Deep Reinforcement Learning toward Robot Learning in the Wild

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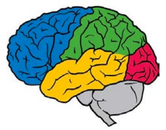
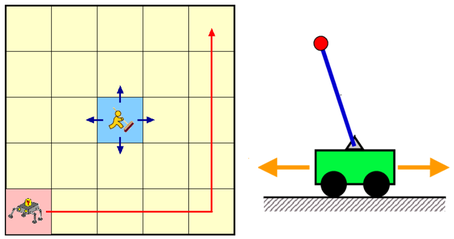
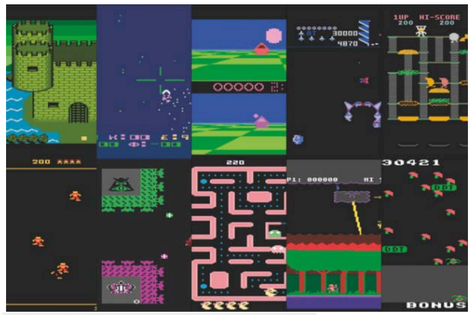


Deep RL: successes and limitations

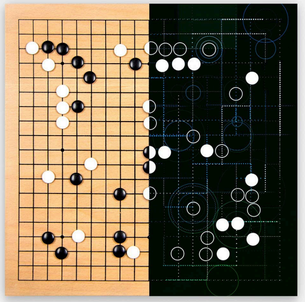


Classic RL
[1990s-2014]

Fast simulators = success is guaranteed



Atari games
[Mnih et. al., 2015]

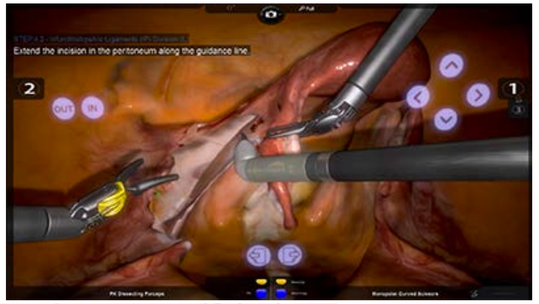


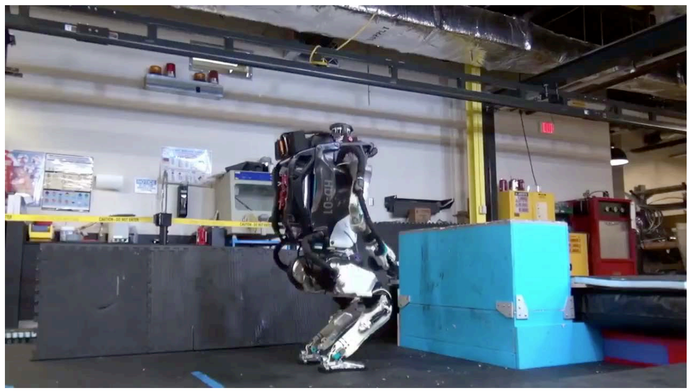
AlphaGo/AlphaZero
[Silver et. al., 2016; 2017]

Parkour
[Heess et. al., 2017]

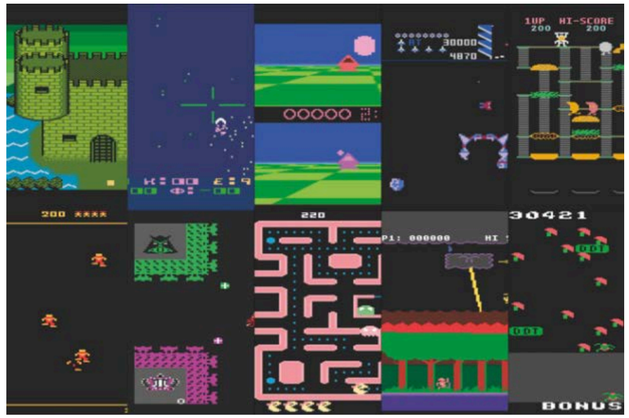
?

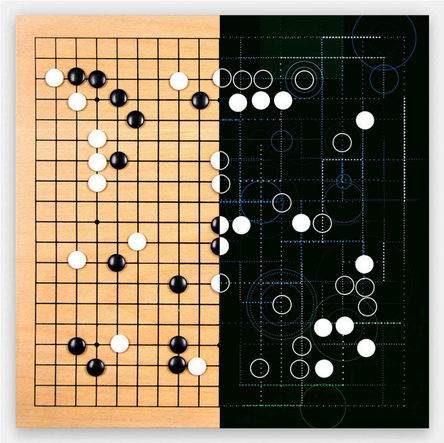
Slow simulators/Real-world = require smart (sample-efficient) algorithms





Why Robotics?

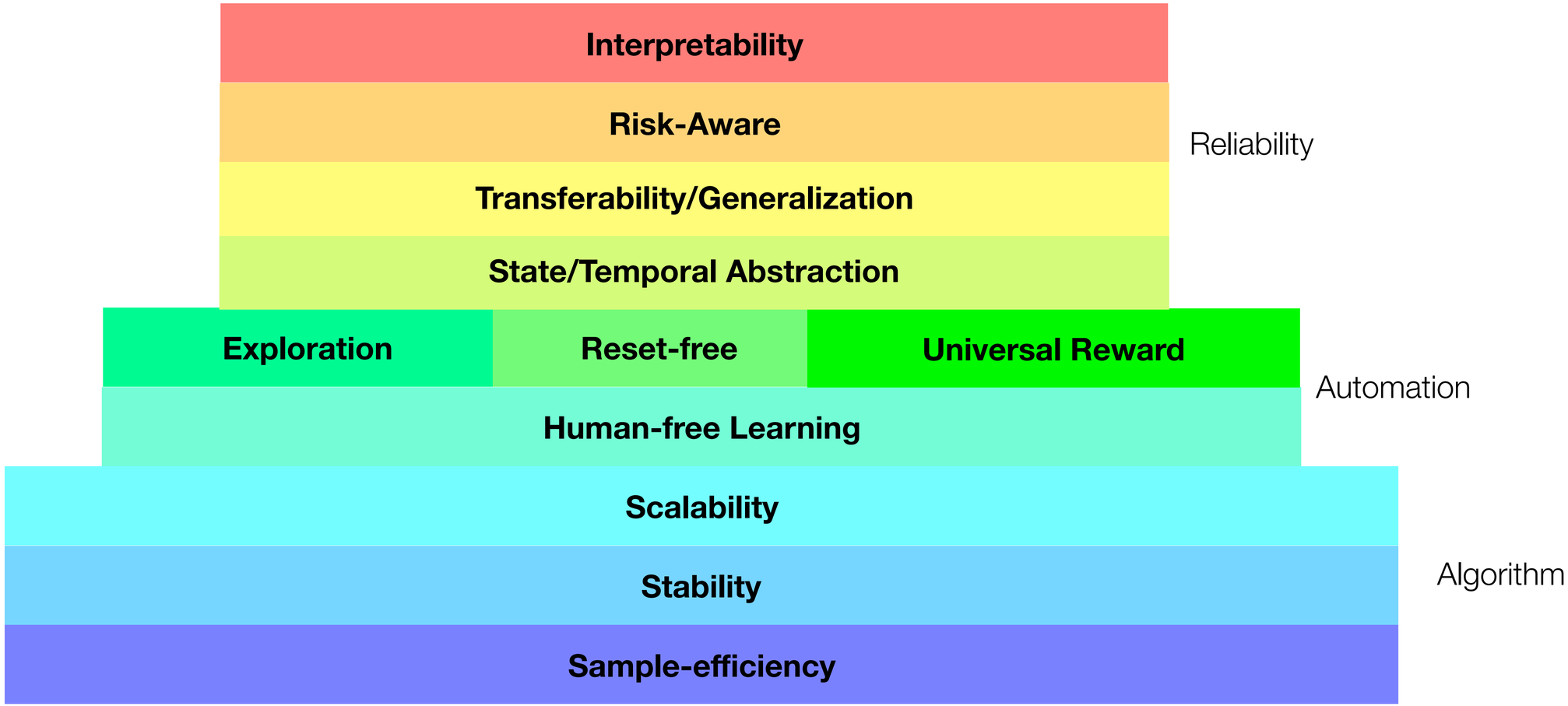




vs

Generally continuous control is a much harder exploration problem than any game.

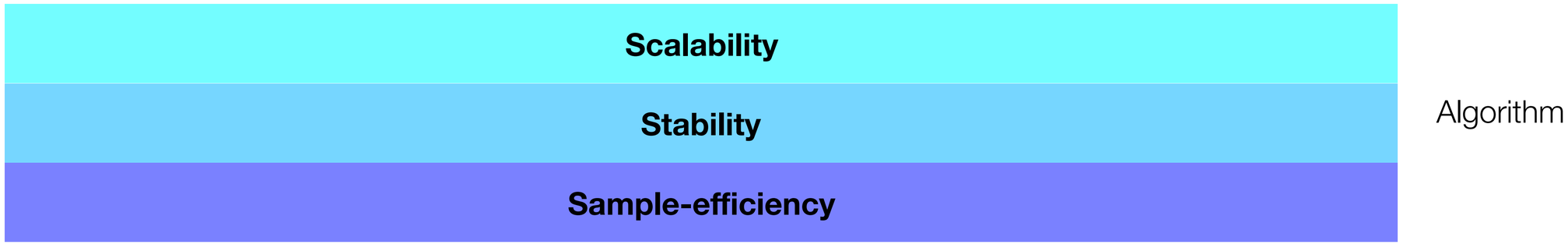
Recipe for a Smart Deep RL Algorithm



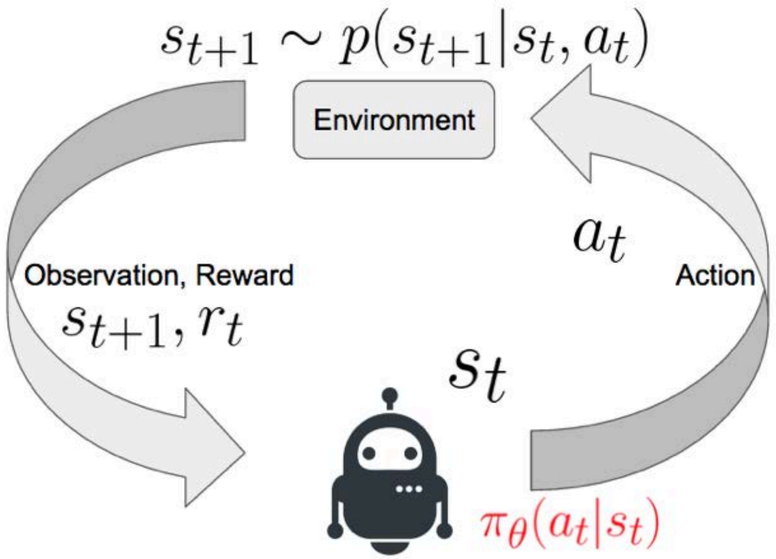
Outline of the talk

- **Sample-efficiency**
  - Good Off-policy Algorithm： **Normalized Advantage Functions** [Gu et al, 2016], **Q-Prop/Interpolated Policy Gradient** [Gu et al, 2017/2017]
  - Good Model-based Algorithm： **Temporal Differene Models** [Pong*, Gu* et al, 2018]
- **Human-free Learning**
  - Safe & reset-free RL： **Leave No Trace** [Eysenbach, Gu et al, 2018]
  - “Universal” reward function： **Temporal Difference Models** [Pong*, Gu* et al, 2018]
- **Hierarchical RL**
  - Data-efficient hierarchical RL： **HIRO** [Nachum, Gu et al, 2018, 2018]

Toward Efficient and Stable RL Algorithms

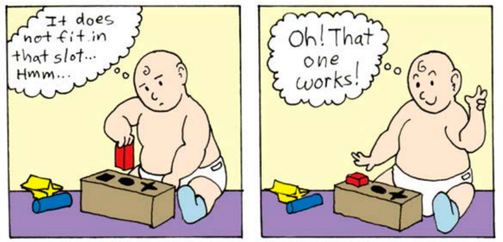


RL: Notations & Definitions



on-policy model-free: e.g. policy search ~ trial and error

$$\pi^* = \arg\max_\pi \mathbb{E}_\pi \left[\sum_t \gamma^t r_t \right]$$



off-policy model-free: e.g. Q-learning ~ introspection

$$Q^* = \arg\min_Q \mathbb{E}_\beta \left[\left(Q(s_t, a_t) - r_t - \gamma \max_a Q(s_{t+1}, a) \right)^2 \right]$$

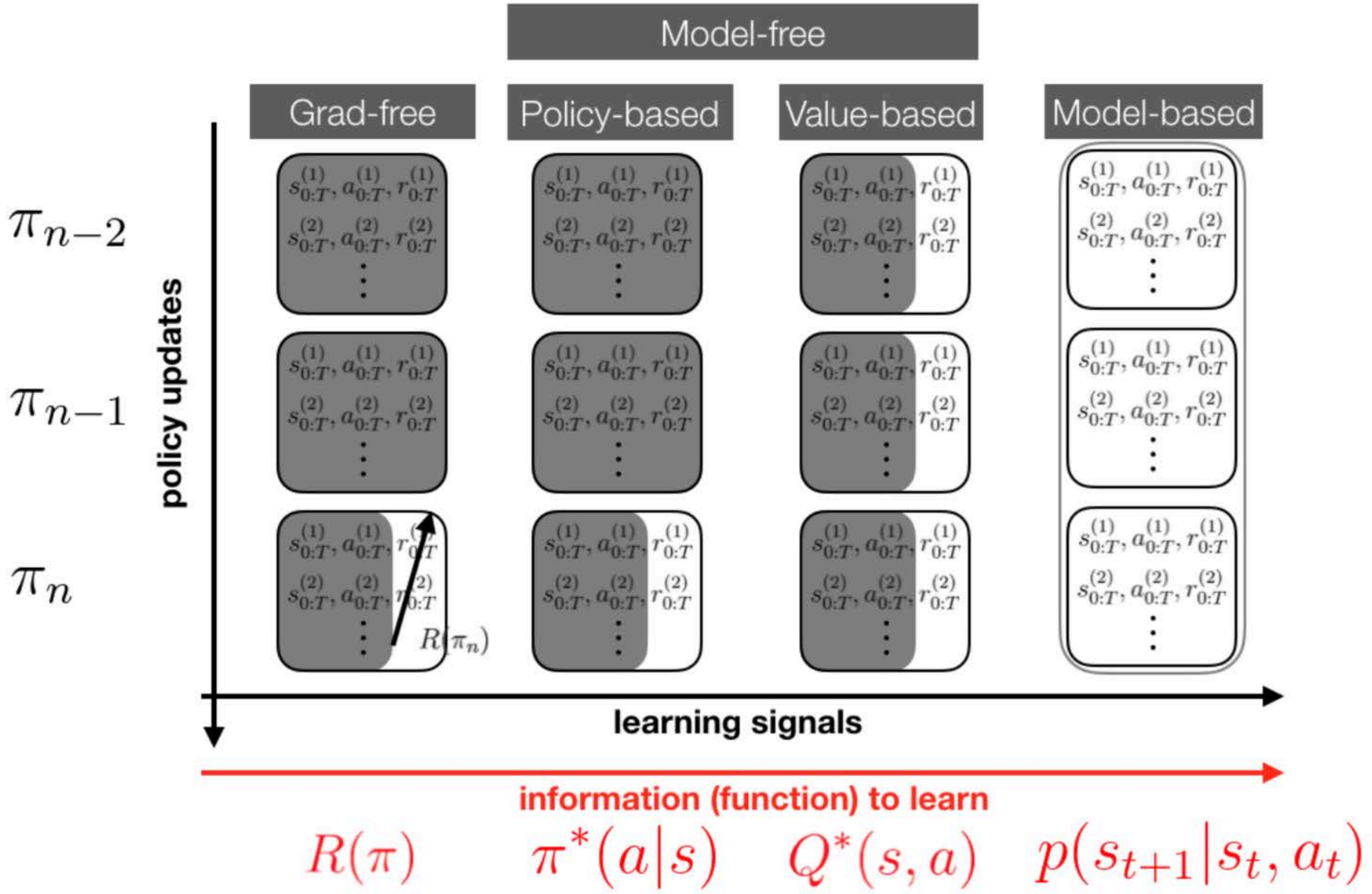
$$\pi^*(a_t|s_t) = \delta \left(a_t = \arg\max_a Q^*(s_t, a) \right)$$

model-based: e.g. MPC ~ imagination

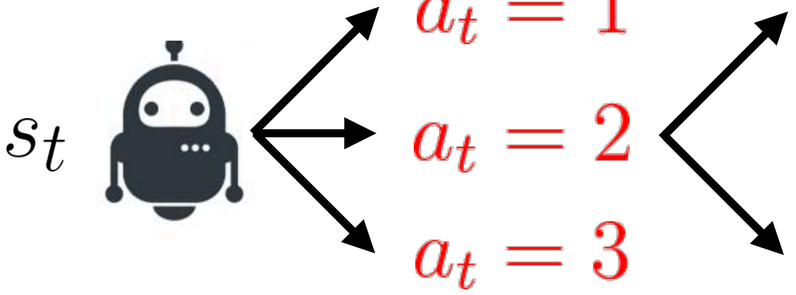
$$f^* = \arg\min_f \mathbb{E}_\beta \left[||f(s_t, a_t) - s_{t+1}||_2 \right]$$

$$\pi^* : a_t^* = \arg\max_{a_{t:t+T}} \sum_{i=0}^{T} \gamma^i r_{t+i}, \quad where \quad s_{t+i+1} = f(s_{t+i}, a_{t+i})$$

Sample-efficiency: trade-off between learning signal & how much to learn



Toward Good Off-policy Deep RL Algorithm



On-policy Monte Carlo policy gradient, e.g. TRPO [Schulman et al, 2015]

- **Many new samples needed per update.**
- Stable but very sample-intensive

$$\hat{Q}(s_t, a_t = 2) = \sum_{t' \geq t} r(s_{t'}, a_{t'})$$

$$\mathbb{E}\left[\hat{Q}(s_t, a_t = 2)\right] = Q^\pi(s_t, a_t = 2)$$

$$Q_w(s_t, a_t = 2) \approx Q^\pi(s_t, a_t = 2)$$

Off-policy actor-critic, e.g. DDPG [Lillicrap et al, 2016]

- **No new samples needed per update!**
- Quite sensitive to hyper-parameters

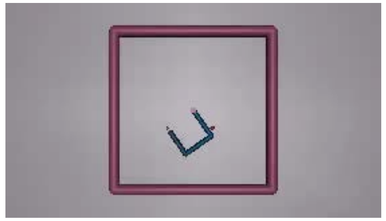
"Better" DDPG

- NAF [Gu et al 2016], Double DQN [Hasselt et al 2016], Dueling DQN [Wang et al 2016], Q-Prop/IPG [Gu et al 2017/2017], ICNN [Amos et al 2017], SQL/SAC [Haarnoja et al 2017/2017], GAC [Tangkaratt et al 2018], MPO [Abdolmaleki et al 2018], TD3 [Fujimoto et al 2018], …

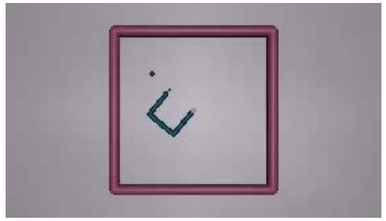
Normalized Advantage Functions (NAF)

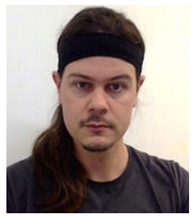
- Benefit: 2 objectives (actor-critic) to 1 objective (Q-learning)
  - Halve #hyperparameters
- Limitation:
  - Doesn't work well on locomotion
  - Works well on manipulation

DDPG



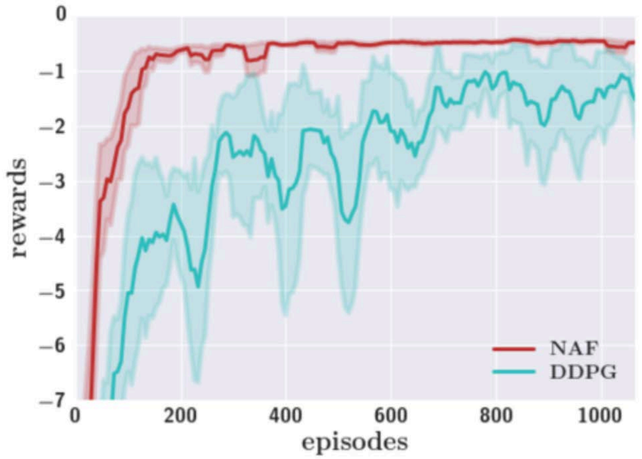
NAF





Continuous Deep Q-Learning with Model-based Acceleration [Gu, Lillicrap, Sutskever, Levine, ICML 2016]

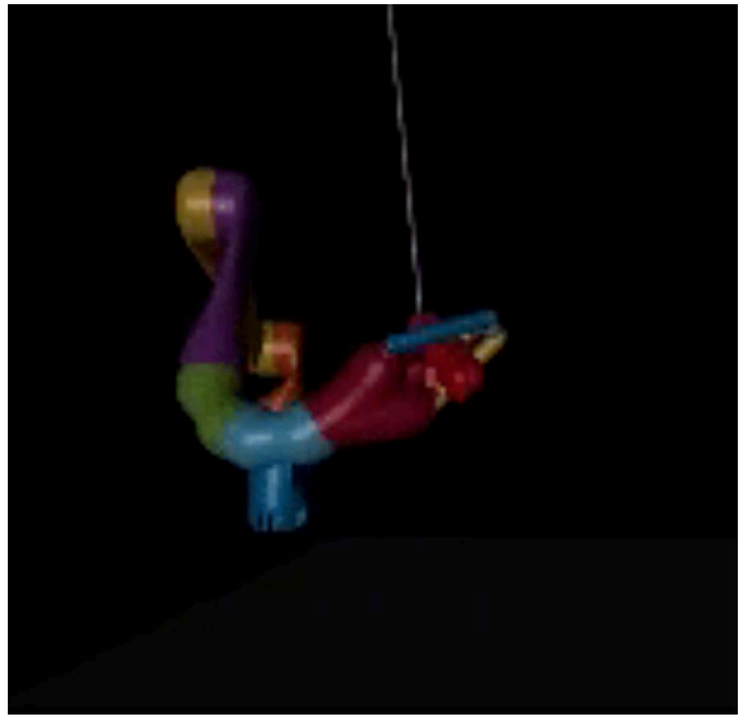
3-joint peg insertion



Related/later work:

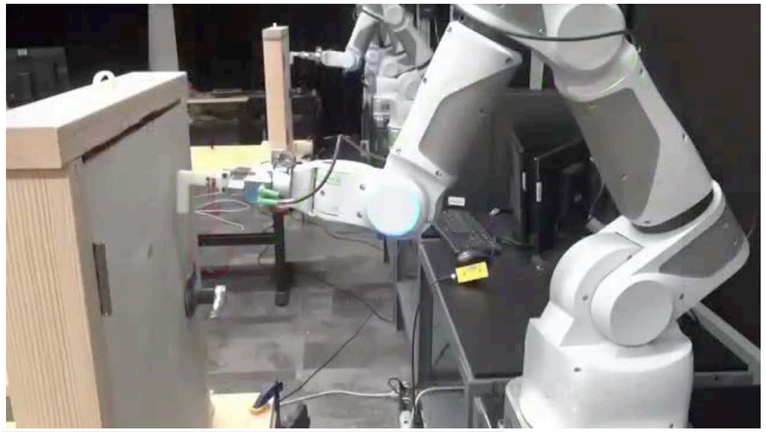
- Dueling Network [Wang et al 2016]
- ICNN [Amos et al 2017]
- SQL [Hajaorna et al 2017]

NAF on JACO arm grasp & reach (100hz)

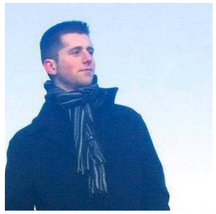


Asynchronous NAF for Simple Manipulation

Train time/Exploration

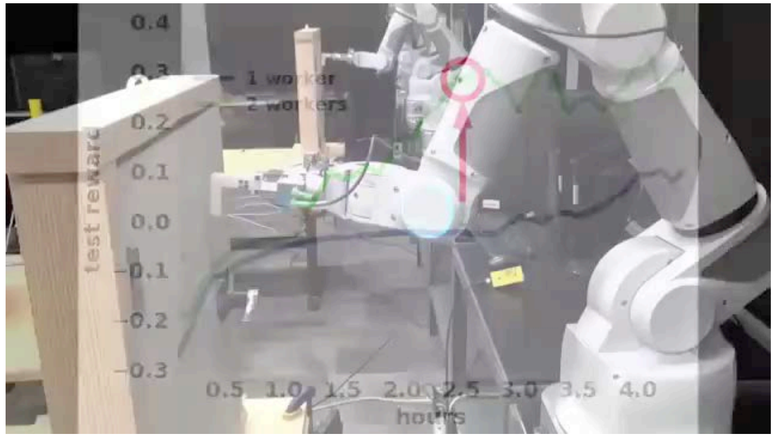


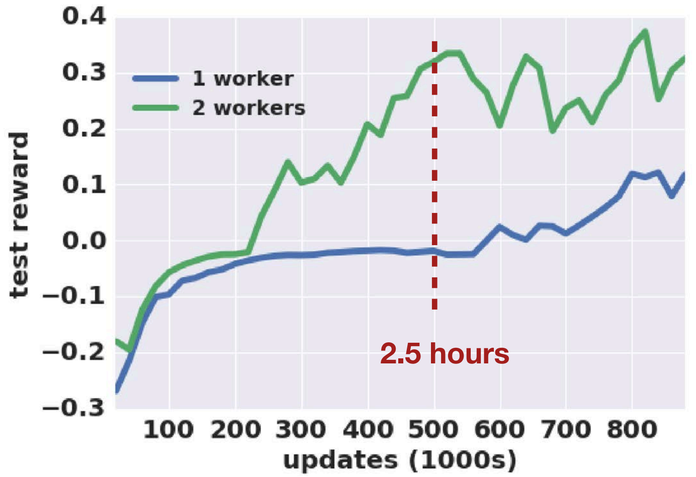
Google



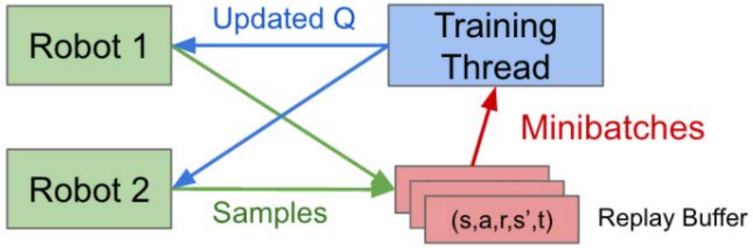
Deep Reinforcement Learning for Robotic Manipulation with Asynchronous Off-Policy Updates [Gu*, Holly*, Lillicrap, Levine, ICRA 2017]

Test time



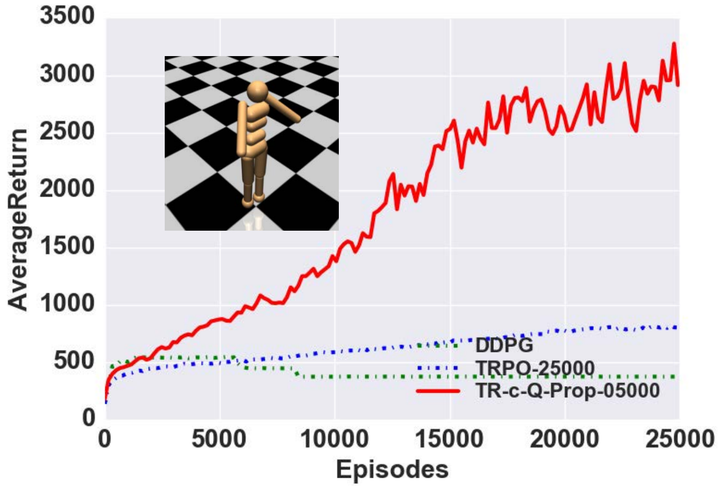


Disturbance test



Q-Prop & Interpolated Policy Gradient (IPG)

- On-policy algorithms are stable. How to make off-policy more on-policy?
  - Mixing Monte Carlo returns
  - Trust-region policy update
  - On-policy exploration
  - Bias trade-offs (theoretically bounded)



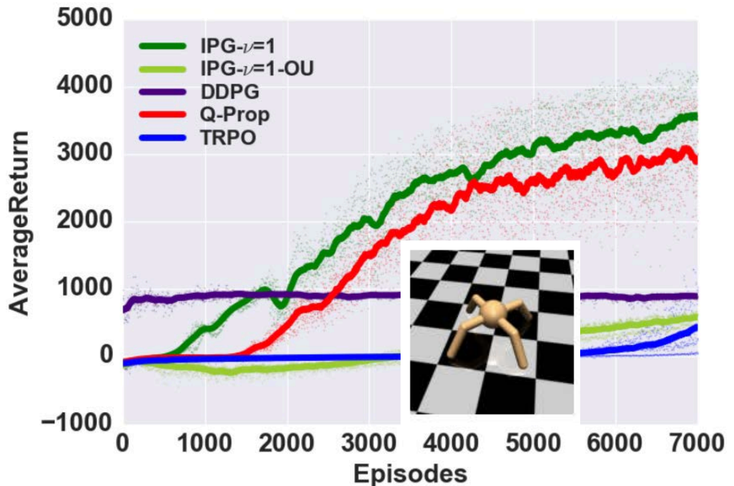
$$(1-\nu)\mathbb{E}_{\rho^\pi,\pi}[\nabla_\theta \log \pi_\theta(a_t|s_t)(\hat{A}(s_t,a_t) - A^\pi_w(s_t,a_t))] + \mathbb{E}_{\rho^\beta}[\nabla_\theta \bar{Q}^\pi_w(s_t)]$$

On-policy Monte Carlo

On-policy deterministic

[Gu, Lillicrap, Ghahramani, Turner, Levine, ICLR 2017]
[Gu, Lillicrap, Ghahramani, Turner, Schoelkopf, Levine, NIPS 2017]

Related concurrent work:
- PGQ [O'Donoghue et al 2017]
- ACER [Wang et al 2017]

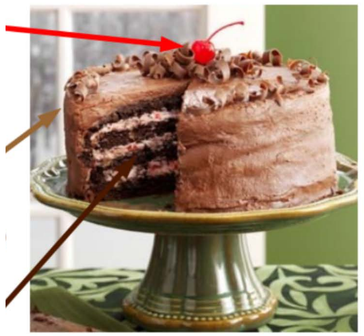


Toward Good Model-based Deep RL Algorithm

- Often, off-policy model-free has higher asymptotic performance than model-based
  - Off-policy model-free is sort of like model-based (model = experience replay). What's the connection/gap?

- Q-learning vs Goal-Conditioned Q-learning

$$Q(s,a) : (s_t, a_t, s_{t+1}, r_t) \sim \beta$$



$$Q(s,a,g) : (s_t, a_t, s_{t+1}) \sim \beta, r_t = r(s_t, a_t, s_{t+1}, g)$$

Off-policy + **Relabeling trick** from HER [Andrychowicz et al, 2017]

Examples:
- UVF [Schaul et al, 2015]
- TDM [Pong*, Gu* et al 2017]

- Off-policy learning can use same memory to learn wrt any goal

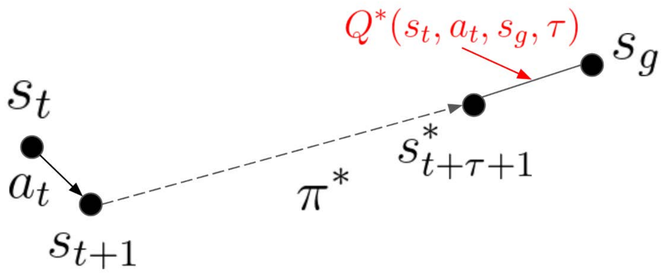
$$Q^*(s_t, a_t, g) = r(s_t, a_t, s_{t+1}, g) + \gamma \max_a Q^*(s_{t+1}, a, g)$$

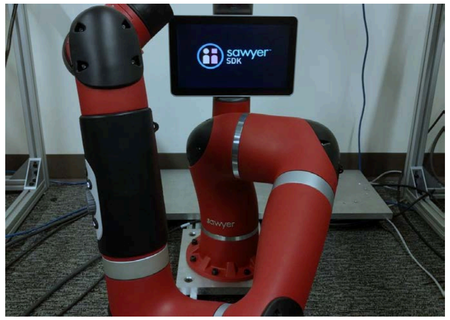
Temporal Difference Models (TDM)

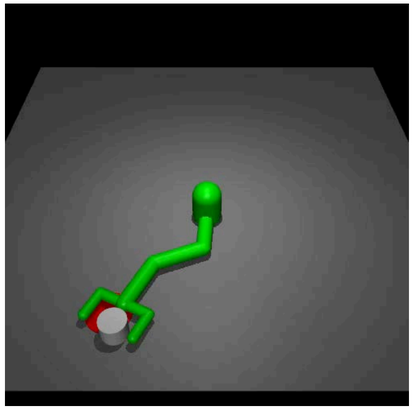
- A certain parameterized Q-function is **a generalization of dynamics model**

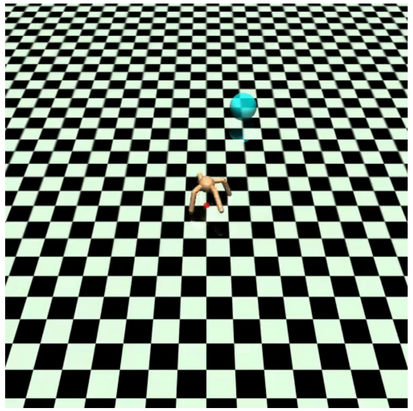
$$r_d(s_t, a_t, s_{t+1}, s_g, \tau) = -D(s_{t+1}, s_g)1[\tau = 0]$$

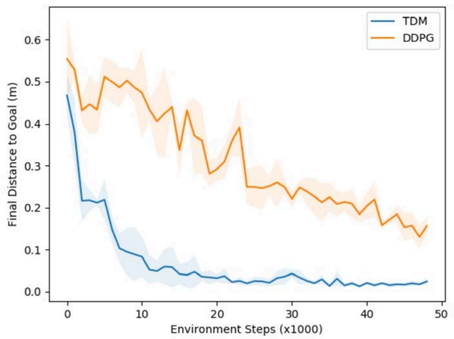
$$a_t = \underset{a_t, a_{t+T}, s_{t+T}}{\text{argmax}} \; r_c(s_{t+T}, a_{t+T}) \text{ such that } Q(s_t, a_t, s_{t+T}, T-1) = 0$$

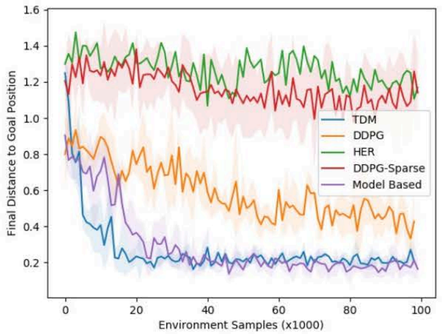


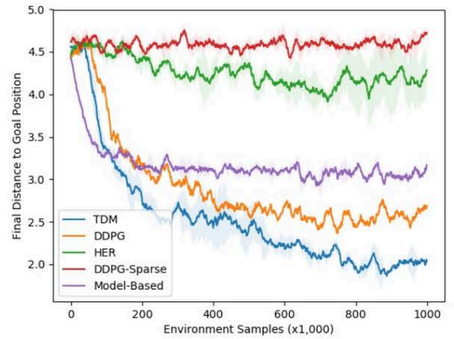






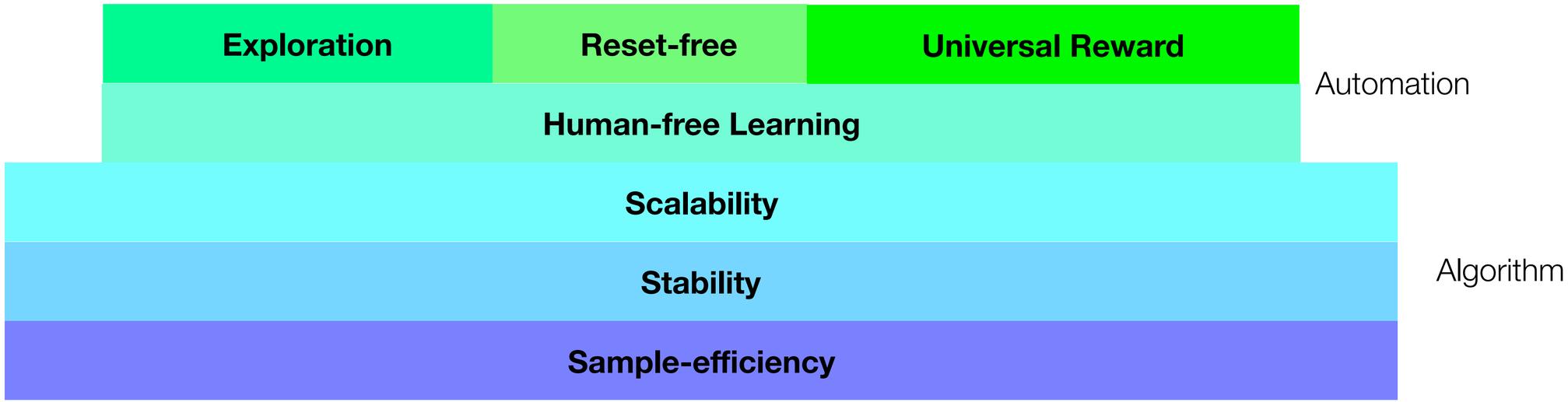




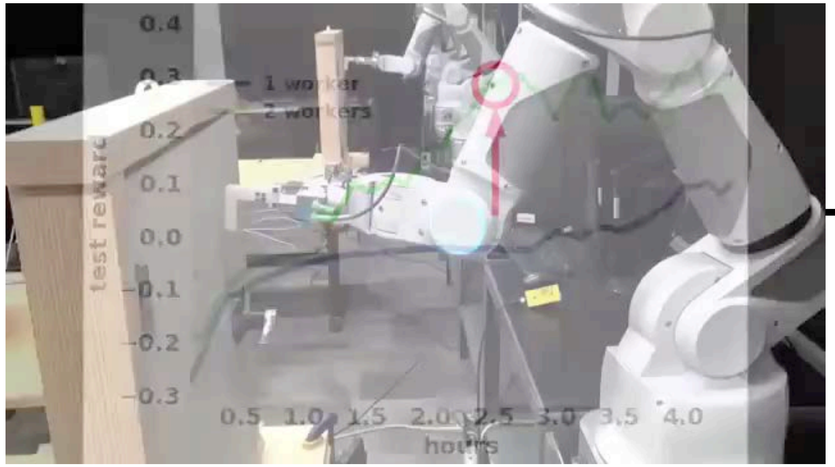


Temporal Difference Models: Model-Free Deep RL for Model-Based Control [Pong*, Gu*, Dalal, Levine, ICLR 2018]

Toward Unsupervised Reinforcement Learning



Toward Human-free Learning



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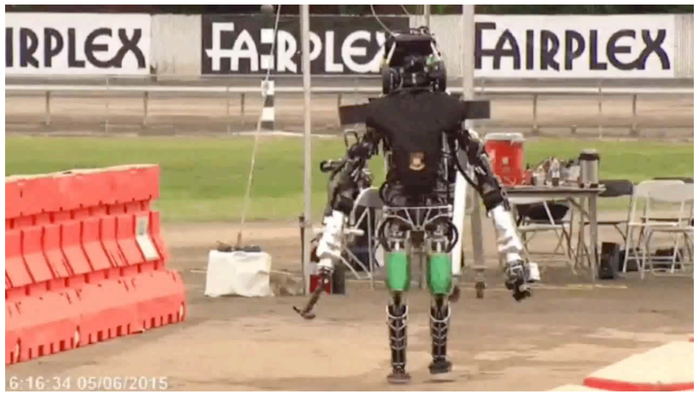
Manual resetting,
Reward engineering,
Human-administered,

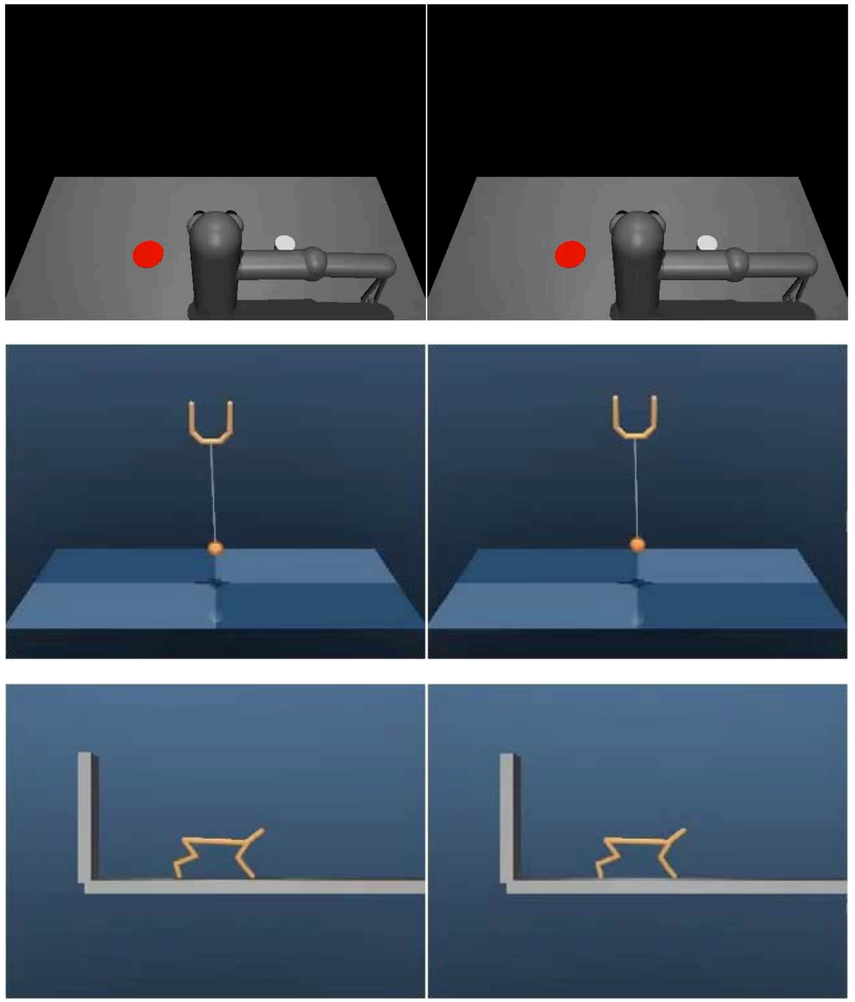
Autonomous, Continual,
Safe, Human-free

Leave No Trace (LNT)

Who resets the robot?

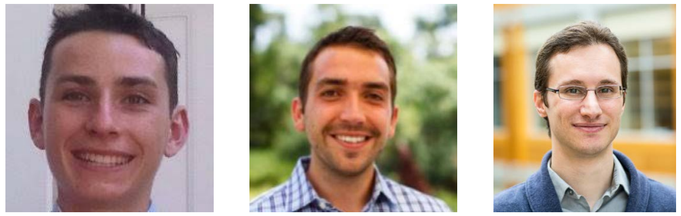
- PhD students





- Learn to reset

$$\mathcal{E}^* \triangleq \{(s,a) \in \mathcal{E} \mid Q_{reset}(s,a) > Q_{min}\}$$



Leave no Trace: Learning to Reset for Safe and Autonomous Reinforcement Learning [Eysenbach, Gu, Ibarz, Levine, ICLR 2018]

Related work:

- Asymmetric self-play [Sukhbaatar et al 2017]
- Automatic goal generation [Held et al 2017]
- Reverse curriculum [Florensa et al 2017]

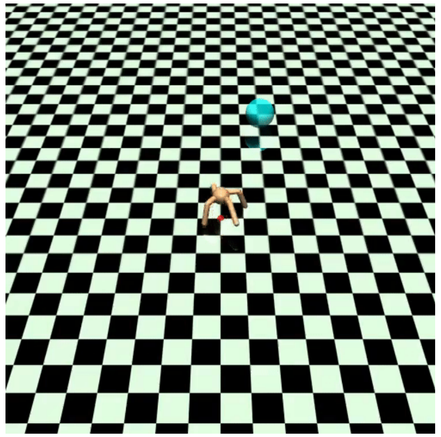
A “Universal” Reward Function + Off-Policy Learning

One reward, One skill → One reward, Many skills

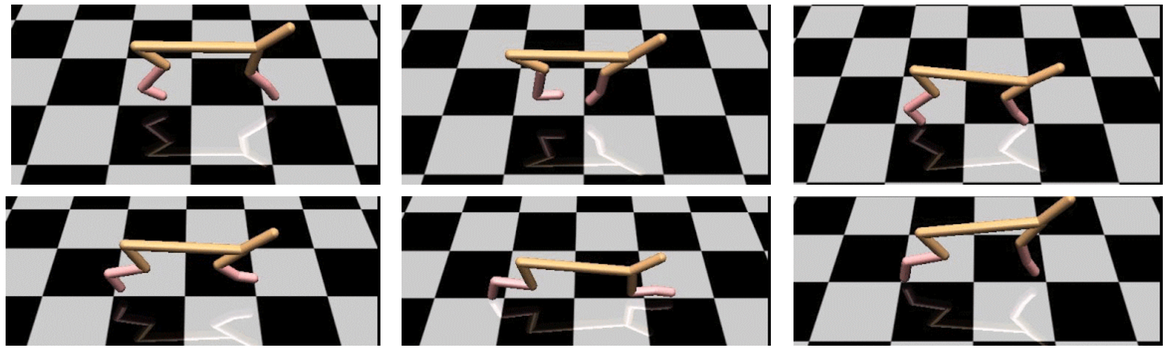
$r_1(s,a)$ $r_2(s,a)$ $r_3(s,a)$ $r(s,a)$

- Goal: learn as **many useful skills** as possible **sample-efficiently** with **minimal reward engineering**
- Examples:

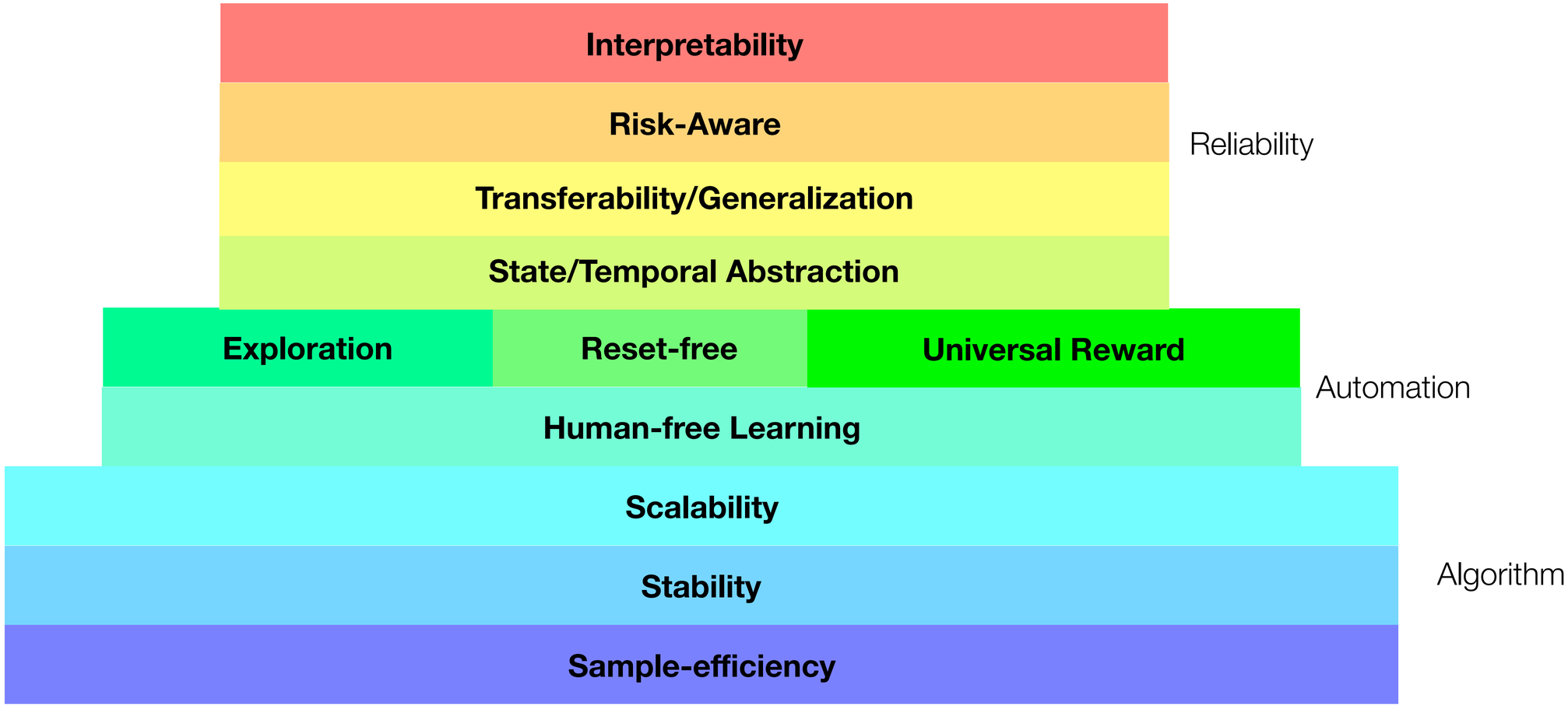
Goal-reaching reward, e.g.
UVF [Schaul et al 2015]/HER[Andrychowicz], **TDM** [Pong*, Gu* et al 2018]



Diversity reward, e.g.
SNN4HRL [Florensa et al 2017], **DIAYN** [Eysenbach et al 2018]

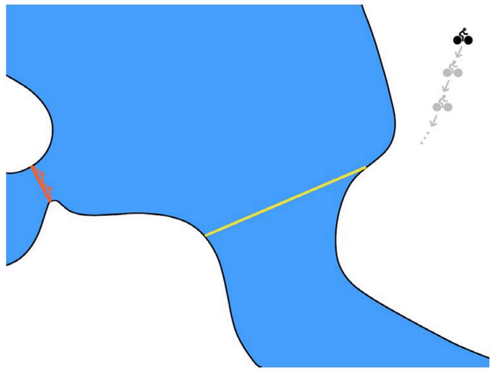


Toward Reliable RL



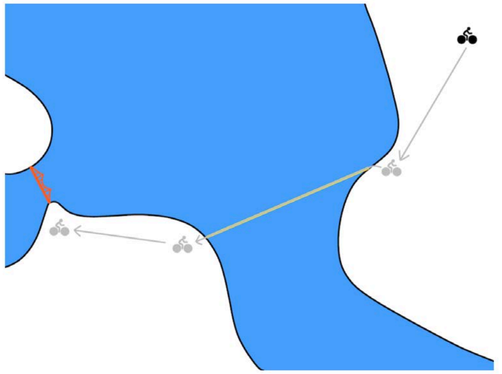
Toward Hierarchical Reinforcement Learning (HRL)

When you don't know how to ride bike…

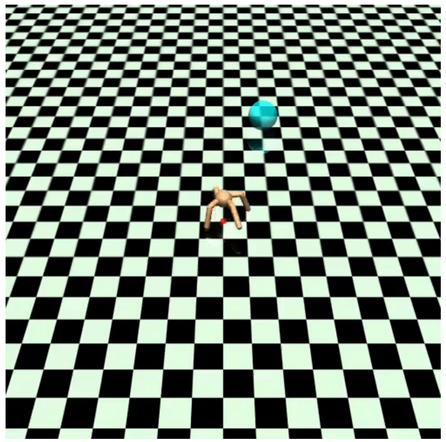


?

When you know how to ride bike…



TDM learns many skills very quickly…



?

How to efficiently solve other problems?

HRL:

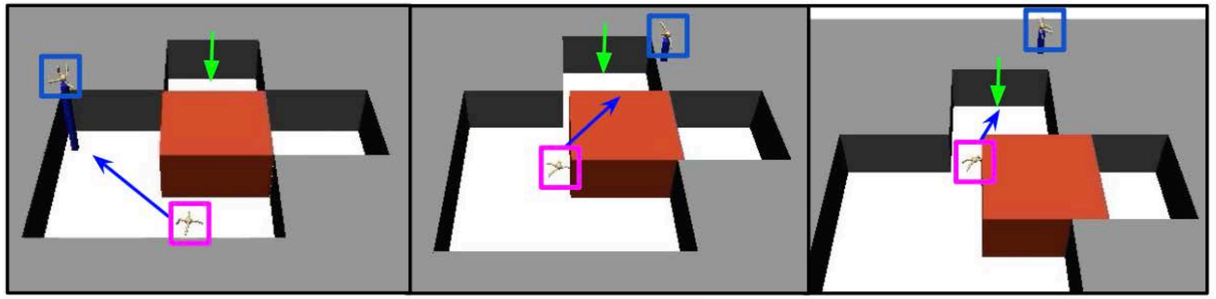
- Longer horizon problems
- More interpretable
- More transferrable policies

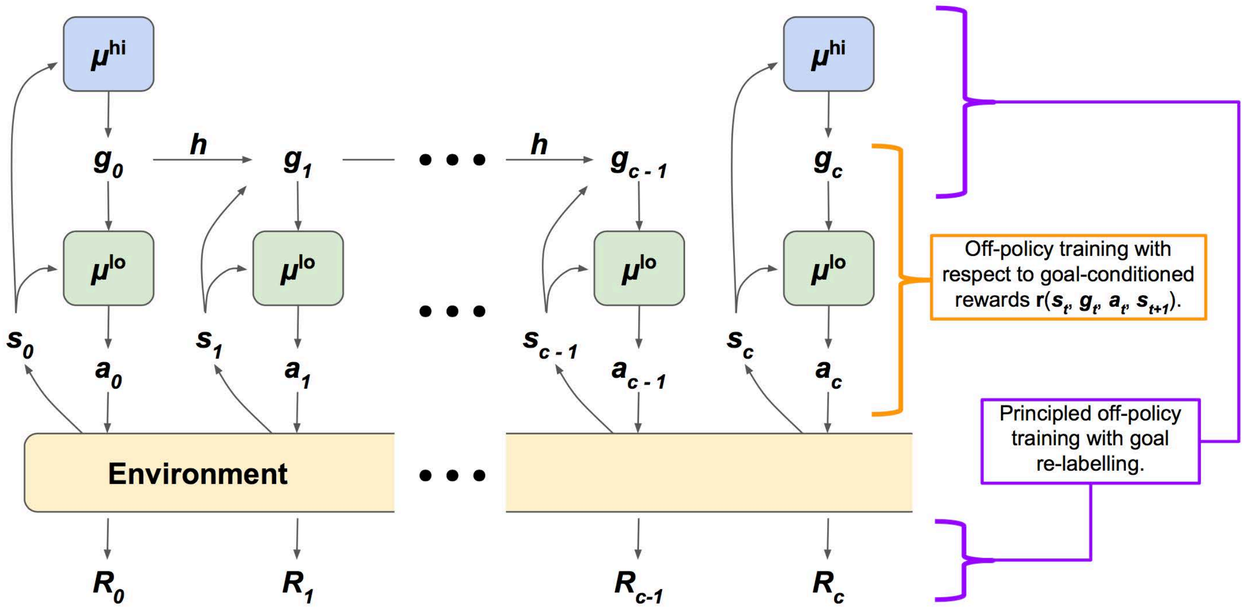
HIerarchical Reinforcement learning with Off-policy correction (HIRO)

- Most recent HRL work is on-policy
  - e.g. option-critic [Bacon et al 2015], FuN [Vezhnevets et al 2017], SNN4HRL [Florensa et al 2017], MLSH [Frans et al 2018]
  - **VERY data-intensive**
- How to correct for off-policy? Relabel the action.

$$(s_t, g_t, s_{t+c}) \longrightarrow (s_t, \tilde{g}_t, s_{t+c})$$

$$\tilde{g}_t = \arg\max_g \log \mu^{lo,new}(a_{t:t+c-1}|s_t, g)$$



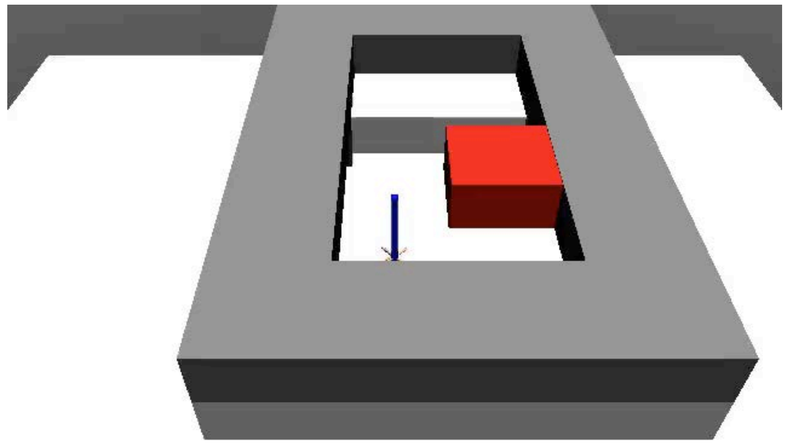




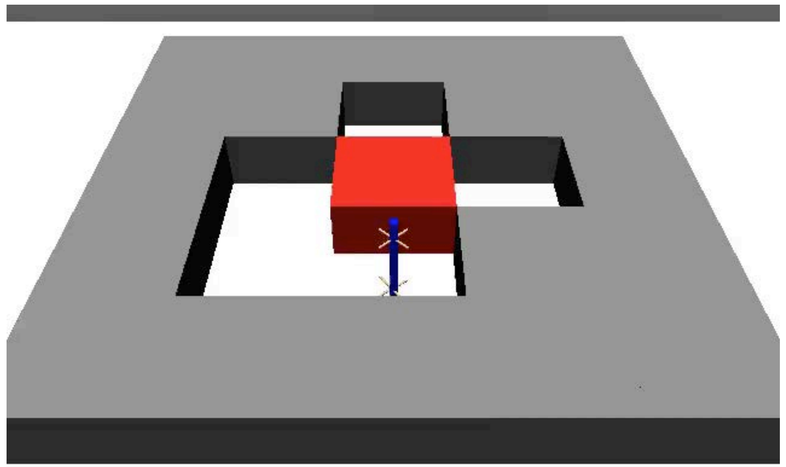
Data-efficient Hierarchical Reinforcement Learning
[Nachum, Gu, Lee, Levine, NIPS 2018]

HIRO (cont.)

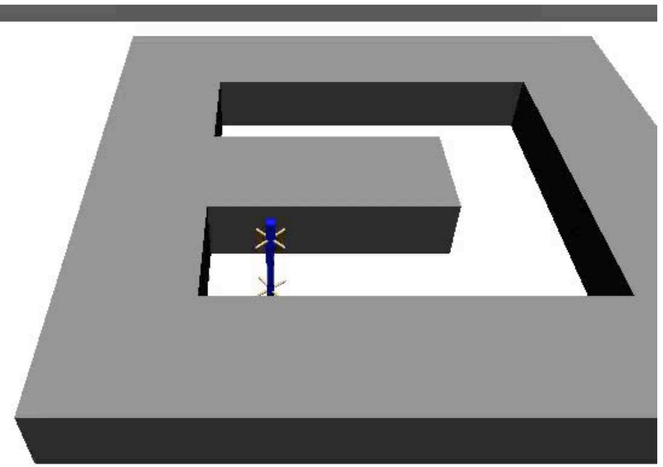
Ant Maze



Ant Push



Ant Fall



Data-efficient Hierarchical Reinforcement Learning
[Nachum, Gu, Lee, Levine, NIPS 2018]

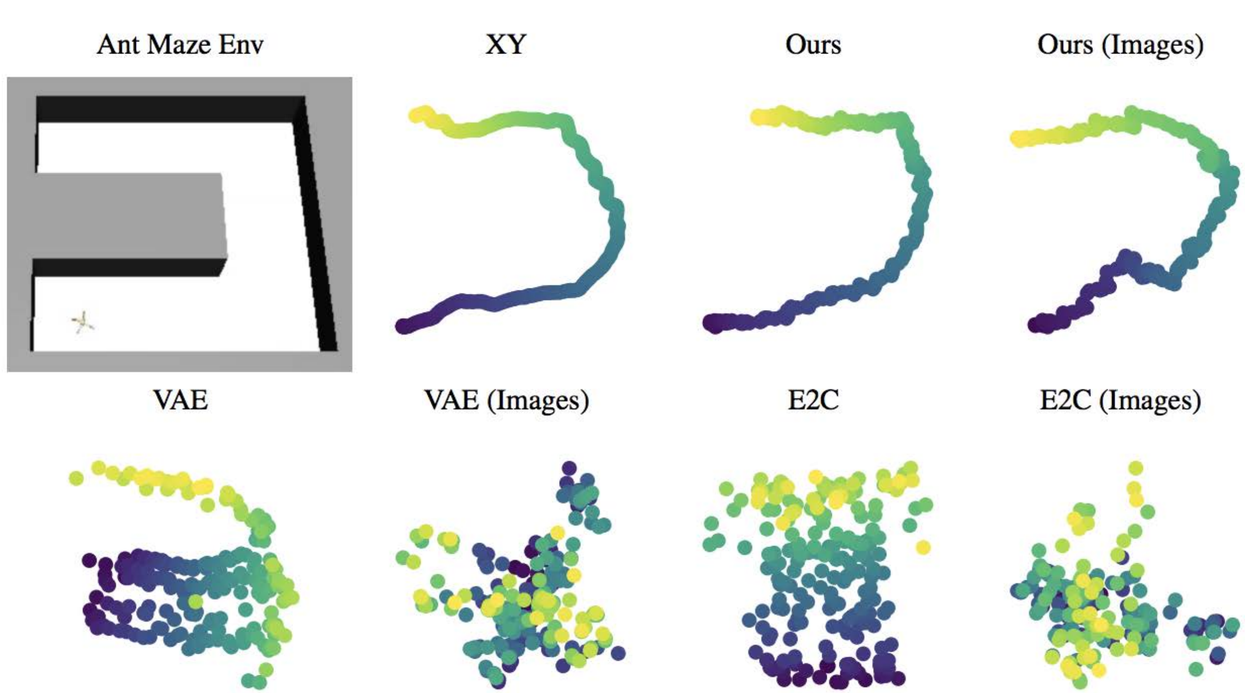
	Ant Gather	Ant Maze	Ant Push	Ant Fall
HIRO	**3.02±1.49**	**0.99±0.01**	**0.92±0.04**	**0.66±0.07**
FuN representation	0.03 ± 0.01	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0
FuN transition PG	0.41 ± 0.06	0.0 ± 0.0	0.56 ± 0.39	0.01 ± 0.02
FuN cos similarity	0.85 ± 1.17	0.16 ± 0.33	0.06 ± 0.17	0.07 ± 0.22
FuN	0.01 ± 0.01	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0
SNN4HRL	1.92 ± 0.52	0.0 ± 0.0	0.02 ± 0.01	0.0 ± 0.0
VIME	1.42 ± 0.90	0.0 ± 0.0	0.02 ± 0.02	0.0 ± 0.0

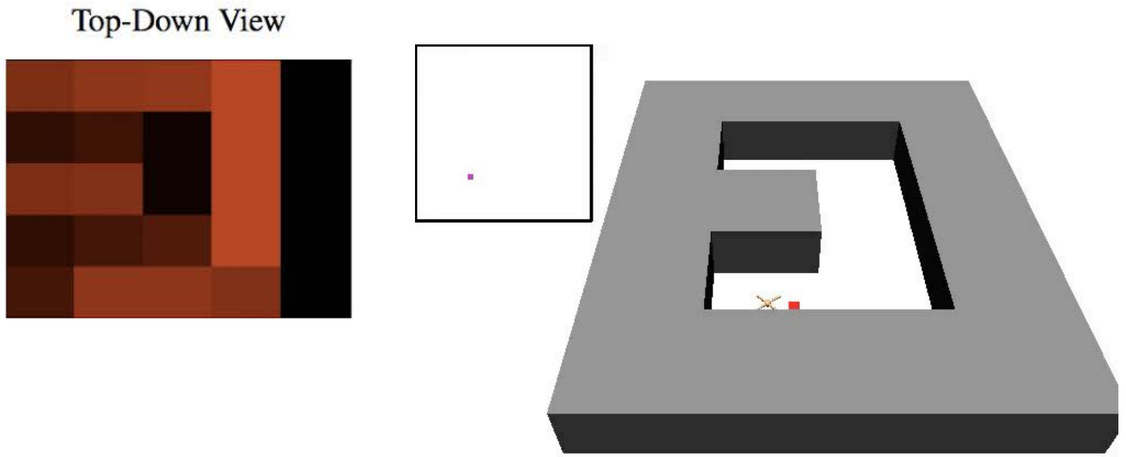
Test rewards at 20000 episodes

[Vezhnevets et al, 2017]

[Florensa et al, 2017]
[Houthooft et al, 2016]

HIRO + Principled Representation Learning





$$\text{SubOpt}(\Psi) = \sup_{s \in S} V^{\pi^*}(s) - V^{\pi^*_{\text{hier}}}(s)$$

Near-Optimal Representation Learning for Hierarchical Reinforcement Learning [Nachum, Gu, Lee, Levine, preprint 2018]

Theorem 1. *If there exists* $\varphi : S \times A \to G$ *such that,*

$$\sup_{s \in S, a \in A} D_{\text{TV}}(P(s'|s,a)||P(s'|s,\Psi(s,\varphi(s,a)))) \leq \epsilon,$$

then $\text{SubOpt}(\Psi) \leq C\epsilon$*, where* $C = \frac{2\gamma}{(1-\gamma)^2} R_{max}$.

Discussion

Natural language, Causality

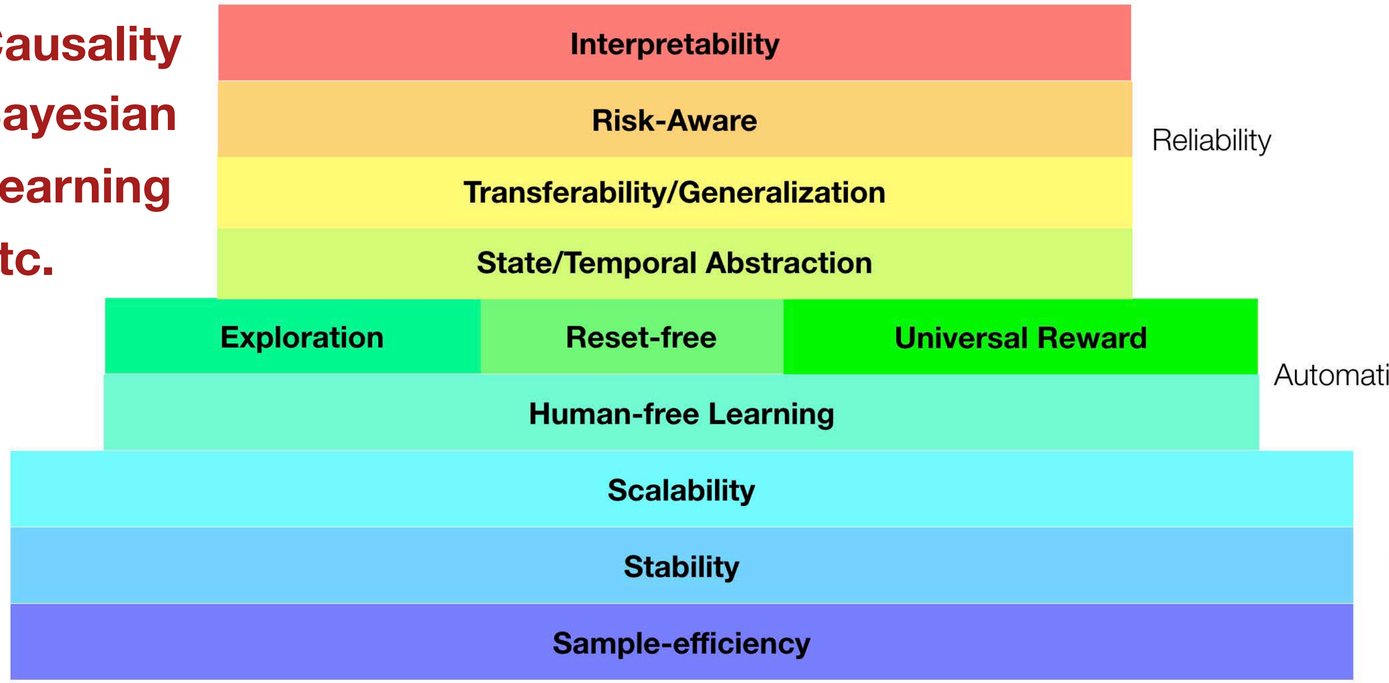
Distributional, Bayesian

Sim2Real, Meta learning

HIRO + etc.

LNT/TDM + etc.

NAF/Q-Prop/IPG/TDM + etc.



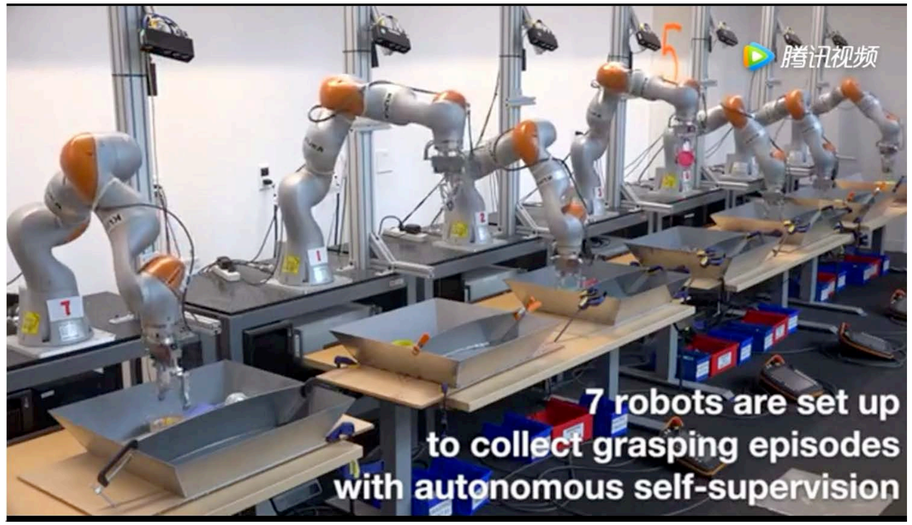
+ Simulation

+ Multi-task

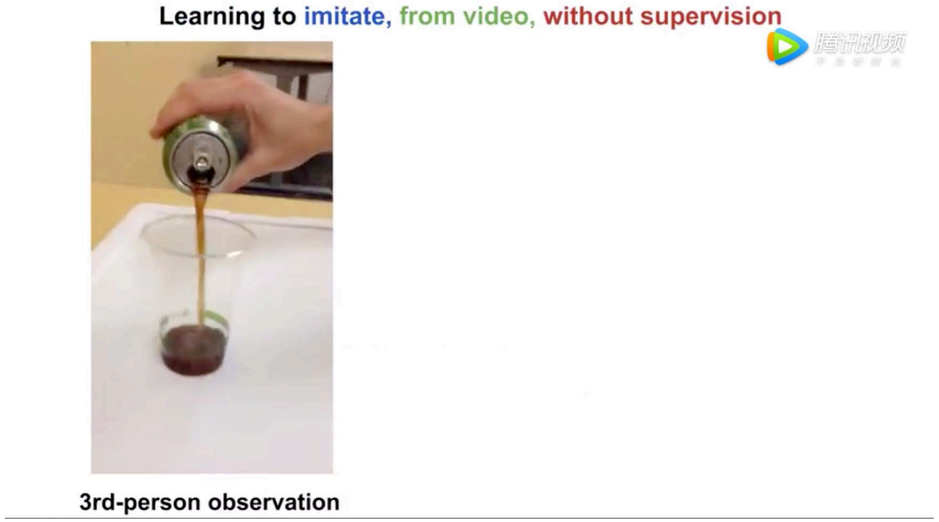
+ Imitation

+ Human-feedback

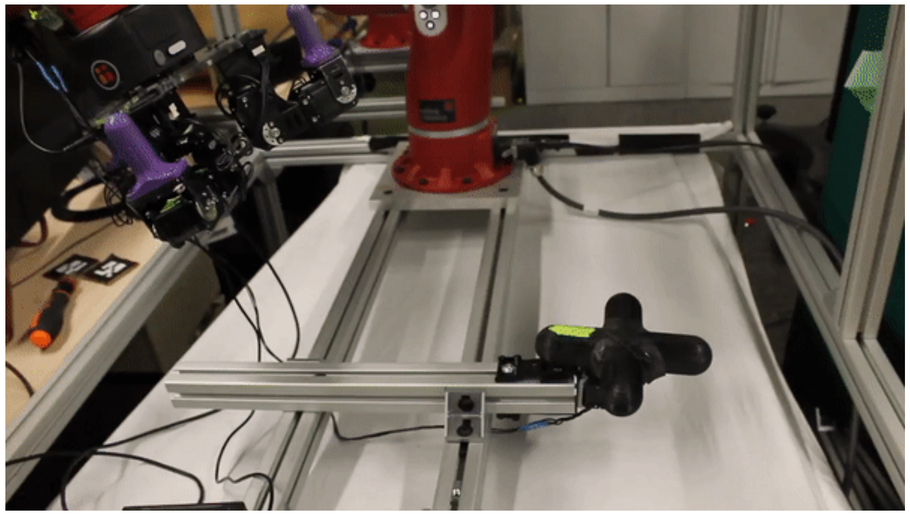
Other work from Google Brain Robotics Team



QT-Opt: Scalable Deep Reinforcement Learning for Vision-Based Robotic Manipulation [2018]



Time-Contrastive Networks: Self-Supervised Learning from Video [2017]



Dexterous Manipulation with Reinforcement Learning: Efficient, General, and Low-Cost [2018]

Check out more at: https://ai.google/research/teams/brain/robotics

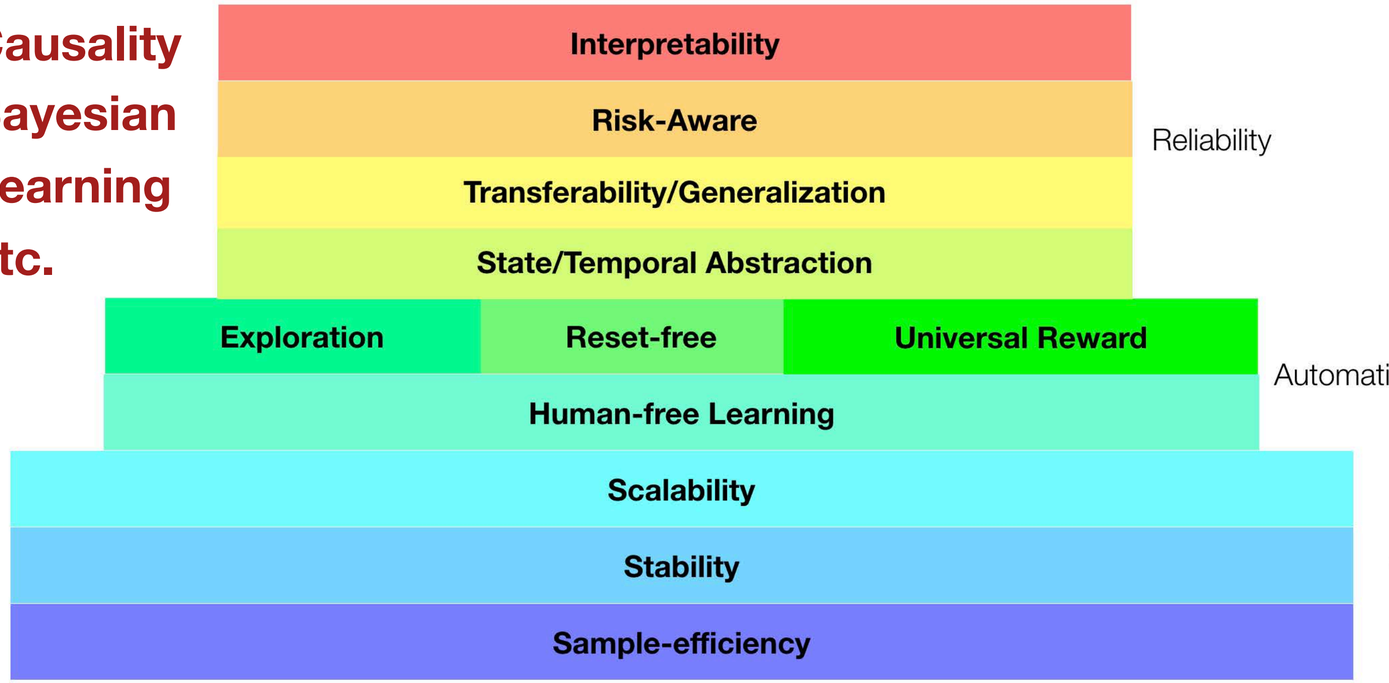
- Legged locomotion
- Navigation
- etc…

Discussion

Natural language, Causality
Distributional, Bayesian
Sim2Real, Meta learning
HIRO + etc.

LNT/TDM + etc.

NAF/Q-Prop/IPG/TDM + etc.



+ Simulation
+ Multi-task
+ Imitation
+ Human-feedback

Unleash them into the wild!

Thank you!

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Sergey Levine, Vitchyr Pong

Timothy Lillicrap

Bernhard Schoelkopf





Ilya Sutskever (now at OpenAI), Ethan Holly, Ben Eysenbach, Ofir Nachum, Honglak Lee

…and other amazing colleagues from: Cambridge, MPI Tuebingen, Google Brain, and DeepMind