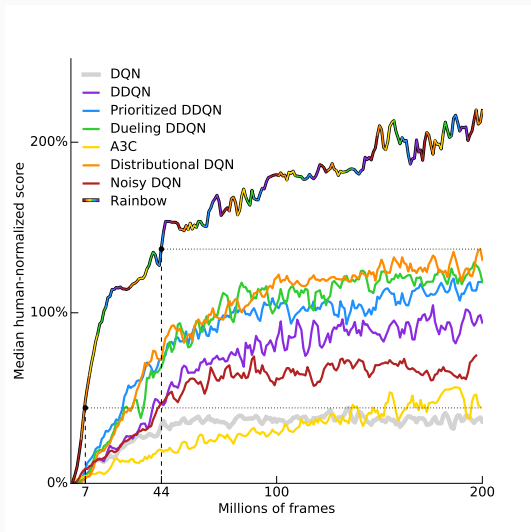


Figure 8: Data-efficient combination & ablation study for DQN extensions across 57 Atari games. Taken from [Hessel et al., 2017].

Github code repositories

TensorFlow

Deep-rl-tensorflow DQN Atari-RL Google-Dopamine Deepmind-TRFL

Keras

Keras-RL DQN-FlappyBird

Pytorch

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