Deep RL ||: Generalization

(what we talk about when we talk about deep RL)

Anna Harutyunyan

Thanks to: Will Dabney, Tom Schaul, Andre Barreto, Diana Borsa, Hado van Hasselt

Deep RL ||

- Advanced research in deep RL that'll matter in 5 years.

Deep RL ||

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DeepMind

Deep RL ||

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- We have no idea! Things are moving extremely quickly. It's exciting!
- Let's focus on the **problems**

Recap

$$v^{\pi}(x)$$

Recap

$$\mathbb{E}_\pi\Big[\sum_{t=0}^{\infty}\gamma^t R_{t+1}|X_0=x\Big]$$

$$v^\pi(x)$$

Recap

$$\mathbb{E}_\pi\Big[\sum_{t=0}^{\infty}\gamma^t R_{t+1}|X_0=x\Big]$$
$$=\mathbb{E}_\pi[R_1+\gamma[v^\pi(X_1)]$$

$$v^\pi(x)$$

Bellman

Recap

$$v^{\pi}(x)$$

Tabular RL

DeepMind

Recap

$$v^{\pi}(x)$$

$$v^{\pi}(x) \approx \phi(x)^{T}\theta$$

Tabular RL

RL with function approximation

Recap

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$$\phi : \mathcal{X} \to \mathbb{R}^{K}$$

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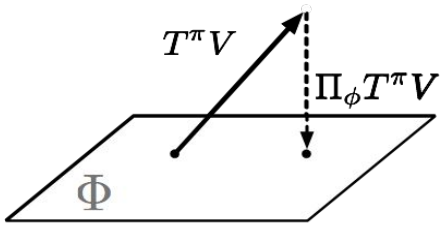
Recap

Targets

Linear RL



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RL with function approximation

$R + \gamma V'$

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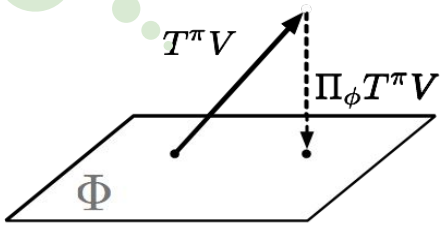

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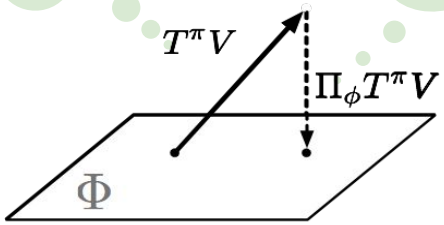
Projection back



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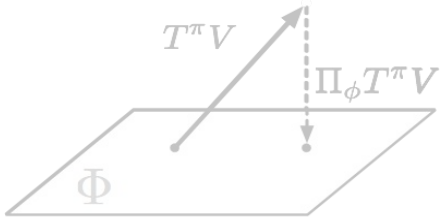

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Representation learning

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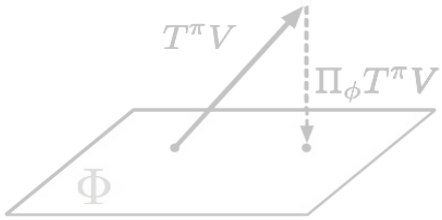

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Jointly, end-to-end

Tabular RL

RL with function approximation

Deep RL

Representation learning

DeepMind

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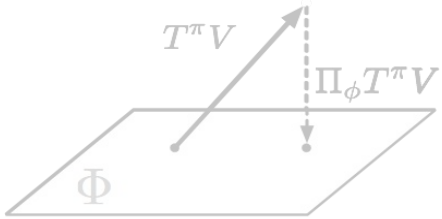

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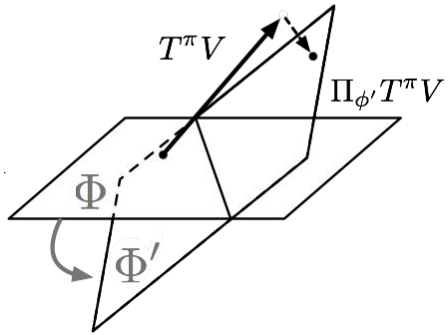

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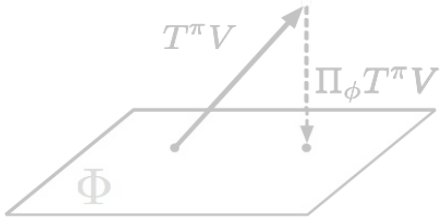

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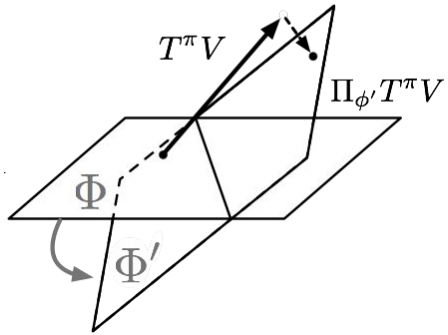

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Representation learning

Key challenge: Generalization

DeepMind

What is generalization in RL?

Usually in ML, this is generalizing to **unseen examples**

What is an unseen example in RL?

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Observations

- Auxiliary tasks
- Distributional RL

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DeepMind

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Dynamics
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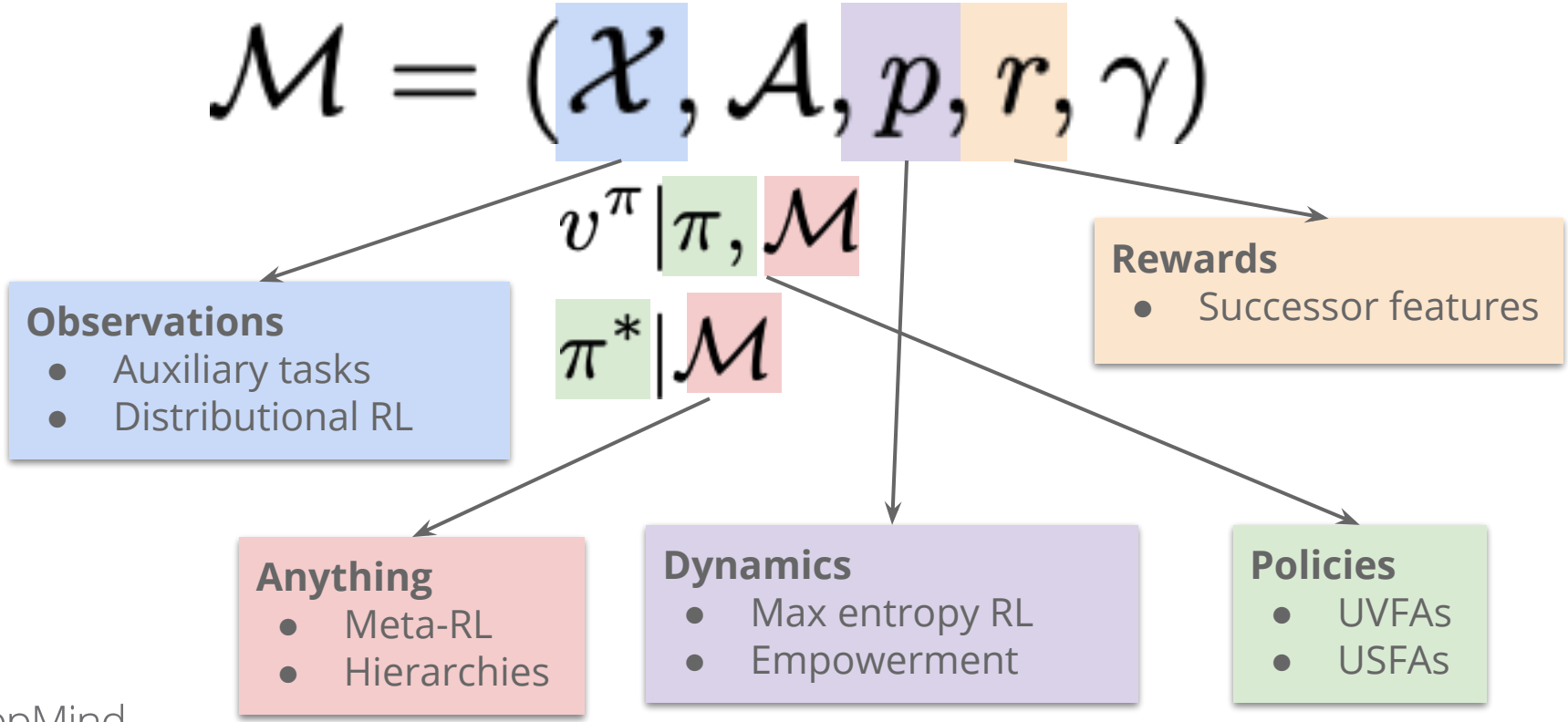

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What is an unseen example in RL?

Time

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Anything
- Meta-RL
- Hierarchies

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DeepMind

This lecture

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1. Generalizing within a task
    - Auxiliary tasks
    - Distributional RL

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2. Generalizing across tasks
    - Successor Features
    - Universal Value Function Approximators
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   -

Goals:

- Understand dimensions of generalization in deep RL
- Give intuition into some key problems / solution families
- *Focus on principles over details and empirical performance*

1) Generalizing within a task

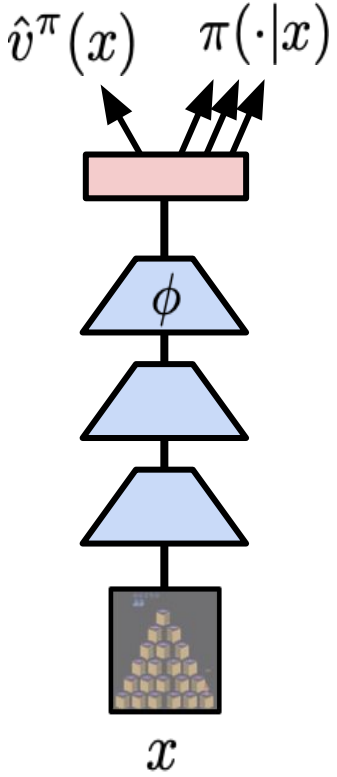
Contents

- Generalizing to new observations
- Auxiliary tasks
- Distributional RL
- Value improvement path

Generalizing to new observations

What determines generalization to unseen observations?

- The **architecture** gives an inductive bias
  - Convolutions like symmetries, invariances, etc
- The **loss** determines what is learned



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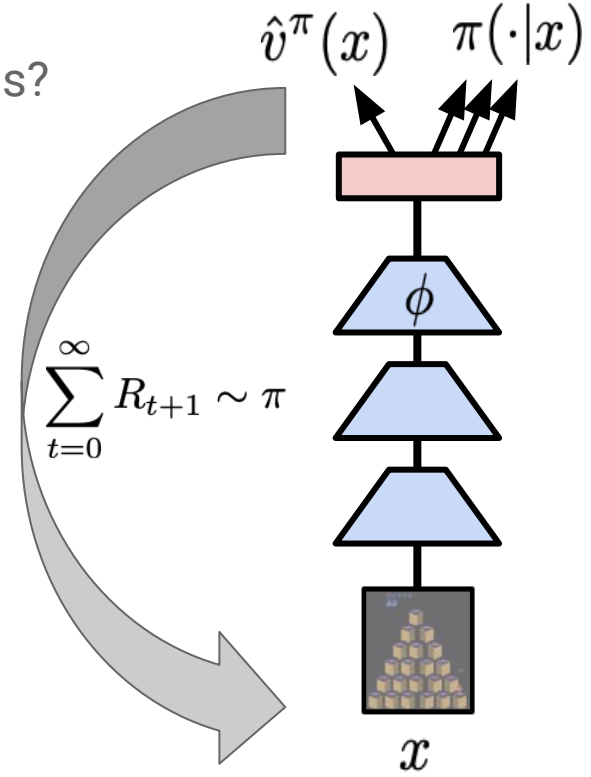

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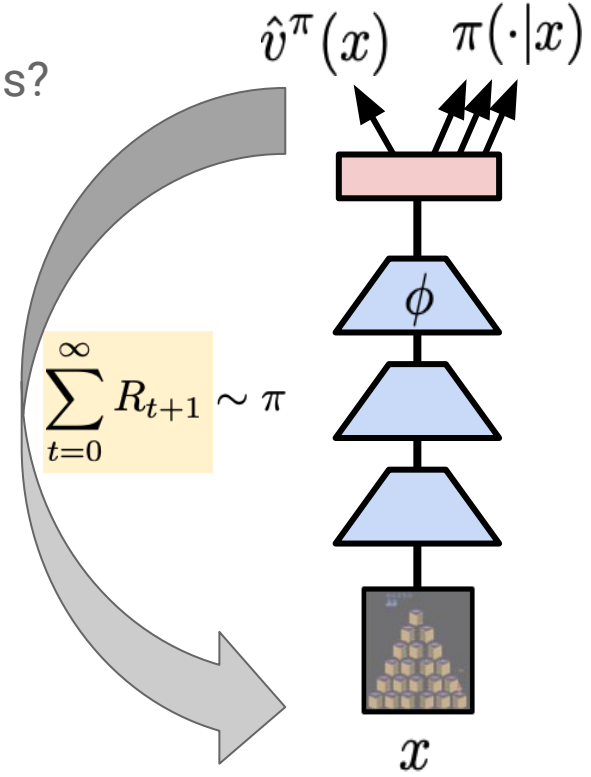

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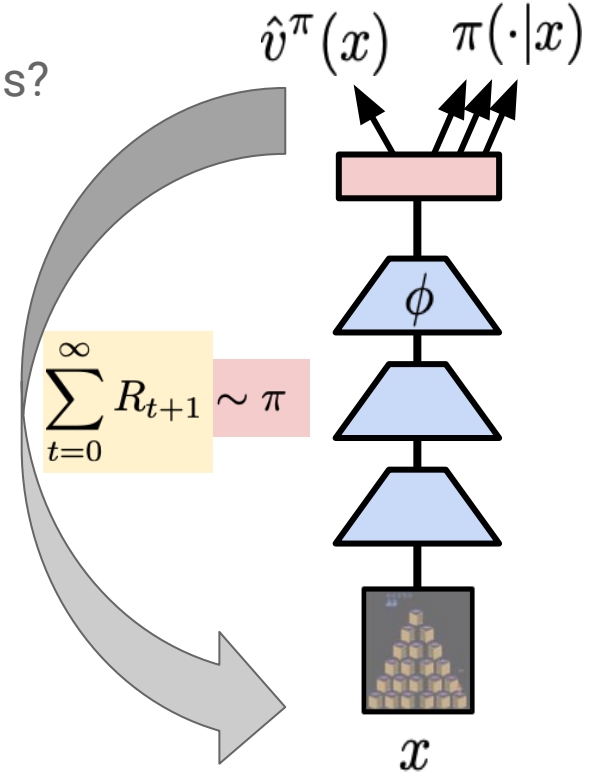

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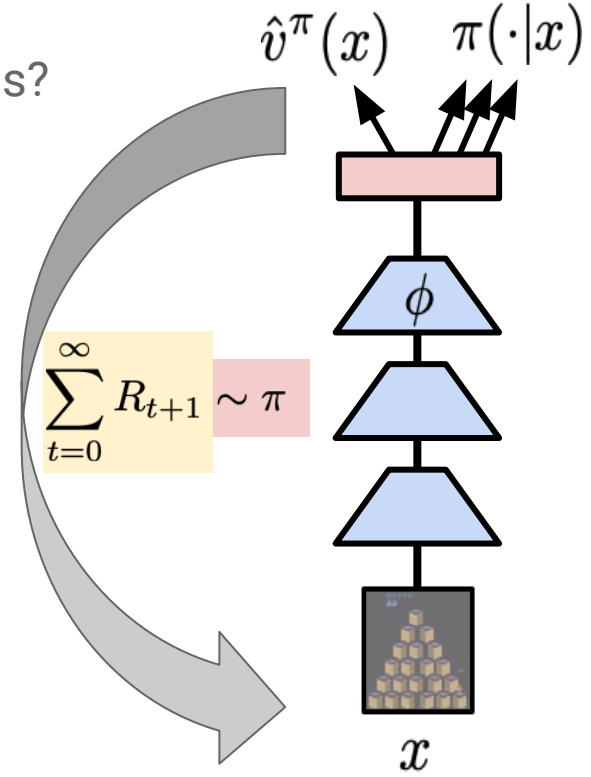

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Auxiliary tasks

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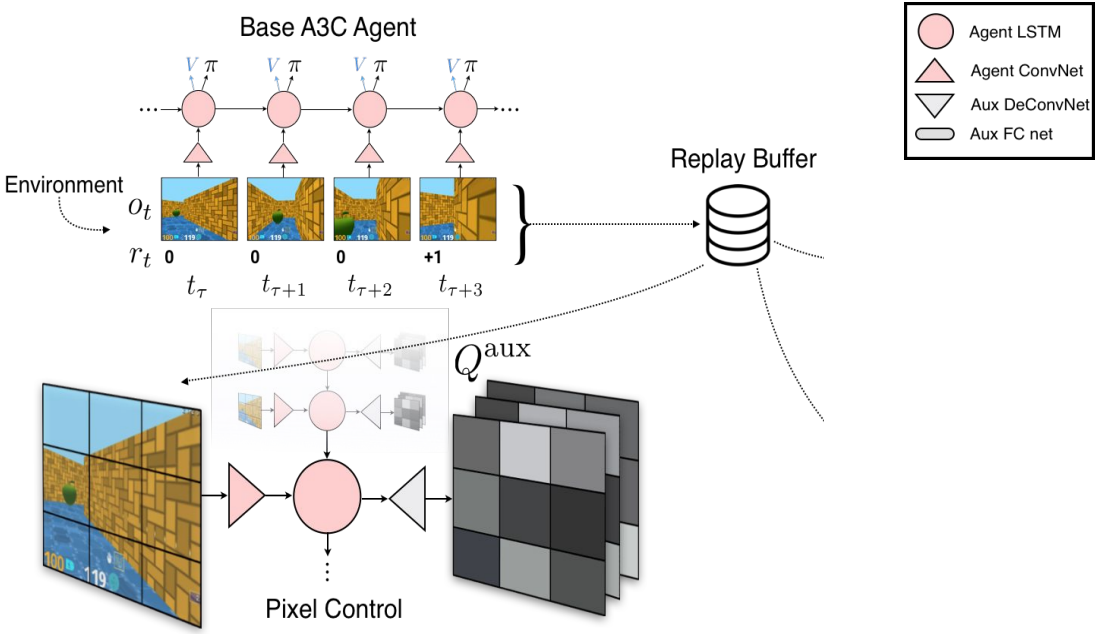
(a part of the) UNREAL architecture



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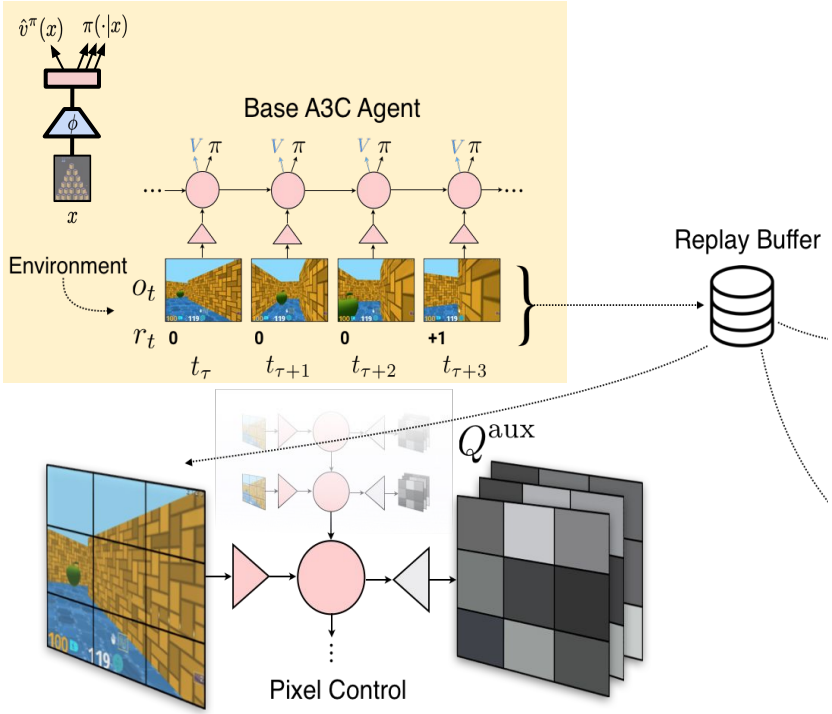
- A3C + a few types of auxiliary tasks



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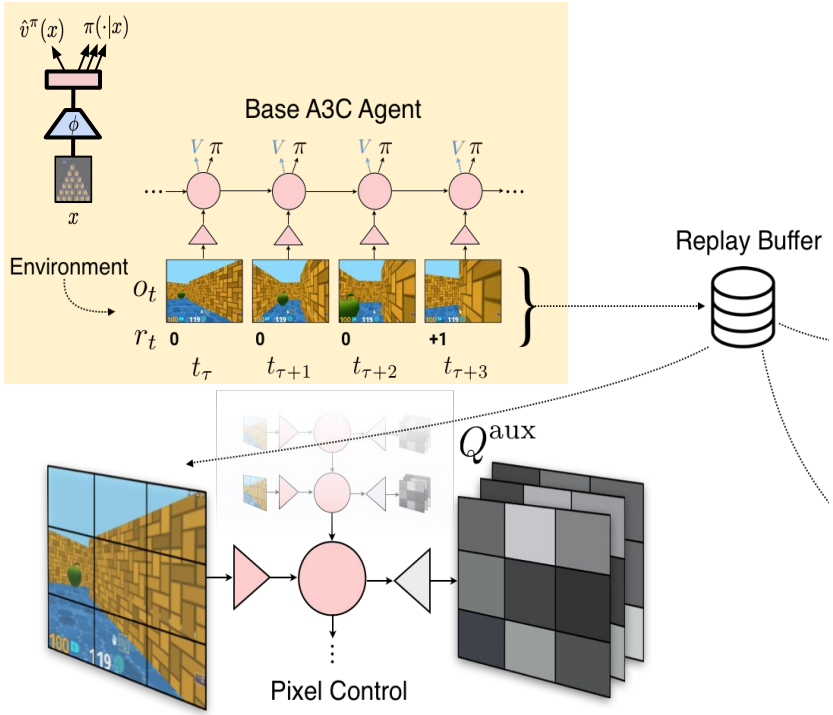

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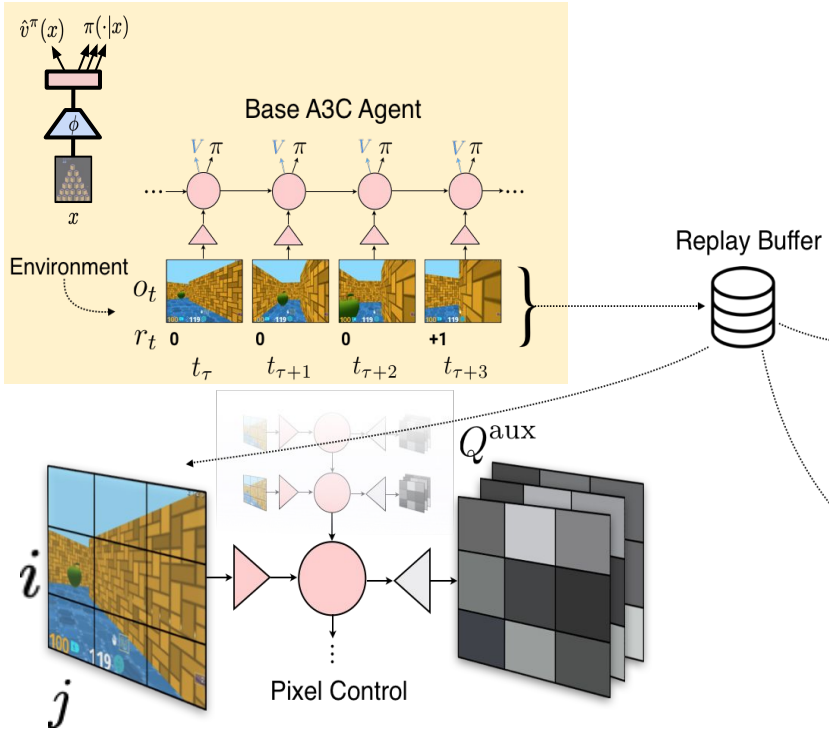
$$c(x, a, x') = x[i, j] - x'[i, j]$$



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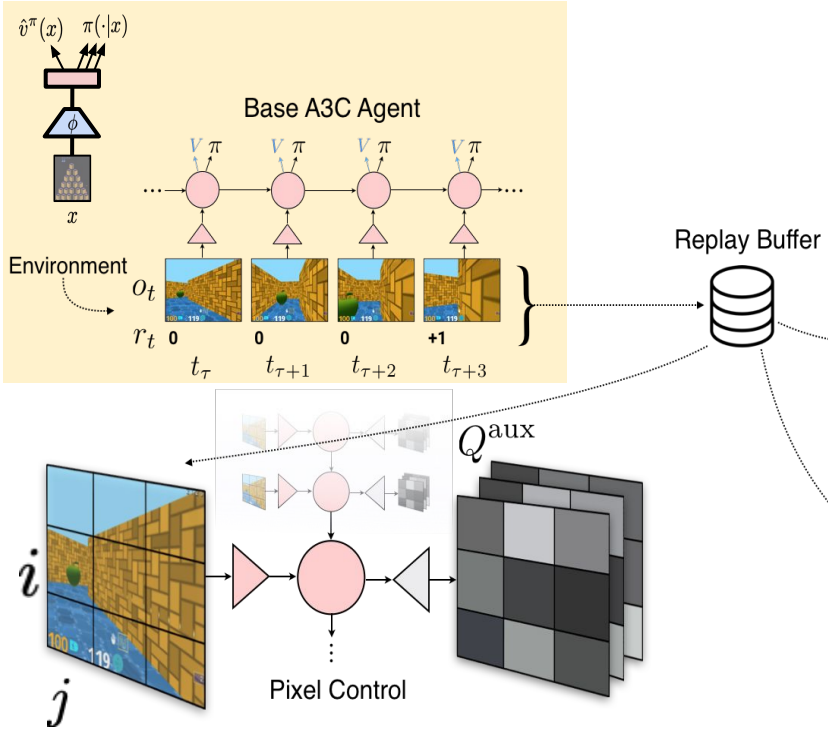
- **Unsupervised**, just observations
  - Follow bright lights, etc



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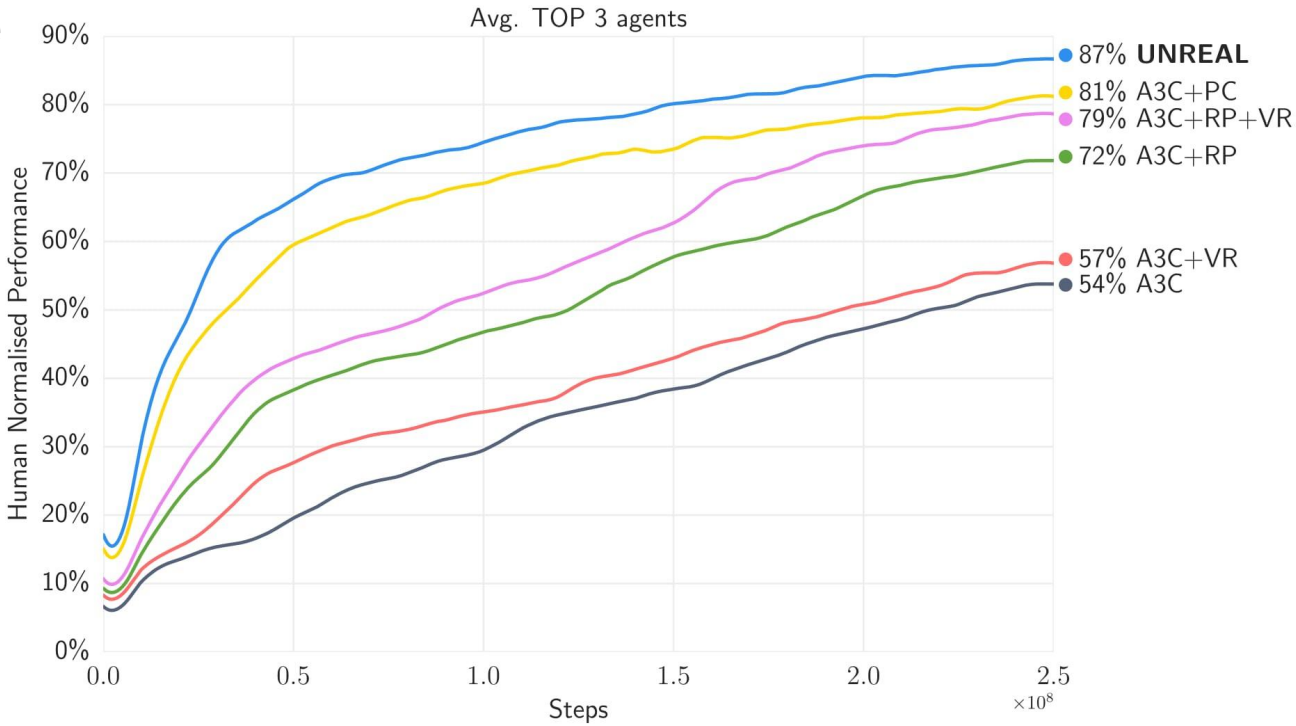
DeepMind Lab Results

- Average human-normalized performance on 13 3D environments from DeepMind Lab.
- Tasks include random maze navigation and laser tag.
- Roughly a 10x improvement in data efficiency over A3C.
- 60% improvement in final performance.



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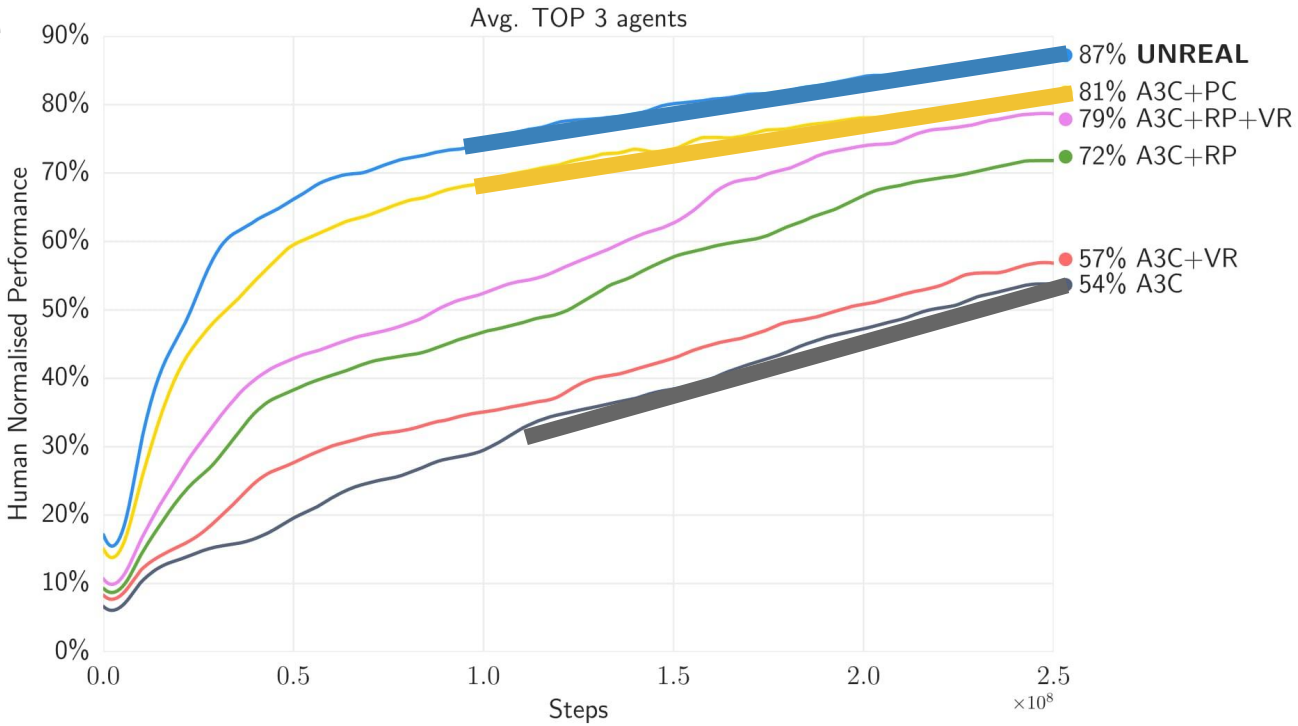
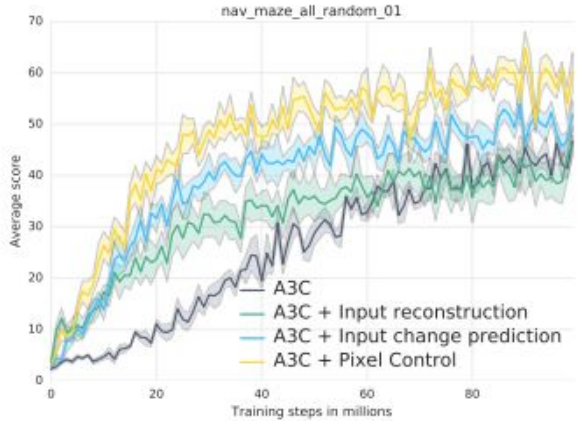
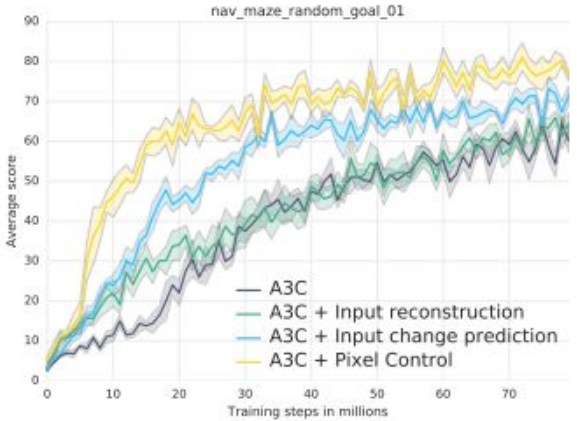


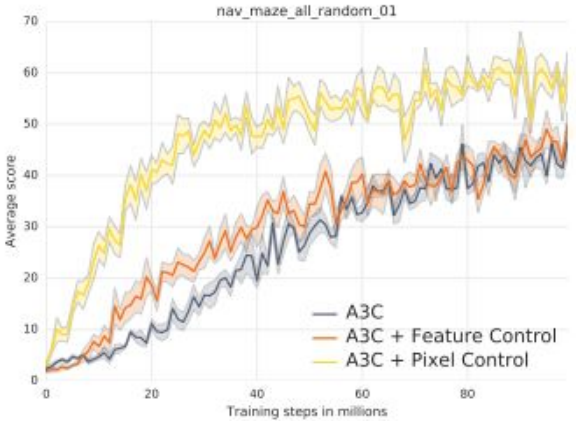
DeepMind

What types of tasks can be helpful?

- Random maze results
- Input change > input reconstruction
- Pixel control > prediction







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Auxiliary tasks

- Learn about many things, not just reward
  - Predict / control pixels, features, actions; past, present or future
- Even if the policy is still bad, there will at least be ground to learn it on
- Often has to do with learning values for other **cumulants** = reward functions:

$$c : \mathcal{X} \times \mathcal{A} \times \mathcal{X} \to \mathbb{R}$$

- Don't have to use the extra predictions in the RL algorithm itself
- Just shaping the representation can be very powerful
- Learning about lots of things was also the key idea behind **Horde**
  - Intuition was to build predictive knowledge
- Condensing that knowledge into the representation (or the agent state) is a way to think about it

Sutton, Richard S., et al. "Horde: A scalable real-time architecture for learning knowledge from unsupervised sensorimotor interaction." *AAMAS,* 2011.
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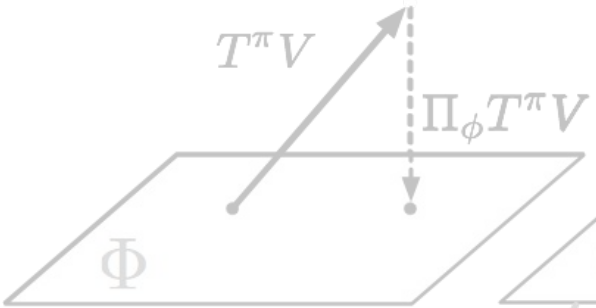
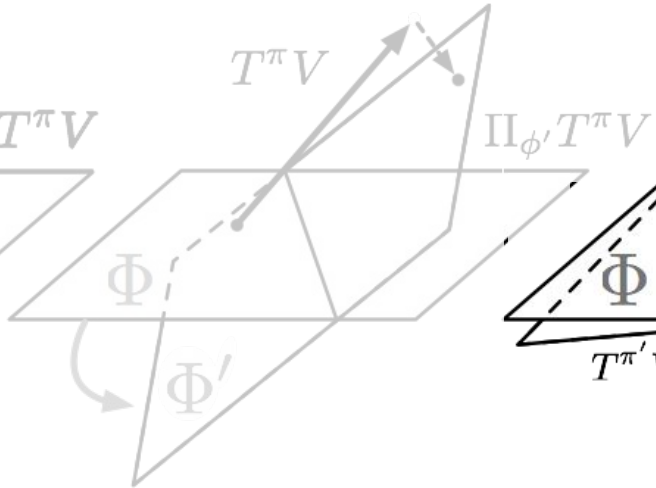
Regularizing the representation?

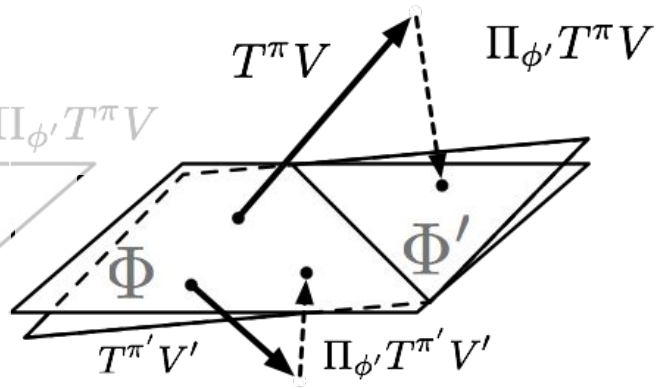
Linear RL



Deep RL



Deep RL
(with auxiliary)



DeepMind

Distributional RL

- Algorithms that learn statistics of the return beyond the mean:

$$Z^\pi(x,a) = \sum_{t=0}^{\infty} \gamma^t R_{t+1}$$

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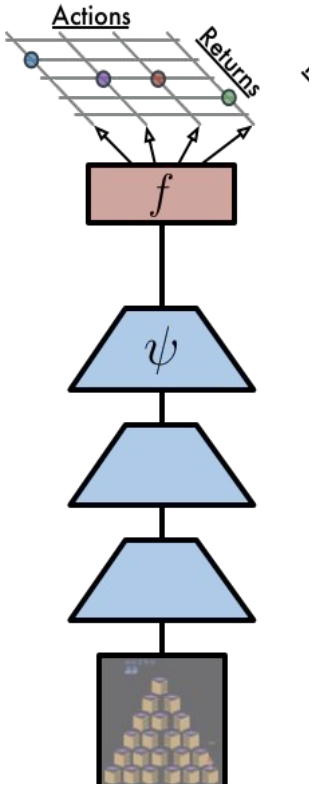
- A particular family of auxiliary tasks

Q-Learning / DQN



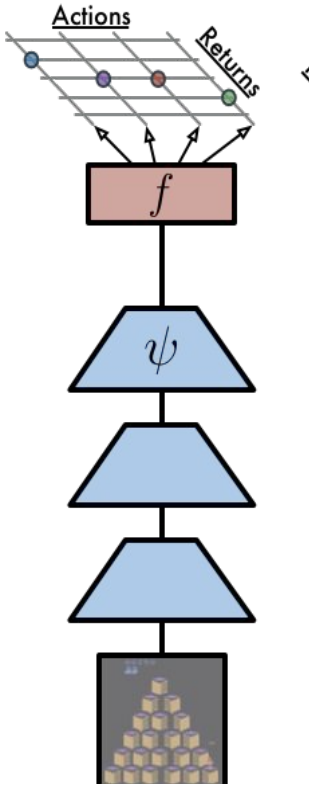
Targets

Loss

DeepMind

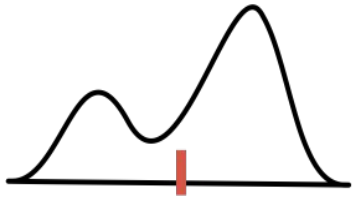
Watkins, Christopher JCH, and Peter Dayan. "Q-learning." *Machine learning* 8.3-4 (1992): 279-292.

Q-Learning / DQN



Targets

$$\mathbb{E}[Z^{\pi}(x, a)]$$



Estimate the expected value of the return distribution.

Loss

DeepMind

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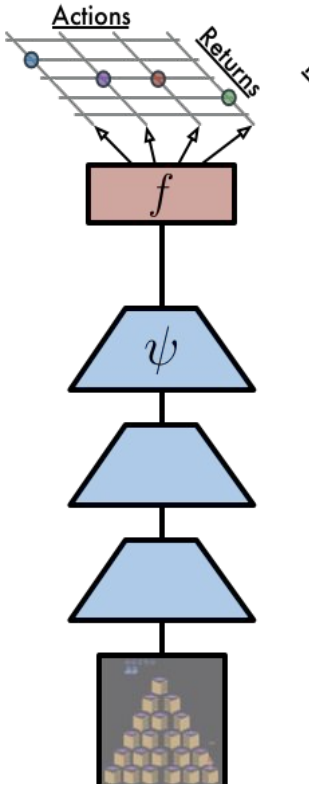
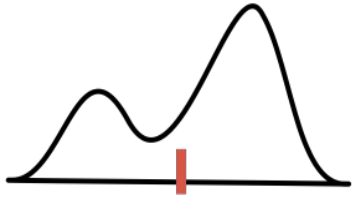
Q-Learning / DQN



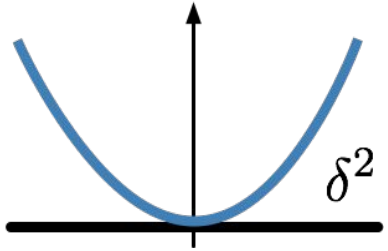
Targets

$$\mathbb{E}[Z^\pi(x,a)]$$



Loss

$$\mathcal{T}^\pi Q - Q$$



Estimate the expected value of the return distribution.

DeepMind

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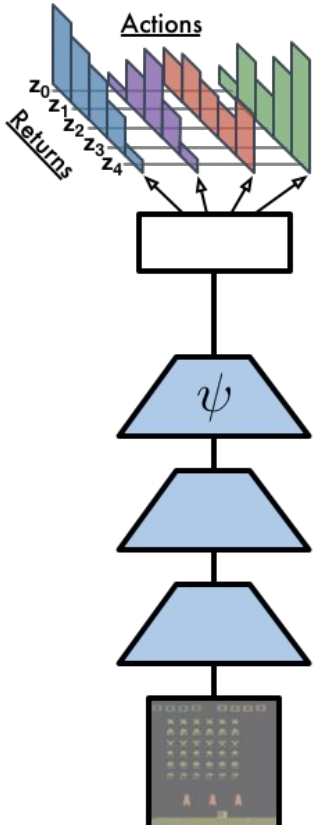
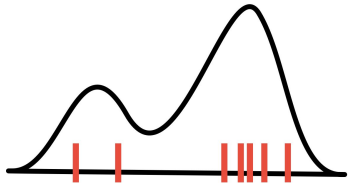
Categorical Distributional RL



Targets

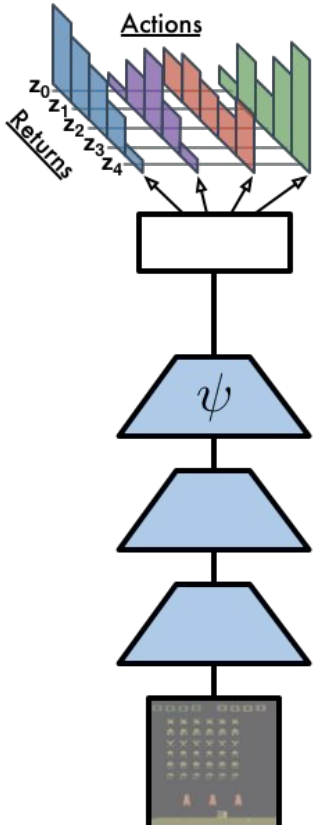


Loss

DeepMind

Bellemare, Marc G., Will Dabney, and Rémi Munos. "A distributional perspective on reinforcement learning." *ICML,* 2017.

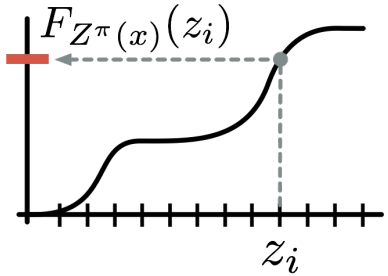
Categorical Distributional RL



Targets

Loss

$$\mathbb{P}\{Z^\pi(x,a) \leq z_k\}$$



Estimate k probabilities of getting a return of a certain value

DeepMind

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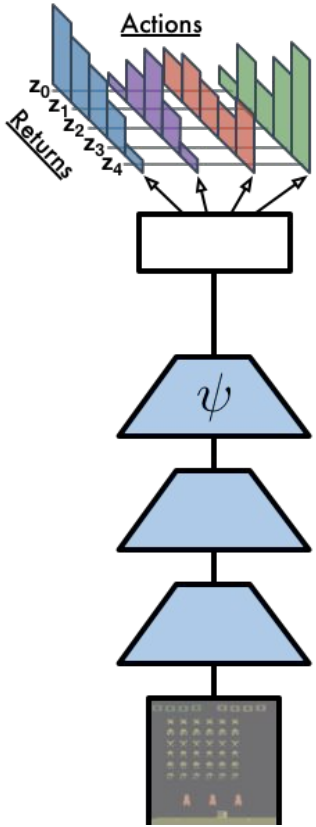
Categorical Distributional RL



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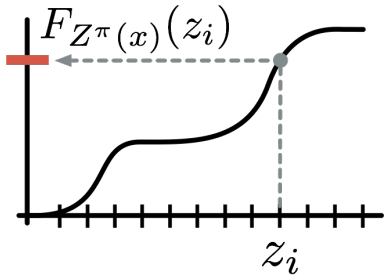

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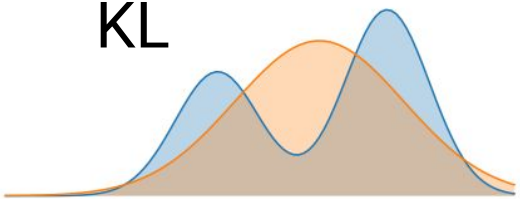

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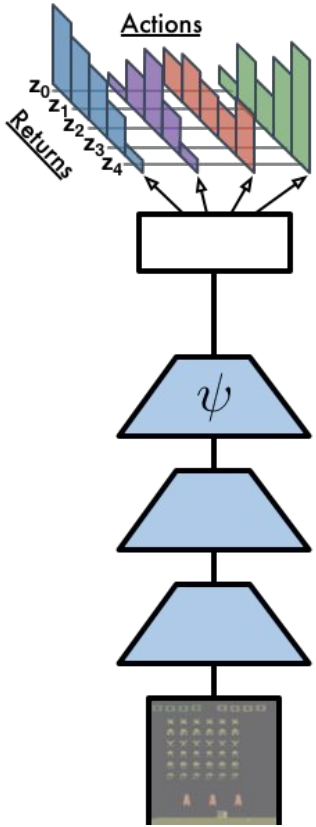

Targets

Loss

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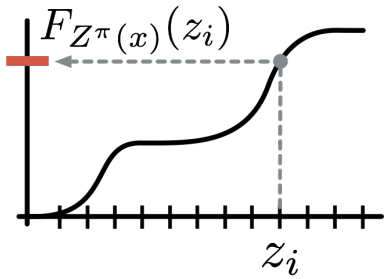
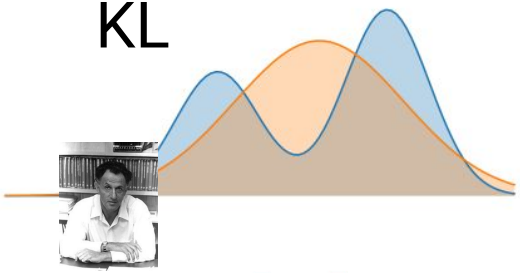
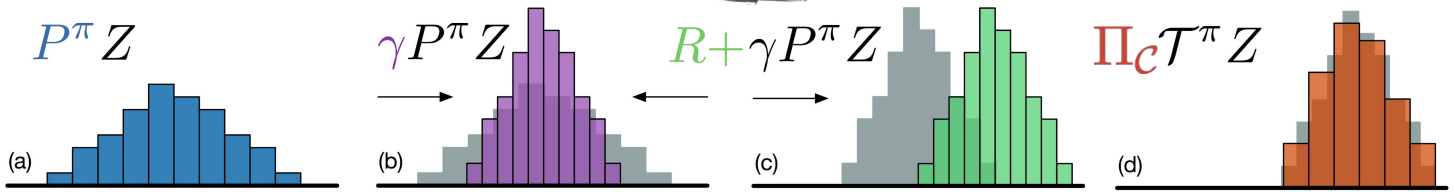


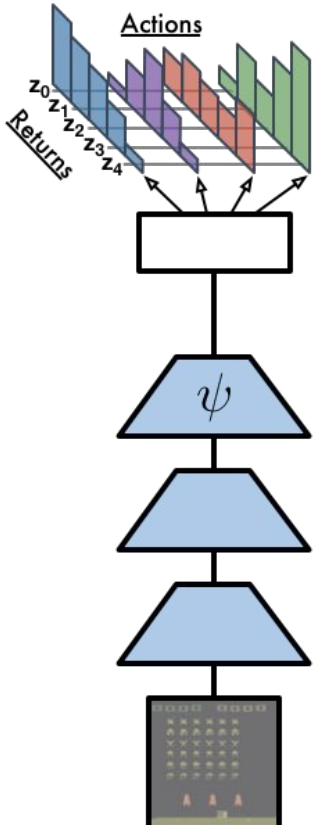
KL





DeepMind

Categorical Distributional RL



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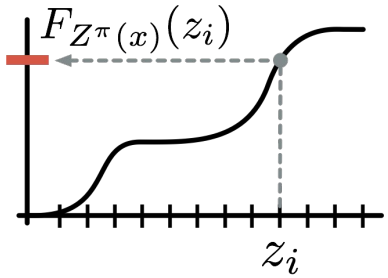
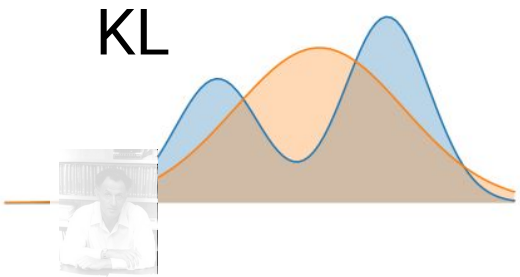
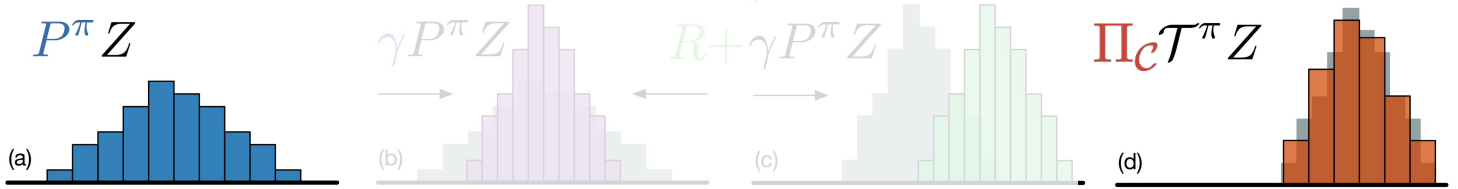


Loss

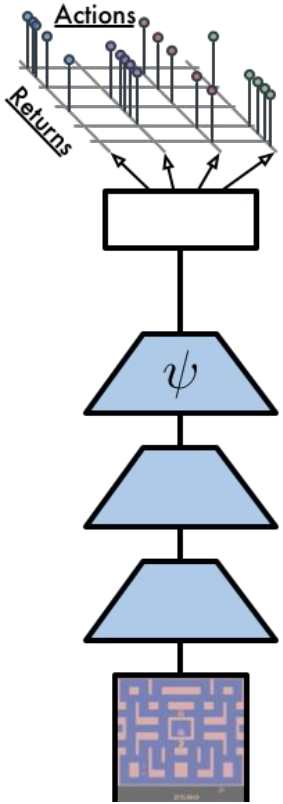
$$\Pi_c \mathcal{T}^\pi Z \| Z$$





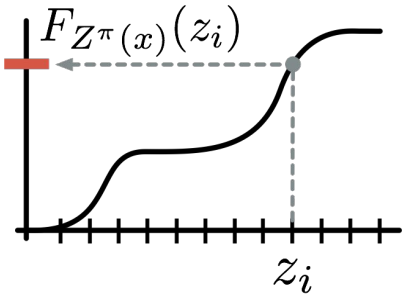
DeepMind

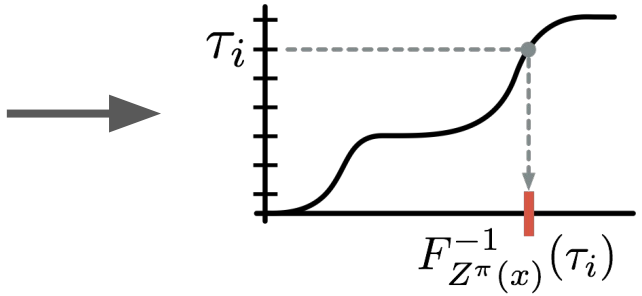
Quantile Distributional RL



Targets

Loss



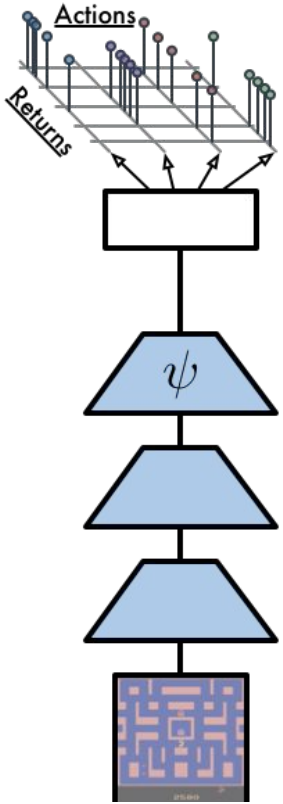


Can also do the inverse: Estimate the return values for given probability thresholds = distribution **quantiles**

Dabney, Will, et al. "Distributional reinforcement learning with quantile regression." *AAAI*, 2018.

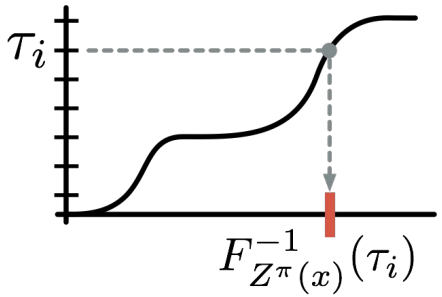
DeepMind

Quantile Distributional RL



Targets

$$F^{-1}_{Z^\pi(x)}(\tau_k)$$



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DeepMind

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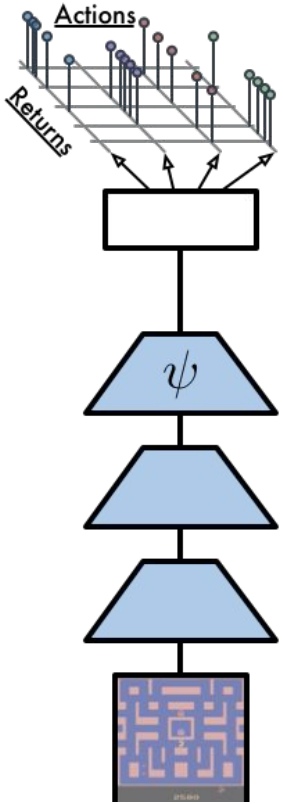

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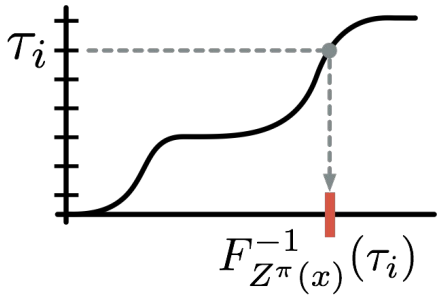
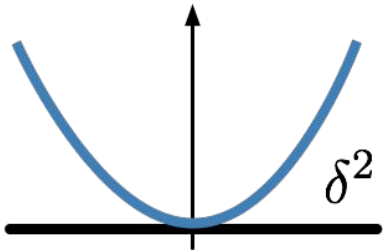


Can also do the inverse: Estimate the return values for given probability thresholds = distribution **quantiles**

Loss

$$\mathcal{T}^\pi Z - Z$$



Dabney, Will, et al. "Distributional reinforcement learning with quantile regression." *AAAI,* 2018.

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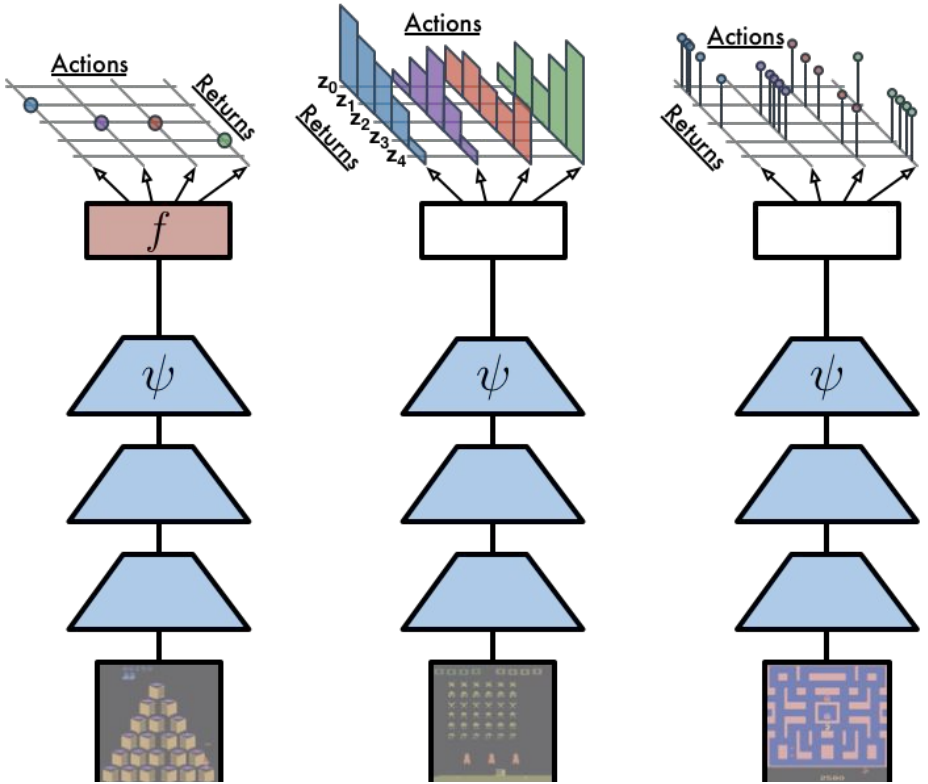
Distributional RL

- Algorithms that learn statistics of the return beyond the mean:

$$Z^\pi(x,a) = \sum_{t=0}^{\infty} \gamma^t R_{t+1}$$

- A particular family of auxiliary tasks



DeepMind

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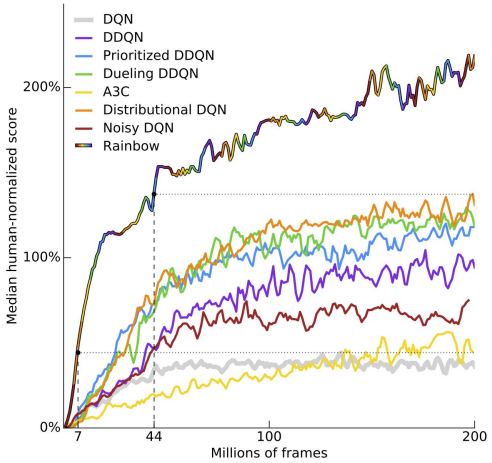
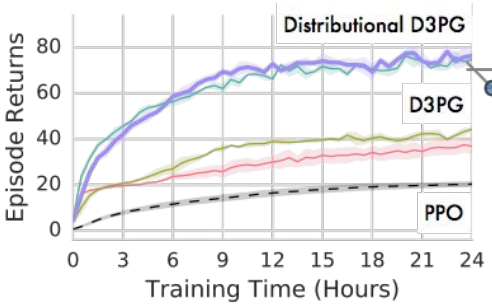
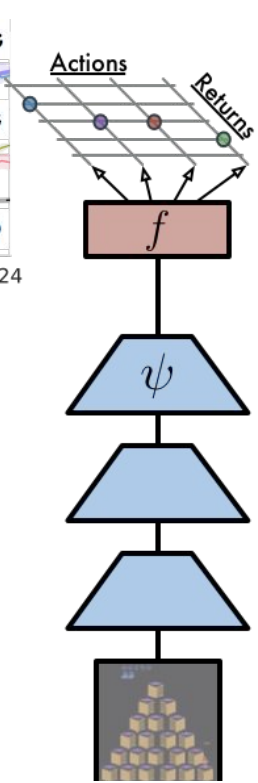
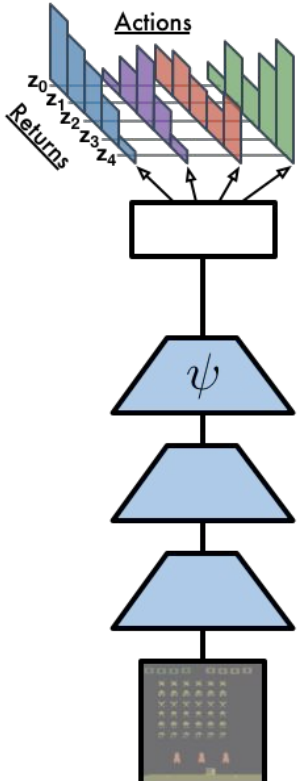
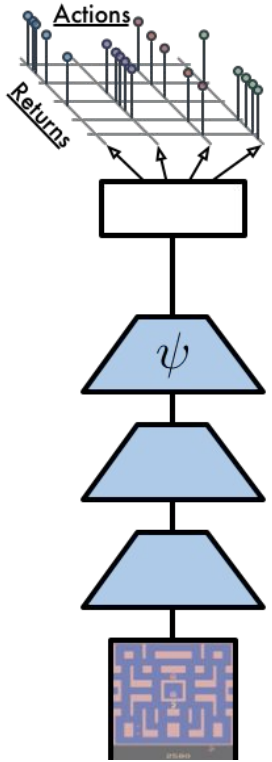
Distributional RL





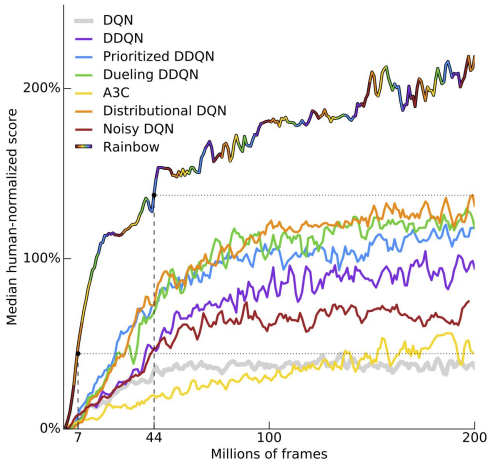


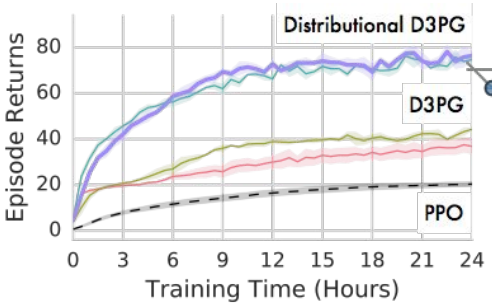


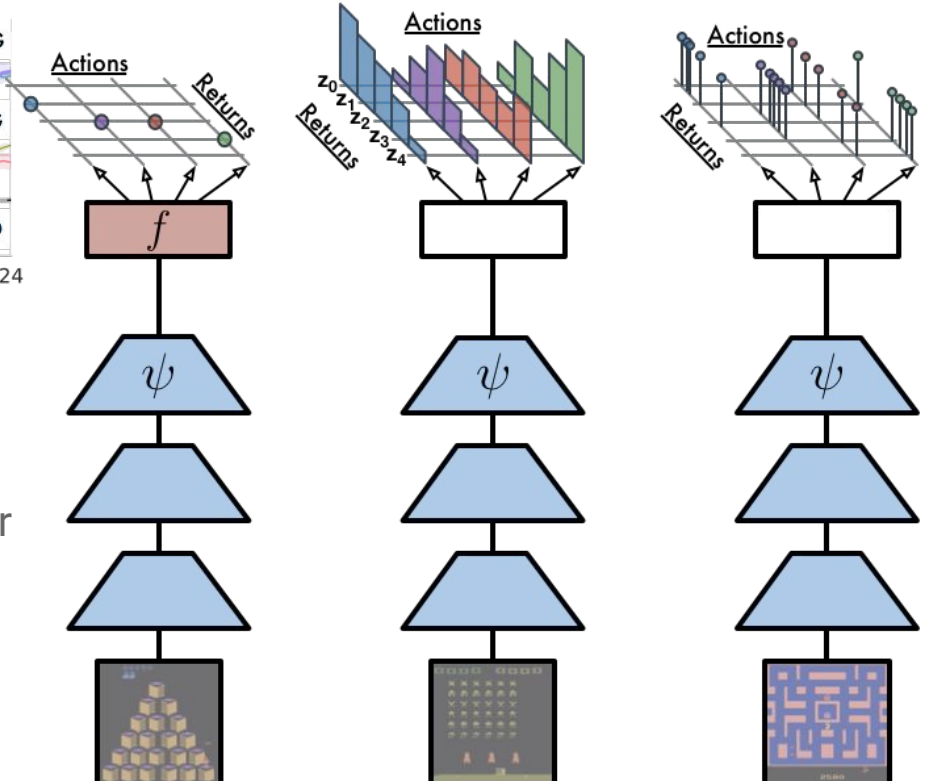


DeepMind

Distributional RL







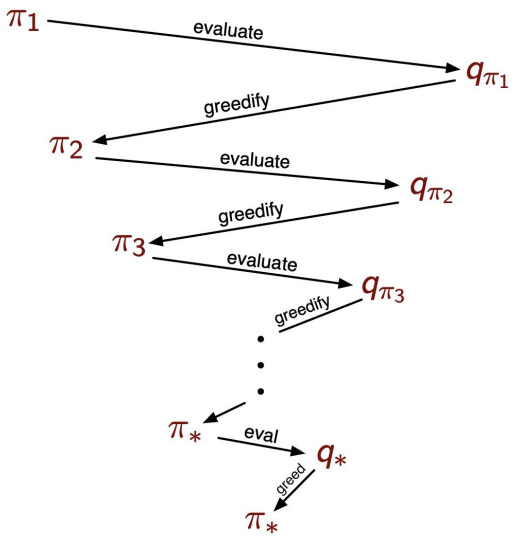
- **Why** does it help?
  - We still act w.r.t. the mean
  - Doesn't affect anything in the tabular case
- **Hypothesis:** return statistics are particularly good auxiliary tasks

DeepMind

Lyle, Clare, Marc G. Bellemare, and Pablo Samuel Castro. "A comparative analysis of expected and distributional reinforcement learning." *AAAI,* 2019.

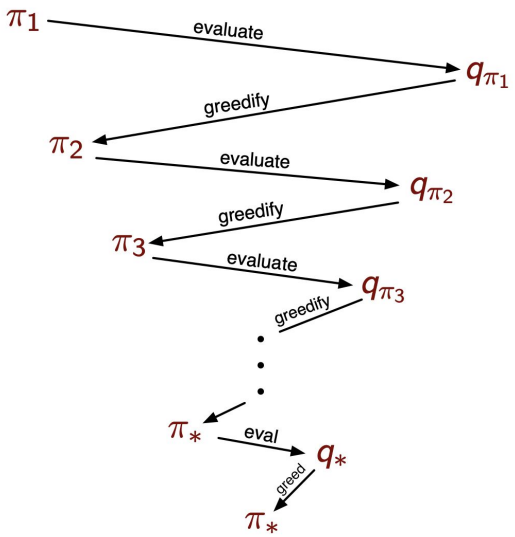
Value functions are temporarily useful

Value functions are temporarily useful



“The dance of policy and value”, cf. Rich

Value functions are temporarily useful



- The policy iteration dance is particularly treacherous in deep RL

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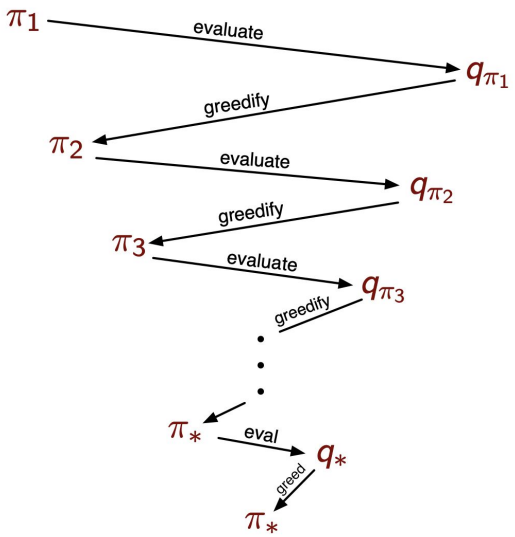
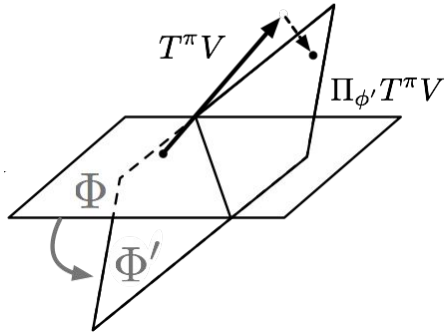


- The policy iteration dance is particularly treacherous in deep RL
- Every new policy/value wants its own set of features!



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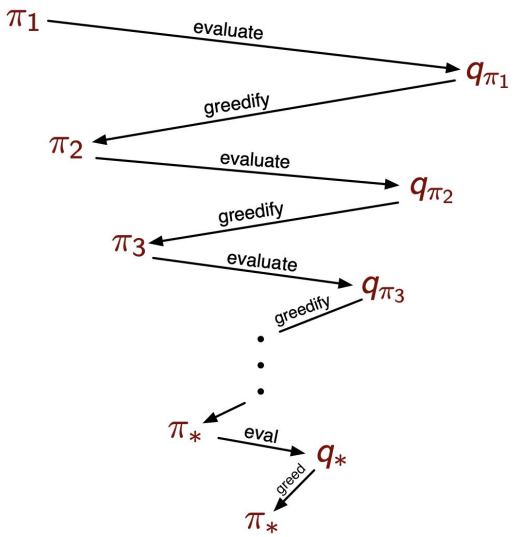

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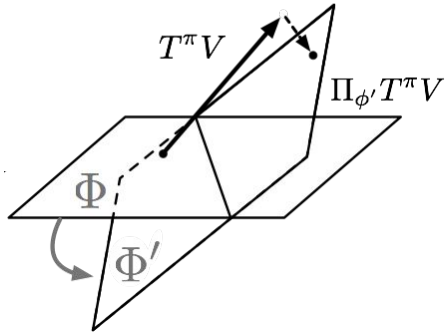
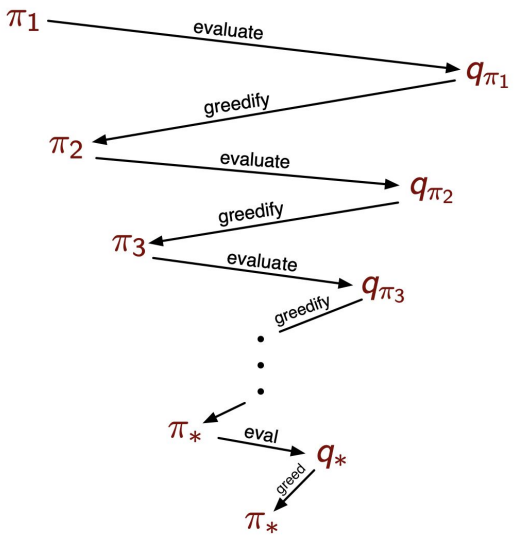


- There is a risk that the features overfit and are **unable** to learn the future optimal policy

DeepMind

Value functions are temporarily useful



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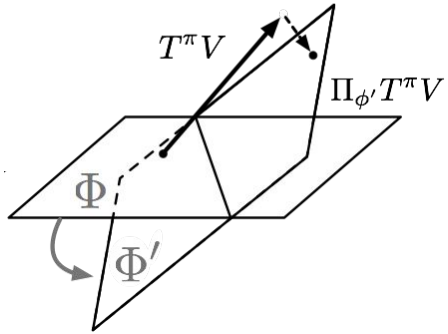

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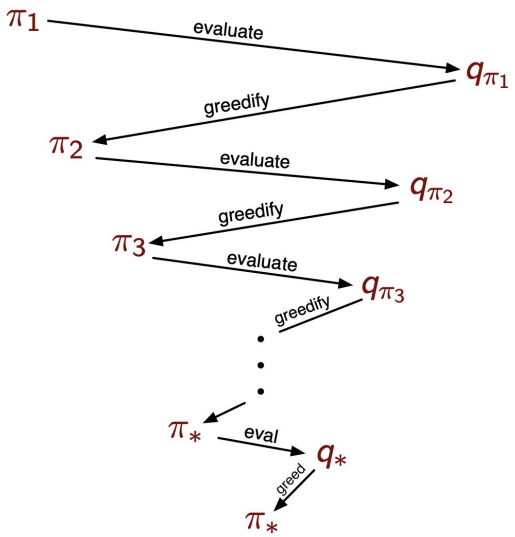
Need to generalize across **time** as well

DeepMind

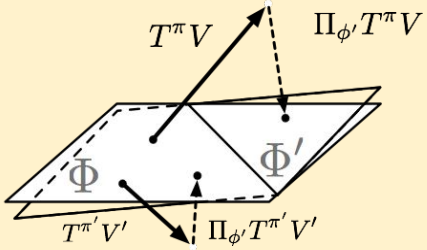
Value functions are temporarily useful



"The dance of policy and value", cf. Rich

- The policy iteration dance is particularly treacherous in deep RL
- Every new policy/value wants its own set of features!

Auxiliary tasks?



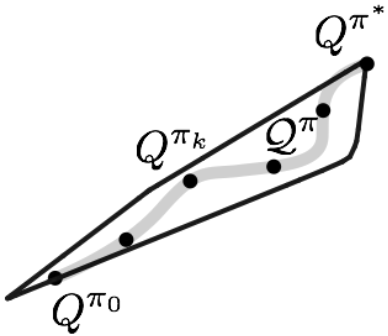
- There is a risk that the features overfit and are **unable** to learn the future optimal policy

Need to generalize across **time** as well

DeepMind

Value improvement path

Value-Improvement Path

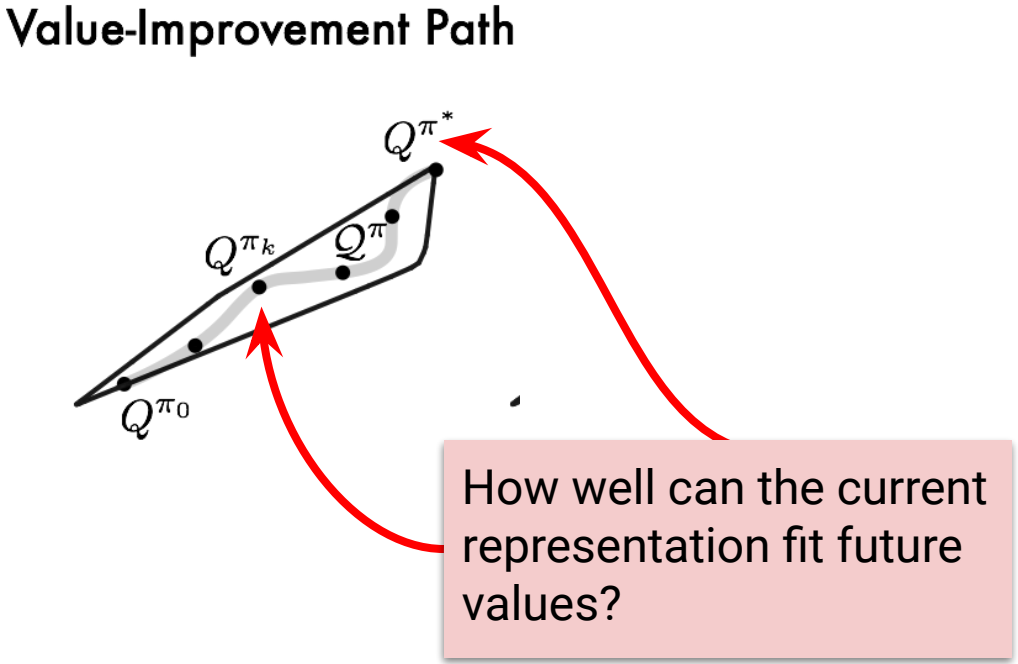


Value function polytope = space of possible value functions w.r.t. the reward

DeepMind

Dabney, Will, et al.. "The value improvement path: understanding representation for reinforcement learning." In submission.

Value improvement path



DeepMind

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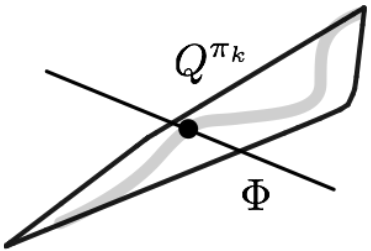
Value improvement path

Value-Improvement Path

Value-Only



DeepMind

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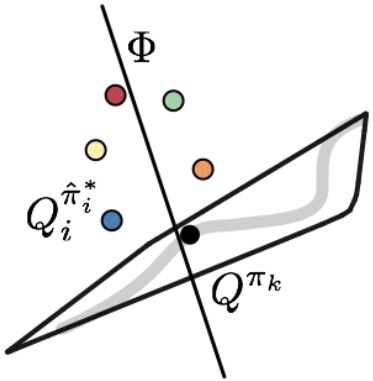
Value improvement path

Value-Improvement Path

Value-Only

Cumulant Value



Auxiliary tasks / cumulants can help, but it's arbitrary if they're aligned correctly

DeepMind

Dabney, Will, et al.. "The value improvement path: understanding representation for reinforcement learning." In submission.

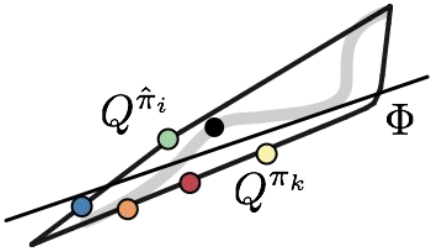
Value improvement path

Value-Improvement Path

Value-Only

Cumulant Value

Cumulant Policy



When evaluated w.r.t. the same reward, they do lie on the polytope, so it's more likely

DeepMind

Dabney, Will, et al.. "The value improvement path: understanding representation for reinforcement learning." In submission.

Value improvement path

Path | Value-Only | Cumulant Value | Cumulant Policy | **Past Policies**

Can explicitly ask to continue accommodating values of past policies

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Dabney, Will, et al.. "The value improvement path: understanding representation for reinforcement learning." In submission.

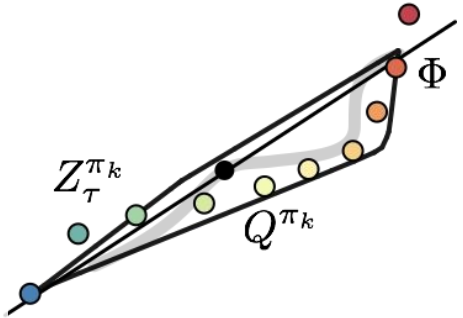
Value improvement path

Cumulant Value

Cumulant Policy

Past Policies

Distributional RL

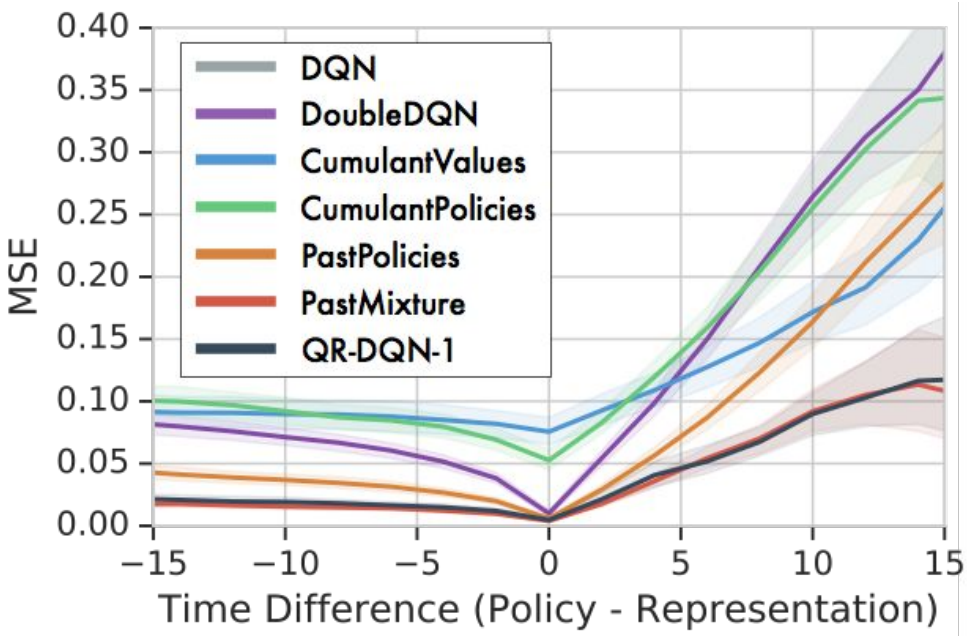


Distributional RL might be estimating statistics that are well aligned with value improvement

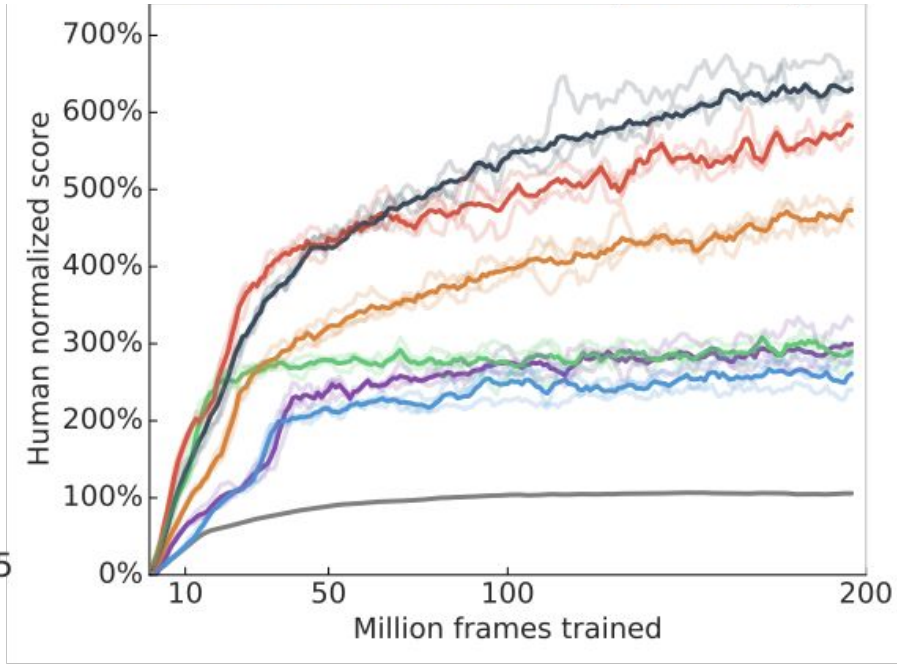
DeepMind

Dabney, Will, et al.. "The value improvement path: understanding representation for reinforcement learning." In submission.

Generalization error



Performance (mean)



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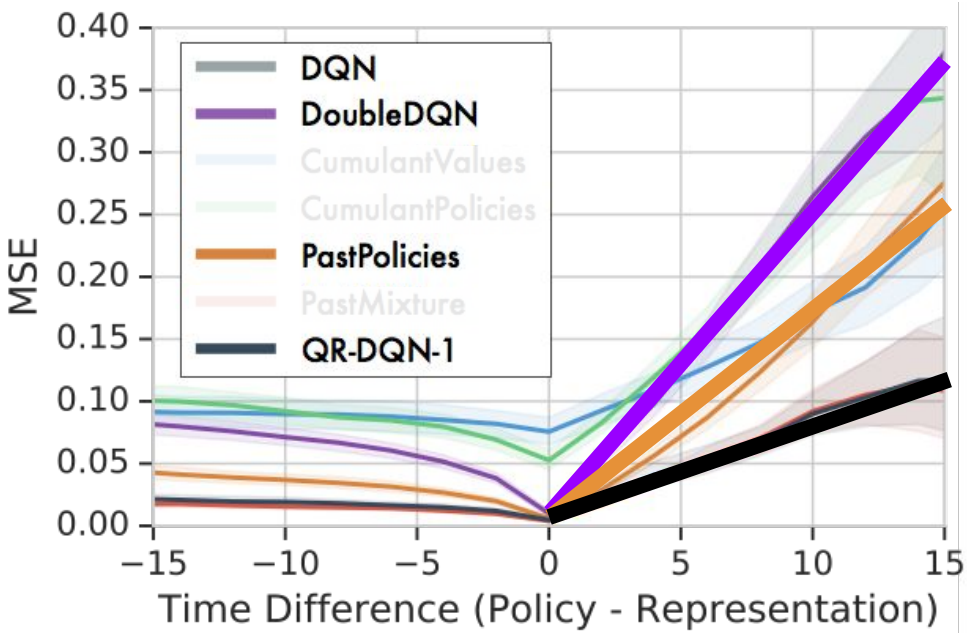

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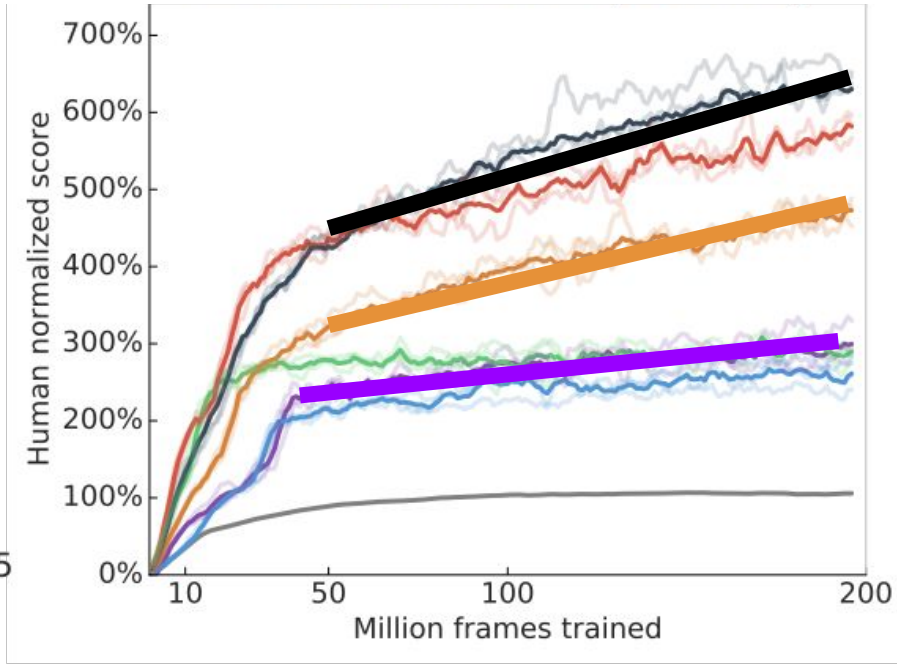


DeepMind

Dabney, Will, et al.. "The value improvement path: understanding representation for reinforcement learning." *In submission.*

Recap

- Generalizing to new observations
  - **Architecture** + **loss** determine what features are learned
- Auxiliary tasks
  - **Issue 1:** The RL loss based on reward might be uninformative,
  - So let's learn other things -- pixels, features, etc
- Distributional RL
  - One type of auxiliary tasks is to learn various statistics of return
  - It helps, but we don't quite know why
- Value improvement path
  - **Issue 2:** Policies change! Past values should fit future policies
  - Perhaps distributional RL / aux tasks help this kind of generalization across time

2) Generalizing across tasks

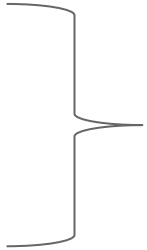
Contents

- Successor representation
- Successor features
- Universal Value Function Approximators (UVFAs)
- Generalized Policy Iteration (GPI)
- Universal Successor Features (USFAs)

Contents

- Successor representation

1) Successor features
2) Universal Value Function Approximators (UVFAs)
3) Generalized Policy Iteration (GPI)



USFAs

Successor representation

DeepMind

Dayan, Peter. "Improving generalization for temporal difference learning: The successor representation." *Neural Computation* (1993)

Successor representation

Value function

$$q^{\pi}(x,a) = \mathbb{E}_{\pi}\left[\sum_{t=0}^{\infty} \gamma^t R_{t+1} | X_0 = x, A_0 = a\right]$$

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= how much time are we expected to spend in x' from x,a under π

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How much time in x'?

How much reward in x'?

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Reward independent!

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If we have s, we can instantly evaluate any cumulant!

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Problem:
Quickly evaluate **new** reward functions w.r.t. the **same** policy

Reward independent!

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How to use with function approximation?

1) Successor features

Assume the reward is linear in some features:

$$r(x, a) = \phi(x, a)^T \mathbf{w} \qquad R_{t+1} = \phi_t^T \mathbf{w}$$

DeepMind

Barreto, André, et al. "Successor features for transfer in reinforcement learning." *NeurIPS,* 2017.

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DeepMind

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= expected cumulative reward features from x,a

DeepMind

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DeepMind

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If we have ψ, we can instantly evaluate any reward parameters **w**!

DeepMind

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Learning SFs

$$\hat{q}^{\pi}(x, a) = \hat{\psi}^{\pi}(x, a)^{T} \hat{\mathbf{w}}$$

DeepMind

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Regression

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DeepMind

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RL

$$\phi + \gamma\hat{\psi}' - \hat{\psi}$$

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Features φ also can be learned
(but are usually given)

DeepMind

Barreto, André, et al. "Successor features for transfer in reinforcement learning." *NeurIPS,* 2017.

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RL

$$\phi + \gamma\hat{\psi}' - \hat{\psi}$$

Regression

$$r(x,a) - \phi(x,a)^{T}\hat{\mathbf{w}}$$

- Zero-shot (and good quality!) evaluation

- Policy dependent
- Reward linearity assumption

DeepMind

Barreto, André, et al. "Successor features for transfer in reinforcement learning." *NeurIPS,* 2017.

2) Universal Value Function Approximators

Problem:
Generalize in the space of value functions to **new** tasks, policies, rewards, etc

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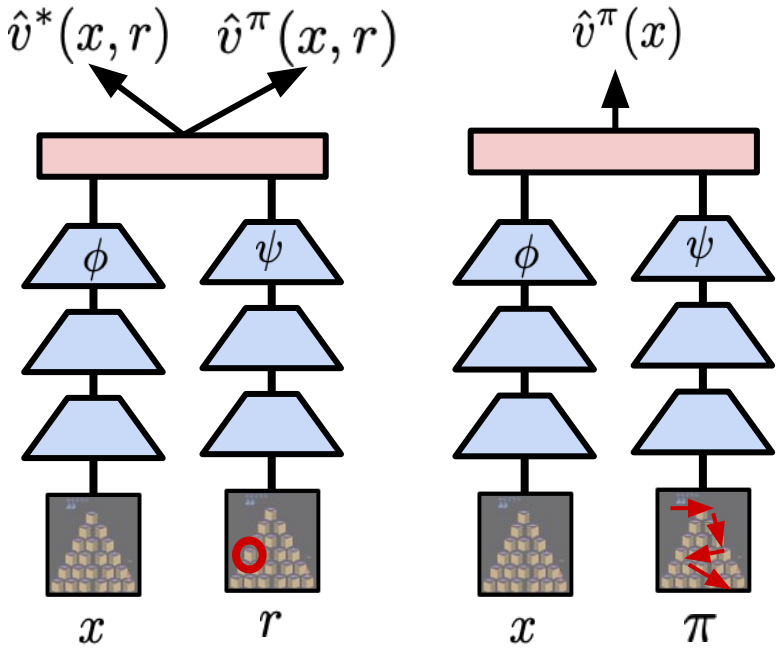
- A **UVFA** takes the extra conditioning as an input and learns a joint representation



Tasks / Rewards Policies

DeepMind

Schaul, Tom, et al. "Universal value function approximators." *ICML*. 2015.

2) Universal Value Function Approximators

Problem:
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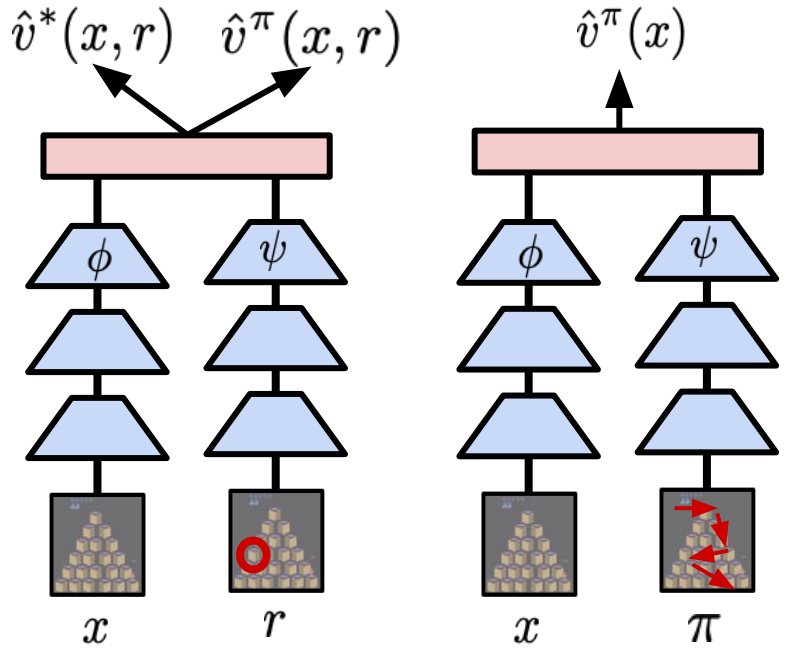
- A **UVFA** takes the extra conditioning as an input and learns a joint representation

- Zero-shot, cheap generalization

- Hard work for the network



Tasks / Rewards Policies

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3) Generalized Policy Improvement (GPI)

Problem:
Given a set of existing policies, solve an arbitrary new task

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DeepMind

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DeepMind

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$$\pi(\cdot|x) = \arg\max_a \max_i q^{\pi_i}(x, a)$$

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- Theoretical guarantees -- better than any of the initial policies!

- Double-max might be expensive / unstable

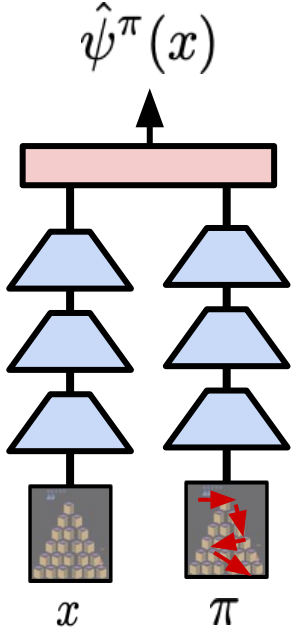
DeepMind

Barreto, André, et al. "Successor features for transfer in reinforcement learning." *NeurIPS,* 2017.

UVFAs vs. Successor Features

- Under the linear assumption, SFs give free accurate generalization to new **w**-s *(evaluation only)*
- How's this different from the way a UVFA generalizes?
  - UVFAs don't assume anything, but rely on the function approximator to figure it out
  - More general, but also a harder problem
- But the successor representation is **policy-dependent**
  - Have to learn a new one for every policy

- **Idea:** why not both! Use a UVFA to learn universal SFs!



Policies

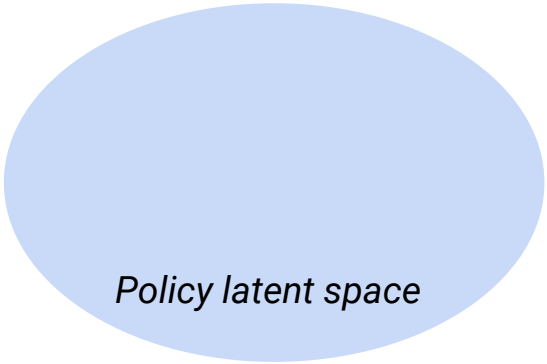
USFAs: How to Solve Anything

DeepMind

Borsa, Diana, et al. "Universal successor features approximators." *ICLR*, 2019.

USFAs: How to Solve Anything

1) **UVFA:** Get the successor features for many policies



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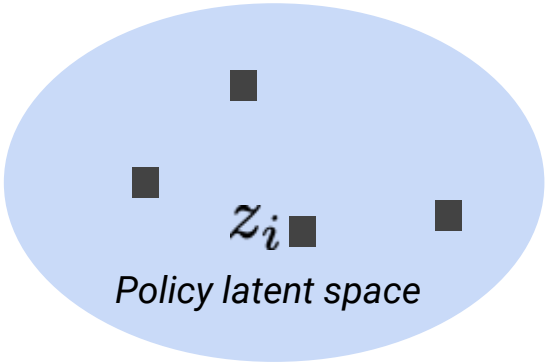

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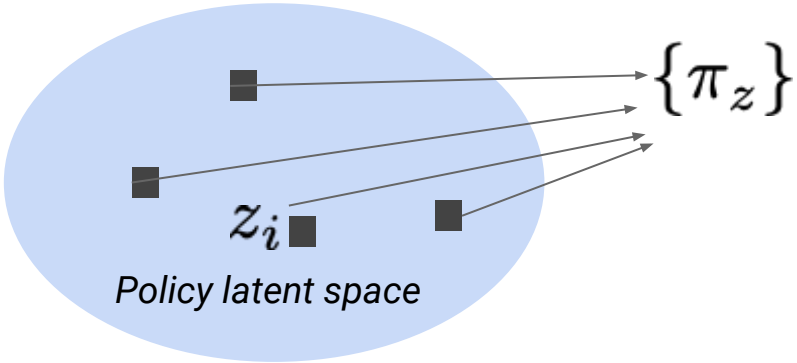

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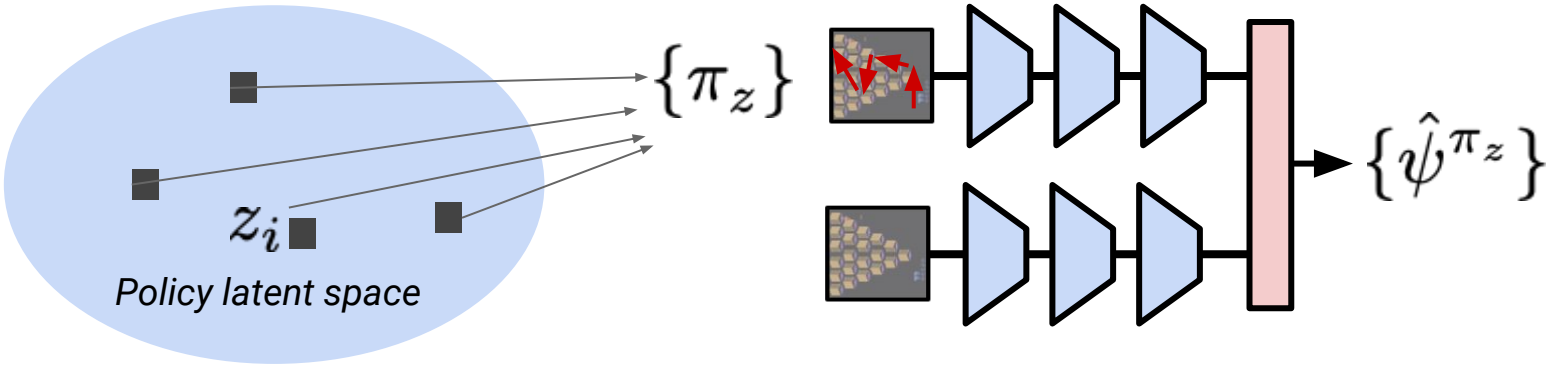

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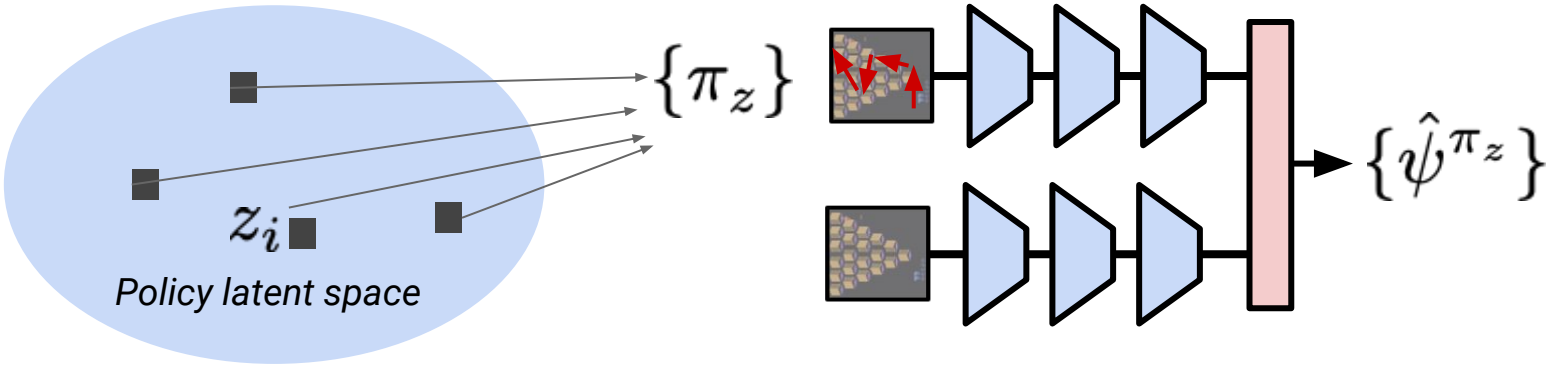

2) **SF:** Evaluate the policies w.r.t. the reward of interest **w**, get Q-functions:

$$\{\hat{q}^{\pi_z}_{\mathbf{w}}(x,a) = \hat{\psi}^{\pi_z}(x,a)\mathbf{w}\}$$

DeepMind

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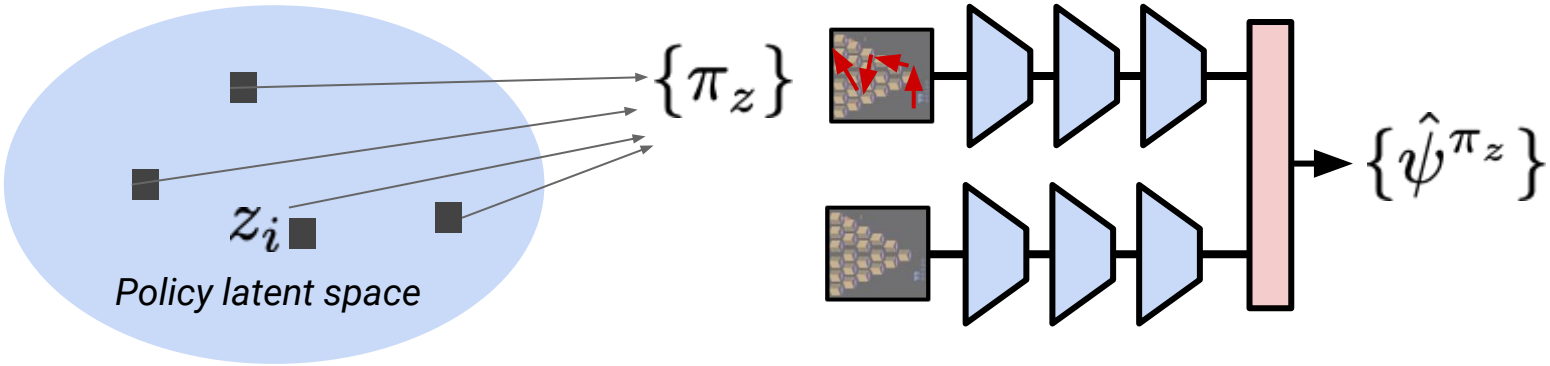

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$$\pi(\cdot|x) = \arg\max_a \max_z \hat{q}^{\pi_z}_{\mathbf{w}}(x,a)$$

DeepMind

Borsa, Diana, et al. "Universal successor f
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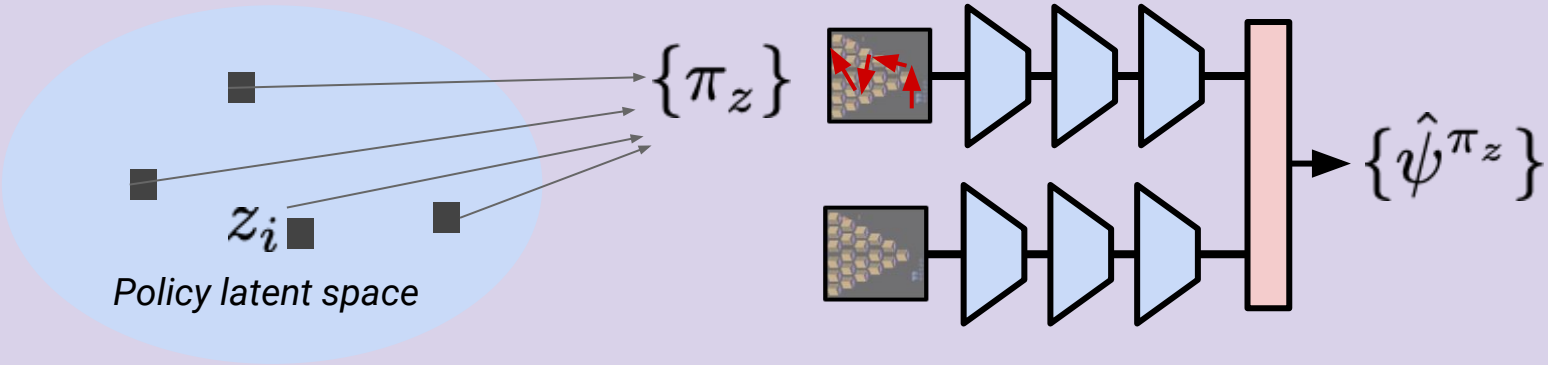
Two types of generalization

Parameteric

1) **UVFA:** Get the successor features for many policies



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Recomposition

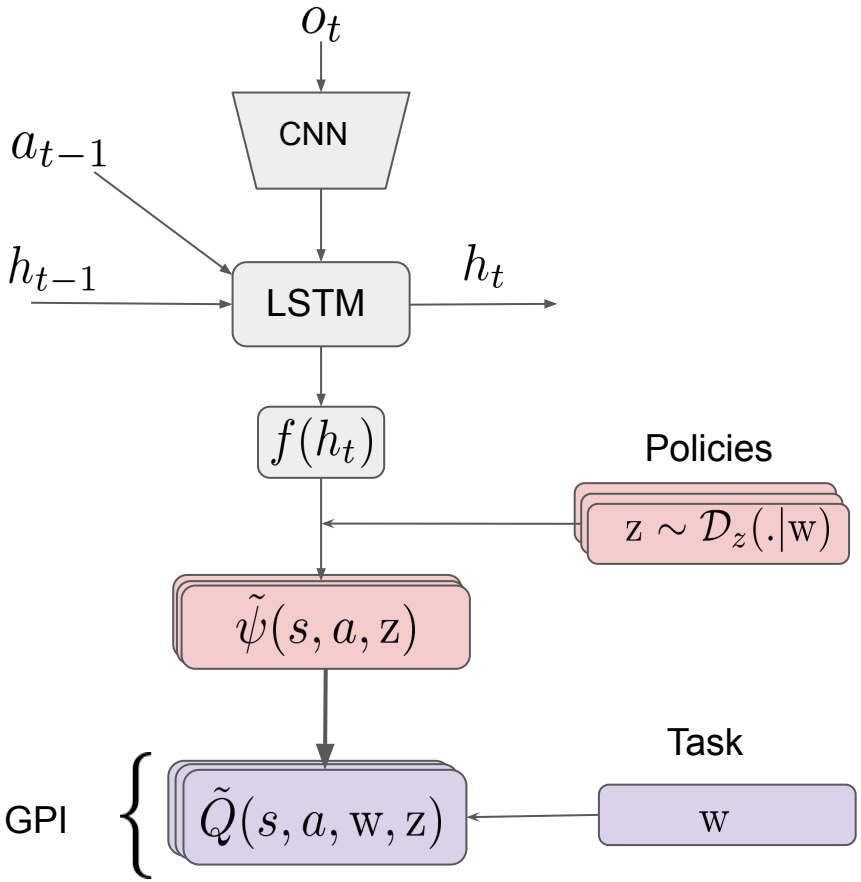
USFAs - Acting

- Sample in policy space:

$$\mathrm{z} \sim \mathcal{D}_z(.|\mathrm{w})$$

- Compute GPI policy:

$$\pi(s) = \arg\max_a \max_z \tilde{Q}(s, a, \mathrm{w}, \mathrm{z})$$



USFAs - Training

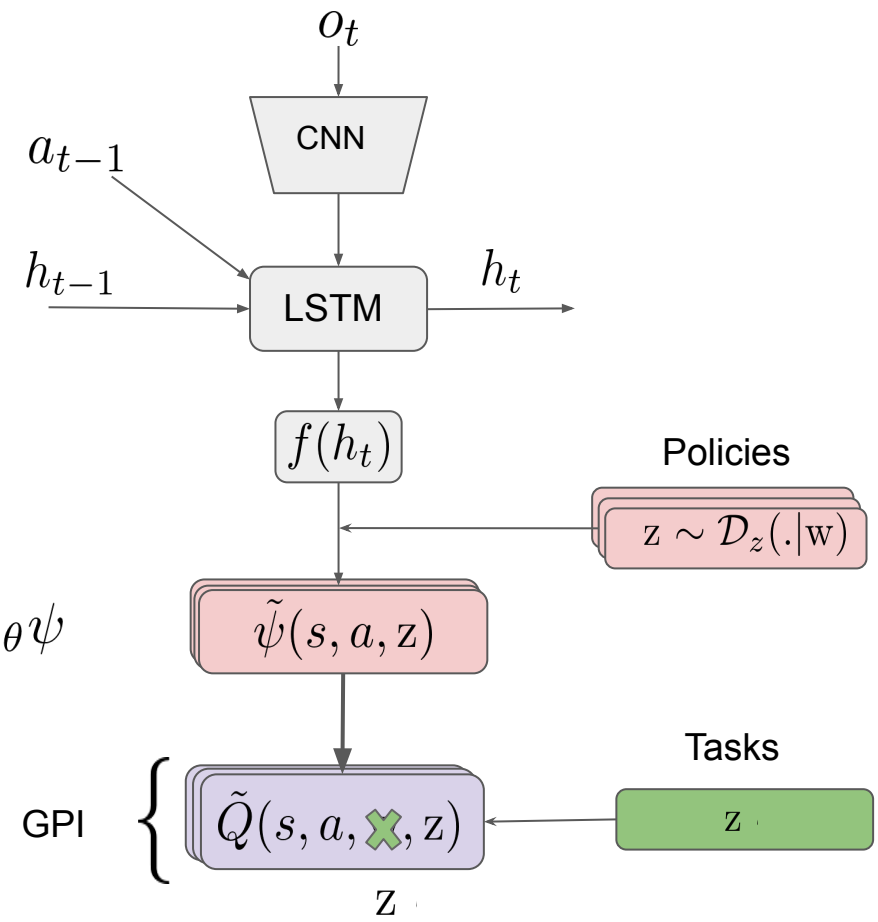
- Sample in policy space:

$$\mathrm{z} \sim \mathcal{D}_z(.|\mathrm{w})$$

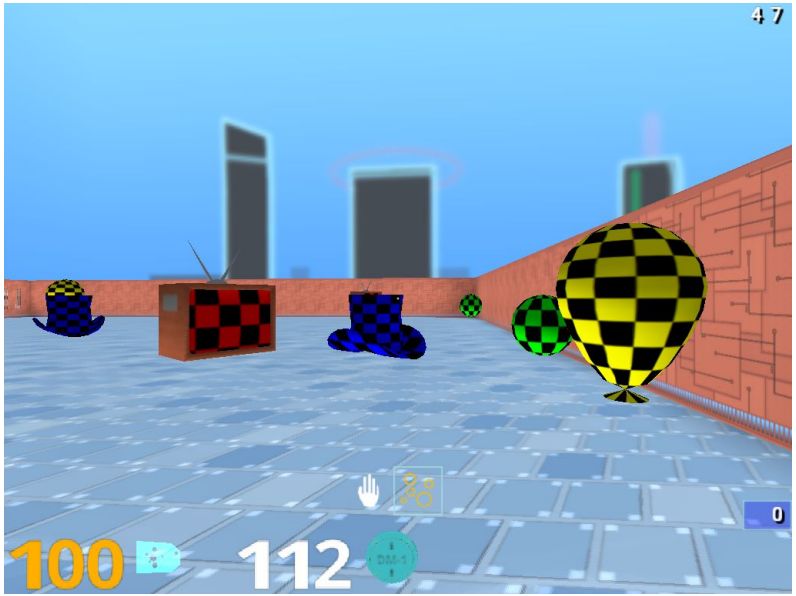
- **Pretend you're in task** z:

$$\theta \xleftarrow{\alpha} \left[\phi + \gamma\psi(s', \pi_{\mathbf{z}}, \mathbf{z}) - \psi(s, a, \mathbf{z})\right] \nabla_\theta \psi$$

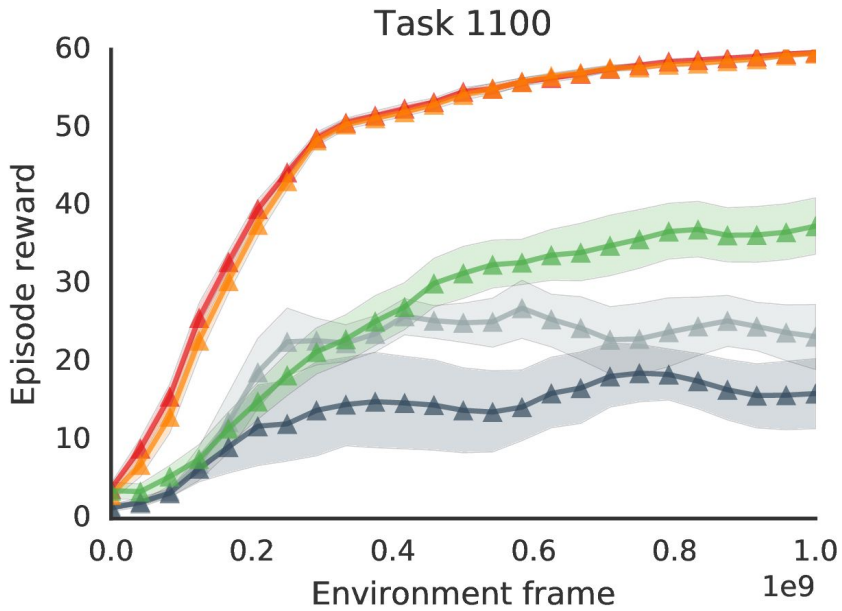
where: $\pi_{\mathbf{z}} = \arg\max_a Q_{\mathbf{z}}^{\pi_{\mathbf{z}}}$



Experiments: DMLab Treasure Island



Observation



UVFA
UVFA (offpolicy)
USFA (GPI over C = M + {w'})
USFA (GPI over C = M)
USFA (GPI over C = {w'})

Recap

Recap

- Successor representation
  - Future expected state visitations

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Problem:
Quickly evaluate **new** reward functions w.r.t. the **same** policy

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  - SR under the assumption of a linear reward decomposition

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Generalize in the space of value functions to **new** policies, rewards, etc

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- Different problems, different generalizations!
  - Parametric with UVFAs and SFs, RL with GPI

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What is an unseen example in RL?

Time

$$\mathcal{M} = (\mathcal{X}, \mathcal{A}, p, r, \gamma)$$

$$v^{\pi} | \pi, \mathcal{M}$$

$$\pi^{*} | \mathcal{M}$$

Observations
- Auxiliary tasks
- Distributional RL

Rewards
- Successor features

Anything
- Meta-RL
- Hierarchies

Dynamics
- Max entropy RL
- Empowerment

Policies
- UVFAs
- USFAs

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Takeaways

- Lots of **things** to generalize over in RL
  - Observations, rewards, policies, transitions, time, ...
- Lots of different **ways** to generalize with in deep RL
  - Pure parametric (like most ML), structured parametric, online recomposition using the structure of the RL problem, meta learning
- Always a tradeoff between **expressivity** and **sample complexity**
  - Related to the bitter lesson
  - Remain as general as possible, while keeping the structure of problem in mind
- The solutions might change, the problems are less likely to

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"Everything's exciting, nothing is solved!"

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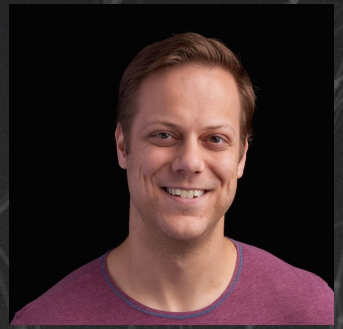



Thank you for your attention!

Questions?

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