Introduction to Deep RL, Part 2

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2.1: What is RL currently achieving?

If you have infinite simulator data and well-defined rewards, you can make substantial progress on extremely hard problems!

- Atari
- Simulated robotics
- Go (Deepmind's AlphaZero)
- Dota (OpenAI Five)
- Starcraft (Deepmind's AlphaStar)

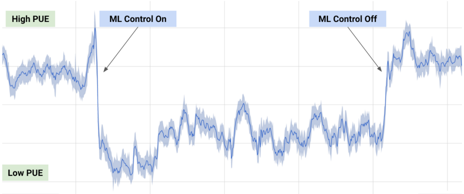
Hard to overstate what an unbelievable accomplishment this was

Previously: Go was considered unassailable stronghold for human experts, AI 10+ years away

What RL Can Currently Do: RL in the Real World

RL is beginning to see profitable real-world applications!

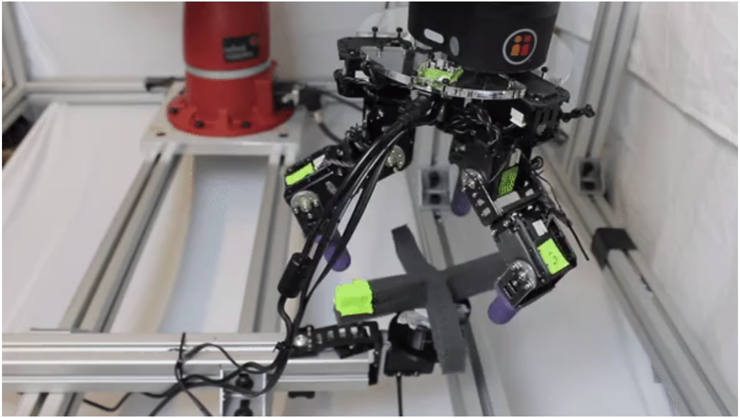
- Facebook uses RL (DQN) for push notifications (Horizon)
- DeepMind integrated RL into data center cooling
- Several promising early efforts at applying RL for robotics



2.1.1: Spotlight on RL for Real-World Robotics

Tasks that can't easily be simulated

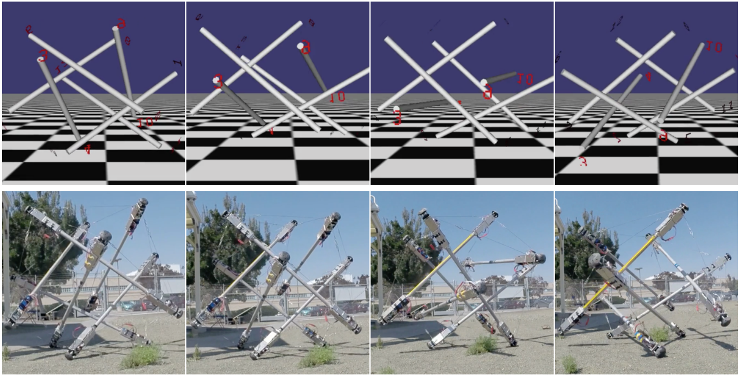
Zhu et al. trained low-cost robots from scratch in the real world on hard-to-simulate tasks using natural policy gradient. (Note: observation space here is hand state and valve state)



[1] Zhu et al, 2018: "Dexterous Manipulation with Deep Reinforcement Learning: Efficient, General, and Low-Cost"

Robots that are hard to control conventionally

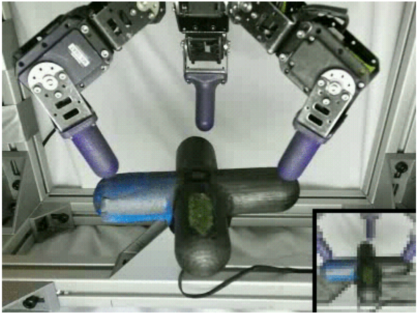
Zhang et al. trained a tensegrity robot with deep RL in simulation and demonstrated transfer to the real world



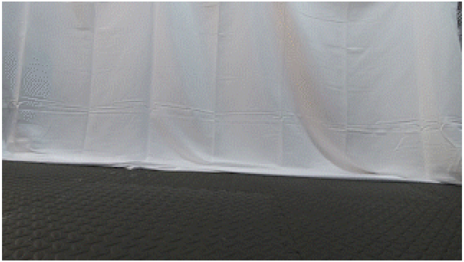
[1]Zhang et al, 2016: "Deep Reinforcement Learning for Tensegrity Robot Locomotion"

Soft Actor-Critic

Haarnoja et al. trained robots in the real world with Soft Actor-Critic, and demonstrated efficient and robust control on hard domains



Manipulation from visual input, agent sees lower-right (took 20 hours to learn)



Robust control of a legged robot (took 2 hours to learn)

[1] Haarnoja et al, 2018: "Soft Actor-Critic Algorithms and Applications"

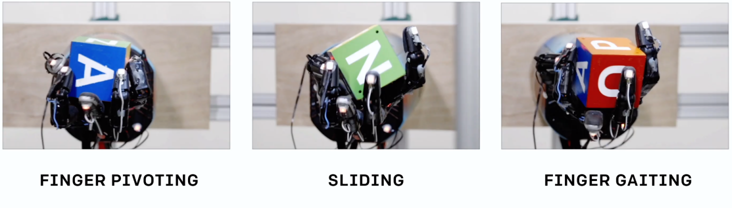
Anymal

Hwangbo et al. used real data to learn a better simulator, and then used lots of simulator data to train complex locomotion and recovery policies with TRPO for the Anymal robot:

[1]Hwangbo et al, 2018: "Learning agile and dynamic motor skills for legged robots"

Learning Dexterity

OpenAI et al. trained policies with PPO to dextrously manipulate a complex hand robot, using sim2real by domain randomization:



[1]OpenAI et al, 2018: "Learning Dexterous In-Hand Manipulation"

2.2: What are the challenges in modern RL?

Some grand challenges for RL

Let's talk about where RL fails, what we need that we aren't getting, and what research is happening.

- **Sample efficiency**: Modern deep RL algorithms are very inefficient with data, requiring in some cases 100x or more experience than a human to achieve good performance. How can we make them faster?

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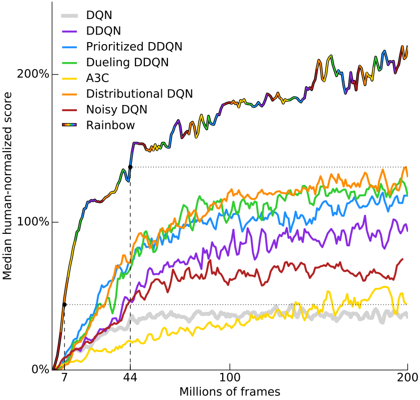
- **Generalization**: Policies trained for one task are brittle and cannot be used outside of training environment: how can we make them generalize?
- **Safety**: How can we make sure that agents trained by deep RL behave in ways consistent with human preferences? (I'll let Dario cover this in his talk, but it's a critical challenge and I would be remiss not to mention it.)

2.2.1: Research on Improving Sample Efficiency

Combining Model-Free Improvements

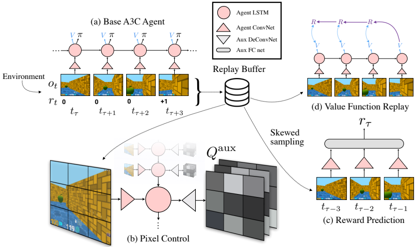
Rainbow DQN: combines...

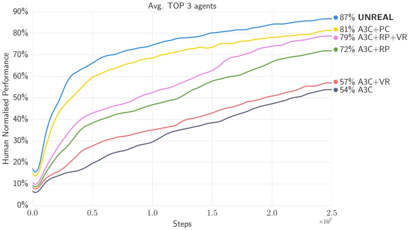
- Dueling architecture
- Double Q-Learning
- Prioritized experience replay
- N-step Q-Learning
- Distributional Q-Learning
- Parameter-space noise



[1] Hessel et al, 2017: “Rainbow: Combining Improvements in Deep Reinforcement Learning”

UNREAL uses various unsupervised auxilliary tasks to speed up learning:

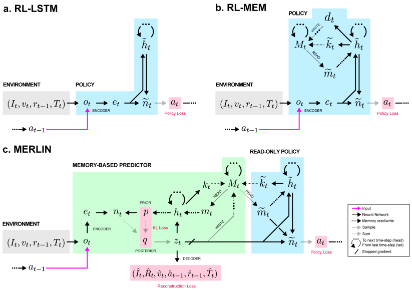


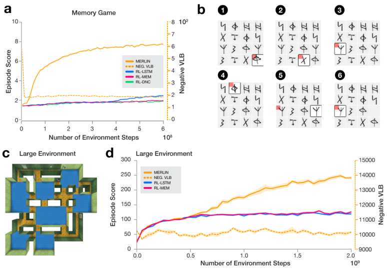


[1] Jaderberg et al, 2016: "Reinforcement Learning with Unsupervised Auxiliary Tasks"

Combining with Memory Mechanisms

MERLIN combines unsupervised learning and attention-based memory to improve over baseline architectures:

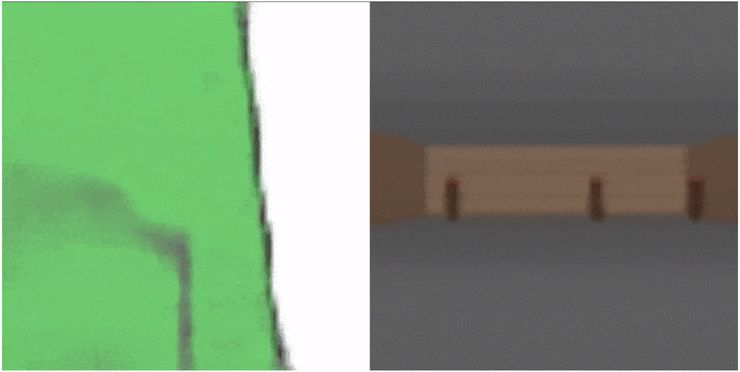




Note: this avenue may not help on arbitrary problems, but seems likely to help on sophisticated partially-observed ones

[1] Wayne et al, 2018: "Unsupervised Predictive Memory in a Goal-Directed Agent"

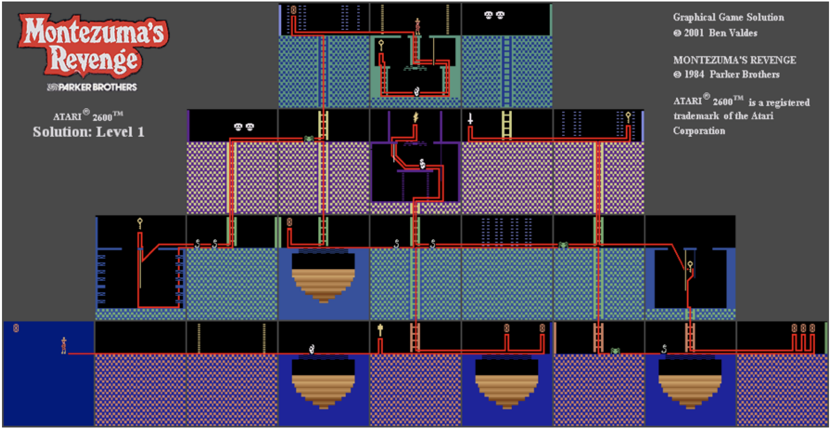
Techniques like **World Models**, that allow an agent to learn from simulated experience, are another way to bring down the needed number of real samples:



[1]Ha and Schmidhuber, 2018: "World Models"

2.2.2: Research on Improving Exploration

AKA, the Quest to Solve Montezuma's Revenge



- Famously hard Atari game
- Most RL algorithms do terribly
- Very sparse rewards, many actions lead to death
- But humans can do just fine!

Various **intrinsic motivation** schemes exist, which work by adding a non-environment-dependent reward:

$$R(s,a,s') \rightarrow R(s,a,s') + \eta R_{int}(s,a,s')$$

Usually, intrinsic reward prefers **new experiences**. Examples:

- Pseudocount-based methods[1]: approximates number of state visitations with density model, rewards are:

$$R_{int}(s,a,s') \propto \frac{1}{\sqrt{N(s)}}$$

- Information gain[2]: approximates change in info state about environment model based on new experience

$$R_{int}(s,a,s') \approx D_{KL}(P(\mathcal{E}|\mathcal{D}_t, s_{t+1})||P(\mathcal{E}|\mathcal{D}_t))$$

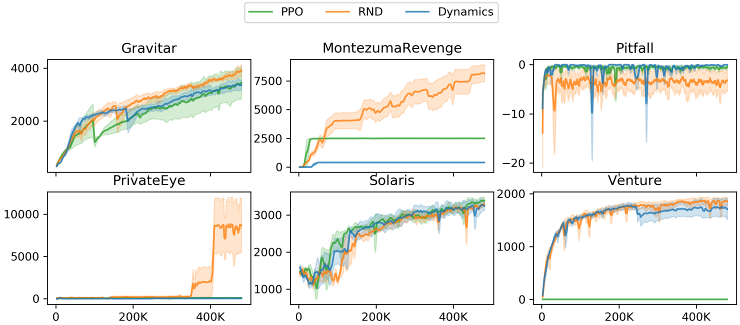
[1] Bellemare et al, 2016: "Unifying Count-Based Exploration and Intrinsic Motivation"
[2] Houthooft et al, 2016: "Variational Information Maximizing Exploration"

Random Network Distillation[3]: A new and appealingly simple form of intrinsic motivation:

$$R_{int}(s) = \|f_\phi(s) - f_\xi(s)\|,$$

where f_ϕ is a random neural network (the target) and f_ξ is trained to match f_ϕ

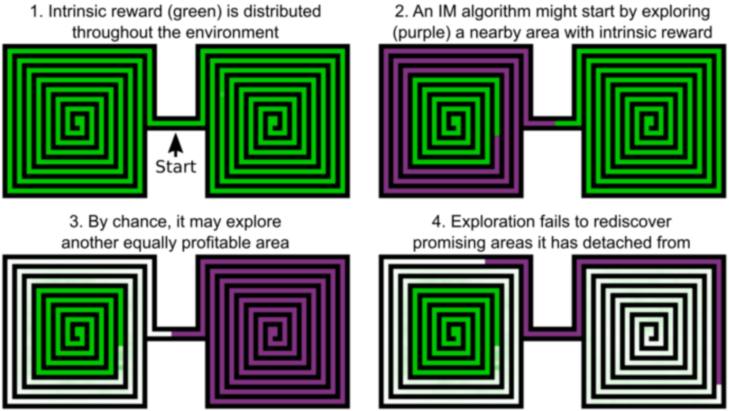
- Exploits generalization properties of networks: f_ϕ matches f_ξ on old states but not new states!



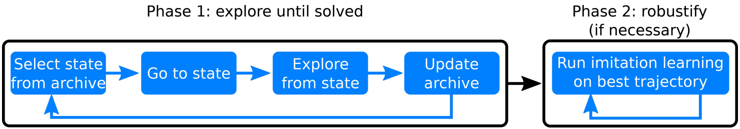
[3] Burda et al, 2018: "Exploration by Random Network Distillation"

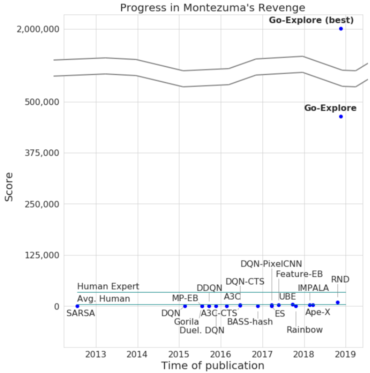
Go-Explore

Ecoffet et al, 2018 identify a problem with intrinsic motivation that they call **detachment**:



They rectify detachment with **Go-Explore**[4] algorithm:



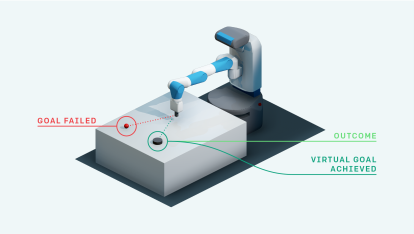


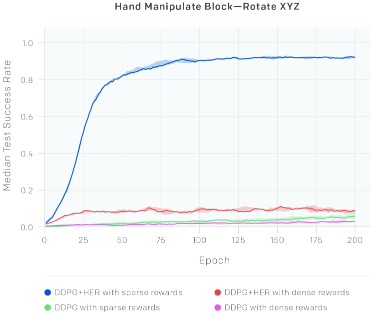
[4] Ecoffet et al, 2018: "Go-Explore: a New Approach for Hard-Exploration Problems"

2.2.3: Research on Generalization

Simple idea behind **HER**[5]:

- If you are trying to learn to go to a goal, goals are hard to get to.
- Unless you pretend that the place you ended up was where you meant to go: then you get to goals all the time!

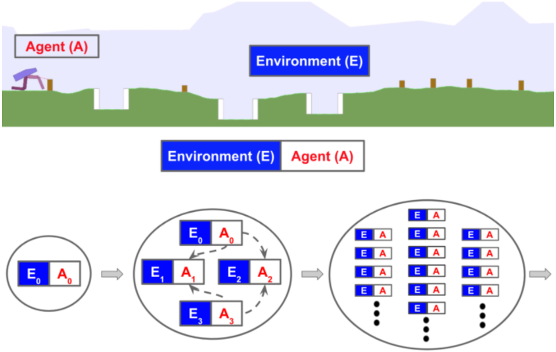




[5] Andrychowicz et al, 2017: "Hindsight Experience Replay"

POET

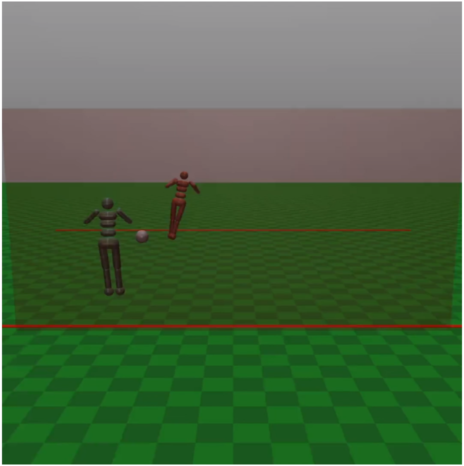
Paired Open-Ended Trailblazer (POET)[6] is an algorithm for evolving populations of agent-environment pairs towards a mix of performance and diversity



Key idea: unboundedly complex environments challenge agents to develop robust, general behaviors

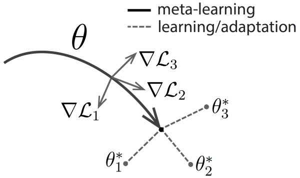
[6] Wang et al, 2019: "Paired Open-Ended Trailblazer (POET): Endlessly Generating Increasingly Complex and Diverse Learning Environments and Their Solutions "

Competitive multi-agent games create natural curricula that inspire general behaviors (because any fault will get exploited by the opponent). In self-play, agents play games against old versions of themselves to improve:[7]



[7] Bansal et al, 2017: "Emergent Complexity via Multi-Agent Competition"

Model Agnostic Meta-Learning (MAML)[8] trains a model with an objective describing its adaptability: the model at optimum should only need a few gradient steps to quickly learn a new task.



[8] Finn et al, 2017: "Model-Agnostic Meta-Learning for Fast Adaptation of Deep Networks"

2.3: Spinning Up in Deep RL

Whether you intend to be a practitioner or a researcher:

- Brush up on math! Be familiar with vectors, matrices, gradients, gradient descent, random variables, expectations, variance, and a few other things.
- Brush up on deep learning! **As much as you can get.**
- Become familiar with TF or PyTorch! **You need to tinker to learn.**
- Stay fresh on RL basics! **Fundamentals go a long way.**

For maximum understanding: learn by doing

- Write your own implementations
- Simplicity is critical
- Start with the basics: VPG, DQN, PPO, DDPG
- Focus on understanding: it's the only way you will catch bugs

How silent are silent RL bugs? Pop quiz:

```
for t in range(total_steps):
    act = get_action(obs, epsilon)
    next_obs, rew, done, _ = env.step(act)
    replay_buffer.store(obs, act, rew, next_obs, done)
    ep_ret += rew
    ep_len += 1

    if done:
        epoch_rets.append(ep_ret)
        epoch_lens.append(ep_len)
        obs, rew, done, ep_ret, ep_len = env.reset(), 0, False, 0, 0

    if t > steps_before_training:
        batch = replay_buffer.sample_batch(batch_size)
        feed_dict = {obs_ph: batch['obs1'],
                     obs_targ_ph: batch['obs2'],
                     act_ph: batch['acts'],
                     rew_ph: batch['rews'],
                     done_ph: batch['done']
                     }
        step_loss, cur_q, _ = sess.run([loss, q_vals, train_op], feed_dict=feed_dict)
        epoch_losses.append(step_loss)
        epoch_qs.append(cur_q)

    if t % target_update_freq == 0:
        sess.run(target_update_op)

    epsilon = 1 + (final_epsilon - 1)*min(1, t/finish_decay)

    if (t - steps_before_training) % steps_per_epoch == 0 and (t - steps_before_training)>0:
        # handle logging outputs
```

- If you read a paper, scour it: read all the ablations and search for tricks!
- Skip the hype: find the thing the author's embarassed to admit about why the method doesn't solve the whole field yet
- But don't overfit: sometimes researchers load more tricks than necessary and their idea is better than they realize

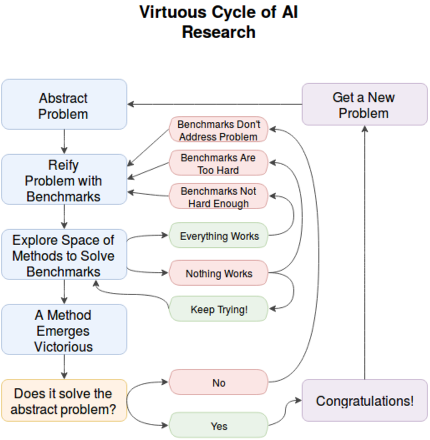
For maximum understanding: "Let all results count with you, but none too much"

- Study existing implementations of algorithms, but don't overfit to them: they made trade-offs you don't have to
- Iterate fast in simple environments, but don't get too confident if your implementation (or new research idea) works in the simplest thing: everything that isn't bugged beats Cartpole, and so do some bugs
- But if it doesn't work, assume there's a bug
- Measure everything. But if your measurements say everything is fine while nothing's working, get new things to measure
- When things start to work, lean in, scale up!
- Keep these habits for research!

If you want to hack with RL tools that are out there...

- OpenAI Gym, Baselines, and Spinning Up
- Many other algorithm libraries: rllab, rllib, rlkit, Intel's Coach, softlearning, ChainerRL, vel, Stable-Baselines, and more
- Very few primitives libraries: TRFL
- Note: there's not a "Tensorflow for RL" yet: if you want it, you have to build it yourself
- RL currently ships as solutions as opposed to modular components

- Do a deep dive in the literature
- Find something you enjoy and care about—"keep only those research ideas which spark joy"
- Consider approach 1: improve something that exists
- Consider approach 2: attack an unsolved benchmark
- Consider approach 3: invent a new problem
- But whatever you pick, really do a thorough lit review to make sure it's new!



End of Part 2

Thank you all! Questions?