off-policy deep RL

Remi Munos

DeepMind Paris
How to do fundamental research in deep RL?

Ingredients of a satisfying research:

1- The need
   ● Observe limitation of current approaches
   ● Identify the core problem

2- The idea
   ● Design an algorithm

3- The benefit
   ● Theoretical analysis in simplified setting
   ● Improved numerical performance
Off-policy deep RL

- The need
  - Limitations of DQN and A3C
  - off-policy, multi-steps RL

- The idea:
  - Truncated importance sampling while preserving contraction property
  - The algorithm: Retrace

- The benefit:
  - Convergence to optimal policy in finite state spaces
  - Practical algorithms (ACER, Reactor, MPO, Impala)
Introduction to Reinforcement Learning (RL)

- Learn to make good decisions
- No supervision. Learn from rewards

Two approaches:
- Value based ([Bellman, 1957]'s dynamic programming)
- Policy based ([Pontryagin, 1956]'s maximum principle)
The RL agent in its environment

\[ x_{t+1} \sim p(\cdot | x_t, a_t) \]

\[ a_t \sim \pi(\cdot | x_t) \]
Bellman’s dynamic programming

- Define the value function $Q^\pi$ of a policy $\pi(a|x)$:

$$Q^\pi(x, a) = \mathbb{E}\left[ \sum_{t \geq 0} \gamma^t r_t \mid x, a, \pi \right],$$

and the optimal value function:

$$Q^*(x, a) = \max_\pi Q^\pi(x, a).$$

(expected sum of future rewards if the agent plays optimally).

- Bellman equations:

$$Q^\pi(x, a) = r(x, a) + \gamma \mathbb{E}_{x'} \left[ \sum_{a'} \pi(a' \mid x') Q^\pi(x', a') \mid x, a \right]$$

$$Q^*(x, a) = r(x, a) + \gamma \mathbb{E}_{x'} \left[ \max_{a'} Q^*(x', a') \mid x, a \right]$$

- Optimal policy $\pi^*(x) = \arg \max_a Q^*(x, a)$
Represent $Q$ using a neural network

- Represent value function $Q_w(x, a)$ with a neural net.
- How to train $Q_w(x, a)$? We don’t have supervised values. We only know we want

$$Q_w(x, a) \approx r(x, a) + \gamma \mathbb{E}_{x'} \left[ \max_{a'} Q_w(x', a') \middle| x, a \right]$$

- After a transition $x_t, a_t \rightarrow x_{t+1}$,

train $Q_w(x_t, a_t)$ to predict $r_t + \gamma \max_a Q_w(x_{t+1}, a)$

- Minimize loss $\left( r_t + \gamma \max_a Q(s_{t+1}, a) - Q(s_t, a_t) \right)^2$.

- Temporal difference $\delta_t$

- At the end of learning, $\mathbb{E}[\delta_t] = 0$. 

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Deep Q-Networks (DQN) [Mnih et al. 2013, 2015]

**Problems:** (1) data is not iid, (2) target values change

**Idea:** be as close as possible to supervised learning

1. Dissociate acting from learning:
   - Interact with the environments by following behavior policy
   - Store transition samples $x_t, a_t, x_{t+1}, r_t$ into a memory replay
   - Train by replaying iid from memory

2. Use target network fixed for a while

   \[
   \text{loss} = \left( r_t + \gamma \max_a Q_{\text{target}}(x_{t+1}, a) - Q_w(x_t, a_t) \right)^2
   \]

**Properties:** DQN is off-policy, and uses 1-step bootstrapping.
DQN network
DQN Results in Atari

![Diagram showing DQN results in Atari games](Image)

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Pontryagin’s maximum principle

- Parametrized policy $\pi_\theta(a|x)$
- **Policy gradient**: optimize

$$J(\theta) = \mathbb{E} \left[ \sum_{t \geq 0} \gamma^t r_t \middle| a_t \sim \pi_\theta(\cdot|x_t) \right],$$

by gradient ascent:

$$\nabla J(\theta) = \mathbb{E} \left[ \sum_{t \geq 0} \gamma^t \nabla \log \pi_\theta(a_t|x_t) \left( r_t + \gamma r_{t+1} + \ldots \right) \right]_{Q^{\pi_\theta}(x_t, a_t)}$$

**Actor-critic** algorithm learn both $\pi_\theta$ and $Q_w$. 
Asynchronous Advantage Actor-Critic (A3C)

A3C [Mnih et al., 2016] is an asynchronous actor-critic algorithm

- Learn state-value function $V^\pi(x) = \mathbb{E} \left[ \sum_{t \geq 0} \gamma^t r_t \mid x, \pi \right]$ by minimizing a $n$-step Temporal Difference:

$$\left( V_w(x_t) - \left( r_t + \gamma r_{t+1} + \ldots + \gamma^{n-1} r_{t+n-1} + \gamma^n V_w(x_{t+n}) \right) \right)^2$$

- $n$-steps target value

- Policy $\pi_\theta(a_t \mid x_t)$ improved by following gradient ascent:

$$\nabla \log \pi_\theta(a_t \mid x_t) \left( r_t + \gamma r_{t+1} + \ldots + \gamma^{n-1} r_{t+n-1} + \gamma^n V_w(x_{t+n}) - V_w(x_t) \right)$$

DQN versus A3C

DQN:

- Pros: Off-policy learning → use memory replay (sample efficiency), allow any exploration strategy
- Cons: One-step learning: Slow to propagate information, accumulates errors, no RNNs

A3C:

- Pros: Multi-steps learning → fast propagation of information, possible use of RNNs
- Cons: On-policy learning: does not allow memory replay, neither exploration

The Need: off-policy, multi-steps learning
Two desired properties of a RL algorithm:

- Off-policy learning
  - use memory replay
  - do exploration
  - lag between acting and learning
- Use multi-steps learning
  - propagate rewards rapidly
  - avoid accumulation of approximation/estimation errors
  - Allow learning from sequences (RNN)

Ex: Q-learning (and DQN) is off-policy but does not use multi-steps returns. Policy gradient (and A3C) use returns but are on-policy.

Both properties are important in deepRL. Can we have both simultaneously?
Off-policy reinforcement learning

Behavior policy $\mu(a|x)$, target policy $\pi(a|x)$

Observe trajectory $\{x_0 = x, a_0 = a, r_0, \ldots, x_t, a_t, r_t, \ldots\}$

where $a_t \sim \mu(\cdot|x_t)$, $r_t = r(x_t, a_t)$ and $x_{t+1} \sim p(\cdot|x_t, a_t)$

Goal:
- Policy evaluation: $Q^\pi(x, a) = \mathbb{E}\left[ \sum_{t \geq 0} \gamma^t r_t | x_0 = x, a_0 = a, \pi \right]$
- Optimal control: $Q^*(x, a) = \max_{\pi} Q^\pi(x, a)$
Off-policy credit assignment problem

Behavior policy $\mu(a|x)$
Target policy $\pi(a|x)$

Can we use the TD $\delta_t$ to estimate $Q^\pi(x_s, a_s)$ for all $s \leq t$?
Importance sampling

\[ \Delta Q(x, a) = \gamma^t \left( \prod_{1 \leq s \leq t} \frac{\pi(a_s | x_s)}{\mu(a_s | x_s)} \right) \delta_t \]

Reweight the trace by the product of IS ratios
Importance sampling

$\Delta Q(x, a) = \gamma^t \left( \prod_{1 \leq s \leq t} \frac{\pi(a_s | x_s)}{\mu(a_s | x_s)} \right) \delta_t$

Unbiased estimate of $Q^\pi$
Importance sampling

Unbiased estimate of $Q^\pi$

Large (possibly infinite) variance

$\Delta Q(x, a) = \gamma^t \left( \prod_{1 \leq s \leq t} \frac{\pi(a_s|x_s)}{\mu(a_s|x_s)} \right) \delta_t$

Not stable!

$Q^\pi(\lambda)$ algorithm

[Harutyunyan et al., 2016]

\[ \Delta Q(x, a) = (\gamma \lambda)^t \delta_t \]

Cut traces by a constant $\lambda^t$
\( Q^\pi (\lambda) \) algorithm

[Harutyunyan et al., 2016]

\[ \Delta Q(x, a) = (\gamma \lambda)^t \delta_t \]

works if \( \| \pi - \mu \|_1 \leq \frac{1 - \gamma}{\lambda \gamma} \)
The $Q^\pi(\lambda)$ algorithm [Harutyunyan et al., 2016] works if $\|\pi - \mu\|_1 \leq \frac{1 - \gamma}{\lambda \gamma}$, may not work otherwise, and there is no guarantee.
Tree backup TB(λ) algorithm

[Precup, Sutton, Singh, 2000]

\[ \Delta Q(x, a) = \lambda^t \prod_{1 \leq s \leq t} \pi(a_s | x_s) \delta_t \]

Reweight the traces by the product of target probabilities
Tree backup TB(λ) algorithm

[Precup, Sutton, Singh, 2000]

\[
\Delta Q(x, a) = \lambda^t \prod_{1 \leq s \leq t} \pi(a_s | x_s) \delta_t
\]

works for arbitrary policies \( \pi \) and \( \mu \)
**Tree backup TB(λ) algorithm**

[Precup, Sutton, Singh, 2000]

\[ \Delta Q(x, a) = \lambda^t \prod_{1 \leq s \leq t} \pi(a_s | x_s) \delta_t \]

- works for arbitrary policies $\pi$ and $\mu$
- cut traces unnecessarily when on-policy

Not efficient!
General off-policy return-based algorithm:

\[
\Delta Q(x, a) = \sum_{t \geq 0} \gamma^t \left( \prod_{1 \leq s \leq t} c_s \right) \left( r_t + \gamma \mathbb{E}_\pi Q(x_{t+1}, \cdot) - Q(x_t, a_t) \right)
\]

<table>
<thead>
<tr>
<th>Algorithm:</th>
<th>Trace coefficient:</th>
<th>Problem:</th>
</tr>
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<tbody>
<tr>
<td>IS</td>
<td>[ c_s = \frac{\pi(a_s</td>
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</tr>
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<td>(Q^\pi(\lambda))</td>
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<td>No guarantee</td>
</tr>
<tr>
<td>(TB(\lambda))</td>
<td>[ c_s = \lambda \pi(a_s</td>
<td>x_s) ]</td>
</tr>
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Off-policy policy evaluation:

**Theorem 1:** Assume finite state space. Generate trajectories according to behavior policy $\mu$. Update all states along trajectories according to:

$$Q_{k+1}(x, a) = Q_k(x, a) + \alpha_k \sum_{t>0} \gamma^t(c_1 \ldots c_t)(r_t + \gamma \mathbb{E}_\pi Q_k(x_{t+1}, \cdot) - Q_k(x_t, a_t))$$

Assume all states visited infinitely often. Under usual SA assumptions,

If $0 \leq c_s \leq \frac{\pi(a_s|x_s)}{\mu(a_s|x_s)}$ then $Q_k \rightarrow Q^{\pi}$ a.s.

Sufficient conditions for a **safe** algorithm (works for any $\mu$ and $\pi$)
Off-policy return-based operator

Lemma:
Assume the traces satisfy $0 \leq c_s \leq \frac{\pi(a_s|x_s)}{\mu(a_s|x_s)}$.

Then the off-policy return-based operator:

$$\mathcal{R}Q(x, a) = Q(x, a) + \mathbb{E}_\mu \left[ \sum_{t \geq 0} \gamma^t (c_1 \ldots c_t) (r_t + \gamma \mathbb{E}_\pi Q(x_{t+1}, \cdot) - Q(x_t, a_t)) \right]$$

is a contraction mapping (whatever $\mu$ and $\pi$) and $Q^\pi$ is its fixed point.
Proof [part 1]

\[ RQ(x, a) = Q(x, a) + \mathbb{E}_{\mu} \left[ \sum_{t \geq 0} \gamma^t (c_1 \ldots c_t)(r_t + \gamma \mathbb{E}_{\pi} Q(x_{t+1}, \cdot) - Q(x_t, a_t)) \right] \]

\[ = \mathbb{E}_{\mu} \left[ \sum_{t \geq 0} \gamma^t (c_1 \ldots c_t)(r_t + \gamma \left[ \mathbb{E}_{\pi} Q(x_{t+1}, \cdot) - c_{t+1} Q(x_{t+1}, a_{t+1}) \right]) \right] \]

Thus

\[ (RQ_1 - RQ_2)(x, a) = \mathbb{E}_{\mu} \left[ \sum_{t \geq 0} \gamma^{t+1} (c_1 \ldots c_t) \left( \mathbb{E}_{\pi} (Q_1 - Q_2)(x_{t+1}, \cdot) - c_{t+1} (Q_1 - Q_2)(x_{t+1}, a_{t+1}) \right) \right] \]

\[ = \mathbb{E}_{\mu} \left[ \sum_{t \geq 0} \gamma^{t+1} (c_1 \ldots c_t) \sum_{a} \left( \pi(a|x_{t+1}) - \mu(a|x_{t+1})c_{t+1}(a) \right) (Q_1 - Q_2)(x_{t+1}, a) \right] \]

which is a linear combination weighted by non-negative coefficients which sum to...
Proof [part 2]

Sum of the coeff.  
\[
\begin{align*}
\sum_{t \geq 0} \gamma^{t+1} (c_1 \ldots c_t) \sum_a (\pi(a|x_{t+1}) - \mu(a|x_{t+1})c_{t+1}(a)) \\
= \mathbb{E}_\mu \left[ \sum_{t \geq 0} \gamma^{t+1} (c_1 \ldots c_t)(1 - c_{t+1}) \right] \\
= \gamma - (1 - \gamma) \mathbb{E}_\mu \left[ \sum_{t \geq 1} \gamma^t (c_1 \ldots c_t) \right] \\
\in [0, \gamma]
\end{align*}
\]

Thus \( \|RQ_1 - RQ_2\|_\infty \leq \gamma \|Q_1 - Q_2\|_\infty \)
Tradeoff for trace coefficients $C_S$

- **Contraction coefficient of the expected operator**

  \[ \eta := \gamma - (1 - \gamma) \mathbb{E}_\mu \left[ \sum_{t \geq 1} \gamma^t (c_1 \cdots c_t) \right] \in [0, \gamma] \]

  \[ \eta = \gamma \text{ when } C_S = 0 \text{ (one-step Bellman update)} \]

  \[ \eta = 0 \text{ when } C_S = 1 \text{ (full Monte-Carlo rollouts)} \]

- **Variance of the estimate** (can be infinite for $C_S = \frac{\pi(a_s|x_s)}{\mu(a_s|x_s)}$)

  Large $C_S$ uses multi-steps returns, but large variance

  Small $C_S$ low variance, but do not use multi-steps returns
Retrace(\(\lambda\))
[Munos et al., 2016]

Our recommendation:

\[
c_s = \lambda \min \left( 1, \frac{\pi(a_s|x_s)}{\mu(a_s|x_s)} \right)
\]

Properties:

- Low variance since \(c_s \leq 1\)
- Safe (off policy): cut the traces when needed \(c_s \in \left[ 0, \frac{\pi(a_s|x_s)}{\mu(a_a|x_s)} \right]\)
- Efficient (on policy): but only when needed. Note that \(c_s \geq \lambda \pi(a_s|x_s)\)
## Summary

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<td>$Q^\pi(\lambda)$</td>
<td>$c_s = \lambda$</td>
<td>not safe (off-policy)</td>
</tr>
<tr>
<td>$TB(\lambda)$</td>
<td>$c_s = \lambda \pi(a_s</td>
<td>x_s)$</td>
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<tr>
<td>Retrace($\lambda$)</td>
<td>$c_s = \lambda \min \left(1, \frac{\pi(a_s</td>
<td>x_s)}{\mu(a_s</td>
</tr>
</tbody>
</table>
Retrace(\(\lambda\)) for optimal control

Let \((\mu_k)\) and \((\pi_k)\) sequences of behavior and target policies and

\[
Q_{k+1}(x, a) = Q_k(x, a) + \alpha_k \sum_{t \geq 0} (\lambda \gamma)^t \prod_{1 \leq s \leq t} \min \left( 1, \frac{\pi_k(a_s|x_s)}{\mu_k(a_s|x_s)} \right) (r_t + \gamma \mathbb{E}_{\pi} Q_k(x_{t+1}, \cdot) - Q_k(x_t, a_t))
\]

**Theorem 2**
Under previous assumptions (+ a technical assumption)
Assume \((\pi_k)\) are “increasingly greedy” wrt \((Q_k)\)
Then, a.s.,

\[
Q_k \to Q^*
\]
Remarks

- If \((\pi_k)\) are greedy policies, then \(c_s = \lambda \mathbb{I}\{a_s \in \arg\max_a Q_k(x_s, a)\}\) → **Convergence of Watkin’s Q(\(\lambda\))** to \(Q^*\) (open problem since 1989)

- “Increasingly greedy” allows for smoother traces thus faster convergence

- The behavior policies \((\mu_k)\) do not need to become greedy wrt \((Q_k)\) → no GLIE assumption (Greedy in the limit with infinite exploration) (first return-based algo converging to \(Q^*\) without GLIE)
Theoretical guarantees of Retrace

Under assumption of finite-state space:

- Convergence to optimal policy
- Cut traces when -and only when- needed
- Adjust the length of the backup to the “off-policy-ness” of the data

Should be useful in deep RL since it allows memory-replay, exploration, distributed acting, and learn from sequences.

Now, does it work in practice?
Retrace for deepRL

Several actor-critic architectures at DeepMind:


- **Reactor** (Retrace-actor) [Gruesly et al., 2018]. Use beta-LOO to update policy. Use LSTM.

- **MPO** (Maximum a posteriori Policy Optimization) [Abdolmaleki et al., 2018] Soft (KL-regularized) policy improvement.

- **IMPALA** (IMPortance Weighted Actor-Learner Architecture) [Espeholt et al., 2018]. Heavily distributed agent. Uses V-trace.
Reactor [Gruesly et al., 2018]

Experience replay

Q(x, a)

\[ \hat{\mu}(x, a) \]

\[ \mu(x, a) \]

Recall Network

Optimize

Correct

Evaluate

Sample

Predict

Observation
Reactor performances on Atari
# Reactor performances on Atari

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Normalized Scores</th>
<th>Mean Rank</th>
<th>ELO</th>
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<tr>
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<td><strong>3.47</strong></td>
<td><strong>280</strong></td>
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Table 1: Random human starts

Table 2: 30 random no-op starts.
Control suite with MPO

MPO (Maximum a posteriori Policy Optimization)

[Abdolmaleki et al., 2018]

on the DeepMind control suite

(set of continuous control tasks intended to serve as performance benchmarks for RL agents)

See: https://www.youtube.com/watch?v=he_BPw32PwU
IMPALA [Espeholt et al., 2018]

**IMP**ortance **Weighted** **Actor-Learner** **Architecture**
- Heavily distributed architecture
- Many actors (CPU), one (or more) learner (GPU)
- Actors generate trajectories and place them into a queue.
- Learner dequeues and performs parameter updates.

Stale experience → requires off-policy learning: V-trace
V-trace: off-policy algorithm using V-values

V-trace = Modified version of Retrace where we learn V instead of Q

- The V-Trace corrected estimate for the value $V(x_s)$ is:

\[
v_s \overset{\text{def}}{=} V(x_s) + \sum_{t=s}^{s+n-1} \gamma^{t-s} \left( \prod_{i=s}^{t-1} c_i \right) \rho_t \left( r_t + \gamma V(x_{t+1}) - V(x_t) \right) \delta_t V
\]

- where $\rho_i \overset{\text{def}}{=} \min \left( \bar{\rho}, \frac{\pi(a_i|x_i)}{\mu(a_i|x_i)} \right)$ and $c_i \overset{\text{def}}{=} \min \left( \bar{c}, \frac{\pi(a_i|x_i)}{\mu(a_i|x_i)} \right)$.

- Converges to

\[
\min \left( \bar{\rho} \mu(a|x), \pi(a|x) \right) \frac{\sum_b \min \left( \bar{\rho} \mu(b|x), \pi(b|x) \right)}{}
\]

- The V-Trace update for the value function is:

\[
(v_s - V(x_s)) \nabla V(x_s)
\]

- The V-Trace update for the policy is:

\[
\rho_s \nabla \log \pi(a_s|x_s) \left( r_s + \gamma v_{s+1} - V(x_s) \right)
\]
Impala Architectures

Small CNN-LSTM

Deep ResNet CNN-LSTM
DMLab-30 Task Set

- Set of 30 cognitive tasks in DeepMind Lab 3D environment.
- Many of the tasks are procedurally generated.

Grounded Language | Memory | Outdoor Foraging | Navigation
DMLab-30 Task Set

**Individual task:**
An agent trained per task

**Multi-tasks:**
A single agent trained on all tasks simultaneously
Performance of Impala on DMLab-30

- IMPALa outperforms A3C (10x more data efficient, 2x overall final performance)
- Positive transfer in multi-task training
IMPALA Videos - Mushroom foraging task

Mushroom foraging task. The agent must collect mushrooms within a naturalistic terrain environment to maximise score. The mushrooms do not regrow. The map is randomly generated. The spawn location is randomized for each episode. Foraging task

See: https://github.com/deepmind/lab/tree/master/game_scripts/levels/contributed/dmlab30
The agent is asked to collect a specified coloured object in a specified coloured room. Example: “Pick the red object in the blue room.” Language task

See: https://github.com/deepmind/lab/tree/master/game_scripts/levels/contributed/dmlab30
The agent must collect as many apples as possible before the episode ends to maximise their score. Upon collecting all of the apples, the level will reset, repeating until the episode ends. Apple locations, level layout and theme are randomized per episode. **Navigation task**

See: https://github.com/deepmind/lab/tree/master/game_scripts/levels/contributed/dmlab30
Agents are required to find the goal as fast as possible, but now with randomly opened and closed doors. **Navigation task**

See: [https://github.com/deepmind/lab/tree/master/game_scripts/levels/contributed/dmlab30](https://github.com/deepmind/lab/tree/master/game_scripts/levels/contributed/dmlab30)
A procedural planning puzzle. The agent must reach the goal object, located in a position that is blocked by a series of coloured doors. Coloured keys can be used to open matching doors once. Collecting keys in the wrong order can make the goal unreachable. Requires planning.

See: https://github.com/deepmind/lab/tree/master/game_scripts/levels/contributed/dmlab30
The agent must choose an object that is different from the one it has seen before. The agent is placed into a first room containing an object and a teleport pad. Touching the pad teleports the agent to a second room containing two objects, one of which matches the object in the previous room. Requires memory

See: https://github.com/deepmind/lab/tree/master/game_scripts/levels/contributed/dmlab30
The agent must find a hidden platform which, when found, generates a reward. This is difficult to find the first time, but in subsequent trials the agent should try to remember where it is and go straight back to this place. Tests episodic memory and navigation ability. Requires episodic memory.

See: https://github.com/deepmind/lab/tree/master/game_scripts/levels/contributed/dmlab30
We need more fundamental research in deep RL!

DeepRL is a super exciting research topic.

We need new idea, new algorithms, new theories!

Please join the fun!
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