CS294-158 Deep Unsupervised Learning

Lecture 12: Representation Learning in Reinforcement Learning

Pieter Abbeel, Xi (Peter) Chen, Jonathan Ho, Aravind Srinivas, Alex Li, Wilson Yan

UC Berkeley

Acknowledgements

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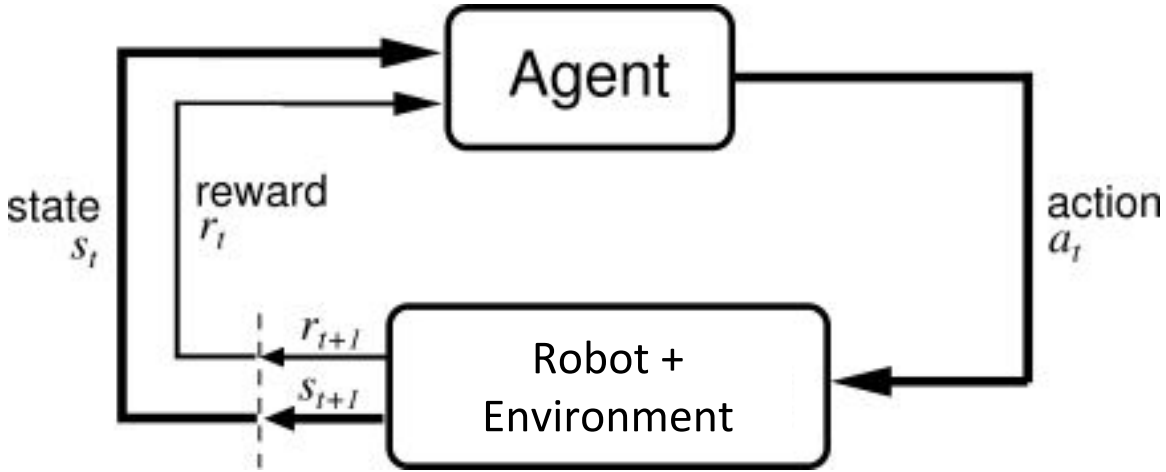
for sharing their insights, illustrations, slides, videos for this lecture

Reinforcement Learning (RL)

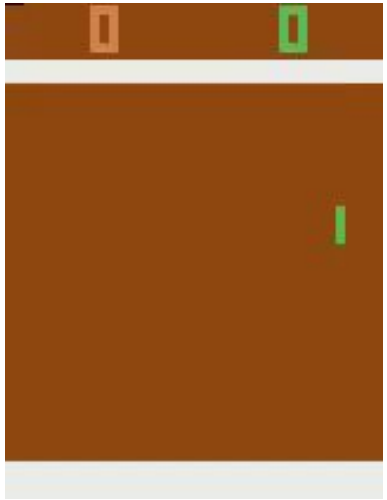


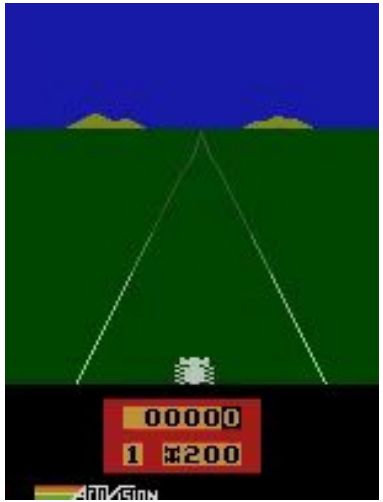
$$\max_{\theta} \quad \mathrm{E}[\sum_{t=0}^{H} R(s_t)|\pi_\theta]$$

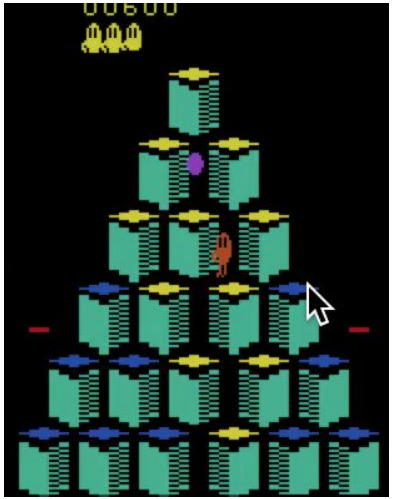
[Image credit: Sutton and Barto 1998]

- **Compared to supervised learning, additional challenges:**
  - **Credit assignment**
  - **Stability**
  - **Exploration**

Deep RL Succes: Atari







DQN Mnih et al, NIPS 2013 / Nature 2015

MCTS Guo et al, NIPS 2014; **TRPO** Schulman, Levine, Moritz, Jordan, Abbeel, ICML 2015; **A3C** Mnih et al, ICML 2016; **Dueling DQN** Wang et al ICML 2016; **Double DQN** van Hasselt et al, AAAI 2016; **Prioritized Experience Replay** Schaul et al, ICLR 2016; **Bootstrapped DQN** Osband et al, 2016; **Q-Ensembles** Chen et al, 2017; **Rainbow** Hessel et al, 2017; **Accelerated** Stooke and Abbeel, 2018; …

Deep RL Success: Go

AlphaGo Silver et al, Nature 2015

AlphaGoZero Silver et al, Nature 2017

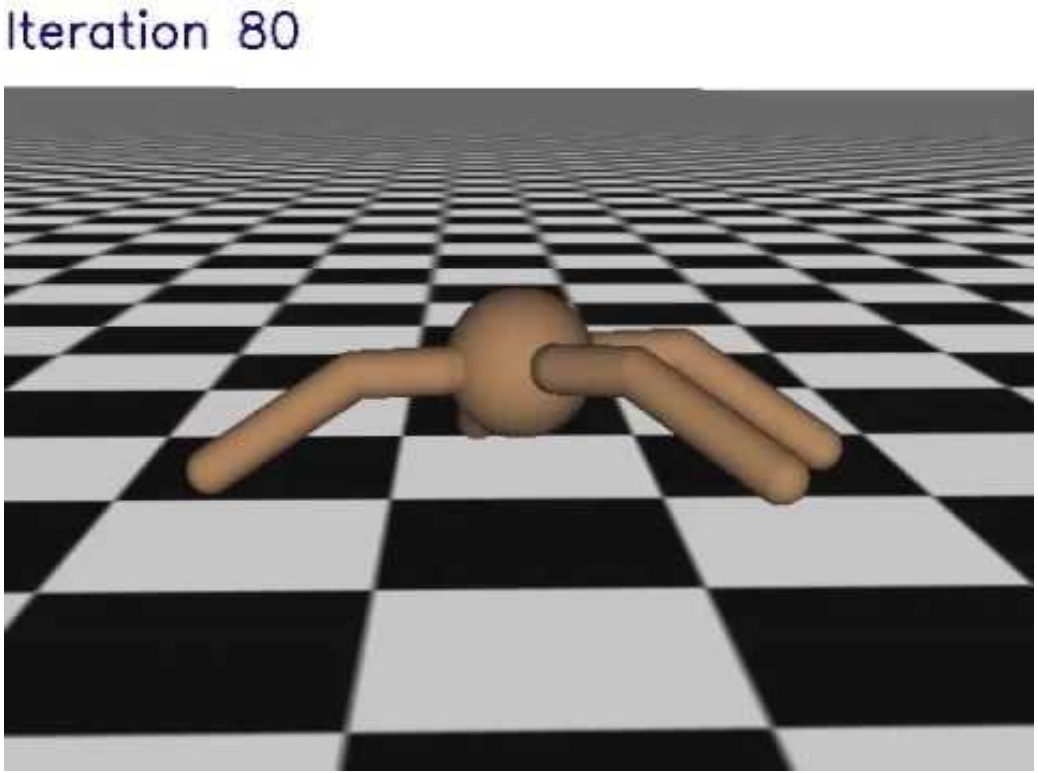
AlphaZero Silver et al, 2017

Tian et al, 2016; Maddison et al, 2014; Clark et al, 2015

OpenAI's 1v1 Dota [2017] and 5v5 [2018, 2019]

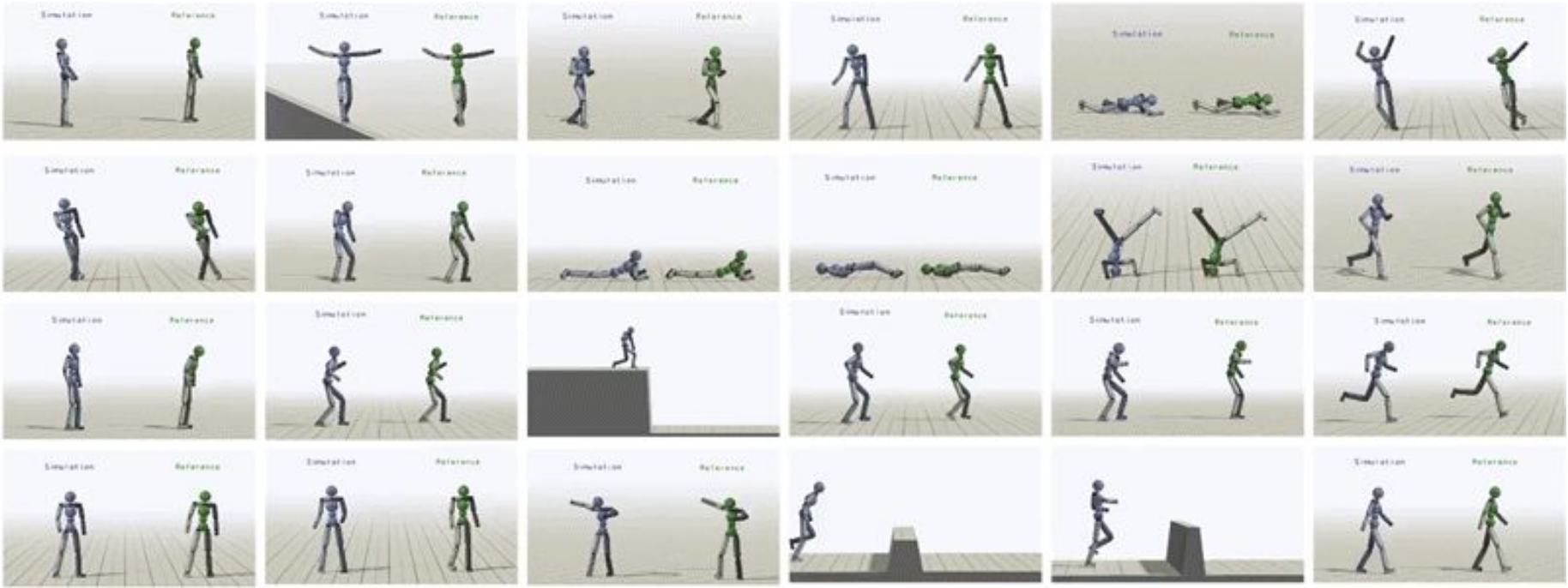
- Super-human agent on a competitive game, enabled by
  - Reinforcement learning
  - Self-play
  - Enough computation
- Cooperation emerges

Deep RL Success: Locomotion



TRPO Schulman, Levine, Moritz, Jordan, Abbeel, 2015 + **GAE** Schulman, Moritz, Levine, Jordan Abbeel, 2016

Deep RL Success: Locomotion



DeepMimic, Peng, Abbeel, Levine, van de Panne 2018

Deep RL Success: Robotic Manipulation

Guided Policy Search, Levine*, Finn*, Darrell, Abbeel, 2016

Catch?

Data inefficiency

Representation Learning in Reinforcement Learning

- Auxiliary losses
- State representation
- Exploration
- Unsupervised skill discovery

Representation Learning in Reinforcement Learning

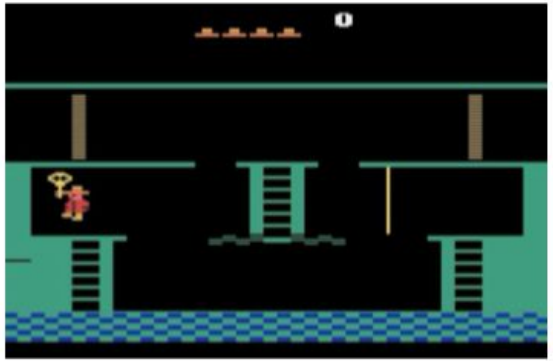
- ***Auxiliary losses***
- State representation
- Exploration
- Unsupervised skill discovery

Reinforcement Learning with Unsupervised Auxiliary Tasks

Max Jaderberg*, Volodymyr Mnih*, Wojciech Marian Czarnecki*,
Tom Schaul, Joel Z Leibo, David Silver, Koray Kavukcuoglu

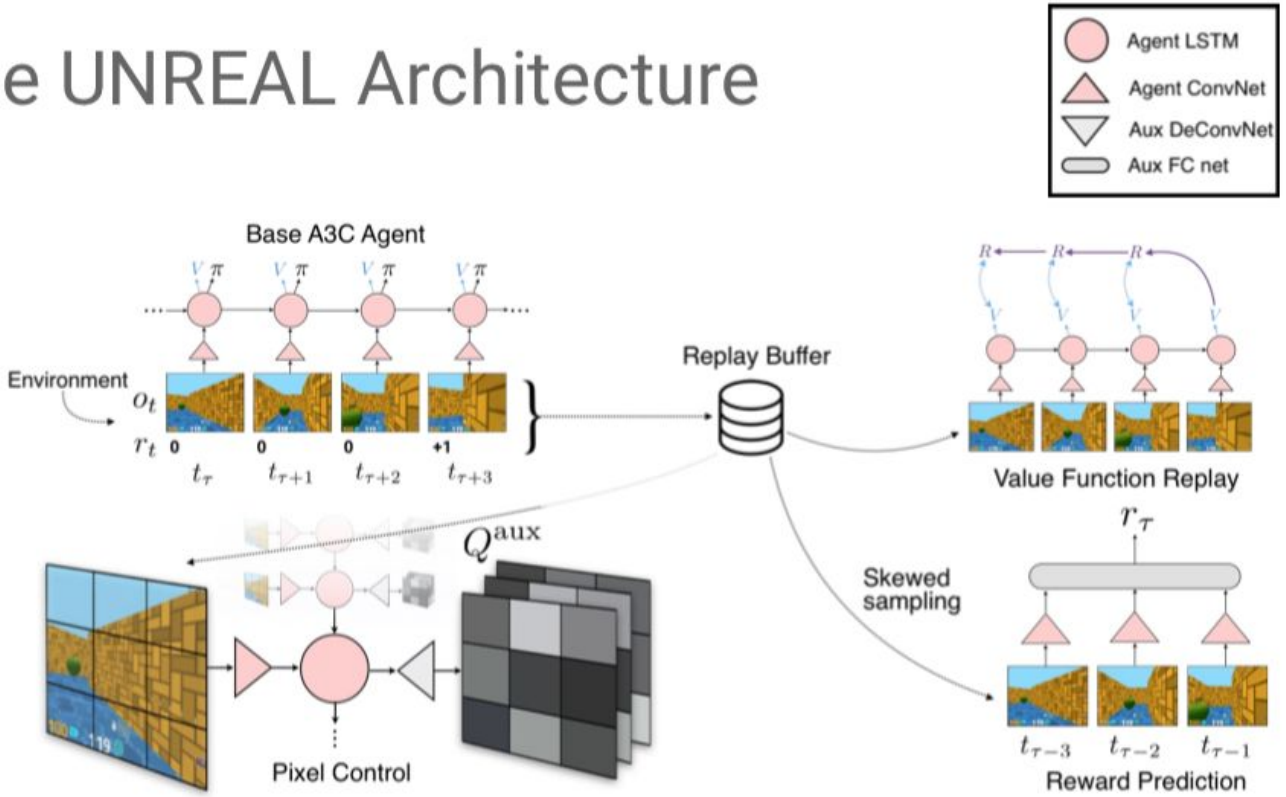
Overview

- Problem - Deep reinforcement learning can be very data hungry. Especially with **sparse rewards**.
- This paper - Augment an RL agent with **auxiliary prediction and control tasks**.
- The UNREAL agent - UNsupervised REinforcement and Auxiliary Learning:
    - **10x improvement in data efficiency** over A3C on 3D DeepMind Lab environments.
    - **60% improvement in final scores** over A3C.



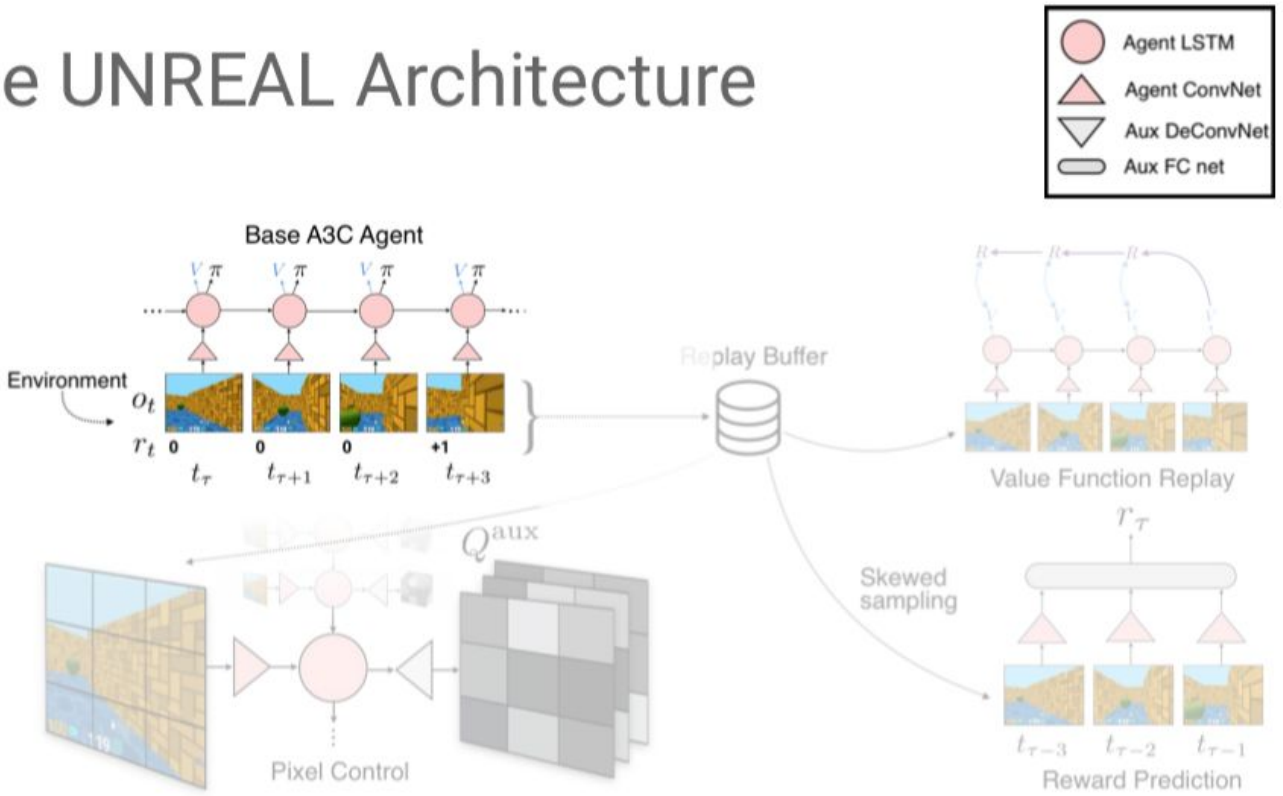
The UNREAL Architecture

- UNREAL augments an LSTM A3C agent with 3 auxiliary tasks.
- Can be used on top of DQN, DDPG, TRPO or other agents.



The UNREAL Architecture

- Base A3C LSTM agent learns from the environment's scalar reward signal.
- UNREAL acts using the base A3C agent's policy.



Sparse Rewards?

Single scalar reward signal

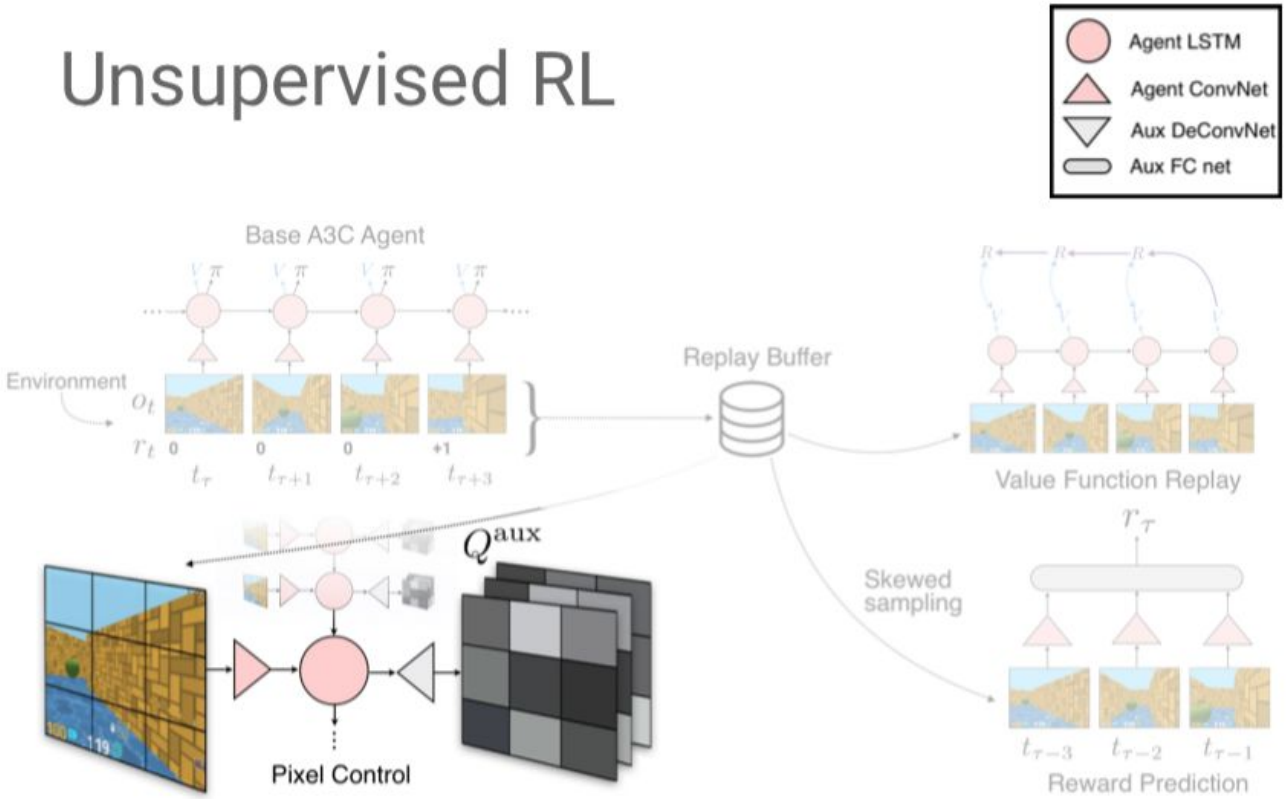
Sparse Rewards? More Cherries!

Single scalar reward signal

Many reward signals

Unsupervised RL

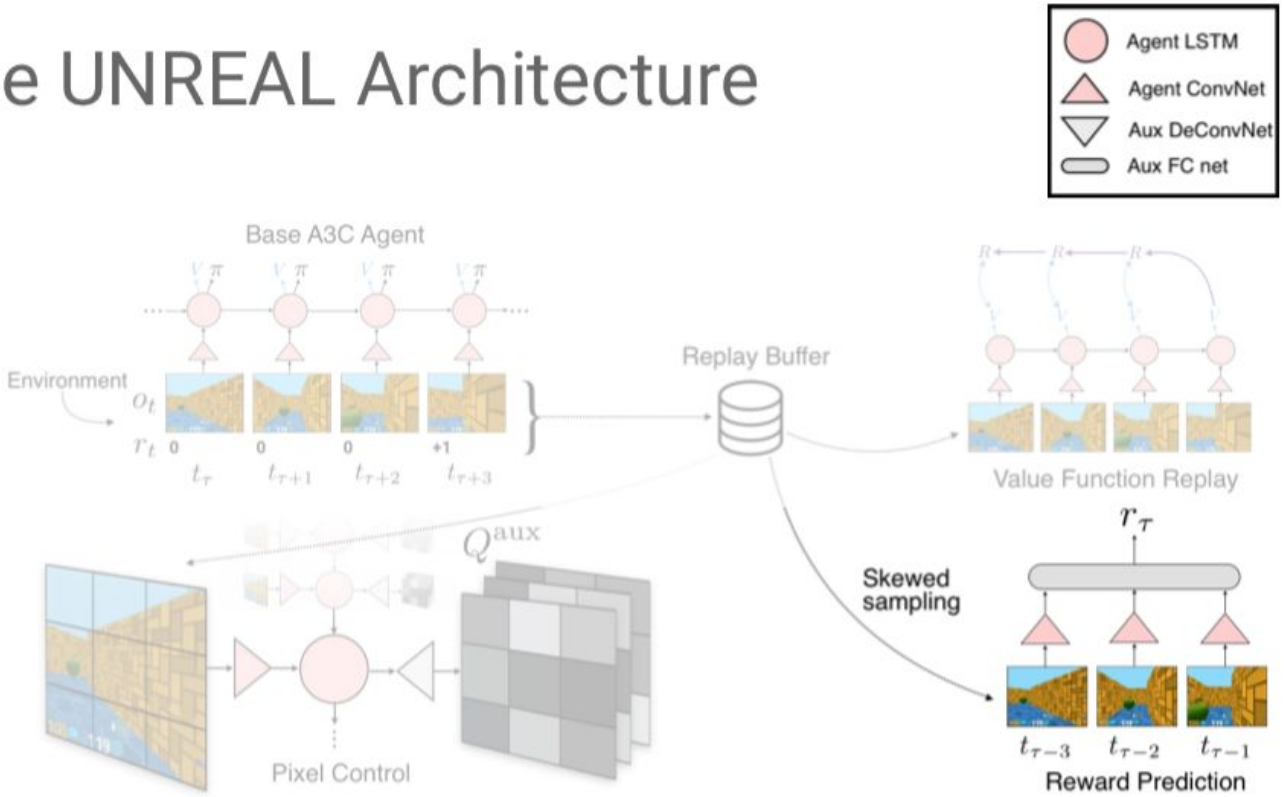
- Augment A3C with many **auxiliary control tasks**.
- Learning to control many aspects of the environment.
- Pixel control - learn to maximally change parts of the screen.
- Feature control (not used by UNREAL) - learn to control the internal representations.



The UNREAL Architecture

Focusing on rewards:

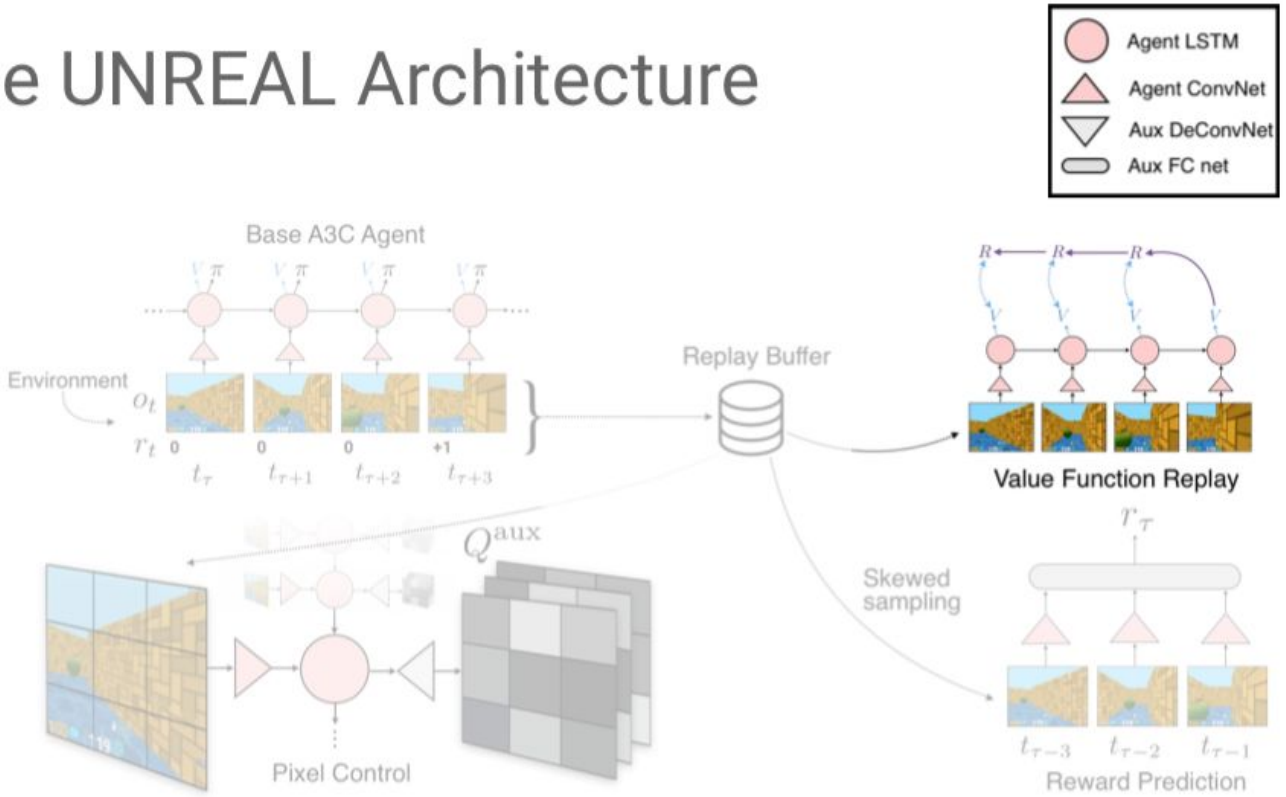
- Rebalanced reward prediction.
- Shape the agent's CNN by classifying whether a sequence of frames will lead to reward.
- No need to worry about off-policy learning.



The UNREAL Architecture

Focusing on rewards:

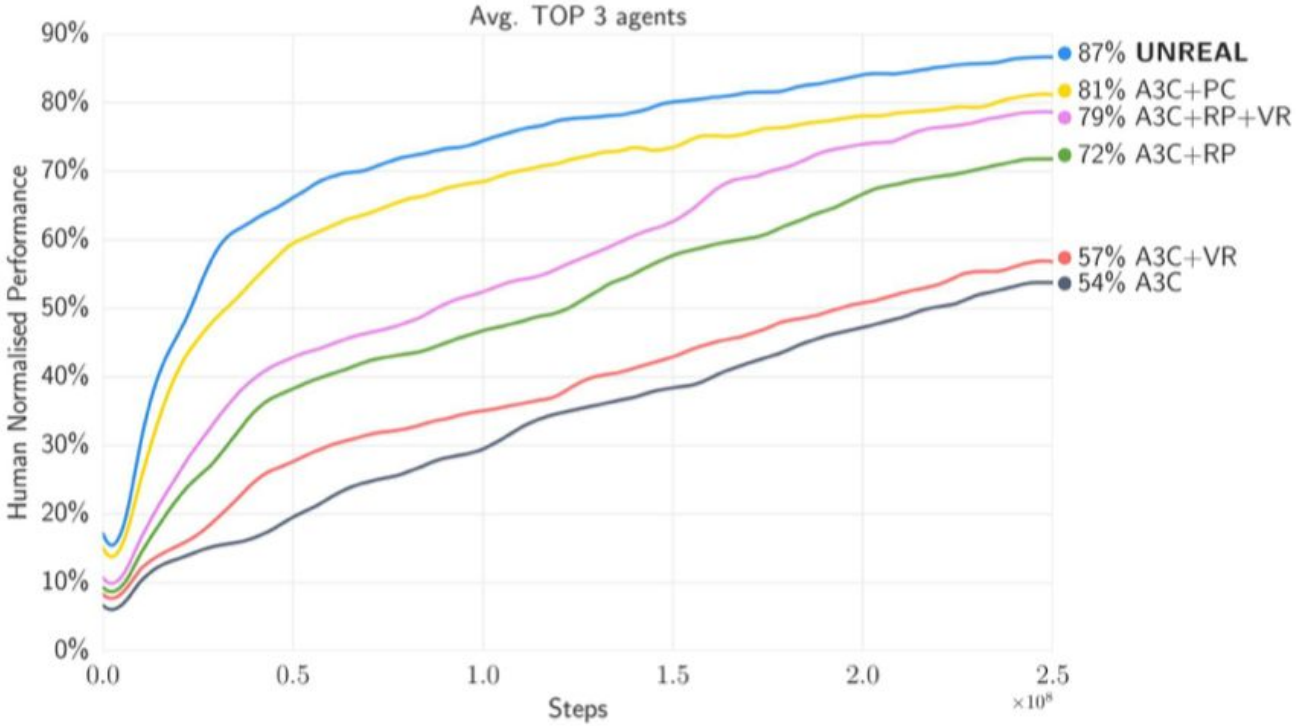
- Value function replay.
- Faster learning of the value function.



DeepMind Lab

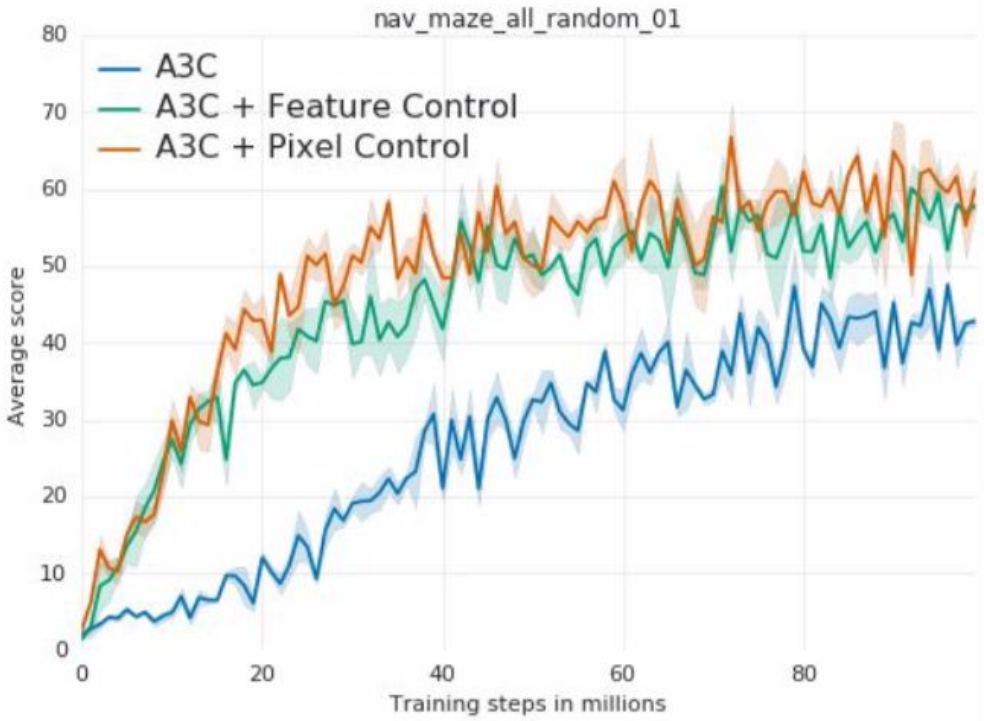
Results

- 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.

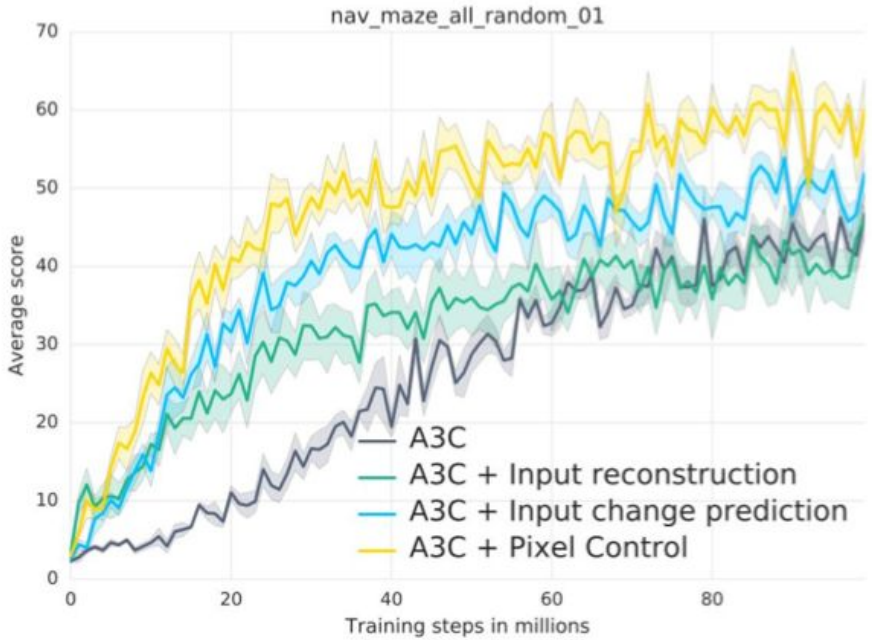


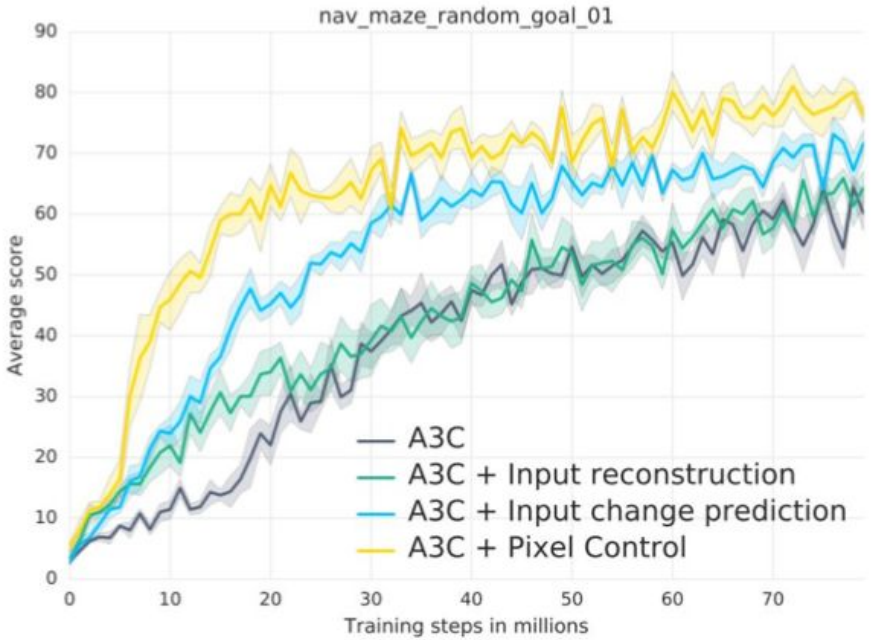
DeepMind

Feature Control



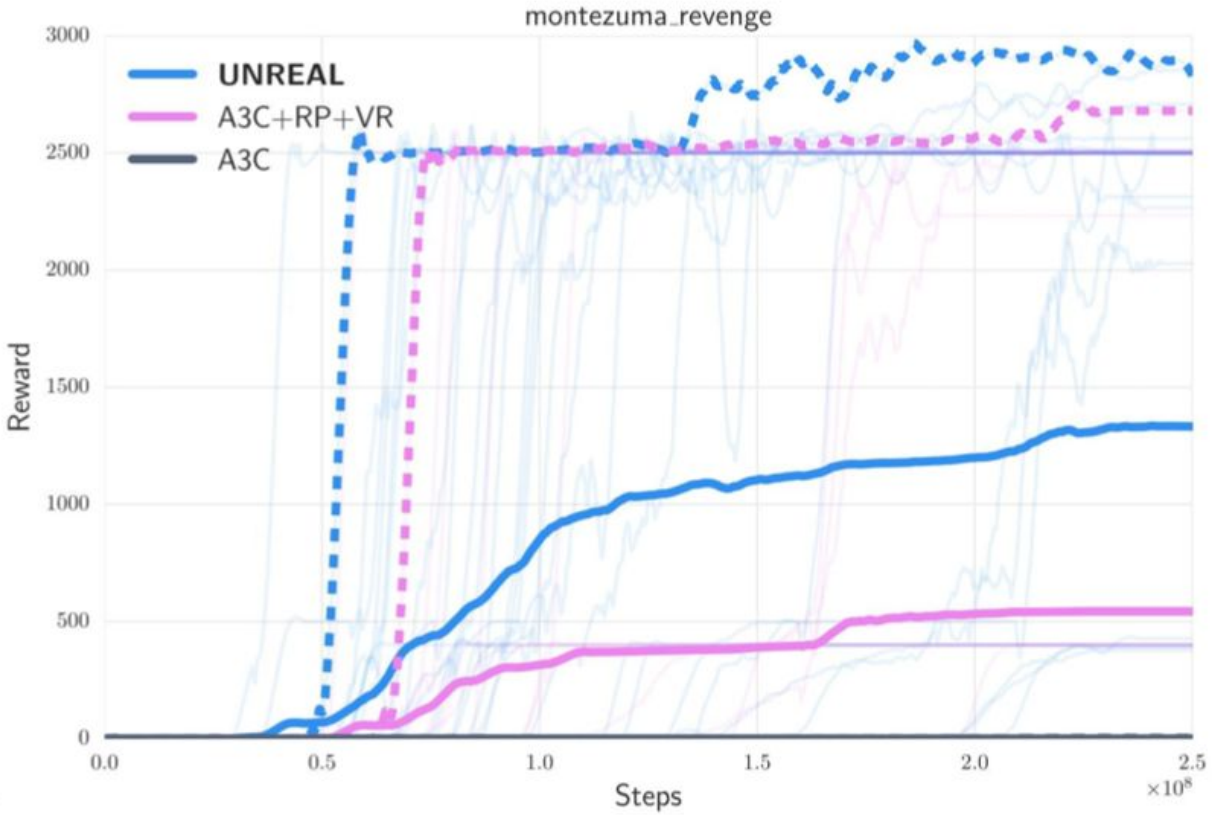
Unsupervised RL Baselines





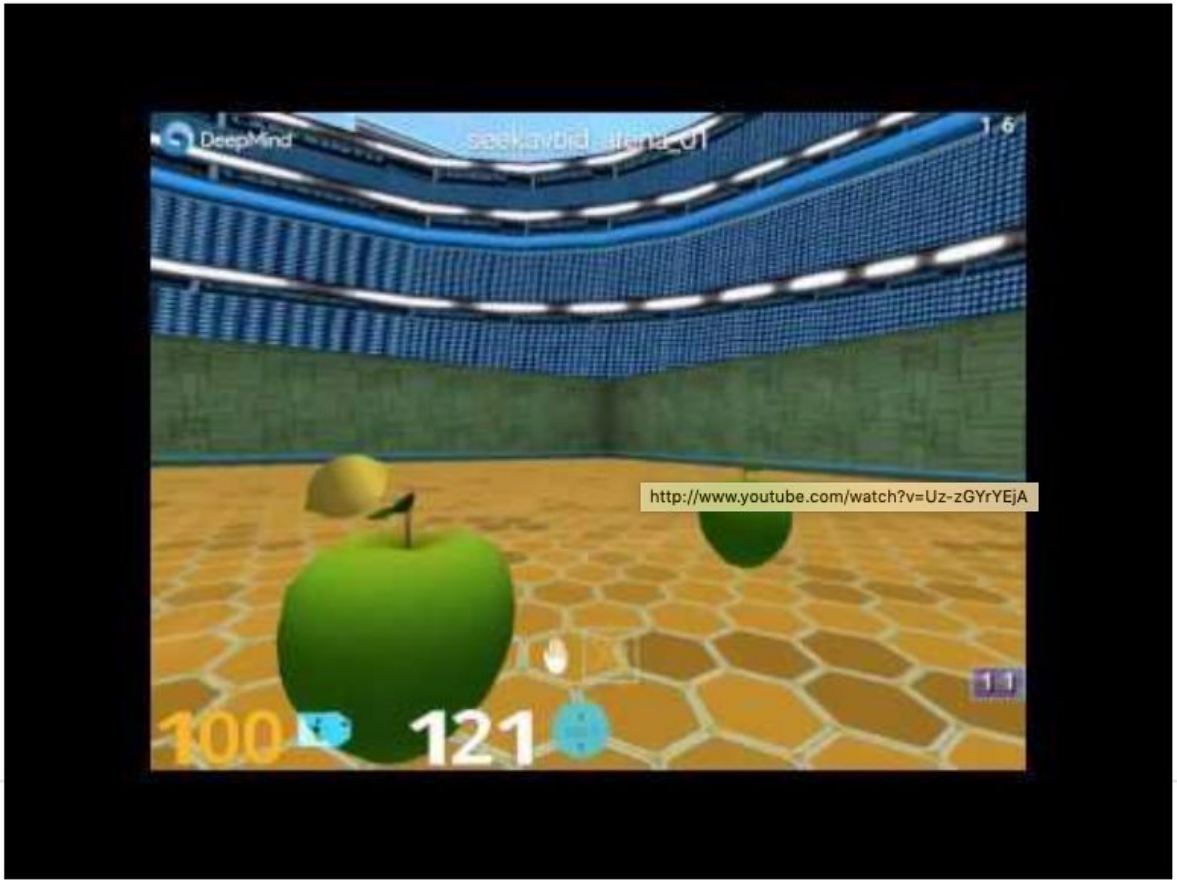
DeepMind

Montezuma's Revenge



DeepMind

UNREAL playing DeepMind Lab




DeepMind
1.6
100
121

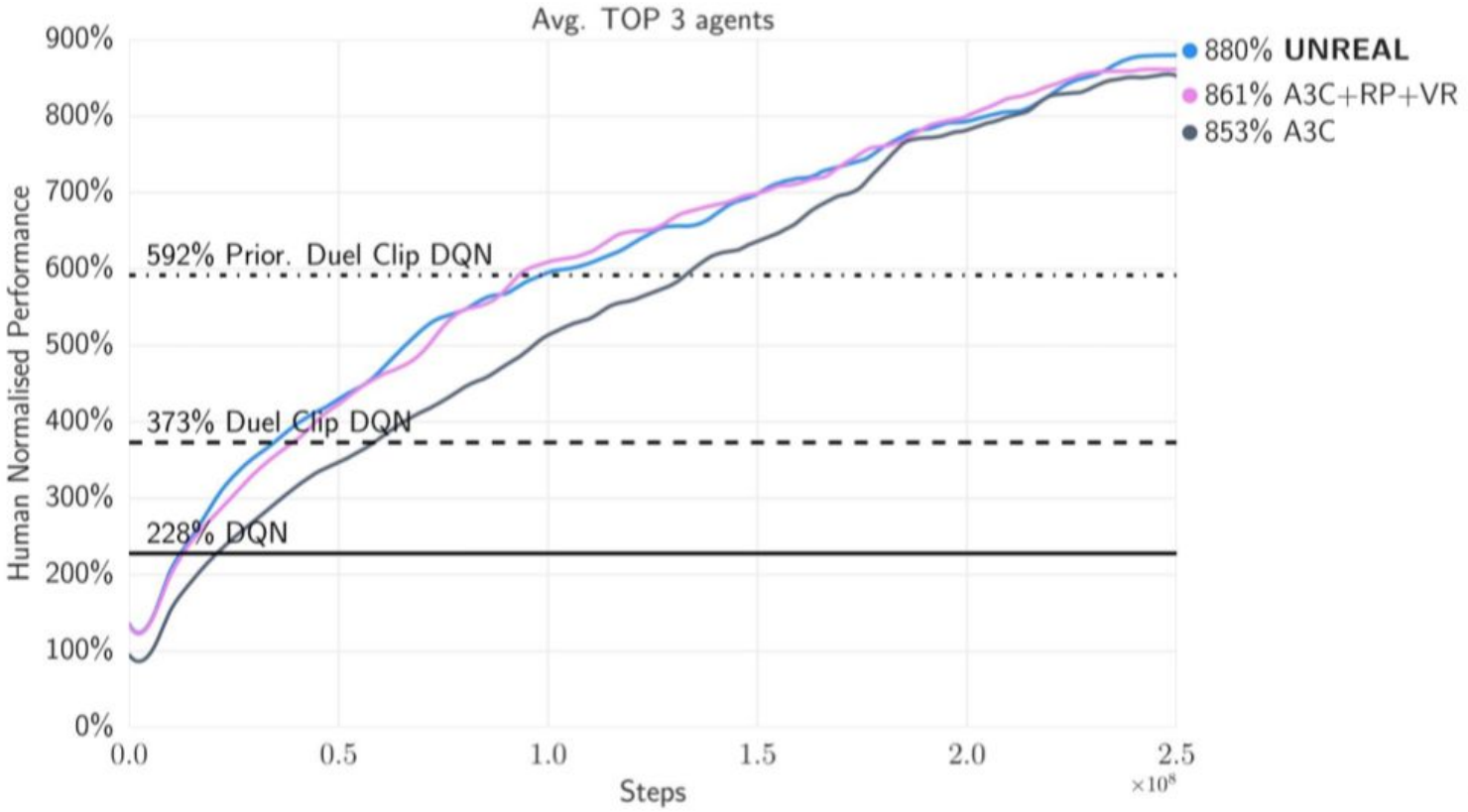
The UNREAL Loss

- The UNREAL loss is defined as:

$$\mathcal{L}_{UNREAL}(\theta) = \mathcal{L}_{\text{A3C}} + \lambda_{\text{VR}}\mathcal{L}_{\text{VR}} + \lambda_{\text{PC}} \sum_{c} \mathcal{L}_{Q}^{(c)} + \lambda_{\text{RP}}\mathcal{L}_{\text{RP}}$$

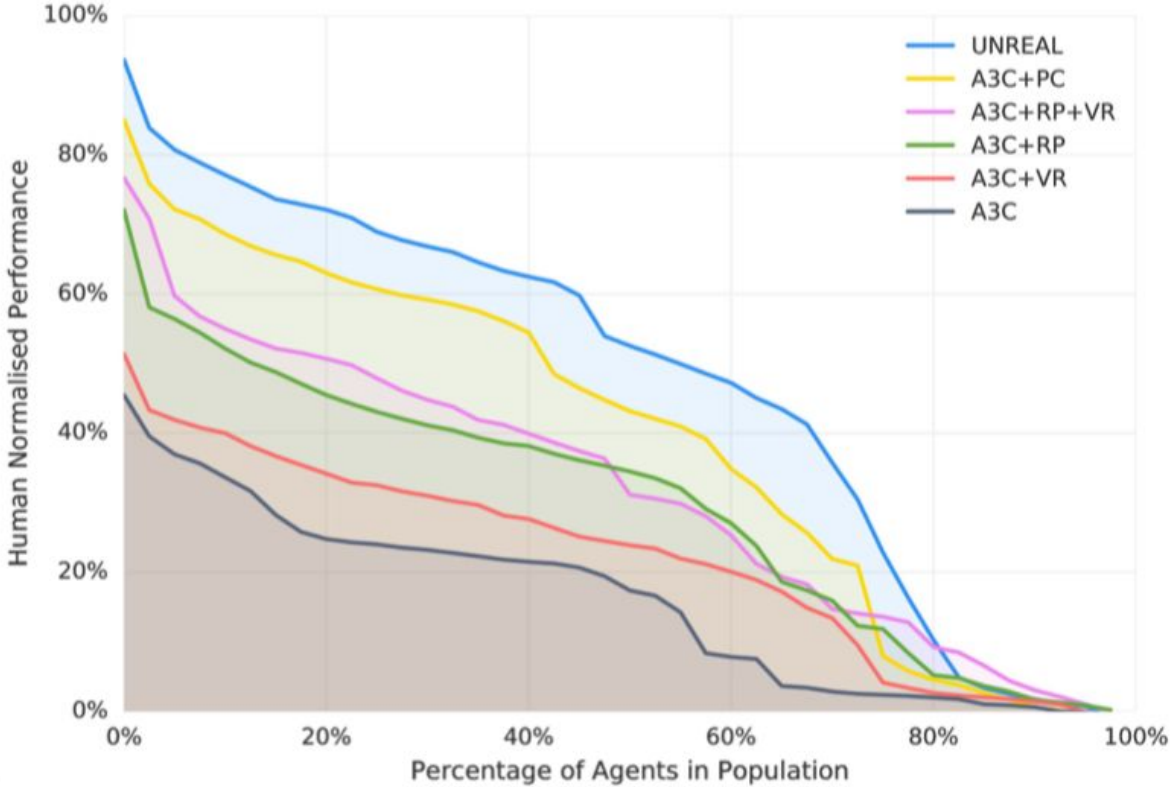
- Reward prediction:
  - Equal proportion of rewarding and non-rewarding examples.
- Pixel control:
  - Divide screen into a 20x20 grid of cells.
  - Use n-step Q-learning to learn a policy to maximally change each cell.
  - Use a deconvolutional network to predict the Ax20x20 tensor of Q-values.

Atari Results



DeepMind

Labyrinth Robustness



DeepMind

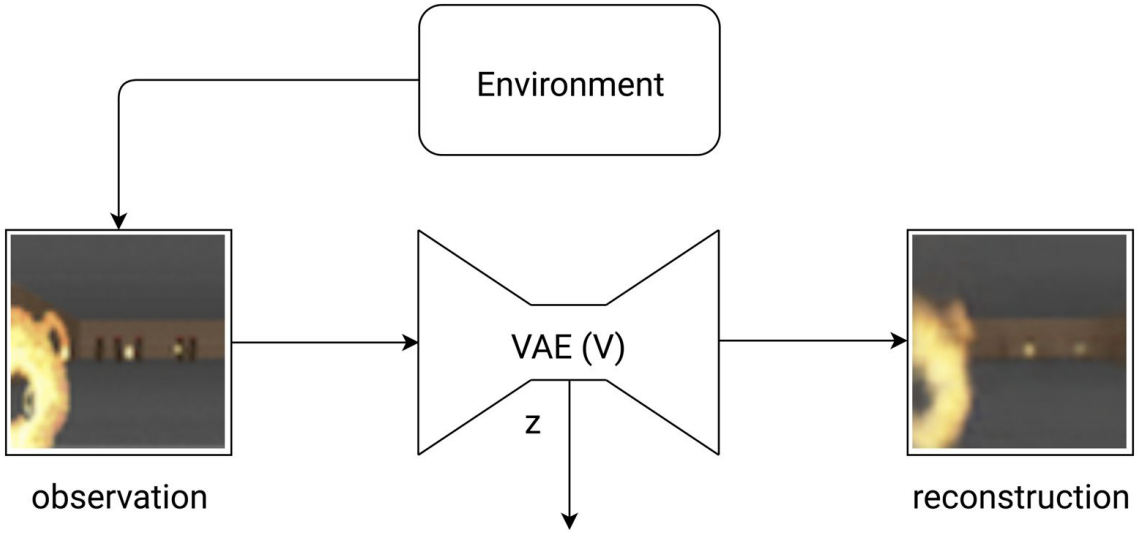
Representation Learning in Reinforcement Learning

- Auxiliary losses
- ***State representation***
- Exploration
- Unsupervised skill discovery

Representation Learning in Reinforcement Learning

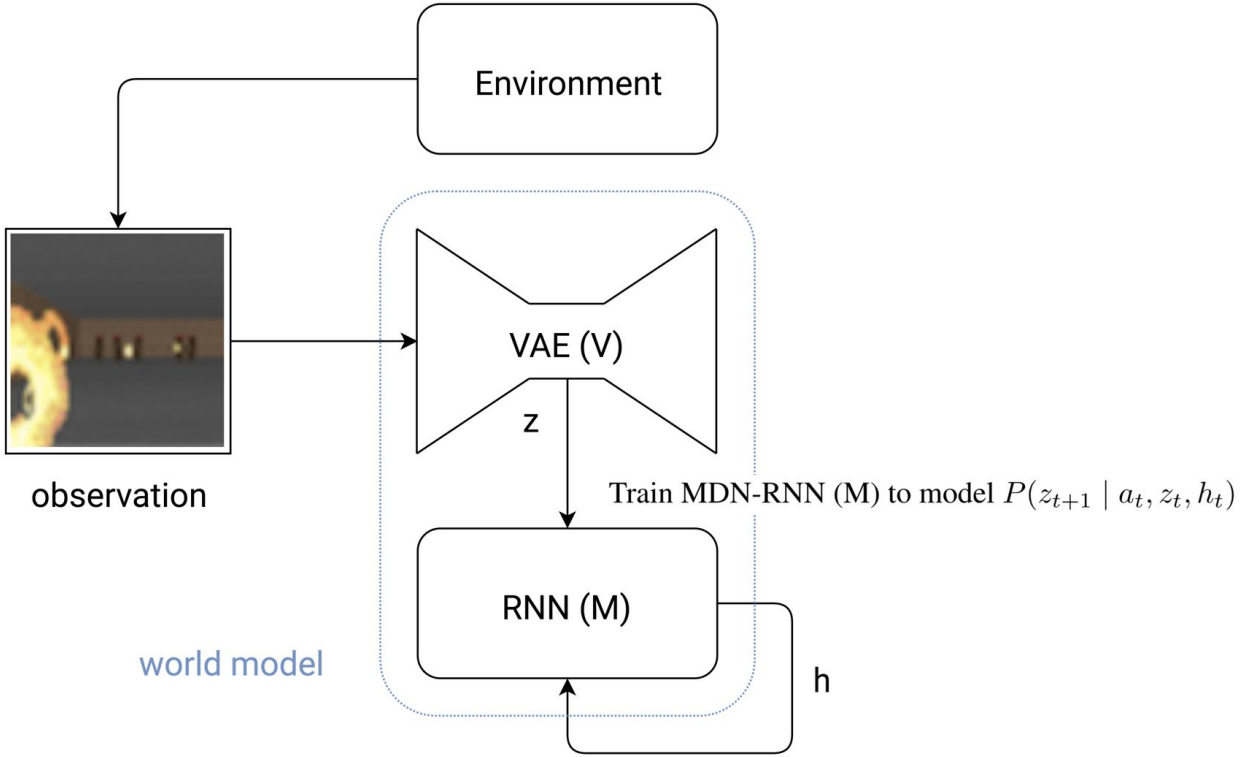
- Auxiliary losses
- ***State representation***
  - ***Observation -> State***
- Exploration
- Unsupervised skill discovery

World Models

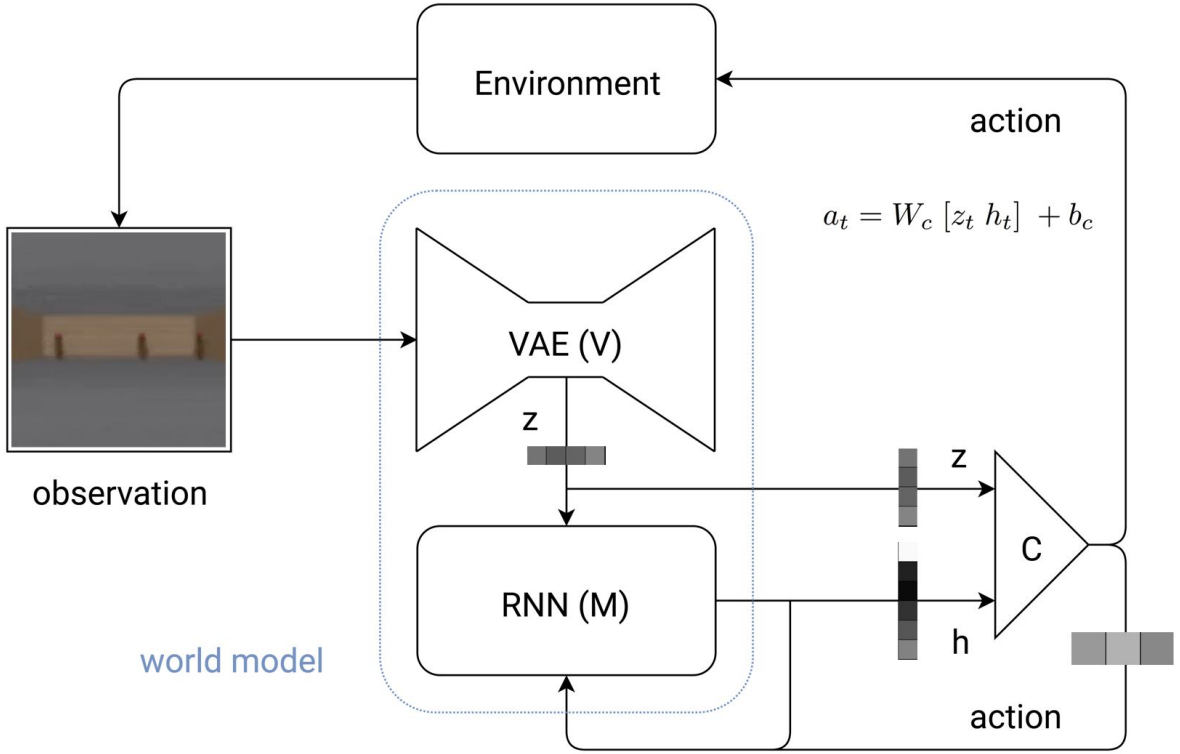


Train VAE (V) to encode frames into z

World Models

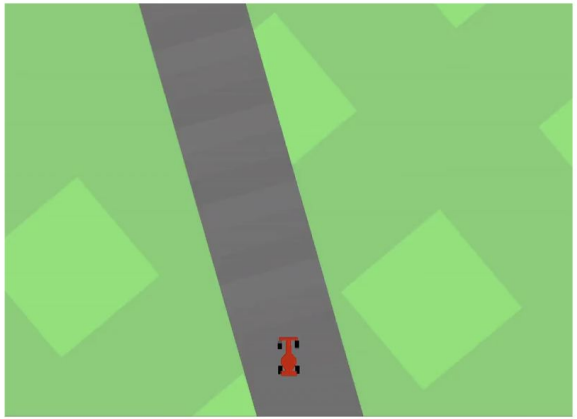


World Models



World Models

CarRacing-v0



- Randomly generated tracks
- Stay on tiles, travel around track
- Average Score > 900 (100 trials) to “solve” task

Procedure:

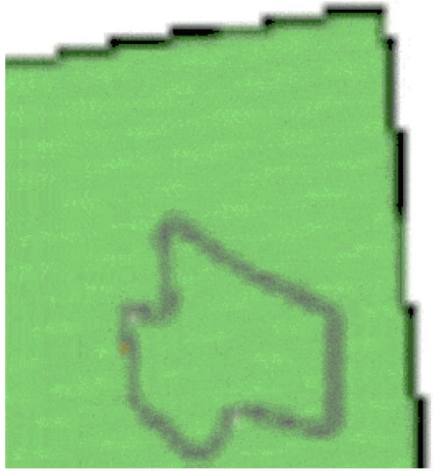
1. Collect 10,000 rollouts from a random policy.
2. Train VAE (V) to encode frames into $z \in \mathcal{R}^{32}$.
3. Train MDN-RNN (M) to model $P(z_{t+1} \mid a_t, z_t, h_t)$.
4. Evolve linear controller (C) to maximize the expected cumulative reward of a rollout. $a_t = W_c \, [z_t \; h_t] \; + b_c$

Model	Parameter Count
VAE	4,348,547
MDN-RNN	422,368
Controller	867

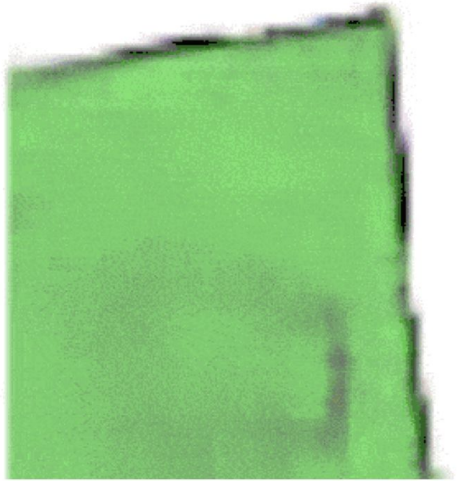
Source: Taste of Home (www.tasteofhome.com)

World Models

Input Frame (64x64px)

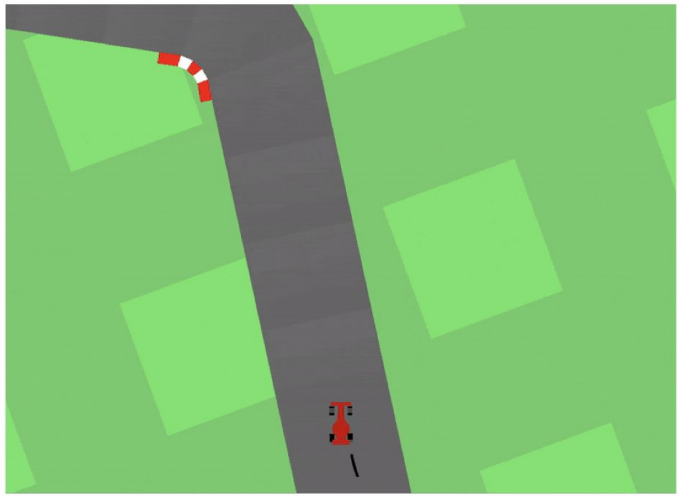


Frame Reconstruction using z

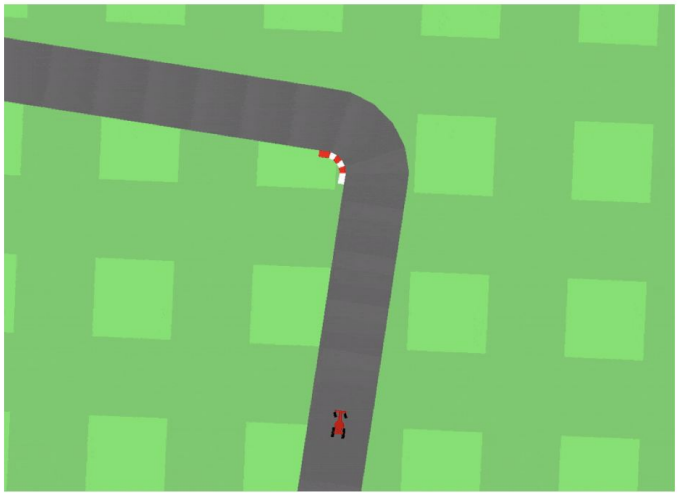


World Models

Car Racing: Spatial Inputs vs Spatial and Temporal Inputs



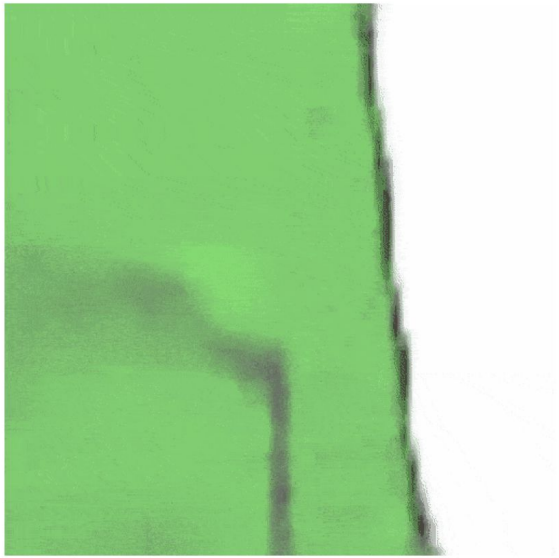
z (spatial) only input



z and h (RNN's hidden state) as inputs

World Models

CarRacing-v0 Results



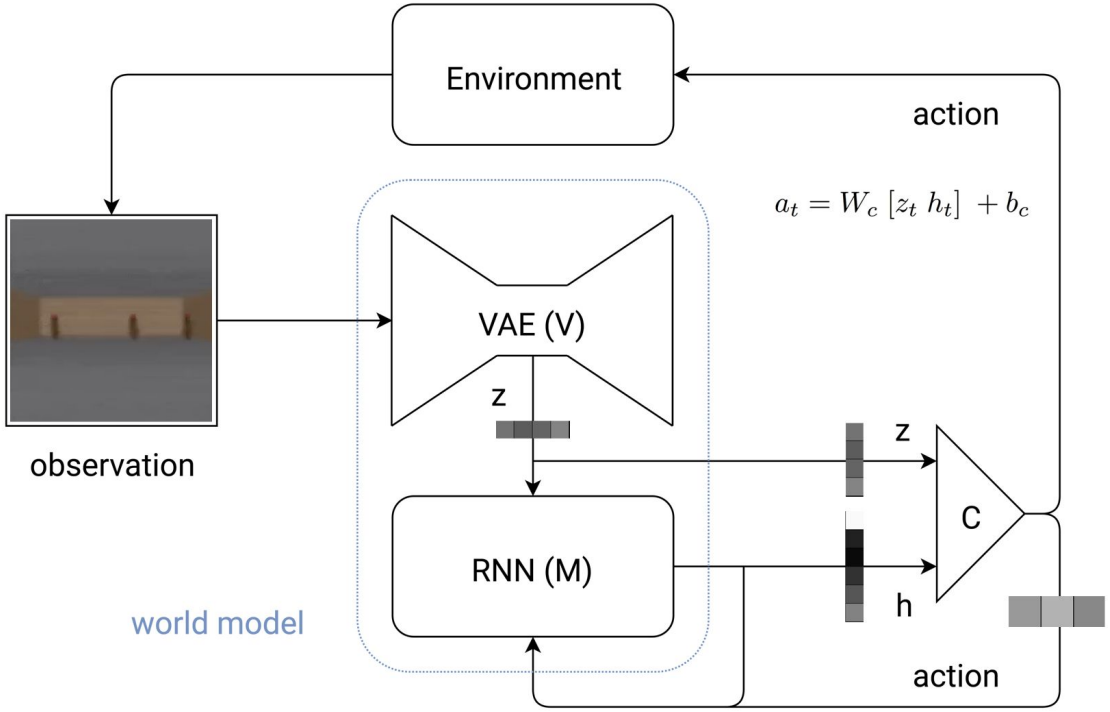
METHOD	AVG. SCORE
DQN (PRIEUR, 2017)	343 ± 18
A3C (CONTINUOUS) (JANG ET AL., 2017)	591 ± 45
A3C (DISCRETE) (KHAN & ELIBOL, 2016)	652 ± 10
CEOBILLIONAIRE (GYM LEADERBOARD)	838 ± 11
V MODEL	632 ± 251
V MODEL WITH HIDDEN LAYER	788 ± 141
FULL WORLD MODEL	$\mathbf{906 \pm 21}$

`CarRacing-v0` scores achieved using various methods.

METHOD	AVG. SCORE
RANDOM WEIGHTS FOR RNN M (TALLEC ET AL., 2018)	870 ± 120
3-LAYER DQN W/ DROPOUT, CURRICULUM LEARNING (GERBER ET AL., 2018)	$900 \pm ?$

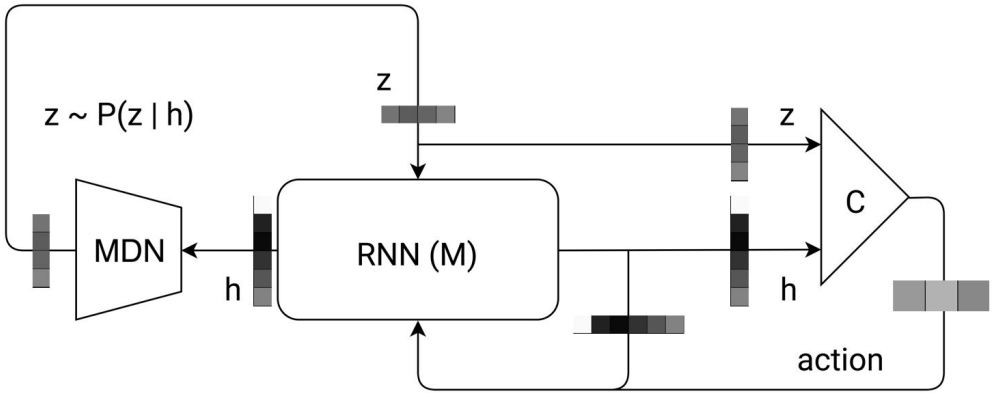
`CarRacing-v0` scores achieved using newer methods.

World Models



World Models

Train controller inside latent space environment.



World Models

DoomTakeCover-v0

Procedure:

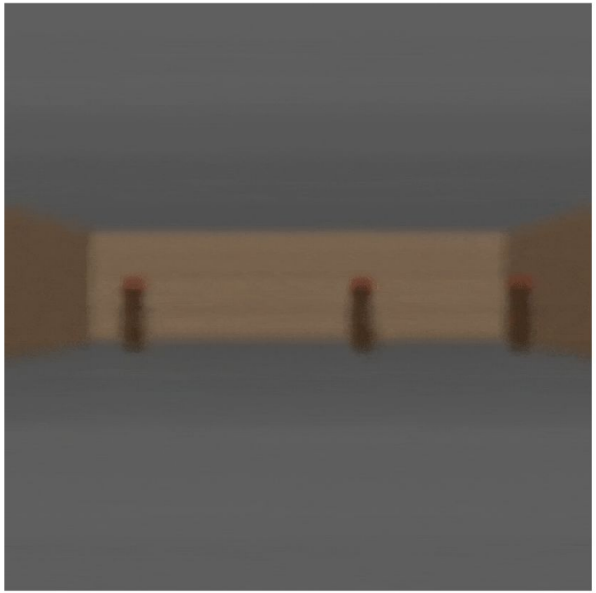
1. Collect 10,000 rollouts from a random policy.
2. Train VAE (V) to encode frames into $z \in \mathcal{R}^{64}$.
3. Train MDN-RNN (M) to model $P(z_{t+1}, d_{t+1} \mid a_t, z_t, h_t)$.
4. Evolve linear controller (C) to maximize the expected cumulative reward of a rollout.
5. Deploy learned policy from (4) on actual environment.

Model	Parameter Count
VAE	4,446,915
MDN-RNN	1,678,785
Controller	1,088

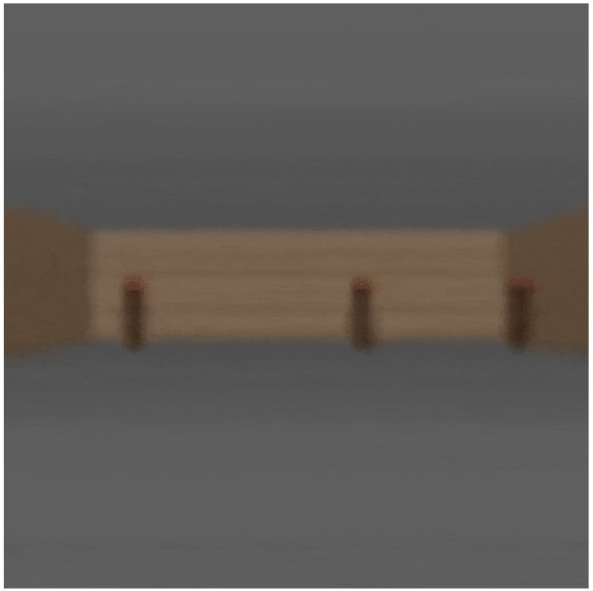
- Avoid fireballs from monsters
- Stay alive for as long as possible
- Average Score > 750 time steps (100 trials) to “solve” task

World Models

Doom TakeCover: Cheating the World Model



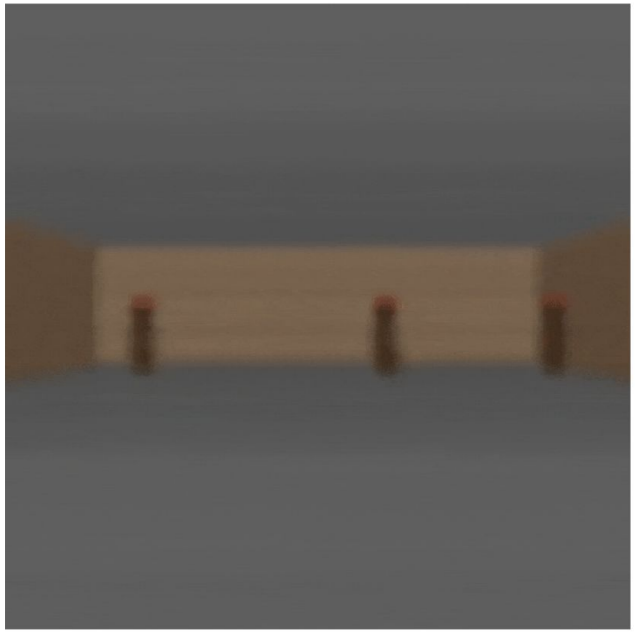
Normal Temperature



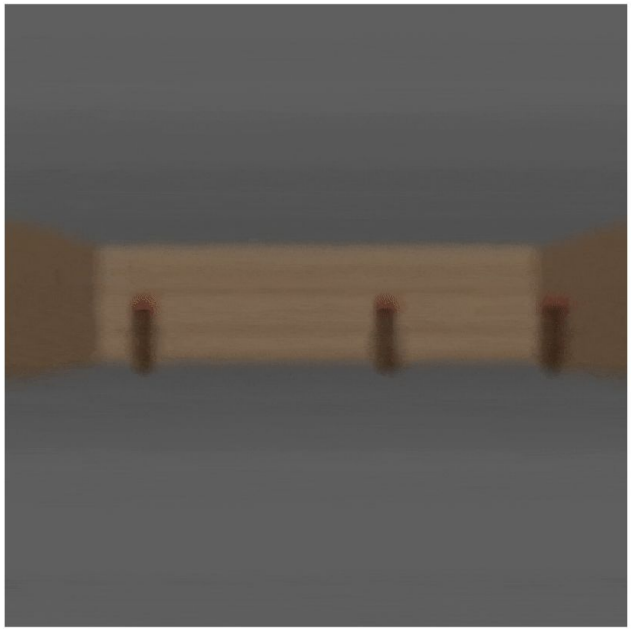
Higher Temperature

World Models

Doom TakeCover: Cheating the World Model



Normal Temperature



Higher Temperature

World Models

DoomTakeCover-v0 Results

Temperature τ	Virtual Score	Actual Score
0.10	2086 ± 140	193 ± 58
0.50	2060 ± 277	196 ± 50
1.00	1145 ± 690	868 ± 511
1.15	918 ± 546	1092 ± 556
1.30	732 ± 269	753 ± 139
Random Policy	N/A	210 ± 108
Gym Leader	N/A	820 ± 58

`DoomTakeCover-v0` scores at various settings of τ.

- Agent learned actions to take advantage of flaws of virtual environment.
- Adjust temperature parameter in the sampling to control uncertainty.

World Models

Iterative Training Policy

Procedure:

1. Initialize M, C with random model parameters.
2. Rollout to actual environment N times. Save all actions a_t and observations x_t during rollouts to storage.
3. Train M to model $P(x_{t+1}, r_{t+1}, a_{t+1}, d_{t+1}|x_t, a_t, h_t)$ and train C to optimize expected rewards inside of M.
4. Go back to (2) if task has not been completed.

Iteration #1

World Models

Iterative Training Policy

Procedure:

1. Initialize M, C with random model parameters.
2. Rollout to actual environment N times. Save all actions a_t and observations x_t during rollouts to storage.
3. Train M to model $P(x_{t+1}, r_{t+1}, a_{t+1}, d_{t+1}|x_t, a_t, h_t)$ and train C to optimize expected rewards inside of M.
4. Go back to (2) if task has not been completed.

Iteration #20

World Models

Action-Conditional Video Prediction using Deep Networks in Atari Games (2015)

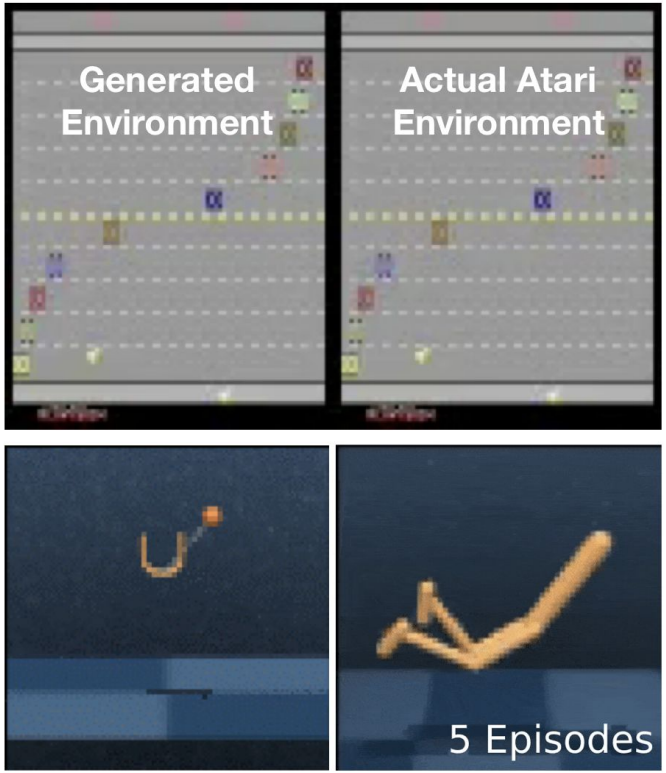
Junhyuk Oh, Xiaoxiao Guo, Honglak Lee, Richard Lewis and Satinder Singh

Model-Based Reinforcement Learning for Atari (2018)

Błażej Osiński, Łukasz Kaiser, Mohammad Babaeizadeh, George Tucker, Dumitru Erhan, Ryan Sepassi, Chelsea Finn, Sergey Levine, Piotr Kozakowski, Konrad Czechowski, Piotr Miłos and Henryk Michalewski

Learning Latent Dynamics for Planning from Pixels (2018)

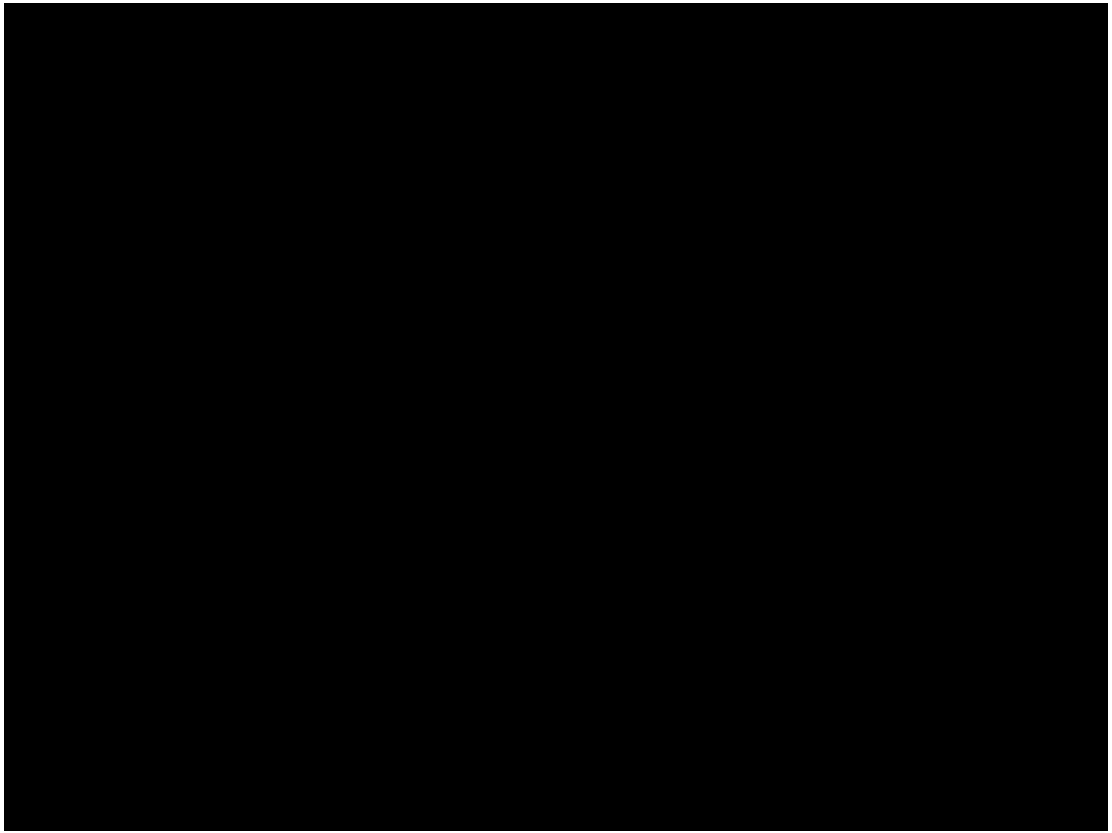
Danijar Hafner, Timothy Lillicrap, Ian Fischer, Ruben Villegas, David Ha, Honglak Lee and James Davidson



World Models

Code + Demo ⟶ https://worldmodels.github.io TensorFlow.js

World Models



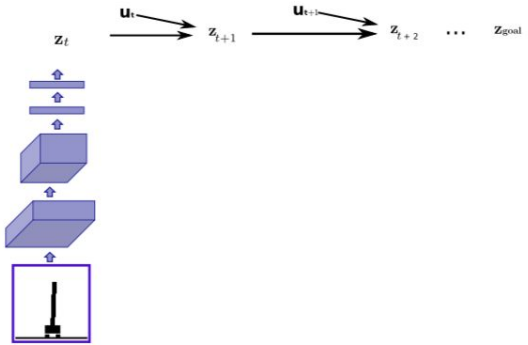
Representation Learning in Reinforcement Learning

- Auxiliary losses
- ***State representation***
  - ***Observation -> State***
  - ***Observation -> State + State,Action -> Next State***
- Exploration
- Unsupervised skill discovery

Embed to Control

Embed to Control: Model based RL from raw images

Can we perform model based RL starting from raw images ?
→ Standard algorithms would fail in pixel space
→ We want to **unsupervisedly** learn latent space $\mathbf{z}_t$ for control from images $\mathbf{x}_t$



Related attempts:

- [Lange et al.:Deep Learning of Visual Control Policies, 2010]
- [Wahlstroem et al.: From Pixels to Torques, 2015]

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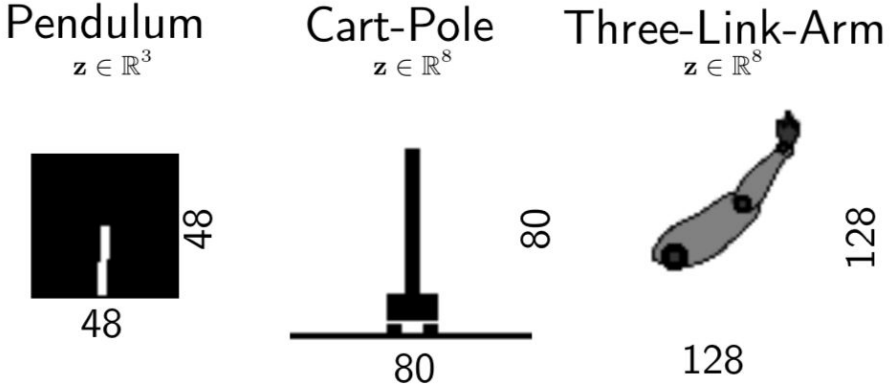
Systems we consider



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Ingredients

1. **Stochastic optimal control (SOC) in a latent space**
2. E2C latent state space model:
   - Variational autoencoder
   - Locally linear latent space model

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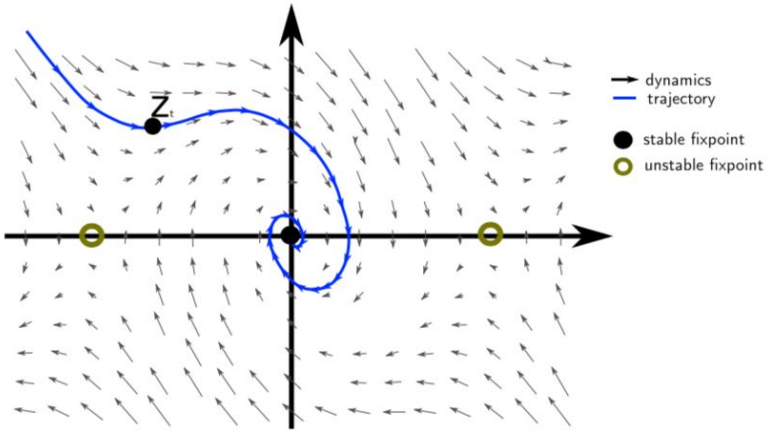
Embed to Control - Stochastic Optimal Control

- Local Gaussian $\mathbf{z}_t$, local **accurate** linearization of dynamics:



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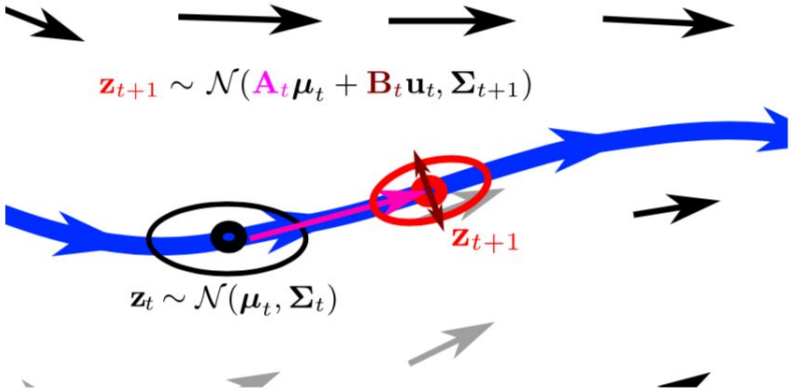
Embed to Control - Stochastic Optimal Control

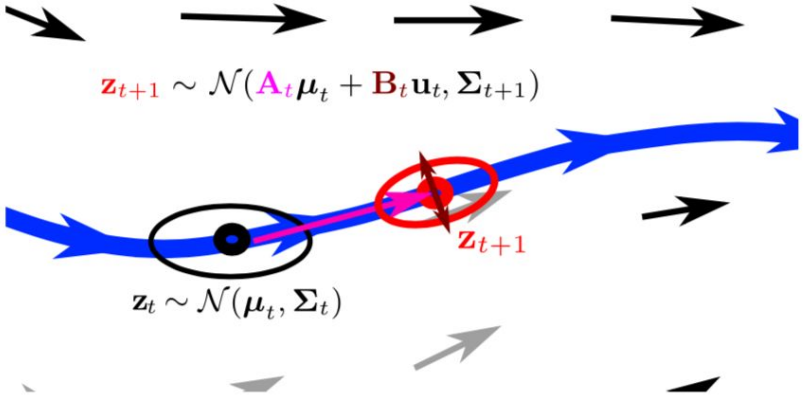
- Local Gaussian $\mathbf{z}_t$, local **accurate** linearization of dynamics:



Embed to Control

Embed to Control - Stochastic Optimal Control

- Local Gaussian $\mathbf{z}_t$, local **accurate** linearization of dynamics:



- assume the costs $c(\mathbf{z}_t, \mathbf{u}_t)$ are quadratic in $\mathbf{z}_t$

$\rightarrow$ locally optimal controls can be found (iLQR, AICO), if we can learn $\mathbf{z}$

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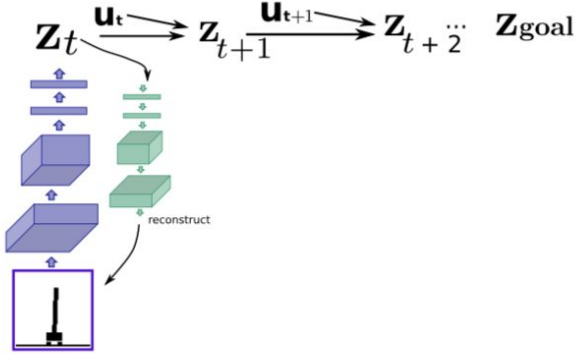
Key Requirements

Requirements for the inferred latent state space z_t:

1. Capture sufficient information about x_t



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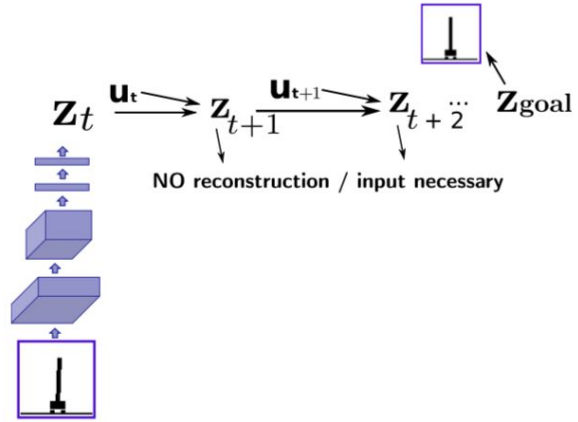
Key Requirements

Requirements for the inferred latent state space z_t:

1. Capture sufficient information about x_t
2. Accurate long-term prediction of latent states



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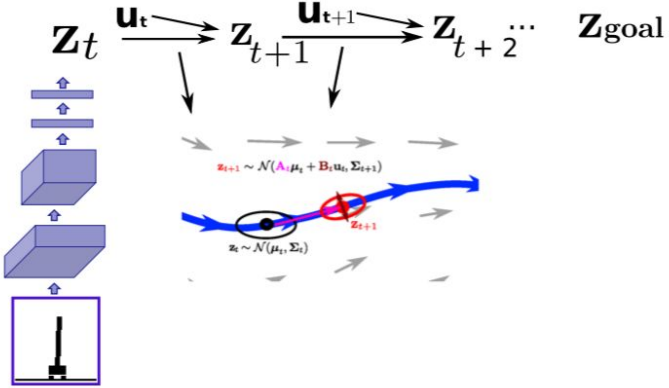
Key Requirements

Requirements for the inferred latent state space $\mathbf{z}_t$:

1. Capture sufficient information about $\mathbf{x}_t$
2. Accurate long-term prediction of latent states
3. The prediction must be locally linearizable *for all valid control magnitudes*



Embed to Control

Key Requirements

Requirements for the inferred latent state space $\mathbf{z}_t$:

1. Capture sufficient information about $\mathbf{x}_t$
2. Accurate long-term prediction of latent states
3. The prediction must be locally linearizable *for all valid control magnitudes*

→ **IF** we can learn $\mathbf{z}$, locally optimal controls can be found

→ present model that follows requirements **by construction**

Embed to Control

Ingredients

1. Stochastic optimal control (SOC) in a latent space
2. **E2C latent state space model:**
   - **Variational autoencoder**
   - Locally linear latent space model

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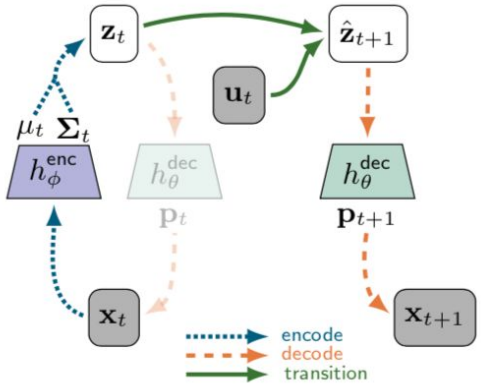
E2C: Modelling Dynamics

- From $(\mathbf{x}_t, \mathbf{u}_t, \mathbf{x}_{t+1})$ to $(\mathbf{z}_t, \mathbf{u}_t, \hat{\mathbf{z}}_{t+1})$
- Transition Model: 2

$$\mathbf{z}_{t+1} \sim \hat{Q}_\psi(\hat{Z}|Z, \mathbf{u}) = ?$$



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Ingredients

1. Stochastic optimal control (SOC) in a latent space
2. **E2C latent state space model:**
   - Variational autoencoder
   - **Locally linear latent space model**

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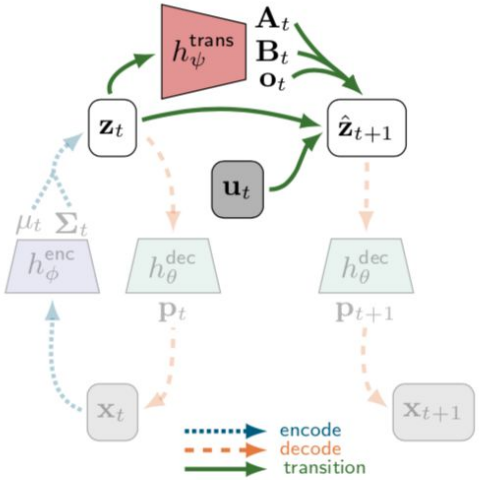
E2C: Locally Linear Latent Dynamics

- Transition Model: 3

$$\hat{Q}_\psi(\hat{Z}|Z,\mathbf{u}) = \mathcal{N}(\mathbf{A}_t\boldsymbol{\mu}_t + \mathbf{B}_t\mathbf{u}_t + \mathbf{o}_t, \mathbf{C}_t)$$
$$\mathbf{C}_t = \mathbf{A}_t\boldsymbol{\Sigma}_t\mathbf{A}_t^T + \mathbf{H}_t$$
$$\boldsymbol{\omega}_t \sim \mathcal{N}(0, \mathbf{H}_t)$$



$$\mathcal{L}(\mathcal{D}) = \mathbb{E}_{\mathbf{z}_t\sim Q_\phi}\left[-\log P_\theta(\mathbf{x}_t|\mathbf{z}_t)\right] + \mathsf{KL}\left(Q_\phi||P(Z)\right)$$
$$+ \mathbb{E}_{\hat{\mathbf{z}}_{t+1}\sim\hat{Q}_\psi}\left[-\log P_\theta(\mathbf{x}_{t+1}|\hat{\mathbf{z}}_{t+1})\right]$$

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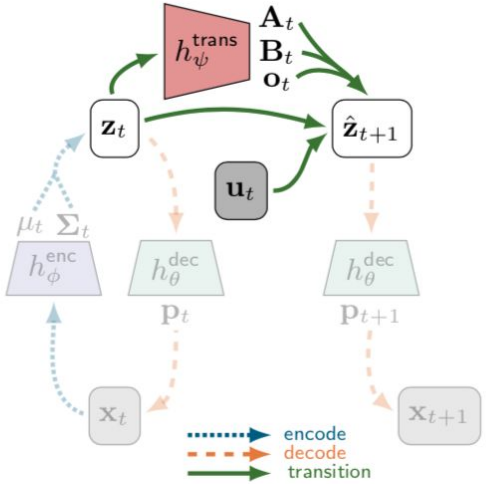
E2C: Locally Linear Latent Dynamics

- Transition Model: 3

$$\hat{Q}_\psi(\hat{Z}|Z,\mathbf{u}) = \mathcal{N}(\mathbf{A}_t\boldsymbol{\mu}_t + \mathbf{B}_t\mathbf{u}_t + \mathbf{o}_t, \mathbf{C}_t)$$
$$\mathbf{C}_t = \mathbf{A}_t\boldsymbol{\Sigma}_t\mathbf{A}_t^T + \mathbf{H}_t$$
$$\boldsymbol{\omega}_t \sim \mathcal{N}(0, \mathbf{H}_t)$$

- Disagreement of inference & transition model



$$\mathcal{L}(\mathcal{D}) = \mathbb{E}_{\mathbf{z}_t\sim Q_\phi}\left[-\log P_\theta(\mathbf{x}_t|\mathbf{z}_t)\right] + \mathsf{KL}\left(Q_\phi||P(Z)\right)$$
$$+ \mathbb{E}_{\hat{\mathbf{z}}_{t+1}\sim\hat{Q}_\psi}\left[-\log P_\theta(\mathbf{x}_{t+1}|\hat{\mathbf{z}}_{t+1})\right]$$

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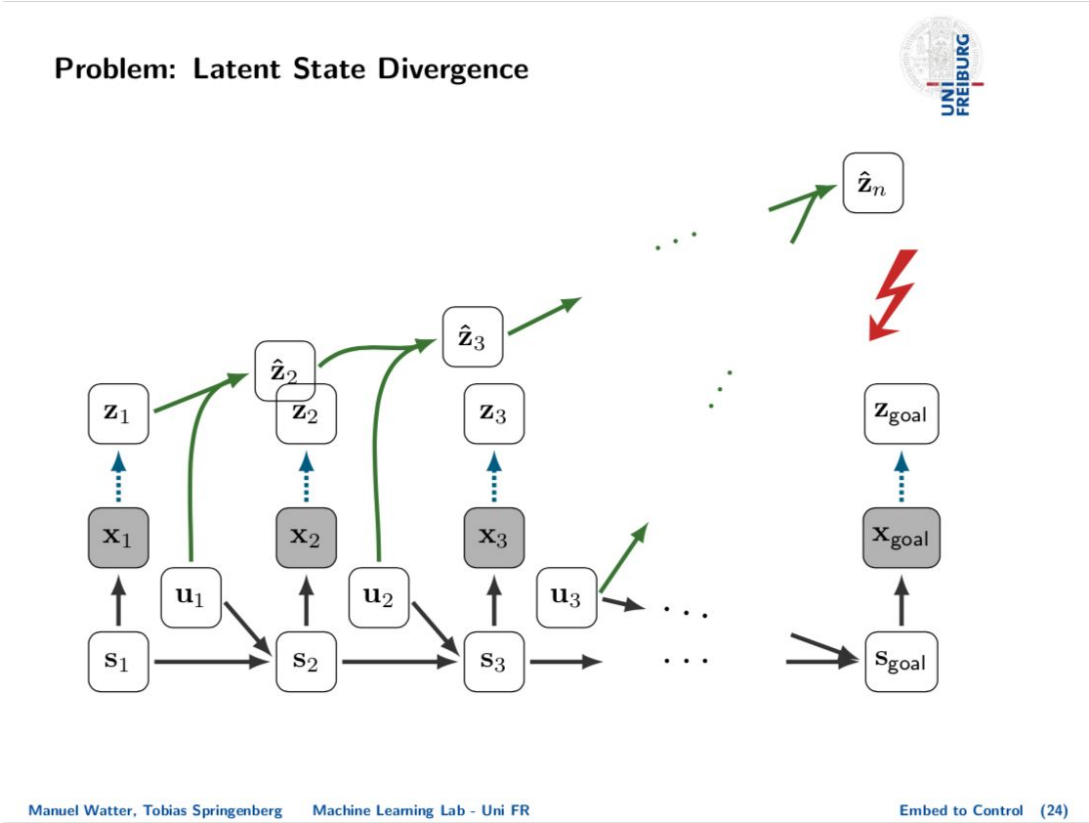

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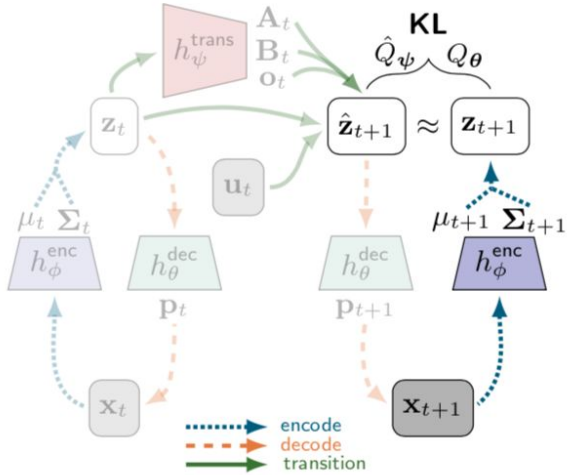
E2C: Long-term Consistency

→ Force encoder and transition model to work in the same latent space



$$\mathcal{L}(\mathcal{D}) = \mathbb{E}_{\mathbf{z}_t \sim Q_\phi}\left[-\log P_\theta(\mathbf{x}_t|\mathbf{z}_t)\right] + \mathsf{KL}\left(Q_\phi||P(Z)\right)$$
$$+ \mathbb{E}_{\hat{\mathbf{z}}_{t+1} \sim \hat{Q}_\psi}\left[-\log P_\theta(\mathbf{x}_{t+1}|\hat{\mathbf{z}}_{t+1})\right] + \lambda \mathsf{KL}\left(\hat{Q}_\psi(\hat{Z}|Z,\mathbf{u})||Q_\phi(Z|X)\right)$$

Embed to Control

Requirements

Requirements for the inferred latent state space $\mathbf{z}_t$:

1. Capture sufficient information about $\mathbf{x}_t$
   → Autoencoder
2. Accurate long-term prediction of latent states
   → Minimize KL of $\hat{Q}_\psi$ and Q_ϕ
3. The prediction must be locally linearizable *for all valid control magnitudes*
   → Predict transformation matrices

Embed to Control

Embed to Control: Full Model

- Inference Model:

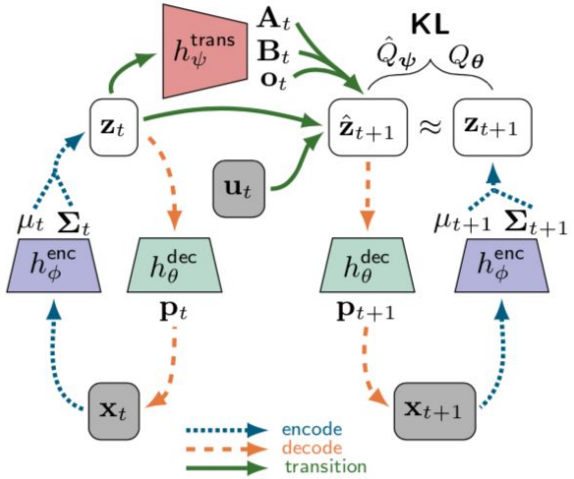
$$\mathbf{z}_t \sim Q_{\boldsymbol{\phi}}(Z|X) = \mathcal{N}(Z|\boldsymbol{\mu}, \boldsymbol{\Sigma}_t))$$

- Generative Model:

$$\mathbf{x}_t \sim P_{\boldsymbol{\theta}}(X|Z) = Bernoulli\,(\mathbf{p}_t)$$
$$\mathbf{x}_{t+1} \sim P_{\boldsymbol{\theta}}(X|\hat{Z}) = Bernoulli\,(\mathbf{p}_{t+1})$$

- Transition Model:

$$\mathbf{z}_{t+1} \sim \hat{Q}_{\boldsymbol{\psi}}(\hat{Z}|Z, \mathbf{u}) = \mathcal{N}(\mathbf{A}_t\boldsymbol{\mu}_t + \mathbf{B}_t\mathbf{u}_t + \mathbf{o}_t, \mathbf{C}_t)$$
$$\mathbf{C}_t = \mathbf{A}_t\boldsymbol{\Sigma}_t\mathbf{A}_t^T + \mathbf{H}_t$$
$$\boldsymbol{\omega}_t \sim \mathcal{N}(0, \mathbf{H}_t)$$



$$\mathcal{L}(\mathcal{D}) = \mathbb{E}_{\mathbf{z}_t \sim Q_{\boldsymbol{\phi}}}\left[-\log P_{\boldsymbol{\theta}}(\mathbf{x}_t|\mathbf{z}_t)\right] + \mathsf{KL}\left(Q_{\boldsymbol{\phi}}||P(Z)\right)$$
$$+ \mathbb{E}_{\hat{\mathbf{z}}_{t+1} \sim \hat{Q}_{\boldsymbol{\psi}}}\left[-\log P_{\boldsymbol{\theta}}(\mathbf{x}_{t+1}|\hat{\mathbf{z}}_{t+1})\right] + \lambda\mathsf{KL}\left(\hat{Q}_{\boldsymbol{\psi}}(\hat{Z}|Z, \mathbf{u})||Q_{\boldsymbol{\phi}}(Z|X)\right)$$

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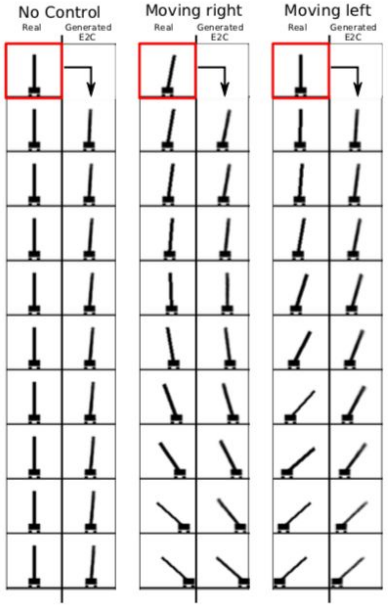
Embed to Control: Full Model

Long term predictions



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Results: comparison

Algorithm	Mean State Loss $\mathbf{p}(\mathbf{x_t}\|\hat{\mathbf{x}}_\mathbf{t})$	Mean Next State Loss $\mathbf{p}(\mathbf{x_{t+1}}\|\hat{\mathbf{x}}_\mathbf{t}, \mathbf{u_t})$	Trajectory Cost Latent	Trajectory Cost Real	Success percentage
		Planar System			
True Model for $\mathbf{s}_t$	-	-	-	20.24 $\pm$ 4.15	100 %
AE†	11.5 $\pm$ 97.8	3538.9 $\pm$ 1395.2	1325.6 $\pm$ 81.2	273.3 $\pm$ 16.4	0 %
VAE†	3.6 $\pm$ 18.9	652.1 $\pm$ 930.6	43.1 $\pm$ 20.8	91.3 $\pm$ 16.4	0 %
VAE with slowness†	10.5 $\pm$ 22.8	104.3 $\pm$ 235.8	47.1 $\pm$ 20.5	89.1 $\pm$ 16.4	0 %
Non-linear E2C	8.3 $\pm$ 5.5	11.3 $\pm$ 10.1	19.8 $\pm$ 9.8	42.3 $\pm$ 16.4	96.6 %
Global E2C	**6.9 $\pm$ 3.2**	**9.3 $\pm$ 4.6**	12.5 $\pm$ 3.9	27.3 $\pm$ 9.7	**100** %
E2C	7.7 $\pm$ 2.0	9.7 $\pm$ 3.2	10.3 $\pm$ 2.8	**25.1 $\pm$ 5.3**	**100** %
		Inverted Pendulum Swing-Up			
True Model for $\mathbf{s}_t$	-	-	-	9.8 $\pm$ 2.4	100 %
AE†	8.9 $\pm$ 100.3	13433.8 $\pm$ 6238.8	1285.9 $\pm$ 355.8	194.7 $\pm$ 44.8	0 %
VAE†	7.5 $\pm$ 47.7	8791.2 $\pm$ 17356.9	497.8 $\pm$ 129.4	237.2 $\pm$ 41.2	0 %
VAE with slowness†	26.5 $\pm$ 18.0	779.7 $\pm$ 633.3	419.5 $\pm$ 85.8	188.2 $\pm$ 43.6	0 %
E2C no latent KL	64.4 $\pm$ 32.8	87.7 $\pm$ 64.2	489.1 $\pm$ 87.5	213.2 $\pm$ 84.3	0 %
Non-linear E2C	**59.6 $\pm$ 25.2**	**72.6 $\pm$ 34.5**	313.3 $\pm$ 65.7	37.4 $\pm$ 12.4	46.6 %
Global E2C	115.5 $\pm$ 56.9	125.3 $\pm$ 62.6	628.1 $\pm$ 45.9	125.1 $\pm$ 10.7	0 %
E2C	84.0 $\pm$ 50.8	89.3 $\pm$ 42.9	275.0 $\pm$ 16.6	**15.4 $\pm$ 3.4**	**90** %

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Results: comparison

Algorithm	True model	VAE + slownes	E2C no latent KL	Non-linear E2C	E2C
			Cart-Pole balance		
Trajectory Cost	15.33 $\pm$ 7.70	49.12 $\pm$ 16.94	48.90 $\pm$ 17.88	31.96 $\pm$ 13.26	**22.23 $\pm$ 14.89**
Success %	100 %	0 %	0 %	63 %	**93** %
			Three-link arm		
Trajectory Cost	59.46	1275.53 $\pm$ 864.66	1246.69 $\pm$ 262.65	460.40 $\pm$ 82.18	**90.23 $\pm$ 47.38**
Success %	100 %	0 %	0 %	40 %	**90** %

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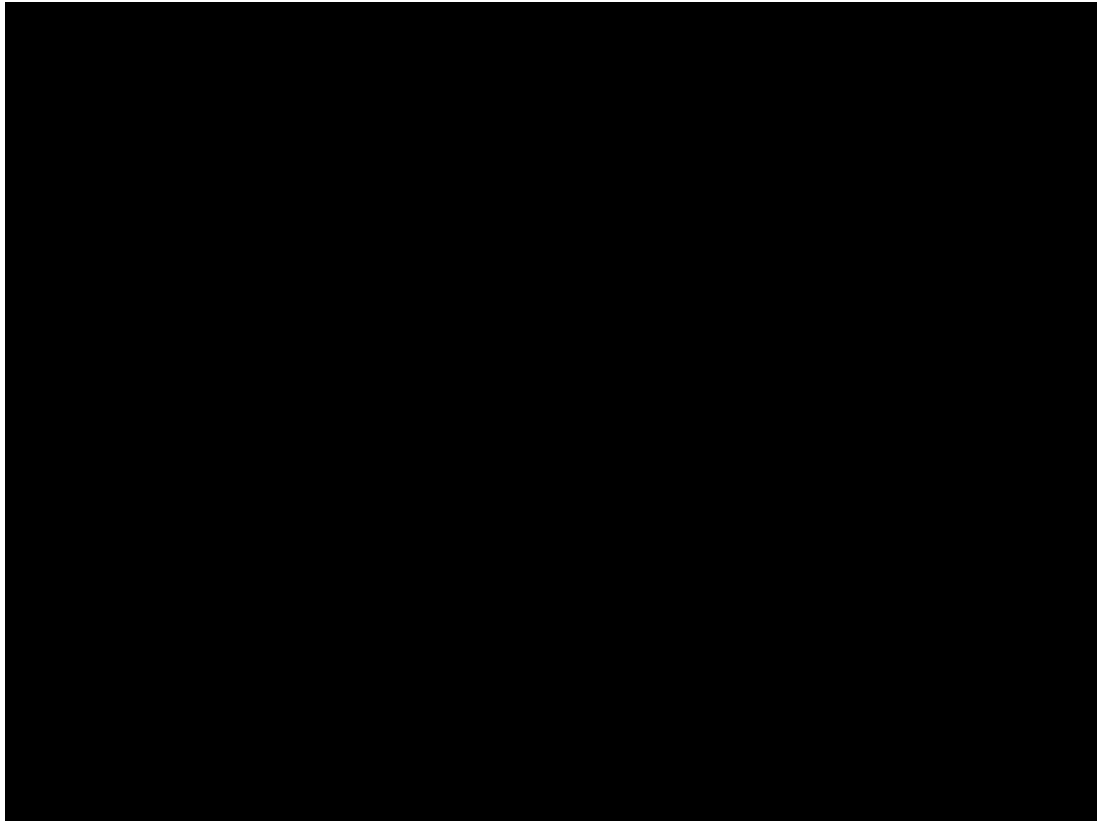
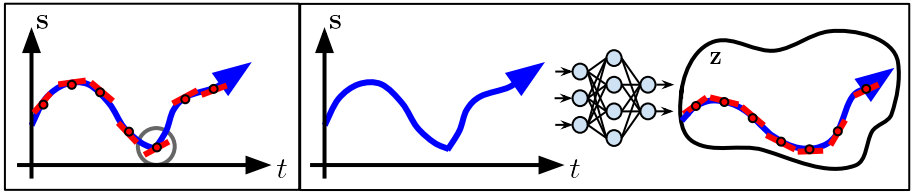
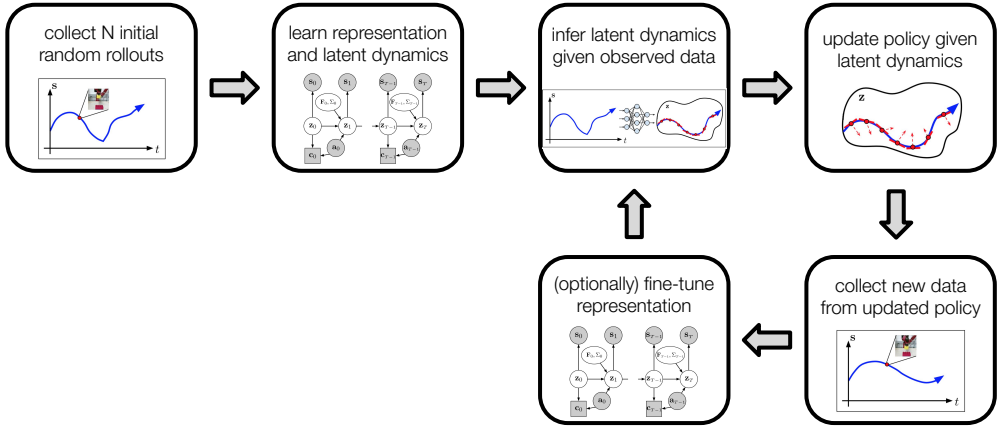
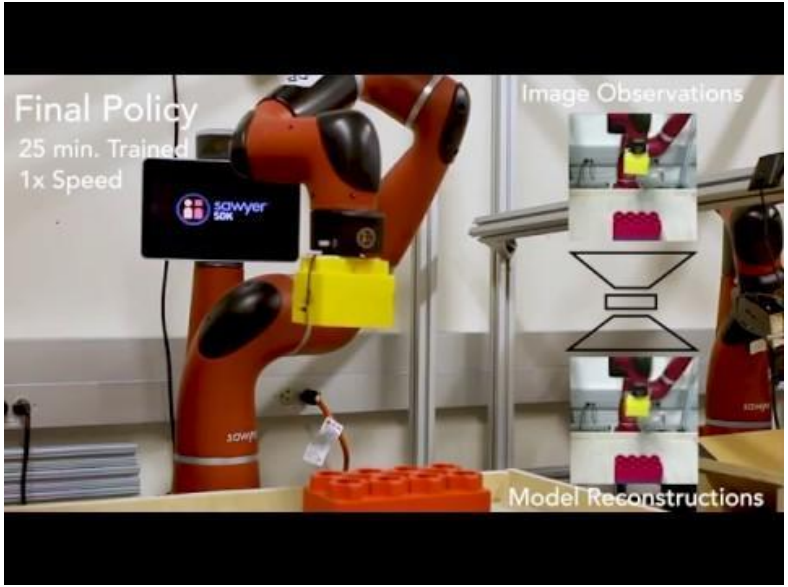


SOLAR: Deep Structured Representations for Model-Based Reinforcement Learning

Marvin Zhang*, Sharad Vikram*, Laura Smith, Pieter Abbeel, Matthew Johnson, Sergey Levine







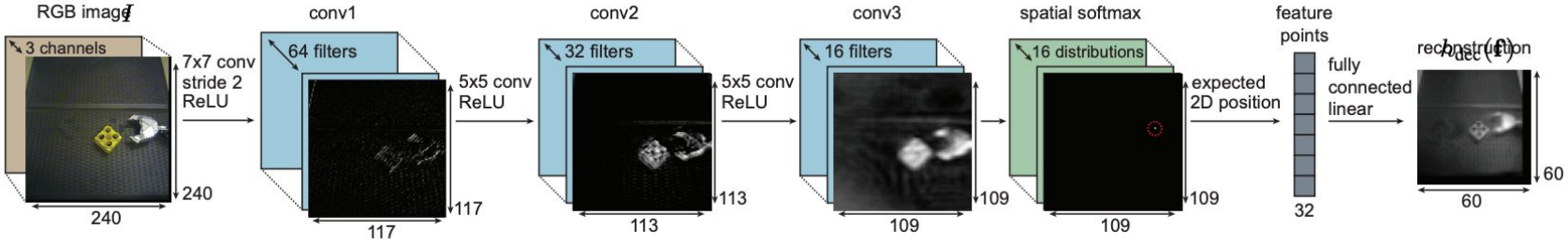
https://goo.gl/AJKocL

Representation Learning in Reinforcement Learning

- Auxiliary losses
- ***State representation***
  - ***Observation -> State***
  - ***Observation -> State + State,Action -> Next State***
- Exploration
- Unsupervised skill discovery

Deep Spatial Autoencoders

- Deep Spatial Autoencoders for Visuomotor Learning, Finn, Tan, Duan, Darrell, Levine, Abbeel, 2016 (https://arxiv.org/abs/1509.06113)
  - Train deep spatial autoencoder
  - Model-based RL through iLQR in the latent space



Robotic Priors / PVEs

- PVEs: Position-Velocity Encoders for Unsupervised Learning of Structured State Representations
  Rico Jonschkowski, Roland Hafner, Jonathan Scholz, and Martin Riedmiller (https://arxiv.org/pdf/1705.09805.pdf)
  - Learn an embedding without reconstruct

$$\mathbf{s}_t^{(p)} = \phi(\mathbf{o}_t)$$

$$\mathbf{s}_t^{(v)} = \alpha(\mathbf{s}_t^{(p)} - \mathbf{s}_{t-1}^{(p)})$$

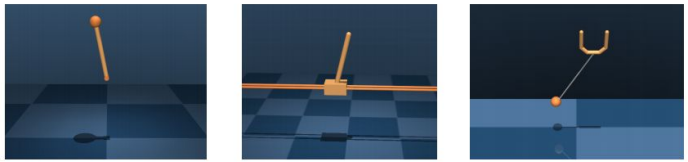
$$L_{\text{conservation}} = \mathbf{E}\left[\left(\|\mathbf{s}_t^{(v)}\| - \|\mathbf{s}_{t-1}^{(v)}\|\right)^2\right]$$

$$L_{\text{variation}} = \mathbf{E}\left[e^{-\|\mathbf{s}_a^{(p)} - \mathbf{s}_b^{(p)}\|}\right]$$

$$L_{\text{controlability (i)}} = e^{-\text{Cov}(\mathbf{a}_{t,i}, \mathbf{s}_{t+1,i}^{(a)})} = e^{-\mathbf{E}\left[\left(a_{t,i} - \mathbf{E}[a_{t,i}]\right)\left(s_{t+1,i}^{(a)} - \mathbf{E}[s_{t+1,i}^{(a)}]\right)\right]}$$

$$L_{\text{slowness}} = \mathbf{E}\left[\|\mathbf{s}_t^{(p)} - \mathbf{s}_{t-1}^{(p)}\|^2\right]$$

$$L_{\text{inertia}} = \mathbf{E}\left[\|\mathbf{s}_t^{(v)} - \mathbf{s}_{t-1}^{(v)}\|^2\right] = \mathbf{E}\left[\|\mathbf{s}_t^{(a)}\|^2\right]$$

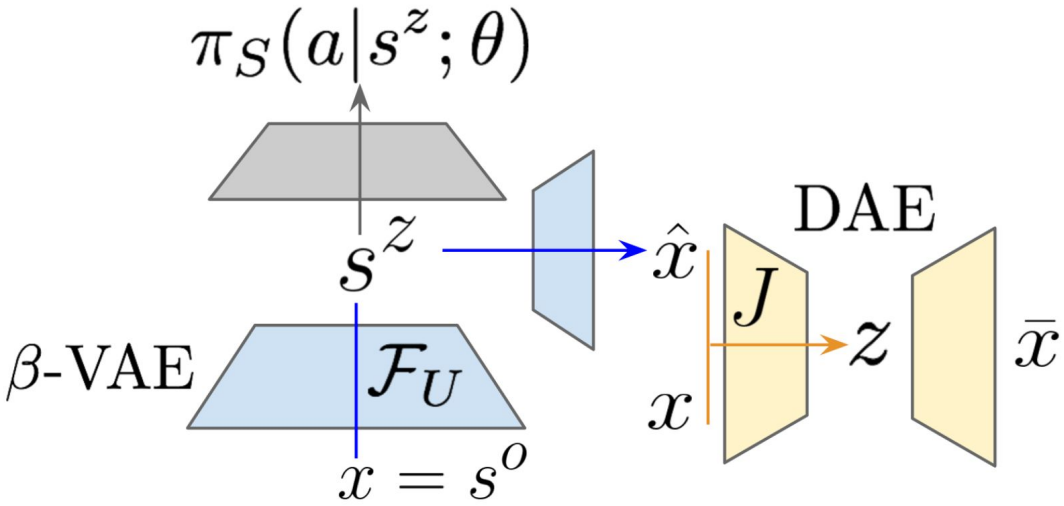


(a) Inverted pendulum (b) Cart-pole (c) Ball in cup

Disentangled Representation Learning Agent (Darla)

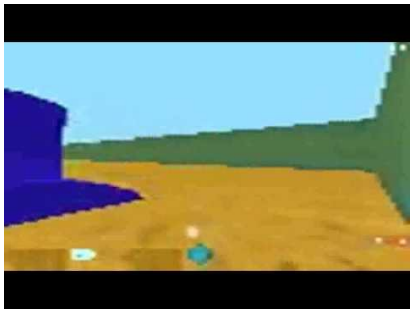
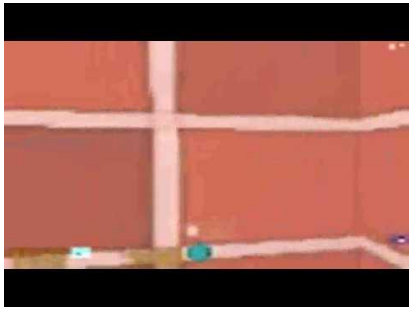
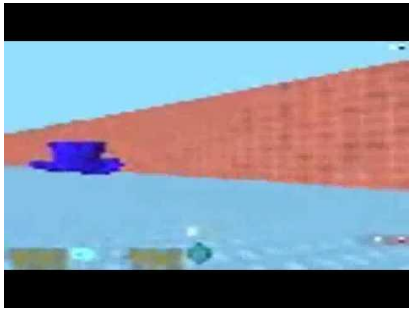
DARLA: Improving Zero-Shot Transfer in Reinforcement Learning

Irina Higgins, Arka Pal, Andrei A. Rusu, Loic Matthey, Christopher P Burgess, Alexander Pritzel, Matthew Botvinick, Charles Blundell, Alexander Lerchner (https://arxiv.org/abs/1707.08475)



DeepMind Lab Transfer

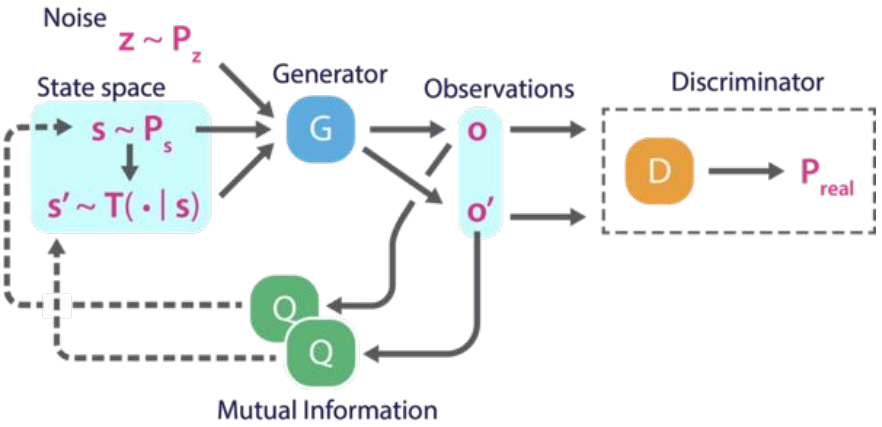
DARLA vs DQN baseline

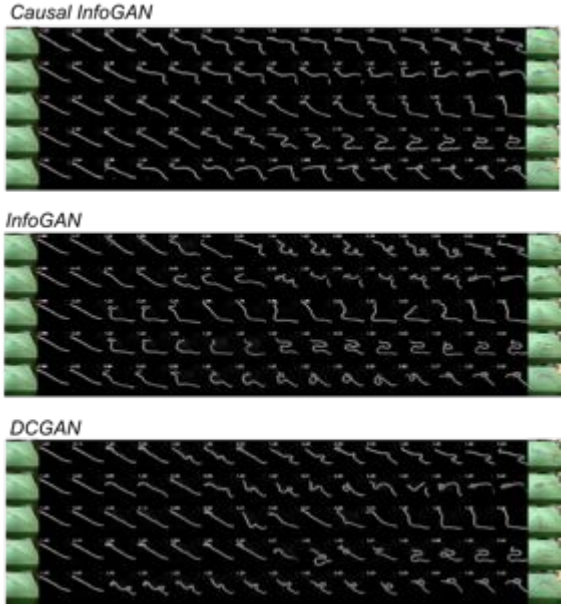
	Train	Transfer
DQN		
DARLA		

Causal InfoGAN

Learning Plannable Representations with Causal InfoGAN

Thanard Kurutach, Aviv Tamar, Ge Yang, Stuart Russell, Pieter Abbeel (https://arxiv.org/pdf/1807.09341.pdf)

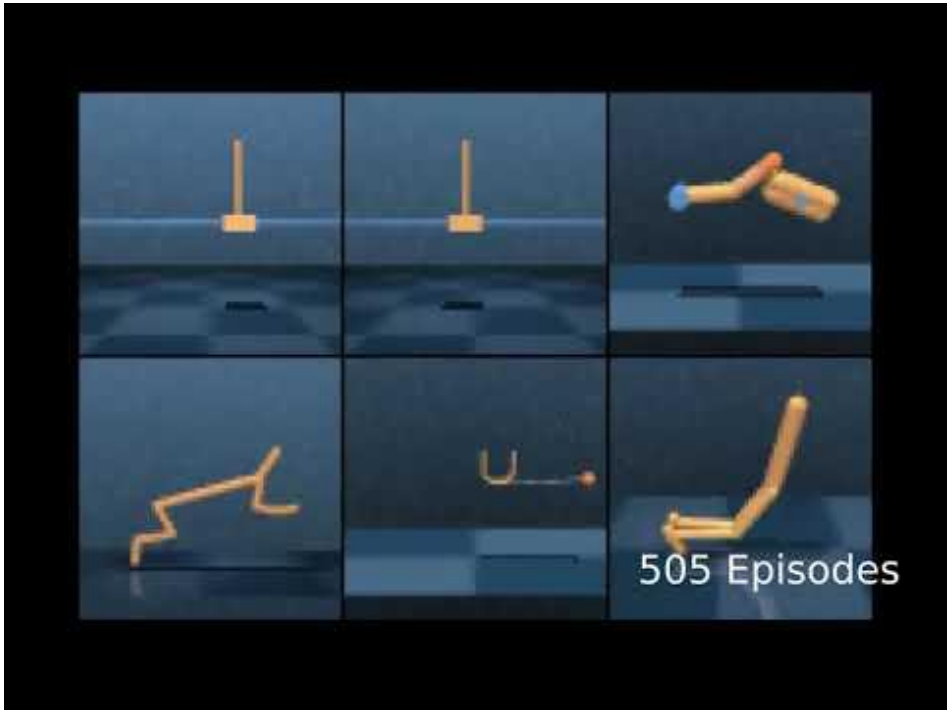




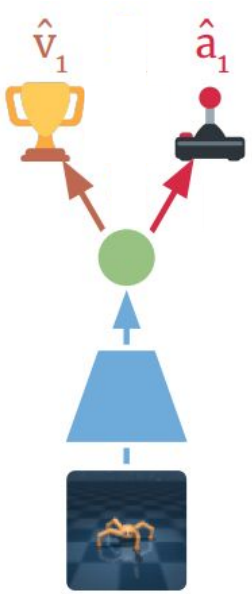
PlaNet: Learn latent dynamics from pixels + plan

Learning latent dynamics for planning from pixels
Danijar Hafner, T. Lillicrap, I Fischer, R Villegas, D Ha, H Lee, J Davidson
(https://arxiv.org/pdf/1811.04551.pdf)

- Learn latent space dynamics model
- Multi-step prediction
- Planning in latent space



Dreamer: Learning actor-critic model on latent space



Action model $q_\phi(a_\tau|s_\tau)$ Value model $v_\psi(s_\tau)$

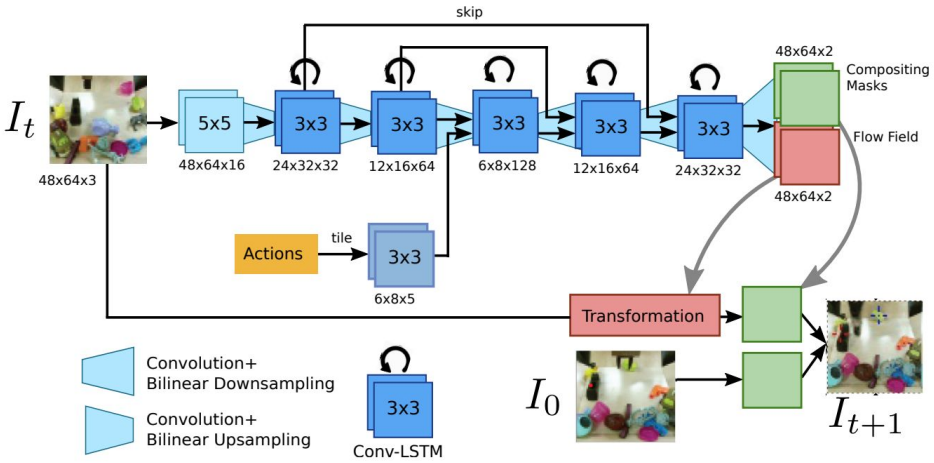
- How to train actor-critic using learned dynamics model?
  - Generate imagined trajectories using dynamics model
  - Interpretation: dyna / model-based policy optimization

Dreamer [Hafner et al., 2020] Hafner, D., Lillicrap, T., Ba, J. and Norouzi, M., Dream to Control: Learning Behaviors by Latent Imagination. In ICLR, 2020.

Visual Foresight

Deep Visual Foresight for Planning Robot Motion, Finn and Levine, ICRA 2017 http://arxiv.org/abs/1610.00696
Visual Foresight: Model-Based Deep Reinforcement Learning for Vision-Based Robotic Control, Frederik Ebert, Chelsea Finn, Sudeep Dasari, Annie Xie, Alex Lee, Sergey Levine, https://arxiv.org/abs/1812.00568,
https://bair.berkeley.edu/blog/2018/11/30/visual-rl/

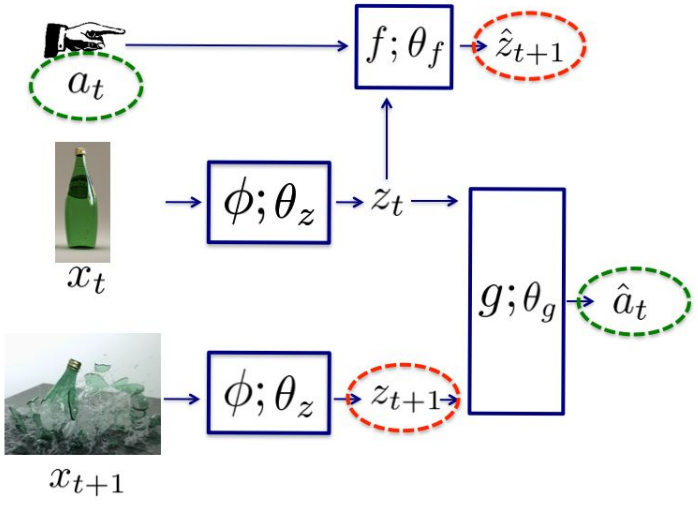
- Video prediction + Cross Entropy Maximization for MPC



Forward + Inverse Dynamics Models

Learning to Poke by Poking: Experiential Learning of Intuitive Physics, Pulkit Agrawal, Ashvin Nair, Pieter Abbeel, Jitendra Malik, Sergey Levine, https://arxiv.org/abs/1606.07419

- Learning a forward model in latent space
- BUT: couldn't the latent features always be zero?
- SOLUTION: require the features from t and t+1 to be sufficient to predict a_t



An alternative to making predictions in the pixel space!

Forward + Inverse Dynamics Models

Learning to Poke by Poking: Experiential Learning of Intuitive Physics, Pulkit Agrawal, Ashvin Nair, Pieter Abbeel, Jitendra Malik, Sergey Levine, https://arxiv.org/abs/1606.07419

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Representation Learning in Reinforcement Learning

- Auxiliary losses
- ***State representation***
  - ***Observation -> State***
  - ***Observation -> State + State,Action -> Next State***
  - ***Observation -> State + State,Action -> Next State, Future Reward***
- Exploration
- Unsupervised skill discovery

Predictron

The Predictron: End-To-End Learning and Planning

David Silver, Hado van Hasselt, Matteo Hessel, Tom Schaul, Arthur Guez, Tim Harley, Gabriel Dulac-Arnold, David Reichert, Neil Rabinowitz, Andre Barreto, Thomas Degris (https://arxiv.org/pdf/1612.08810.pdf)

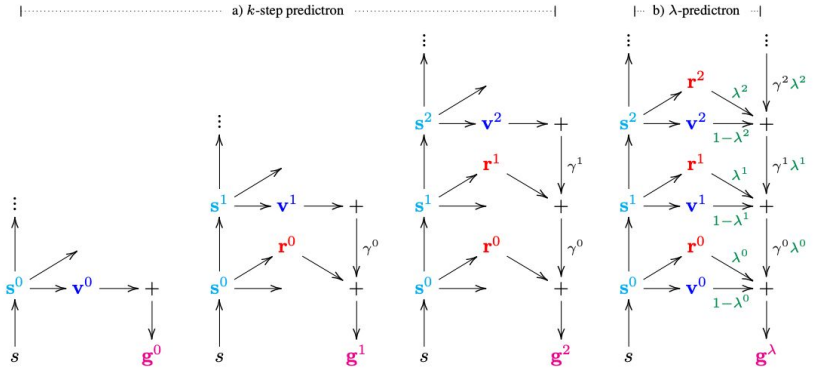
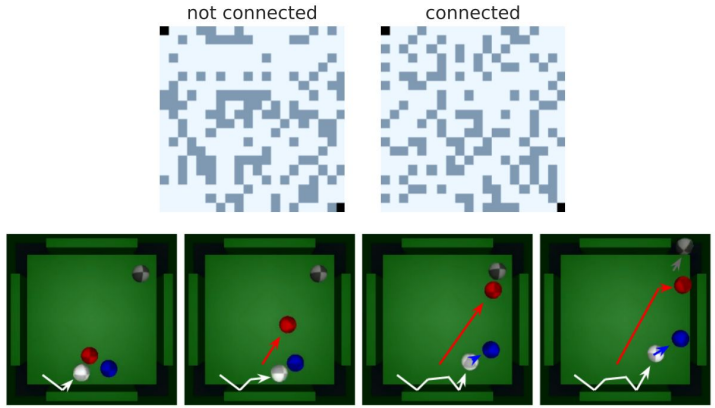


Figure 1. a) The k-step predictron architecture. The first three columns illustrate 0, 1 and 2-step pathways through the predictron. The 0-step preturn reduces to standard model-free value function approximation; other preturns "imagine" additional steps with an internal model. Each pathway outputs a k-step preturn $\mathbf{g}^k$ that accumulates discounted rewards along with a final value estimate. In practice all k-step preturns are computed in a single forward pass. b) The λ-predictron architecture. The λ-parameters gate between the different preturns. The output is a λ-preturn $\mathbf{g}^\lambda$ that is a mixture over the k-step preturns. For example, if $\boldsymbol{\lambda}^0 = \mathbf{1}, \boldsymbol{\lambda}^1 = \mathbf{1}, \boldsymbol{\lambda}^2 = \mathbf{0}$ then we recover the 2-step preturn, $\mathbf{g}^\lambda = \mathbf{g}^2$. Discount factors $\boldsymbol{\gamma}^k$ and λ-parameters $\boldsymbol{\lambda}^k$ are dependent on state $\mathbf{s}^k$; this dependence is not shown in the figure.

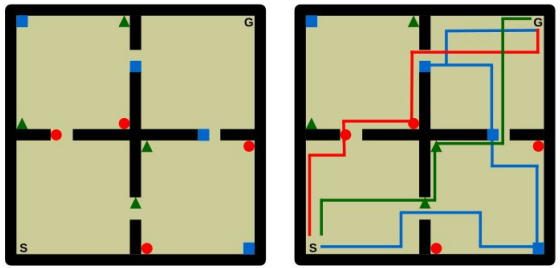


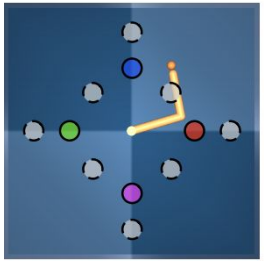
Successor Features

Successor Features for Transfer in Reinforcement Learning

André Barreto, Will Dabney, Rémi Munos, Jonathan J. Hunt, Tom Schaul, Hado van Hasselt, David Silver (https://arxiv.org/abs/1606.05312)

$$
\begin{aligned}
Q^{\pi}(s,a) &= \mathrm{E}^{\pi}\left[r_{t+1} + \gamma r_{t+2} + \ldots \,|\, S_t = s, A_t = a\right] \\
&= \mathrm{E}^{\pi}\left[\boldsymbol{\phi}_{t+1}^{\top}\mathbf{w} + \gamma \boldsymbol{\phi}_{t+2}^{\top}\mathbf{w} + \ldots \,|\, S_t = s, A_t = a\right] \\
&= \mathrm{E}^{\pi}\left[\sum_{i=t}^{\infty} \gamma^{i-t}\boldsymbol{\phi}_{i+1} \,|\, S_t = s, A_t = a\right]^{\top}\mathbf{w} = \boldsymbol{\psi}^{\pi}(s,a)^{\top}\mathbf{w}
\end{aligned}
$$





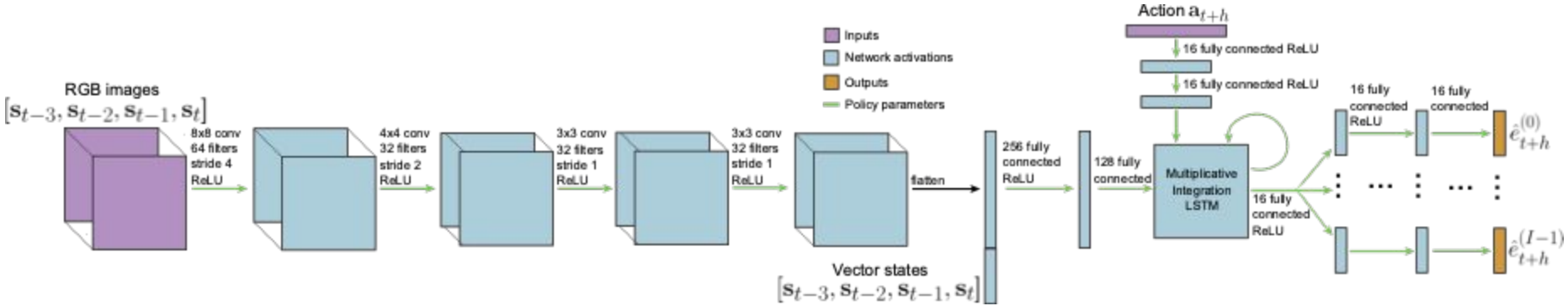
Kahn et al.

Composable Action-Conditioned Predictors: Flexible Off-Policy Learning for Robot Navigation

Gregory Kahn*, Adam Villaflor*, Pieter Abbeel, Sergey Levine, CoRL 2018 (https://arxiv.org/pdf/1810.07167.pdf)

Self-supervised Deep Reinforcement Learning with Generalized Computation Graphs for Robot Navigation

Gregory Kahn, Adam Villaflor, Bosen Ding, Pieter Abbeel, Sergey Levine, ICRA 2018 (https://arxiv.org/pdf/1709.10489.pdf)



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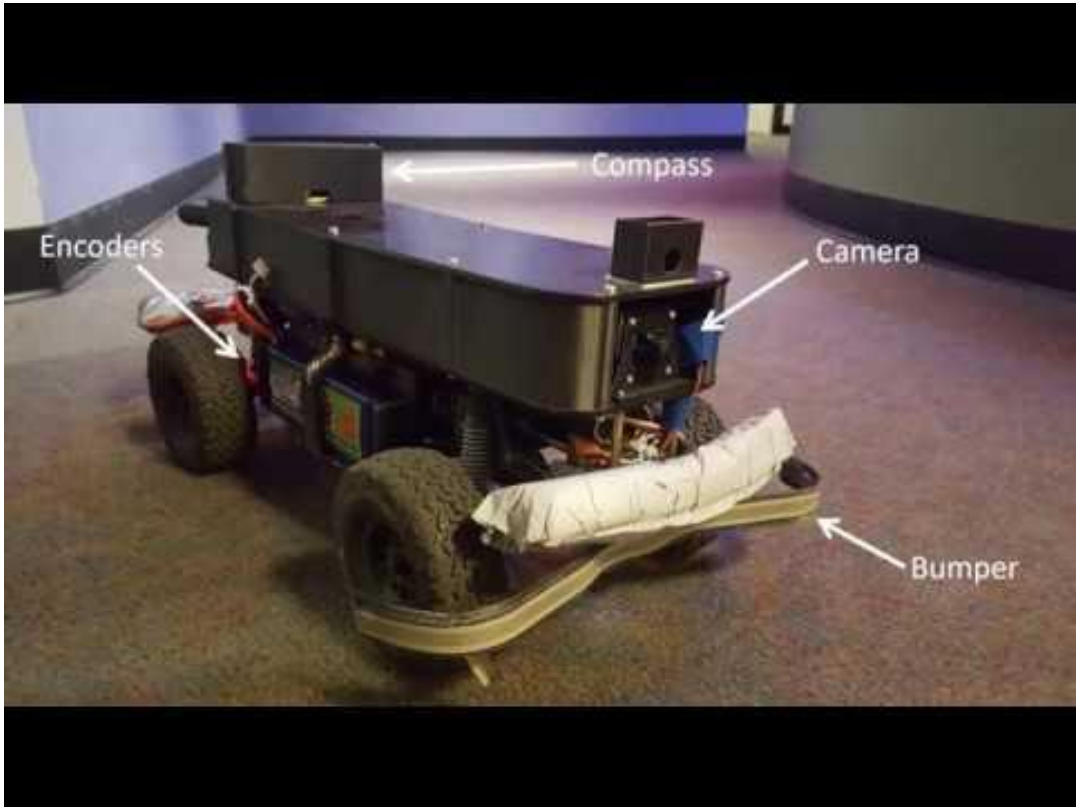


Representation Learning in Reinforcement Learning

- Auxiliary losses
- ***State representation***
  - ***Observation -> State***
  - ***Observation -> State + State,Action -> Next State***
  - ***Observation -> State + State,Action -> Next State, Future Reward***
  - ***Optimal Representations?***
- Exploration
- Unsupervised skill discovery

Some Theory References on State Representations

- From skills to symbols: Learning symbolic representations for abstract high-level planning: https://jair.org/index.php/jair/article/view/11175
- Homomorphism: https://www.cse.iitm.ac.in/~ravi/papers/KBCS04.pdf
- Towards a unified theory of state abstraction for mdps: https://pdfs.semanticscholar.org/ca9a/2d326b9de48c095a6cb5912e1990d2c5ab46.pdf
- Model reduction techniques for computing approximately optimal solutions for markov decision processes.https://arxiv.org/abs/1302.1533
- Adaptive aggregation methods for infinite horizon dynamic programming
- Transfer via soft homomorphisms. http://www.ifaamas.org/Proceedings/aamas09/pdf/01_Full%20Papers/12_67_FP_0798.pdf
- Near optimal behavior via approximate state abstraction https://arxiv.org/abs/1701.04113
- Using PCA to Efficiently Represent State Spaces: http://irll.eecs.wsu.edu/wp-content/papercite-data/pdf/2015icml-curran.pdf

A Separation Principle for Control in the Age of Deep Learning

A Separation Principle for Control in the Age of Deep Learning

Alessandro Achille, Stefano Soatto (https://arxiv.org/abs/1711.03321)

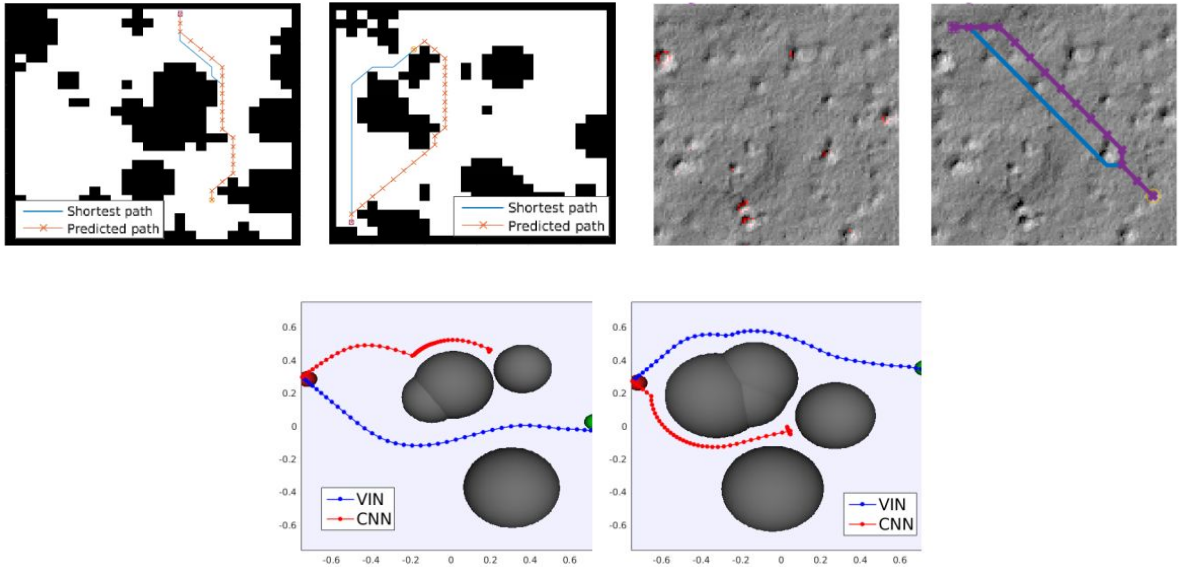
We review the problem of defining and inferring a "state" for a control system based on complex, high-dimensional, highly uncertain measurement streams such as videos. Such a state, or representation, should contain all and only the information needed for control, and discount nuisance variability in the data.

Representation Learning in Reinforcement Learning

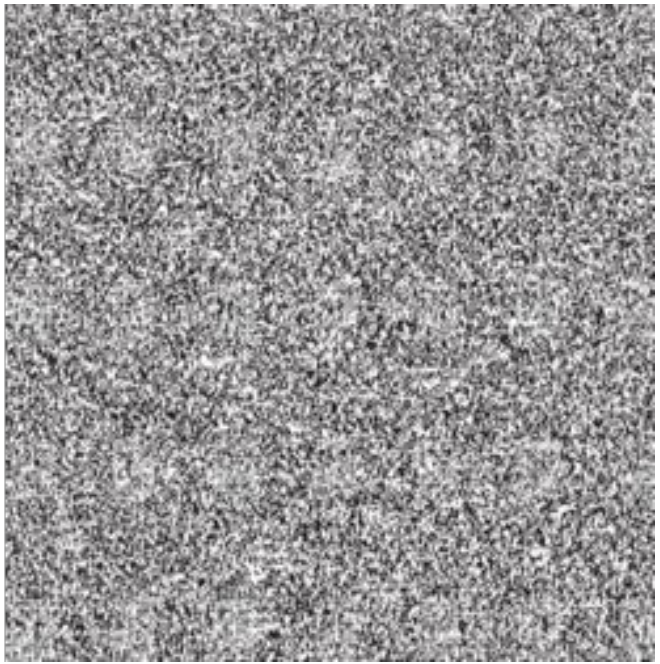
- Auxiliary losses
- ***State representation***
  - ***Observation -> State***
  - ***Observation -> State + State,Action -> Next State***
  - ***Observation -> State + State,Action -> Next State, Future Reward***
  - ***Optimal Representations?***
  - ***"End-to-end": Learning a representation that's good for planning***
- Exploration
- Unsupervised skill discovery

Learning Representations for Planning

- Value Iteration Networks, Aviv Tamar, Yi Wu, Garrett Thomas, Sergey Levine, Pieter Abbeel, NeurIPS2016, https://arxiv.org/abs/1602.02867



Pixel-level Video Prediction?



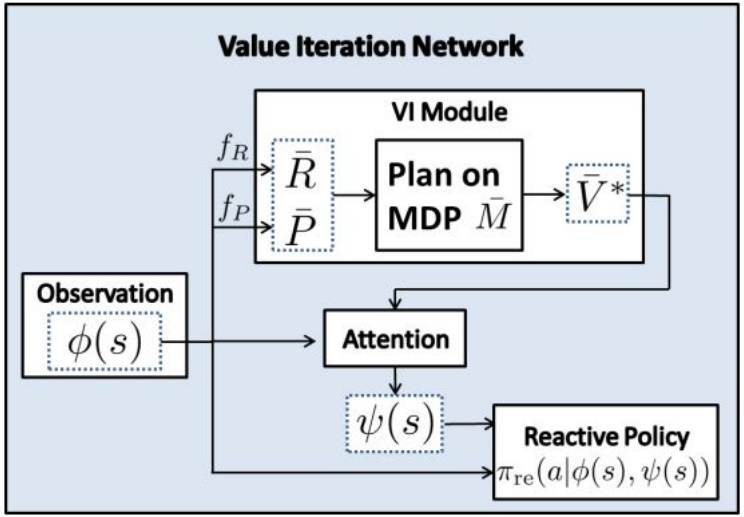
Pixel-level Video Prediction?

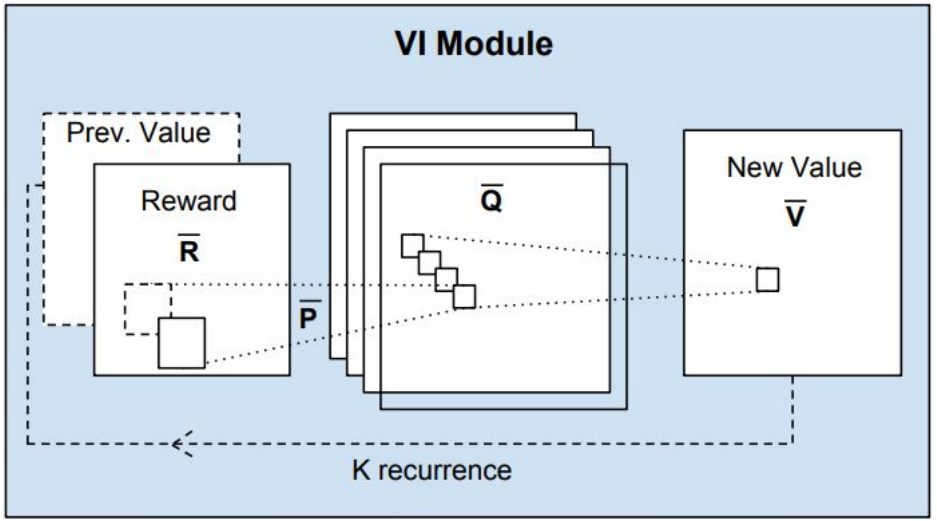
So:

Plannability as the criterion for representation learning

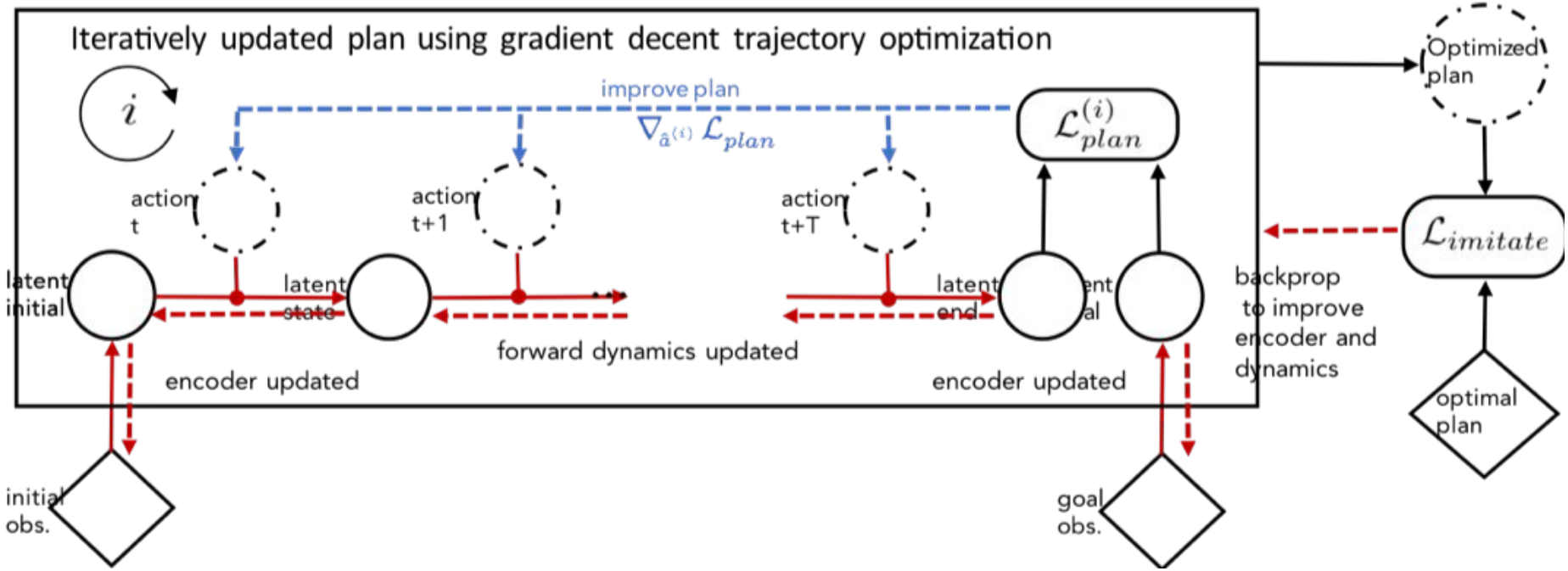
Learning Representations for Planning

- Value Iteration Networks, Aviv Tamar, Yi Wu, Garrett Thomas, Sergey Levine, Pieter Abbeel, NeurIPS2016, https://arxiv.org/abs/1602.02867





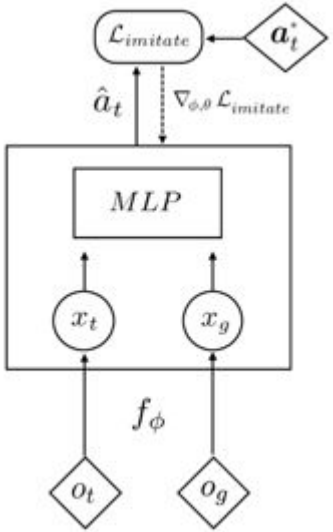
Universal Planning Networks



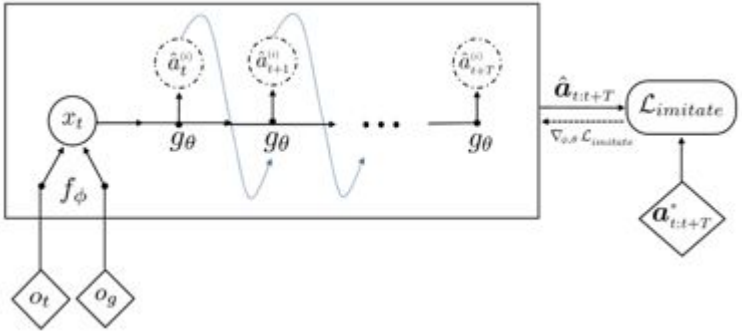
Universal Planning Networks

- Universal (goal-conditioned) policy parameterization wiht gradient-descent trajectory optimization embedded
- Benefits: better generalization (inductive bias)
- More benefits: learned metric in an abstract space

Approaches Compared With:

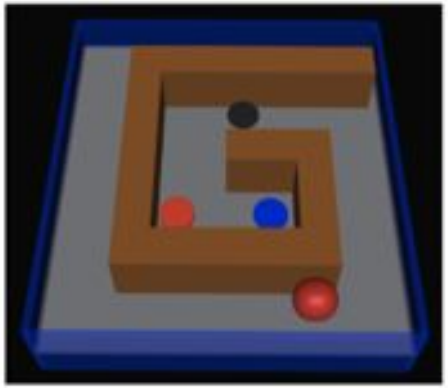
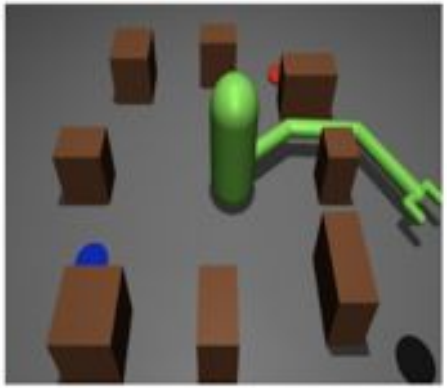
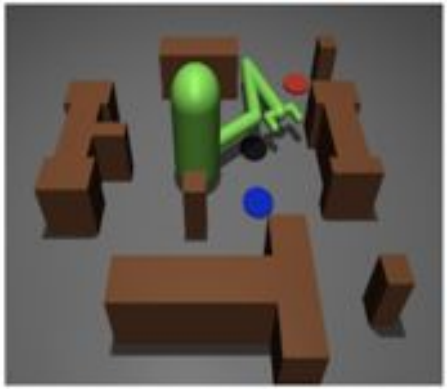


Reactive Imitation Learner

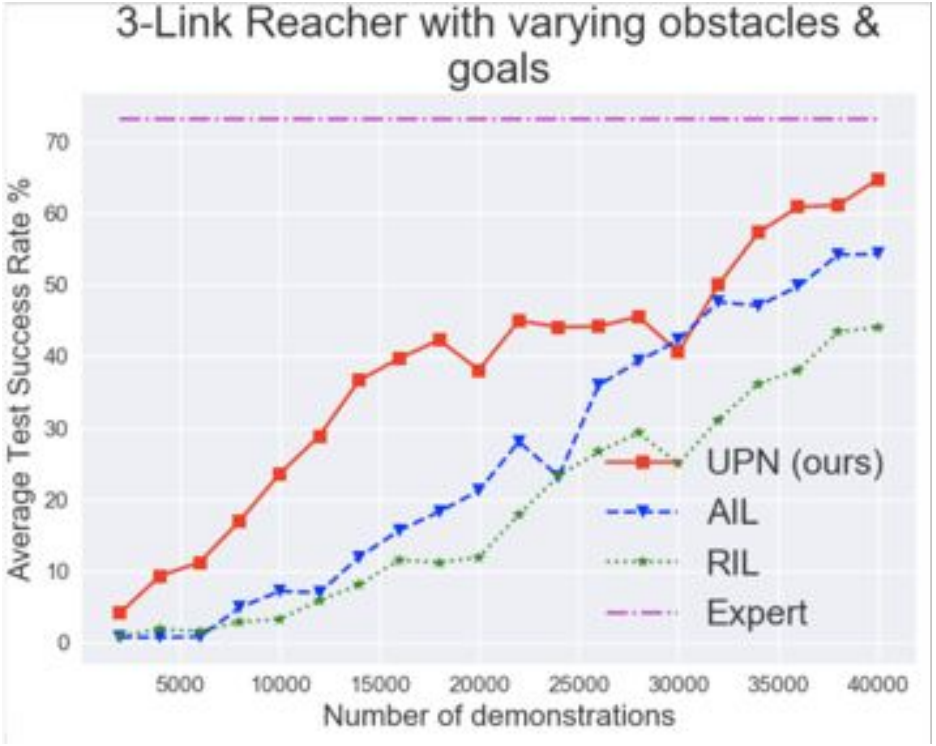


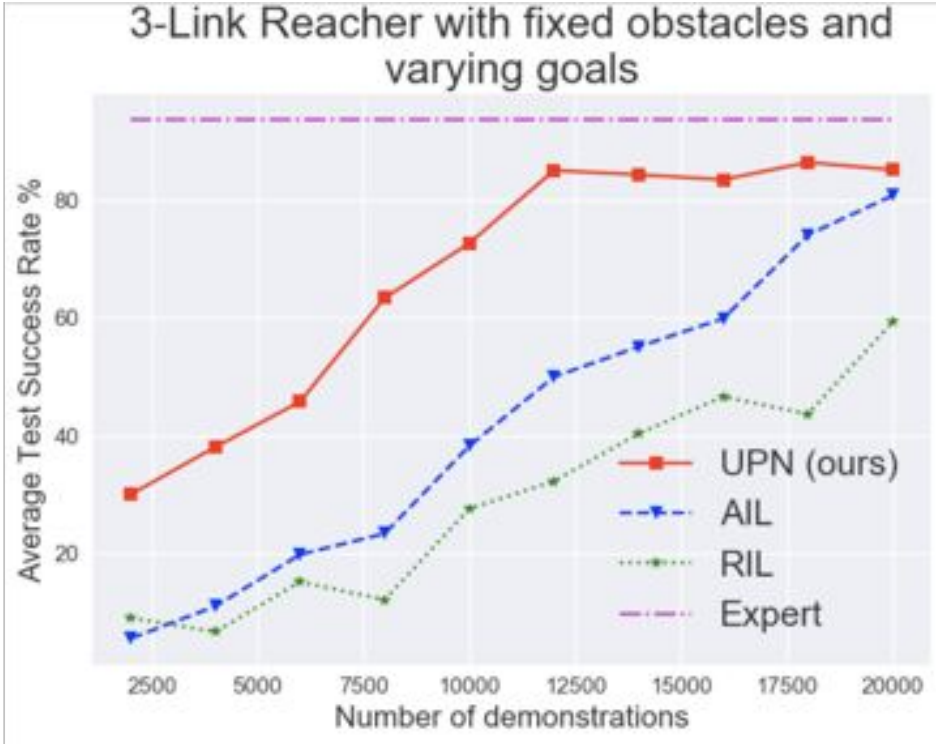
Autoregressive Imitation Learner

Tasks

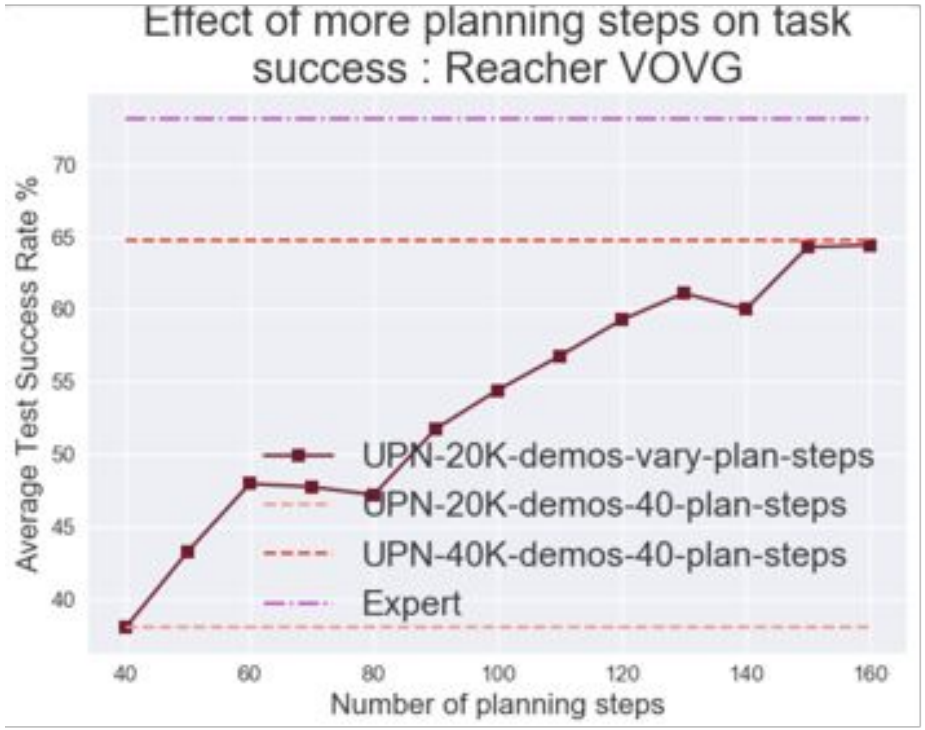





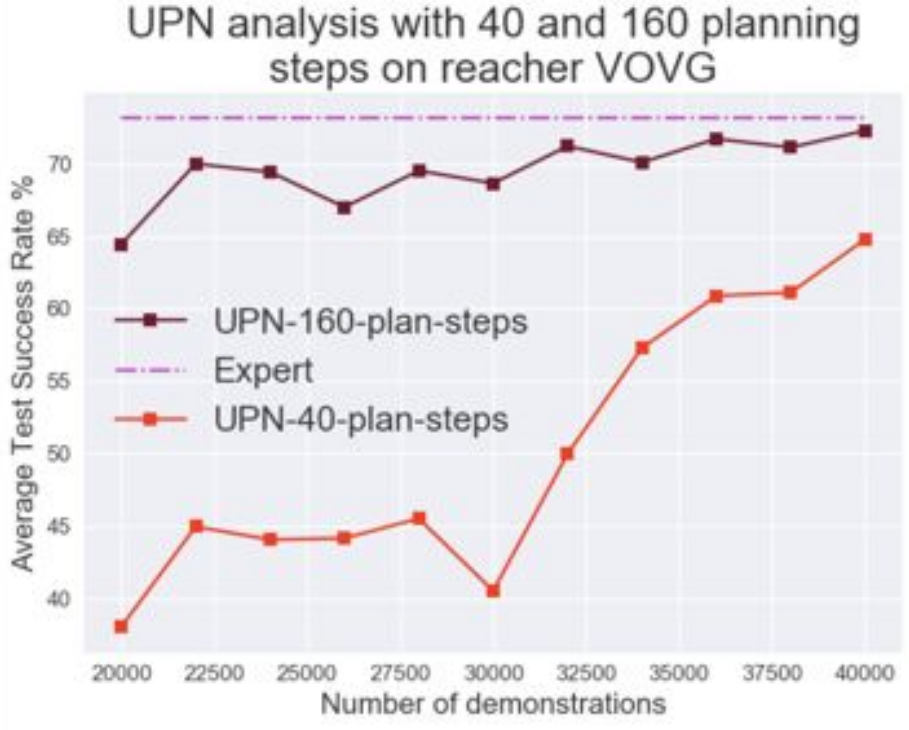
Evaluation


3-Link Reacher with varying obstacles & goals
Average Test Success Rate %
0
10
20
30
40
50
60
70
5000
10000
15000
20000
25000
30000
35000
40000
Number of demonstrations
UPN (ours)
AIL
RIL
Expert


3-Link Reacher with fixed obstacles and varying goals
Average Test Success Rate %
20
40
60
80
2500
5000
7500
10000
12500
15000
17500
20000
Number of demonstrations
UPN (ours)
AIL
RIL
Expert

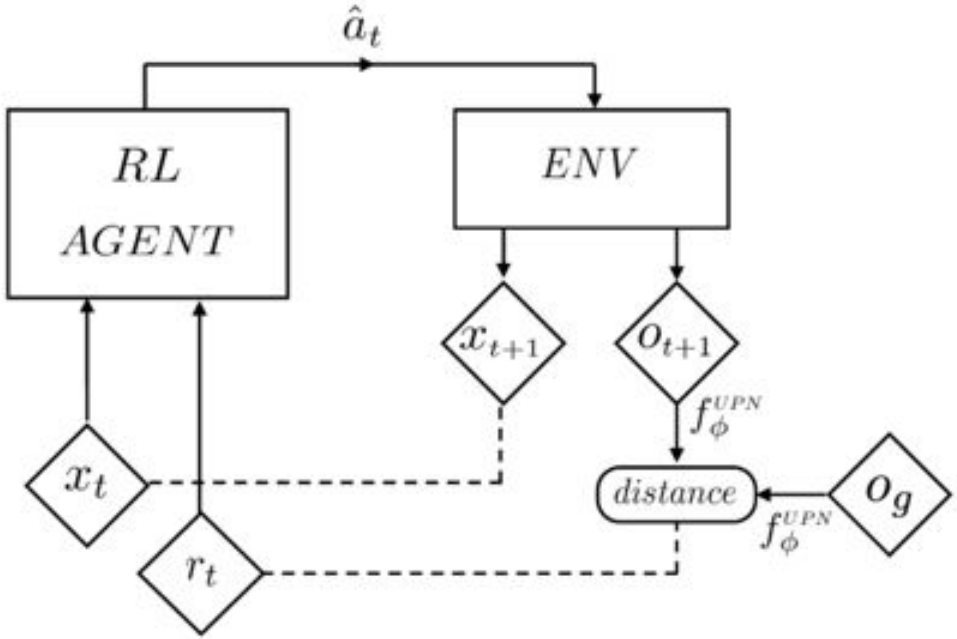
Meta-learning Aspects





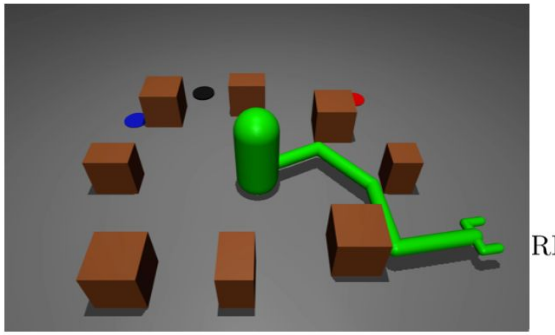
Beyond Imitation...

RL using UPN representations for (shaped) rewards



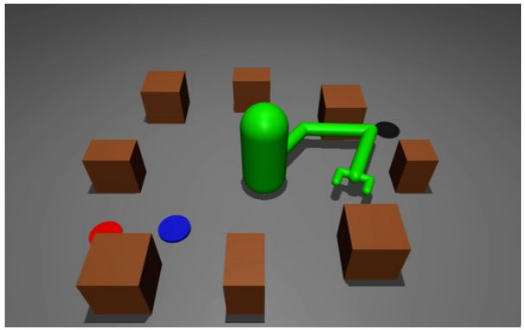
RL using UPN representations

3-link



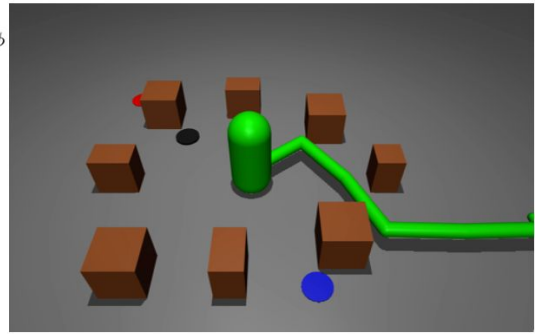
$\text{UPN}(\phi, \theta)$ trained with shared f_ϕ, different g_θ

4-link

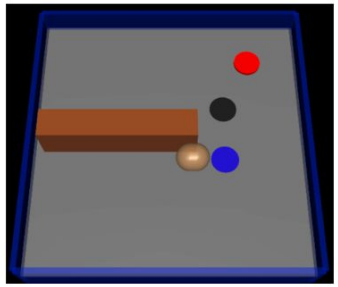


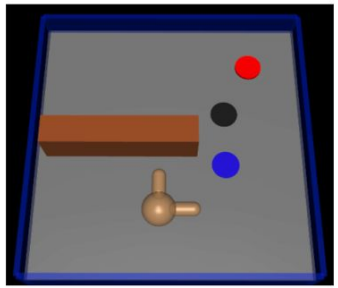
RL using learned f_ϕ

5-link



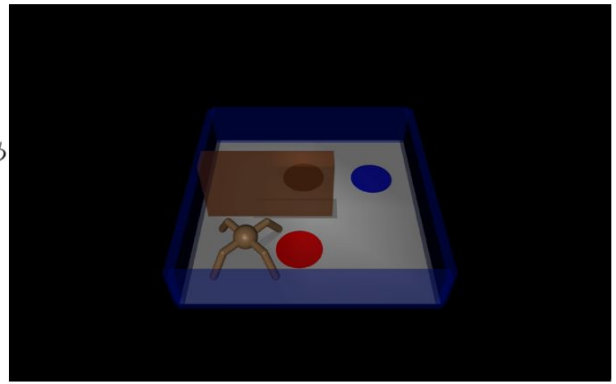
RL using UPN representations





UPN(ϕ, θ) trained across several randomizations of a 2D point robot

RL using learned f_ϕ

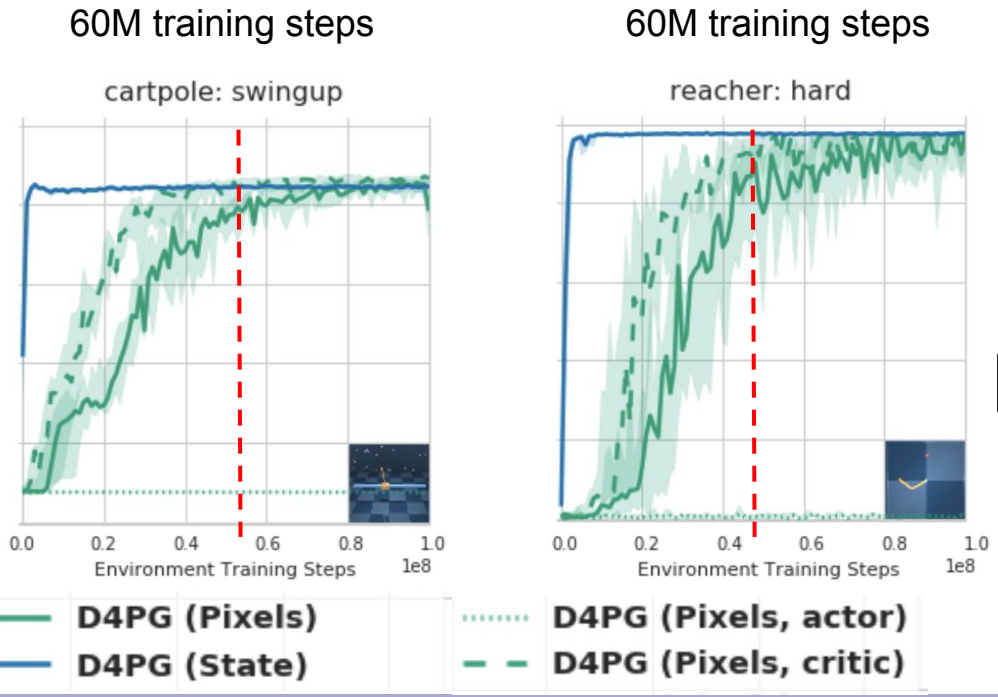


Representation Learning in Reinforcement Learning

- Auxiliary losses
- ***State representation***
  - Observation -> State
  - Observation -> State + State,Action -> Next State
  - Observation -> State + State,Action -> Next State, Future Reward
  - Optimal Representations?
  - "End-to-end": Learning a representation that's good for planning
  - ***CURL: Contrastive Unsupervised representations for Reinforcement Learning***
- Exploration
- Unsupervised skill discovery

Can visual RL achieve same data-efficiency as RL on state?

- State-based D4PG (blue) vs pixel-based D4PG (green)



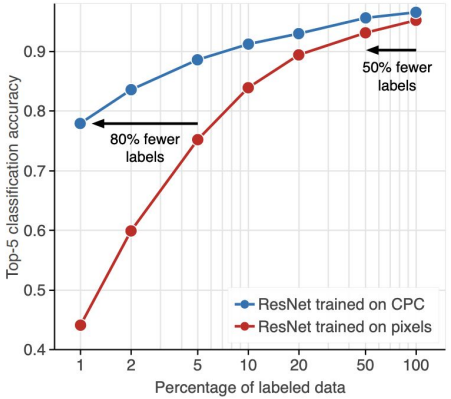
Pixel-based needs > 50M more training steps than state-based to solve same tasks

[Tassa et al., 2018] Tassa, Y., Doron, Y., Muldal, A., Erez, T., Li, Y., Casas, D.D.L., Budden, D., Abdolmaleki, A., Merel, J., Lefrancq, A. and Lillicrap, T DeepMind Control Suite, arxiv:1801.00690, 2018.

Contrastive Learning for Computer Vision

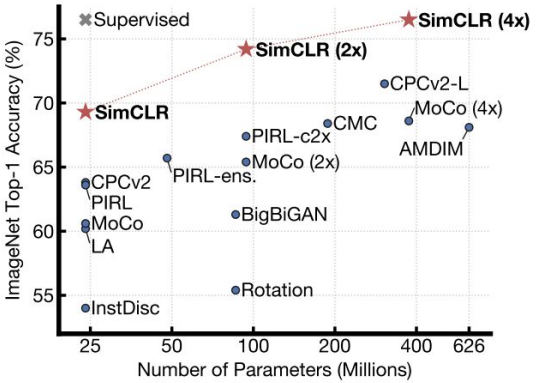
Contrastive learning: SOTA data-efficiency in computer vision

CPCv2 **top-5** ImageNet accuracy as function of labels



[Henaff, Srinivas et al., 2019]

SimCLR **top-1** ImageNet accuracy as function of # of parameters



[Chen et al., 2020]

[Henaff et al., 2019] Olivier J. Hénaff, Aravind Srinivas, Jeffrey De Fauw, Ali Razavi, Carl Doersch, S. M. Ali Eslami, Aaron van den Oord Data-Efficient Image Recognition with Contrastive Coding arxiv:1905.09272, 2019.

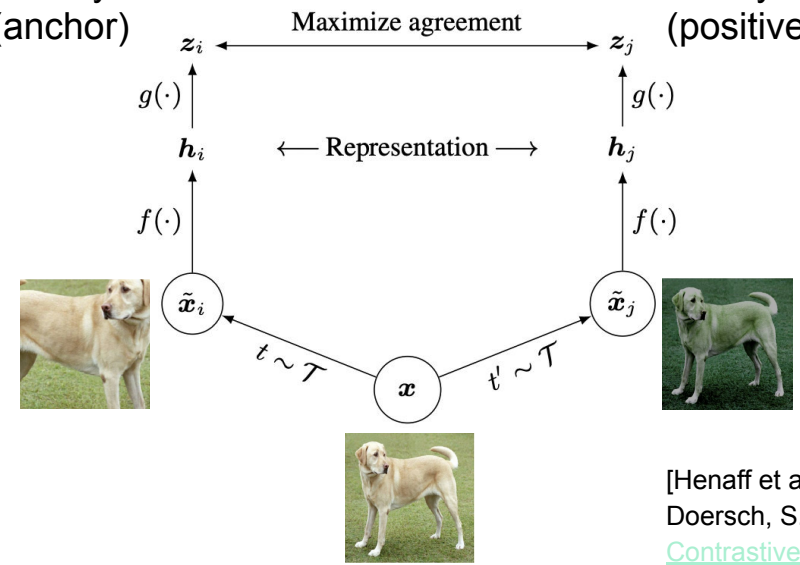
[Chen et al., 2020] Chen, T., Kornblith, S., Norouzi, M. and Hinton, G. A Simple Framework for Contrastive Learning of Visual Representations arxiv:2002.05709, 2020.

Contrastive maximizes agreement between query / key pairs

Contrastive architecture

Query (anchor)

Key (positive)



Energy based loss with temperature

$$\ell_{i,j} = -\log \frac{\exp(\text{sim}(\boldsymbol{z}_i, \boldsymbol{z}_j)/\tau)}{\sum_{k=1}^{2N} \mathbb{1}_{[k \neq i]} \exp(\text{sim}(\boldsymbol{z}_i, \boldsymbol{z}_k)/\tau)}$$

Similarity is cosine product

$$\text{sim}(\boldsymbol{u}, \boldsymbol{v}) = \boldsymbol{u}^\top \boldsymbol{v} / \|\boldsymbol{u}\| \|\boldsymbol{v}\|$$

SimCLR
[Chen et al., 2020]

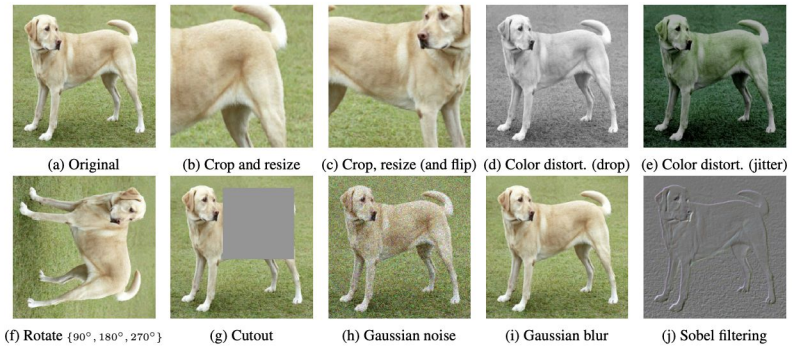
[Henaff et al., 2019] Olivier J. Hénaff, Aravind Srinivas, Jeffrey De Fauw, Ali Razavi, Carl Doersch, S. M. Ali Eslami, Aaron van den Oord Data-Efficient Image Recognition with Contrastive Coding arxiv:1905.09272, 2019.

[Chen et al., 2020] Chen, T., Kornblith, S., Norouzi, M. and Hinton, G. A Simple Framework for Contrastive Learning of Visual Representations arxiv:2002.0570, 2020.

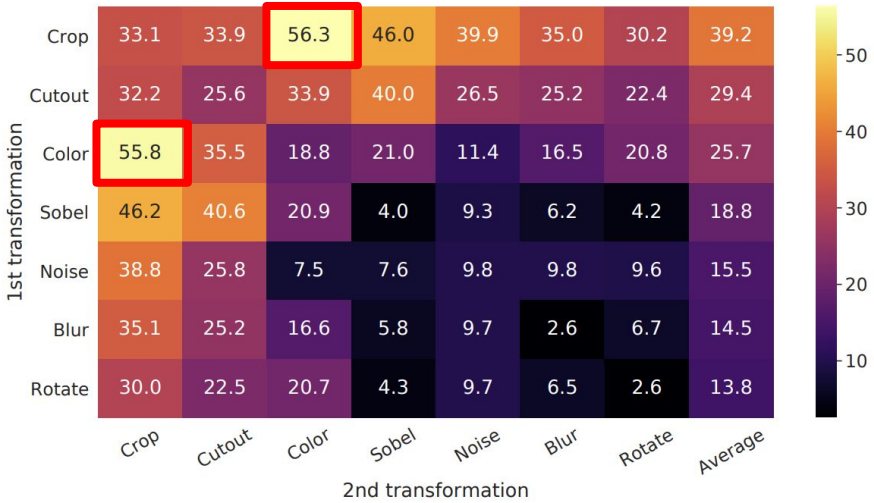
[He et al., 2019] He, K., Fan, H., Wu, Y., Xie, S. and Girshick, R. Momentum Contrast for Unsupervised Visual Representation Learning arxiv:1911.05722, 2019.

Biggest gains come from random crop + color jitter

Query / key pairs generated with data aug



Top-1 ImageNet accuracy



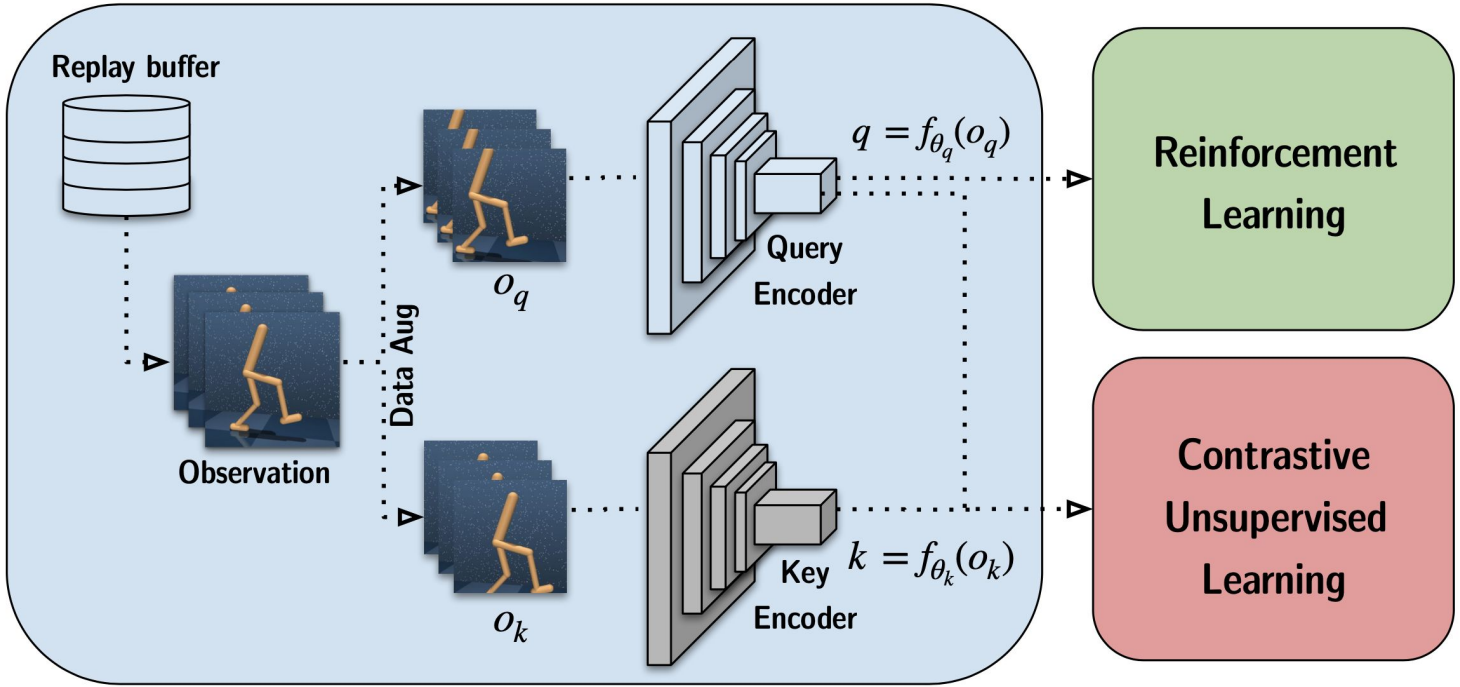
[Henaff et al., 2019] Olivier J. Hénaff, Aravind Srinivas, Jeffrey De Fauw, Ali Razavi, Carl Doersch, S. M. Ali Eslami, Aaron van den Oord Data-Efficient Image Recognition with Contrastive Coding arxiv:1905.09272, 2019.

[Chen et al., 2020] Chen, T., Kornblith, S., Norouzi, M. and Hinton, G. A Simple Framework for Contrastive Learning of Visual Representations arxiv:2002.0570, 2020.

[He et al., 2019] He, K., Fan, H., Wu, Y., Xie, S. and Girshick, R. Momentum Contrast for Unsupervised Visual Representation Learning arxiv:1911.05722, 2019.

CURL Method

Contrastive representations trained jointly with RL objective



[**Srinivas*, Laskin*** et al. 2020] *equal contribution, CURL: Contrastive Unsupervised Representations for Reinforcement Learning, Aravind Srinivas*, Michael Laskin*, Pieter Abbeel https://arxiv.org/abs/2004.04136

Bilinear inner product with learned weight matrix for similarity measure

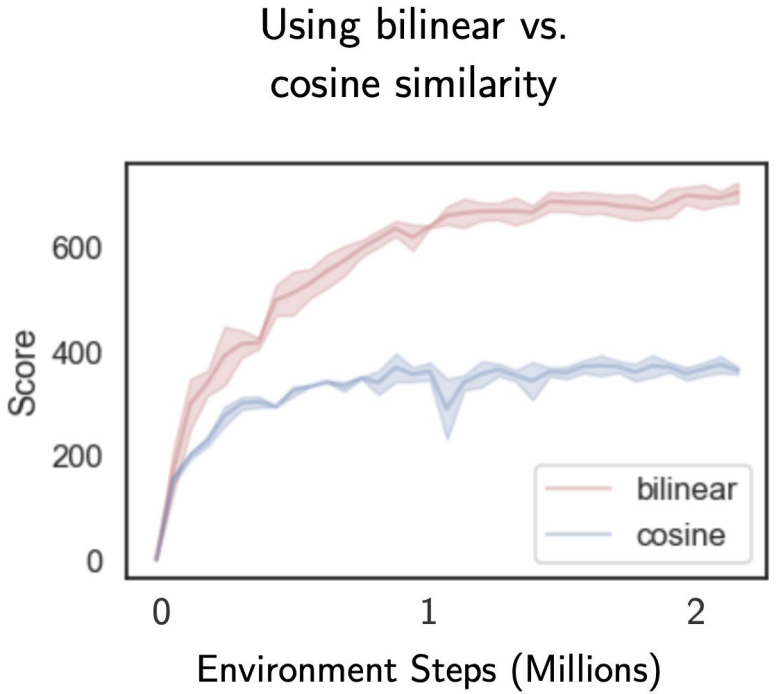
logits

$$\begin{bmatrix} q_0^T W k_0 & q_0^T W k_1 & \dots & q_0^T W k_j \\ q_1^T W k_0 & q_1^T W k_1 & \dots & q_1^T W k_j \\ \vdots & \vdots & \ddots & \vdots \\ q_j^T W k_0 & q_j^T W k_1 & \dots & q_k^T W k_j \end{bmatrix}$$

labels

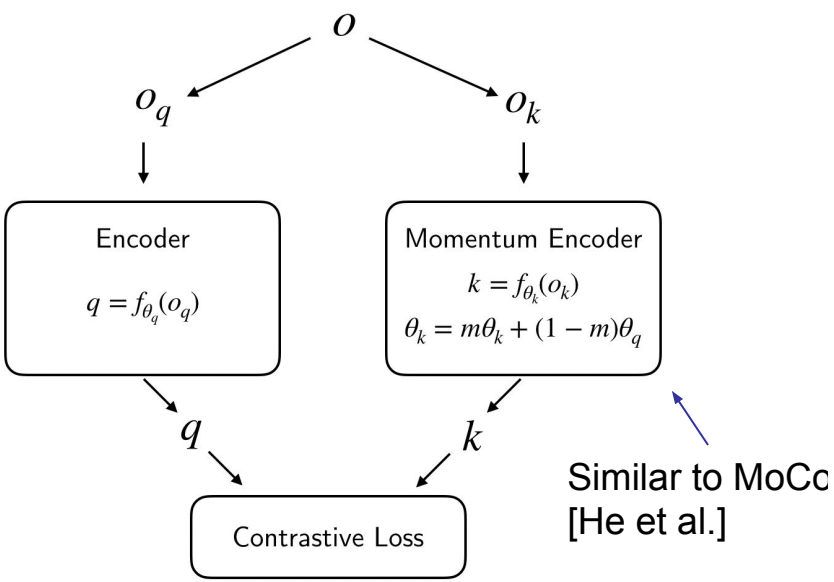
$$\begin{bmatrix} 1 & 0 & \dots & 0 \\ 0 & 1 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 1 \end{bmatrix}$$

$$\mathscr{L}_q = \frac{\exp(q^T W k_+)}{\exp(q^T W k_+) + \sum_{i=0}^{K-1} \exp(q^T W k_i)}$$

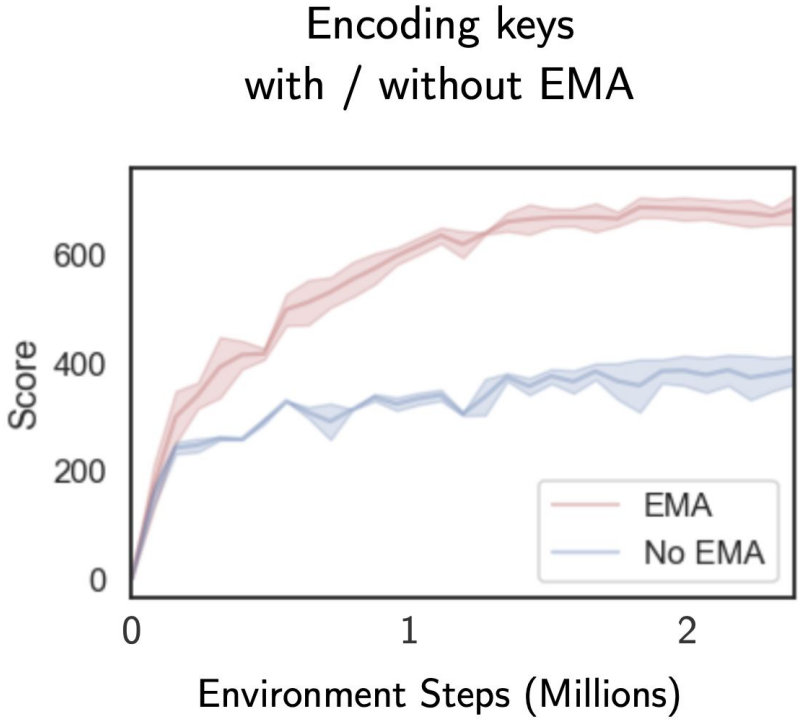


[**Srinivas*, Laskin*** et al. 2020] *equal contribution, CURL: Contrastive Unsupervised Representations for Reinforcement Learning, Aravind Srinivas*, Michael Laskin*, Pieter Abbeel https://arxiv.org/abs/2004.04136

Keys encoded with exponentially moving average of query encoder (momentum)



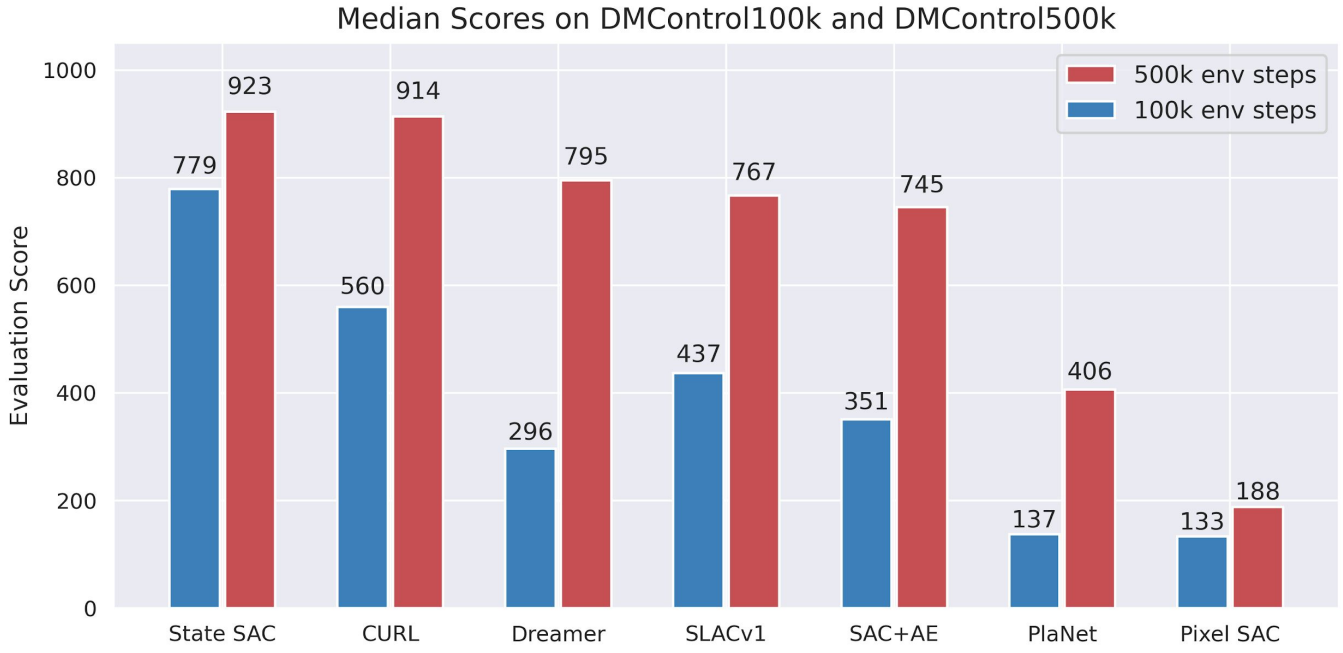
Similar to MoCo [He et al.]



[He et al., 2019] He, K., Fan, H., Wu, Y., Xie, S. and Girshick, R. Momentum Contrast for Unsupervised Visual Representation Learning arxiv:1911.05722, 2019.

CURL outperforms both prior model-based and model-free SoTA methods

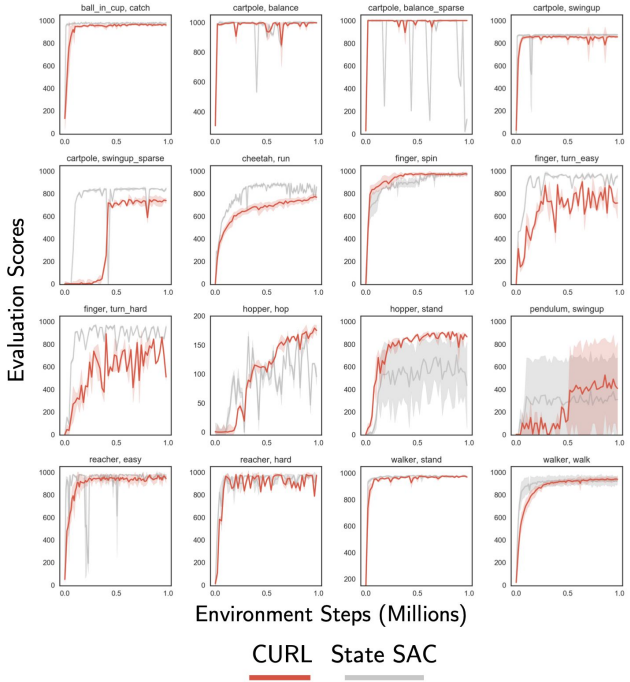
And matches state performance after only 500k simulator steps



[**Srinivas*, Laskin*** et al. 2020] *equal contribution, CURL: Contrastive Unsupervised Representations for Reinforcement Learning, Aravind Srinivas*, Michael Laskin*, Pieter Abbeel https://arxiv.org/abs/2004.04136

CURL matches data efficiency of state-based SAC on many DM control tasks

RED: CURL, **GRAY**: SAC State



Easy - matches state:
- cartpole (*balance, balance sparse, swingup)*
- ball in cup *(catch)*
- hopper *(hop, stand)*
- reacher *(easy, hard)*
- walker *(stand)*
- finger *(spin)*

Medium - close but noticeable gap from state:
- walker *(walk)*
- finger *(turn_easy, turn_hard)*
- cheetah *(run)*

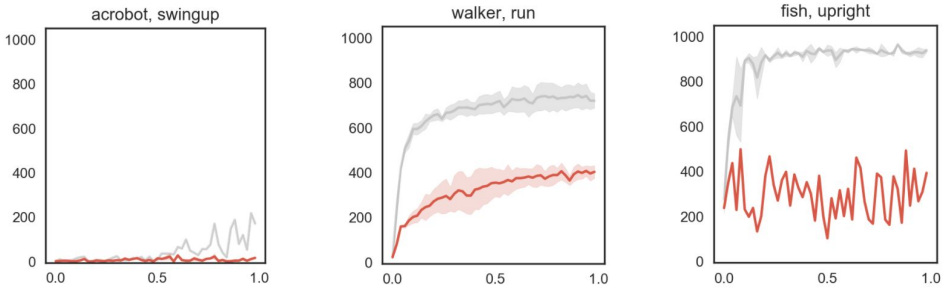
Hard - far from state:
- Humanoid
- fish / swimmer
- acrobot

CURL compared to existing methods on DeepMind control environments

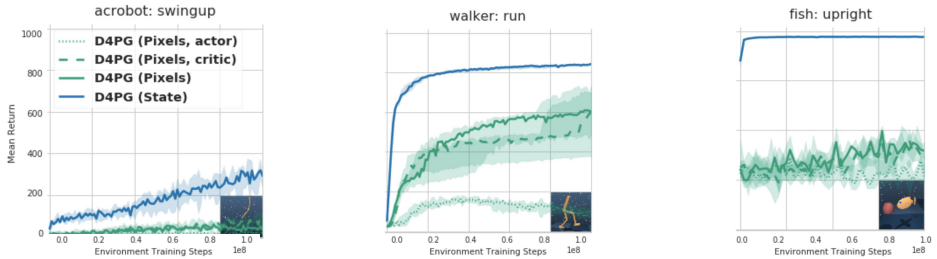
500K step scores	CURL	PlaNet	Dreamer	SAC+AE	SLACv1	Pixel SAC	State SAC
Finger, spin	**926 ± 45**	561 ± 284	796 ± 183	884 ± 128	673 ± 92	179 ± 166	923 ± 21
Cartpole, swingup	**841 ± 45**	475 ± 71	762 ± 27	735 ± 63	-	419 ± 40	848 ± 15
Reacher, easy	**929 ± 44**	210 ± 390	793 ± 164	627 ± 58	-	145 ± 30	923 ± 24
Cheetah, run	518 ± 28	305 ± 131	**732 ± 103**	550 ± 34	640 ± 19	197 ± 15	795 ± 30
Walker, walk	**902 ± 43**	351 ± 58	897 ± 49	847 ± 48	842 ± 51	42 ± 12	948 ± 54
Ball in cup, catch	**959 ± 27**	460 ± 380	879 ± 87	794± 58	852 ± 71	312± 63	974 ± 33
100K step scores							
Finger, spin	**767 ± 56**	136 ± 216	341 ± 70	740 ± 64	693 ± 141	179 ± 66	811±46
Cartpole, swingup	**582±146**	297±39	326±27	311±11	-	419±40	835±22
Reacher, easy	**538±233**	20±50	314±155	274±14	-	145±30	746±25
Cheetah, run	299 ±48	138±88	238± 76	267±24	**319±56**	197±15	616±18
Walker, walk	**403±24**	224±48	277±12	394±22	361±73	42±12	891±82
Ball in cup, catch	**769 ± 43**	0 ± 0	246 ± 174	391± 82	512 ± 110	312± 63	746±91

CURL fails to learn in environments with complex dynamics

RED: CURL, **GRAY**: SAC State



Agent steps 1 = 1M

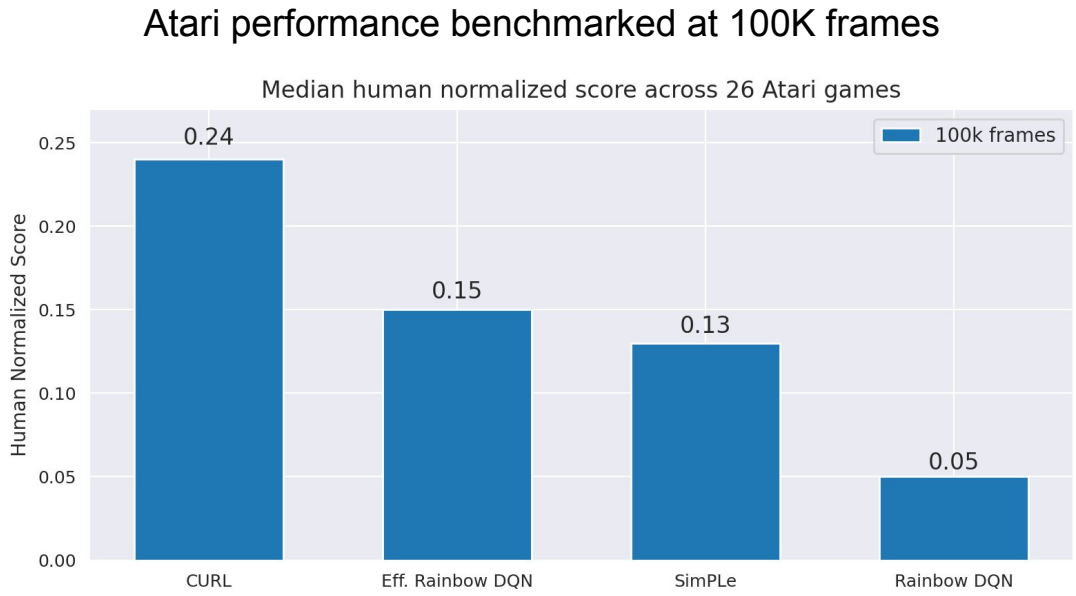


Environment steps 1 = 100M

[Tassa et al., 2018] Tassa, Y., Doron, Y., Muldal, A., Erez, T., Li, Y., Casas, D.D.L., Budden, D., Abdolmaleki, A., Merel, J., Lefrancq, A. and Lillicrap, T DeepMind Control Suite, arxiv:1801.00690, 2018.

Last year has seen **5x increase in data-efficiency** on Atari games…

Starting to close gap with human efficiency



CURL: 220% improvement on data efficiency for Atari

Atari performance benchmarked at 100K frames

100K STEP SCORES	CURL RAINBOW	SIMPLE	RAINBOW	HUMAN	RANDOM
ALIEN	**1148.2**	616.9	318.7	6875	184.8
AMIDAR	**232**	74.3	32.5	1676	11.8
ASSAULT	473	**527.2**	231	1496	248.8
BATTLEZONE	**11208**	4031.2	3285.71	37800	2895
FREEWAY	**27**	16.7	0	29.6	0
FROSTBITE	**924**	236.9	60.2	4335	74
JAMESBOND	**400**	100.5	47.4	406.7	29.2
QBERT	**1352**	1288.8	123.46	13455	166.1
SEAQUEST	408	**683.3**	131.69	20182	61.1

Can pixel-based RL match human data-efficiency?

Current SOTA Method

Algorithm vs human performance at 100k frames (~2 hrs of gameplay)

	Algorithm	Algorithm Score	Human Score	Human Normalized Algorithm Score
Alien	CURL	1148.2	6875	16.7%
Amidar	CURL	232	1676	13.8%
Assault	SimPLE	527.2	1496	35.2%
BattleZone	CURL	11208	37800	29.6%
Freeway	CURL	27	29.6	**91.2%**
Frostbite	CURL	924	4335	21.3%
Jamesbond	CURL	400	406.7	**98.3%**
Qbert	CURL	1352	13455	10.0%
Seaquest	SimPLE	683.3	20182	3.4%

Only on-par with human performance on 2/9 games!

Representation Learning in Reinforcement Learning

- Auxiliary losses
- State representation
- ***Exploration***
- Unsupervised skill discovery

Representation Learning in Reinforcement Learning

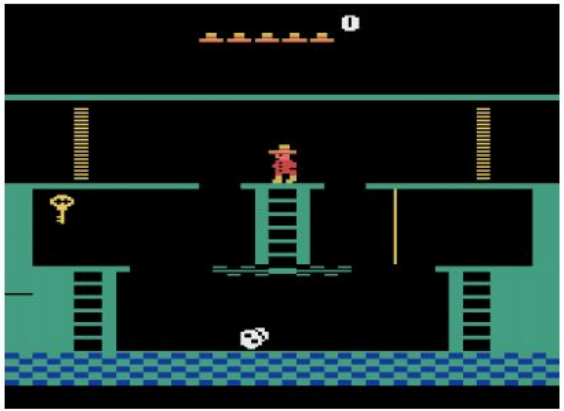
- Auxiliary losses
- State representation
- ***Exploration***
  - ***Exploration bonuses***
- Unsupervised skill discovery

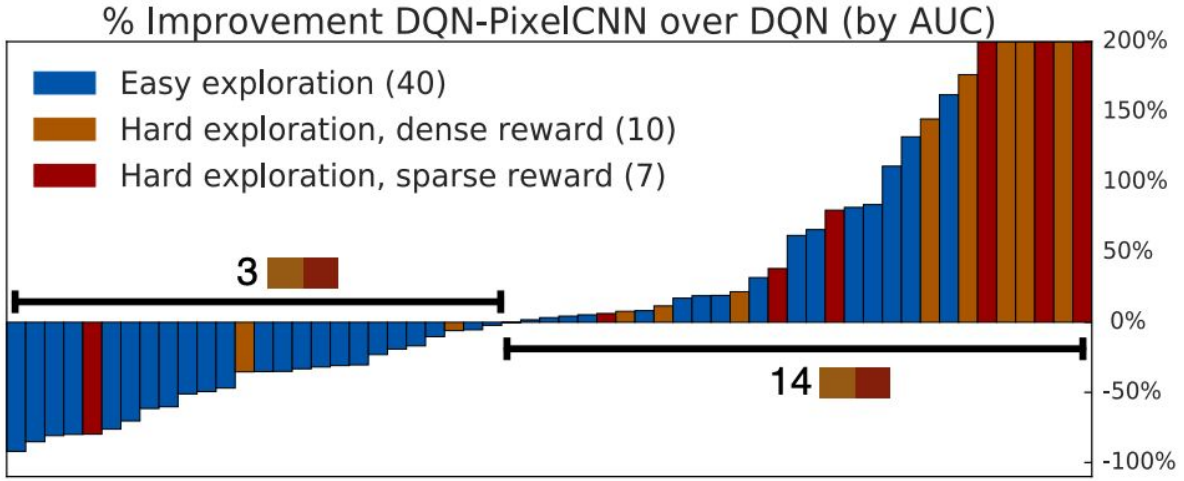
Exploration Bonuses

- Tabular RL exploration bonuses:
  - Give exploration bonus when visiting state that hasn't been visited very often before
- But: impractical for large / continuous state spaces
  - Similarity of states matters, not just individual states

Exploration Bonuses (1)

- Count-Based Exploration with Neural Density Models, Georg Ostrovski, Marc G. Bellemare, Aaron van den Oord, Remi Munos, https://arxiv.org/abs/1703.01310
  - PixelCNN for density estimation





Exploration Bonuses (2)

- #Exploration: A Study of Count-Based Exploration for Deep Reinforcement Learning, Haoran Tang, Rein Houthooft, Davis Foote, Adam Stooke, Xi Chen, Yan Duan, John Schulman, Filip De Turck, Pieter Abbeel (https://arxiv.org/abs/1611.04717)
  - VAE embedding / hash → classical counts in the discrete hash space

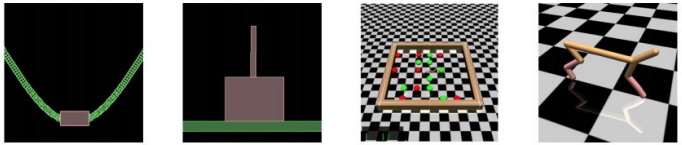
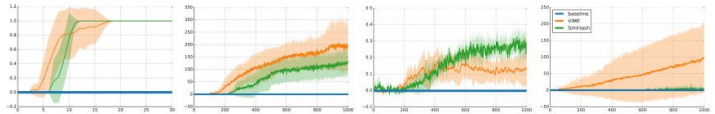
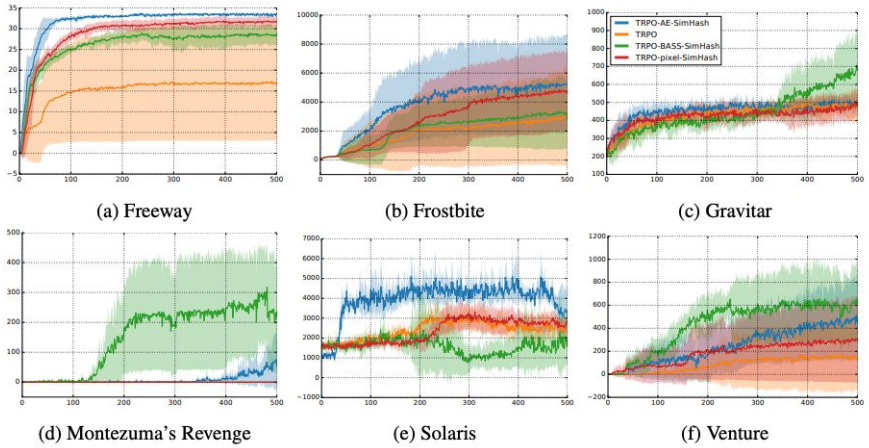


Figure 2: Illustrations of the rllab tasks used in the continuous control experiments, namely MountainCar, CartPoleSwingup, SimmerGather, and HalfCheetah; taken from [8].



(a) MountainCar (b) CartPoleSwingup (c) SwimmerGather (d) HalfCheetah

Figure 3: Mean average return of different algorithms on rllab tasks with sparse rewards. The solid line represents the mean average return, while the shaded area represents one standard deviation, over 5 seeds for the baseline and SimHash (the baseline curves happen to overlap with the axis).



(a) Freeway (b) Frostbite (c) Gravitar

(d) Montezuma's Revenge (e) Solaris (f) Venture

Exploration Bonuses (3)

- VIME: Variational Information Maximizing Exploration, Rein Houthooft, Xi Chen, Yan Duan, John Schulman, Filip De Turck, Pieter Abbeel (https://arxiv.org/abs/1605.09674)
  - Bayesian neural net dynamics model
  - Exploration bonus based on KL divergence between pre and post update model distribution

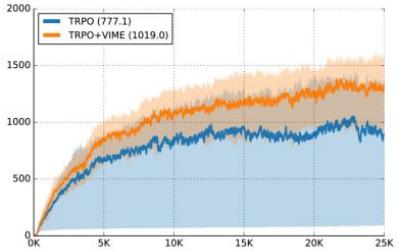


Figure 3: Performance of TRPO with and without VIME on the high-dimensional Walker2D locomotion task.

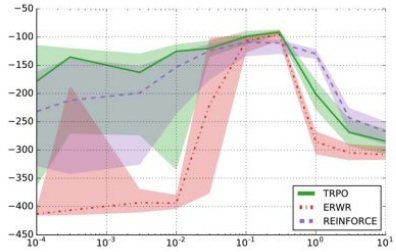


Figure 4: VIME: performance over the first few iterations for TRPO, REINFORCE, and ERWR i.f.o. η on MountainCar.

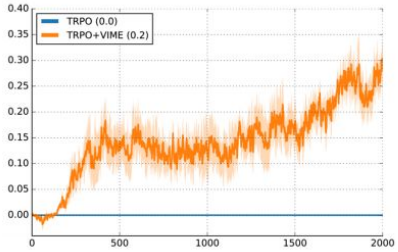


Figure 5: Performance of TRPO with and without VIME on the challenging hierarchical task SwimmerGather.

Exploration Bonuses (4)

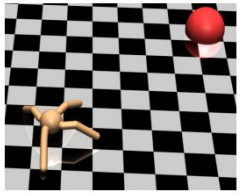
- Curiosity:
  - Curiosity-driven Exploration by Self-supervised Prediction, Deepak Pathak, Pulkit Agrawal, Alexei A. Efros, Trevor Darrell (https://arxiv.org/abs/1705.05363)
  - Large-Scale Study of Curiosity-Driven Learning, Yuri Burda, Harri Edwards, Deepak Pathak, Amos Storkey, Trevor Darrell, Alexei A. Efros (https://arxiv.org/abs/1808.04355)

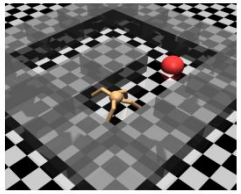
Representation Learning in Reinforcement Learning

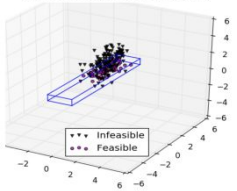
- Auxiliary losses
- State representation
- ***Exploration***
  - ***Exploration bonuses***
  - ***Exploration through goal generation***
- Unsupervised skill discovery

GoalGAN

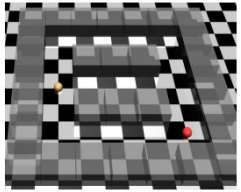
- Automatic Goal Generation for Reinforcement Learning Agents, Carlos Florensa, David Held, Xinyang Geng, Pieter Abbeel (https://arxiv.org/abs/1705.06366)
  - Train goal-conditioned policy
  - Achieve curriculum by setting goals that become gradually more difficult
  - How? GAN is continually retrained to generate goals of right level of difficulty based on recent performance on previous goals

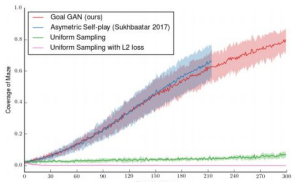

(a) Free Ant Locomotion


(b) Maze Ant Locomotion

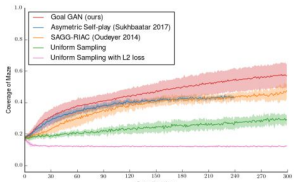


(c) Point-mass 3D

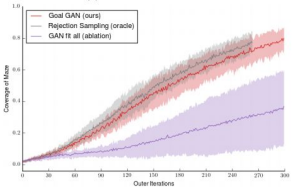

(d) Multi-path point-mass



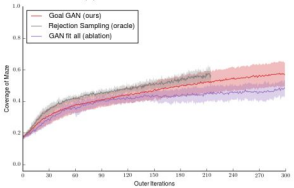
(a) Free Ant - Baselines



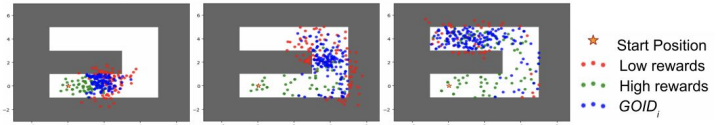
(b) Maze Ant - Baselines



(c) Free Ant - Variants



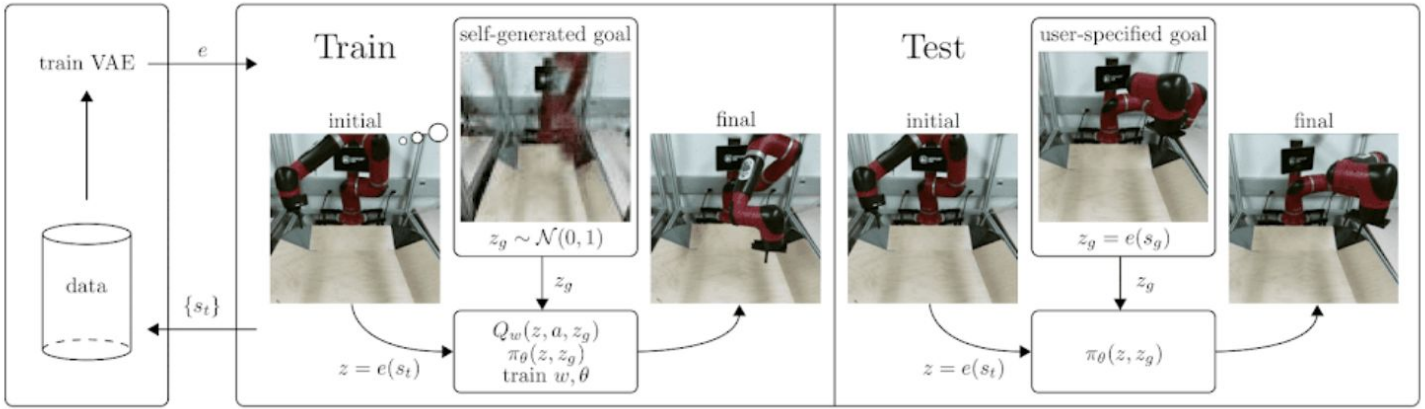
(d) Maze Ant - Variants



(a) Iteration 5 (b) Iteration 90 (c) Iterartion 350

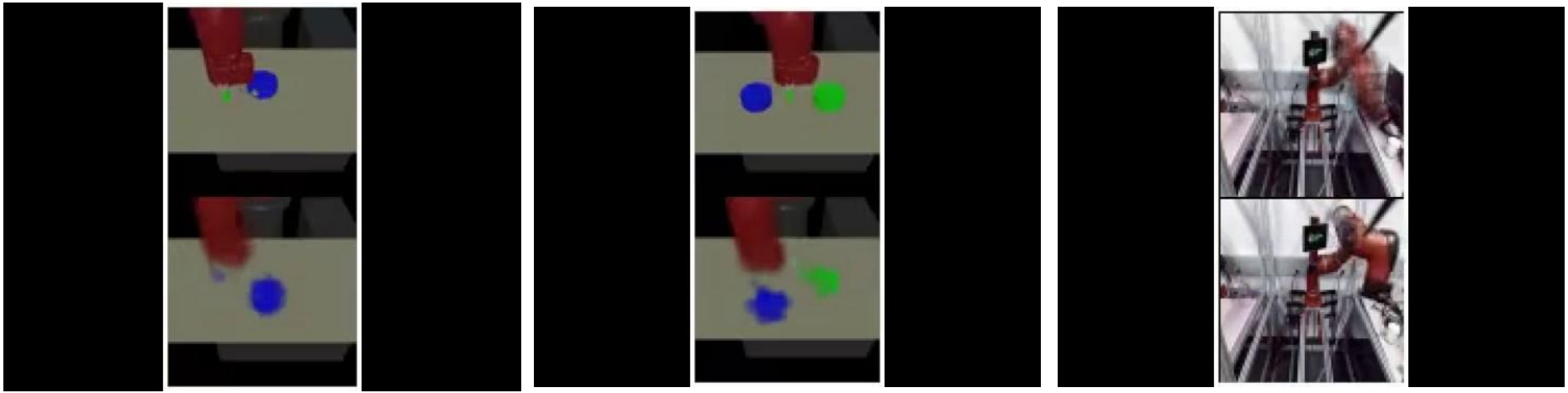
RIG

- Visual Reinforcement Learning with Imagined Goals, Ashvin Nair, Vitchyr Pong, Murtaza Dalal, Shikhar Bahl, Steven Lin, Sergey Levine (https://arxiv.org/abs/1807.04742)
- Learn probabilistic latent variable model (Variational Auto-Encoder)
- Use latent representation for state and goal representation.
- Sample goals for hindsight experience relabeling
- Sample goals for exploration
- Use latent distance for reward



RIG

- Visual Reinforcement Learning with Imagined Goals (RIG)
  Ashvin Nair, Vitchyr Pong, Murtaza Dalal, Shikhar Bahl, Steven Lin, Sergey Levine
  (https://arxiv.org/abs/1807.04742)

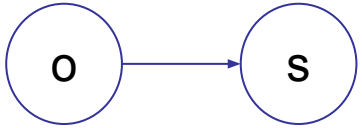


Representation Learning in Reinforcement Learning

- Auxiliary losses
- State representation
- ***Exploration***
  - ***Exploration bonuses***
  - ***Exploration through goal generation***
  - ***Exploration through skill transfer***
- Unsupervised skill discovery

Traditional view on Representation Learning in RL

Typical focus on learning good representations of observations allowing for better learning, modeling, etc



- Embed2Control [Watter et al]
- Deep Predictive Policy Training [Ghadirzadeh et al]
- DARLA [Higgins et al]
- Robotic Priors [Jonschkowski and Brock]
- UPN [Aravind, Allan, Chelsea, etc]
- Causal InfoGAN [Kurutach, Tamar et al]

Especially useful when trying to learn from pixel inputs and complex observations

Alternative View on Representation Learning

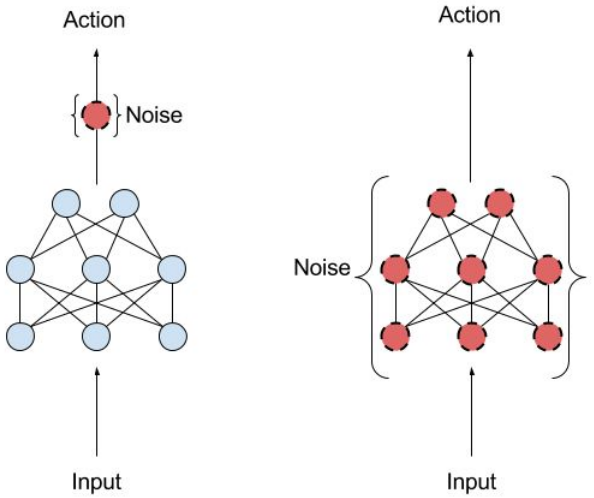
Can we learn representations of things other than the mapping from observations to low level hidden state

- Trajectories
- Behaviors/tasks?
- …

Question: How do we supervise representation learning for these things?

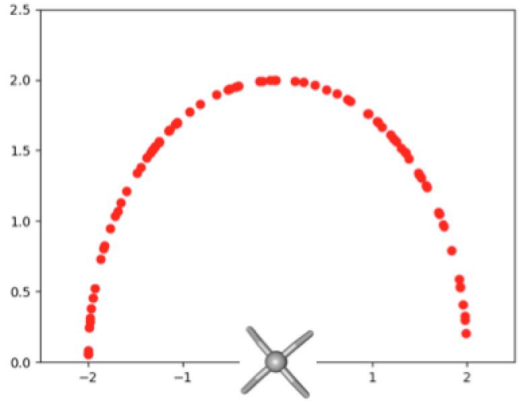
Representation learning for Exploration

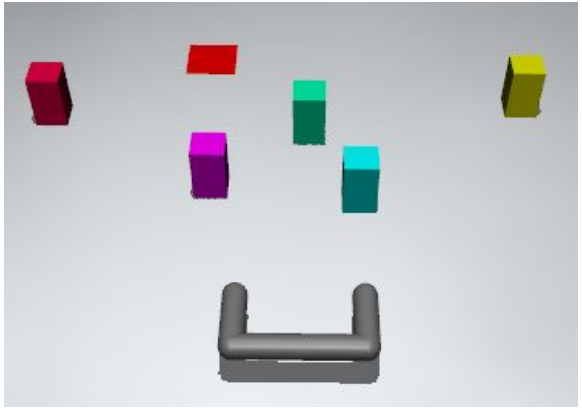
Exploration typically with stochasticity in the space of actions or in parameter space



Can we better inform exploration spaces using prior experience?

Why is this important?



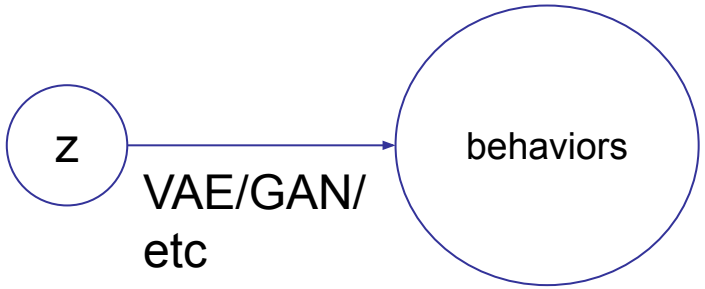


More efficient exploration for test tasks based on prior knowledge

Latent Exploration Spaces

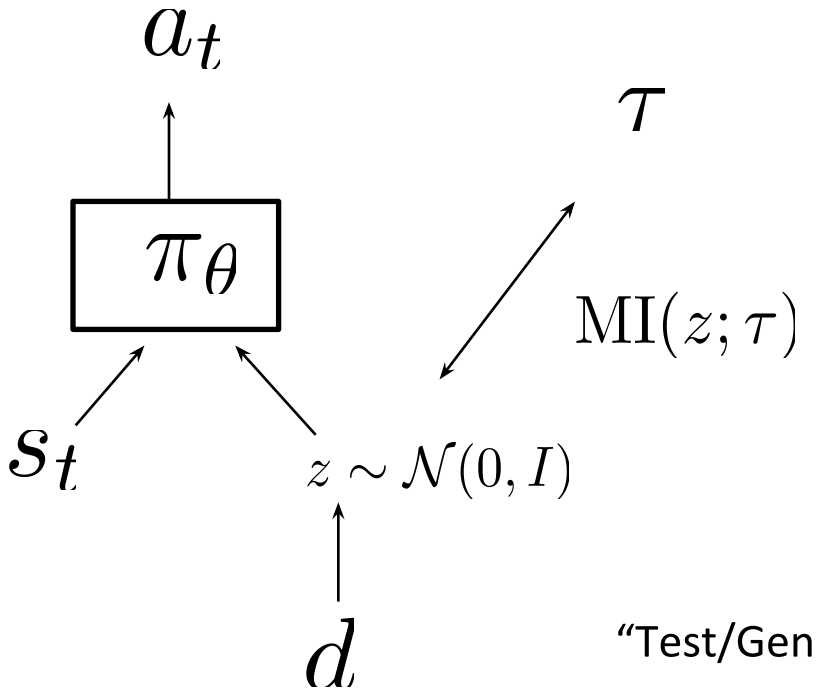
Can we learn better spaces to inject noise instead of simply into action/parameter space?

- What if we learned a latent space of behaviors which spans the input task distribution? i.e can we learn a generative model of behaviors and use it to generate novel exploratory behavior



Approach 1: Hausman et al 2018

Train against many tasks
(each task indexed by d):

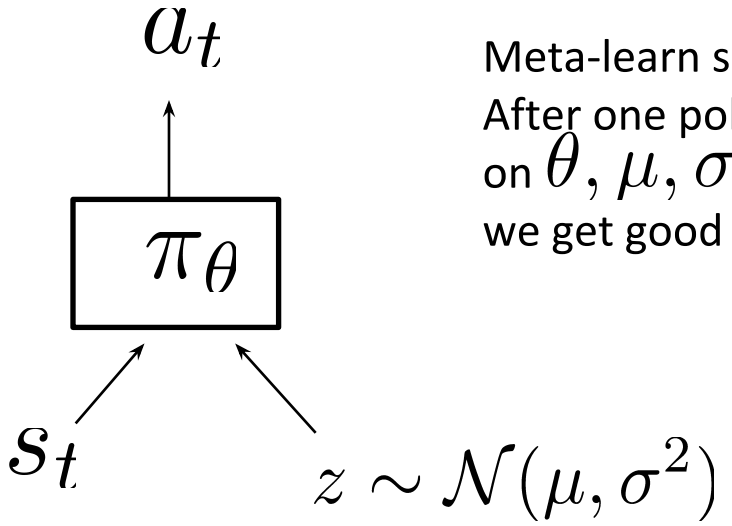


"Test/Generalize" in z-space

Learning an Embedding Space for Transferrable Skill, Hausman, Springenberg, Wang, Heess, Riedmiller, ICLR 2018

Approach 2: Gupta et al 2018

Train against many tasks



Meta-learn such that:
After one policy gradient update on θ, μ, σ
we get good behavior

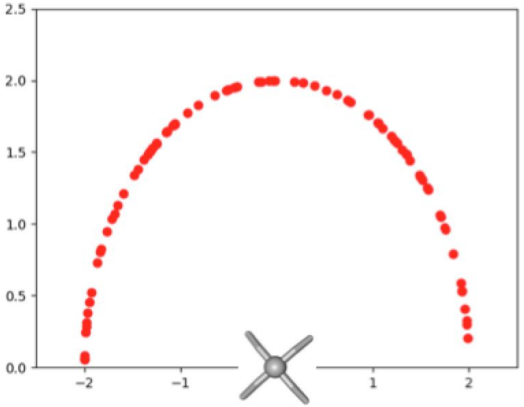
"Test/Generalize" in z-space

Model-Agnostic Exploration with Structured Noise (MAESN), Gupta, Mendonca, Liu, Abbeel, Levine, 2018

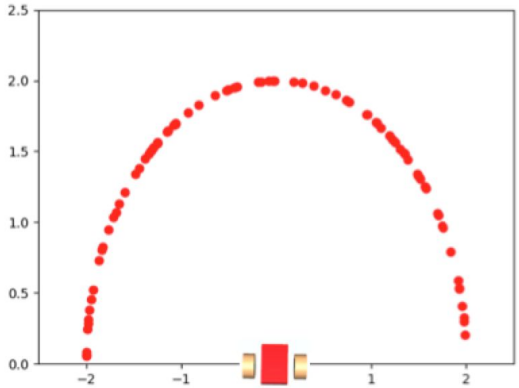
Experiments

3 task families:

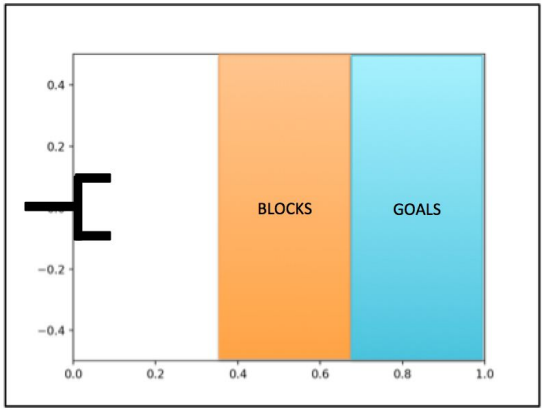
Ant



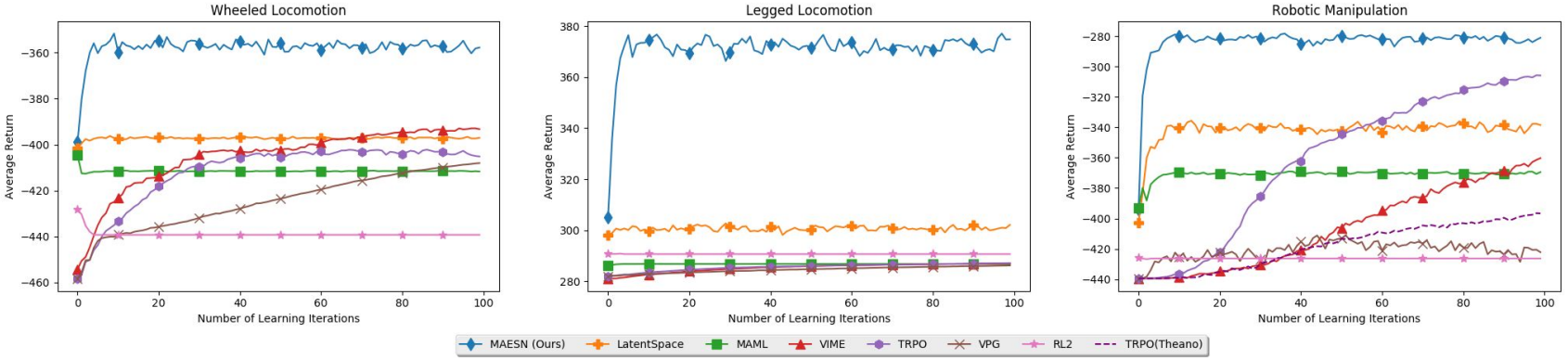
Wheeled Locomotion

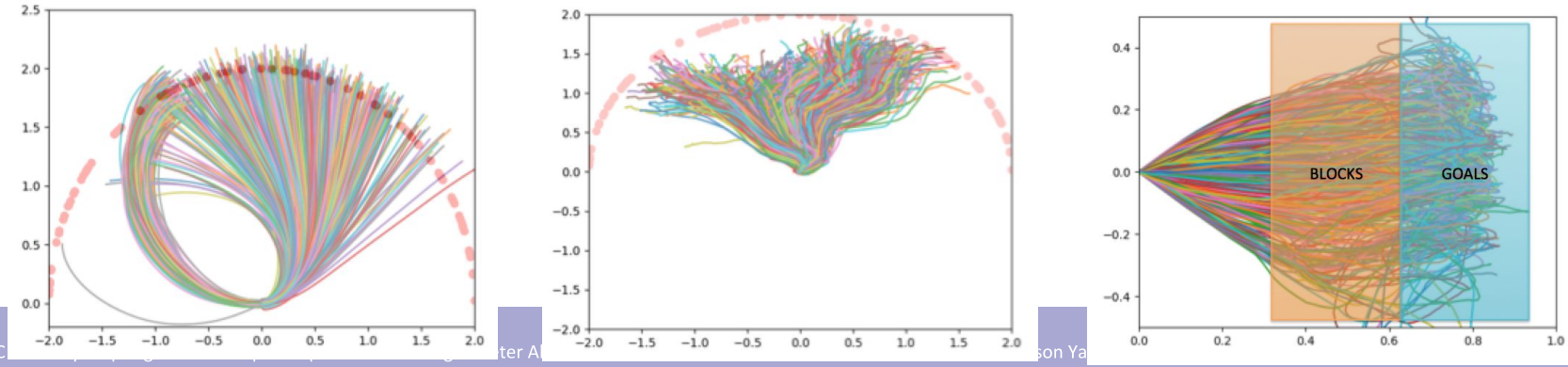


Block Manipulation



Experiments





Representation Learning in Reinforcement Learning

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Representation Learning in Reinforcement Learning

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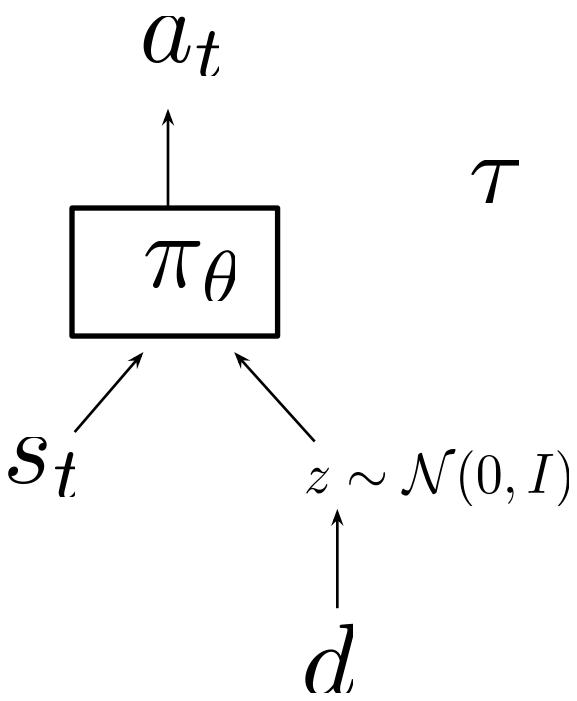
Unsupervised Skill Discovery



- SSN4HRL (Florensa, Duan, Abbeel, 2016)

$$\mathrm{MI}(d; \tau)$$

- Variational Intrinsic Control (Gregor et al 2016)

$$\mathrm{MI}(z; s_H)$$

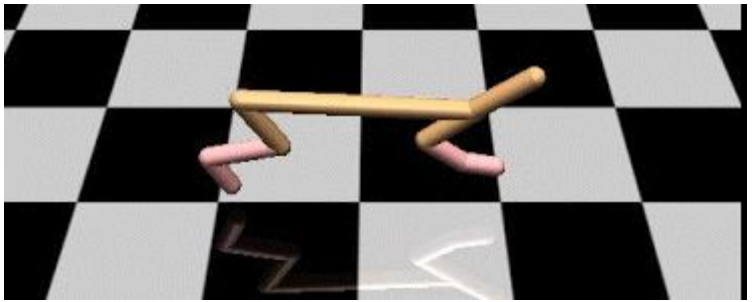
- Diversity is all you need (Eysenbach et al 2018)

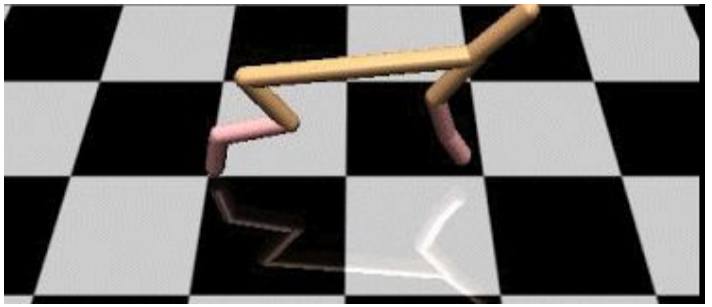
$$\sum_t \mathrm{MI}(z; s_t)$$

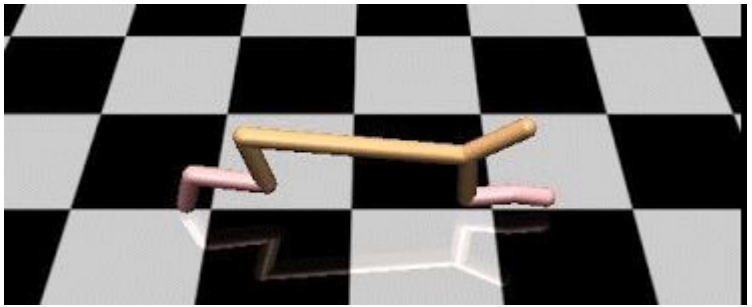
- VALOR (Achiam et al 2018)

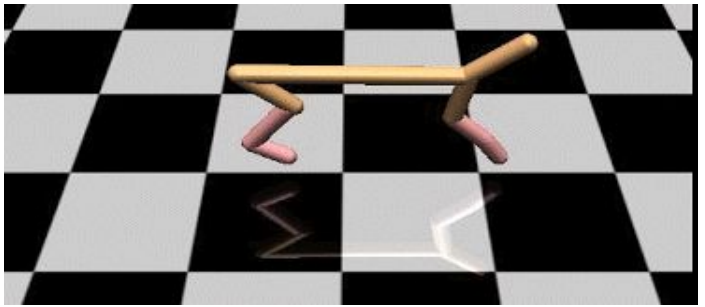
$$\mathrm{MI}(z; \tau)$$

Here are cool videos from Eysenbach et al

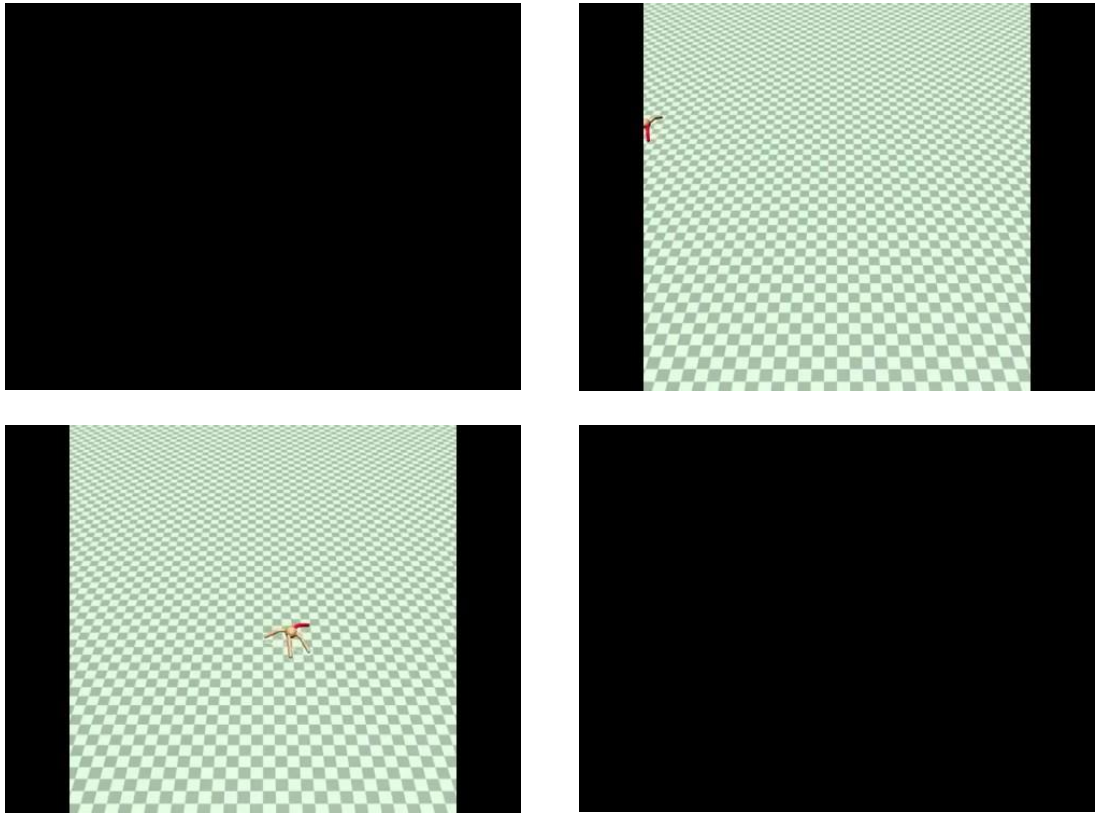








Here are cool videos from Achiam et al



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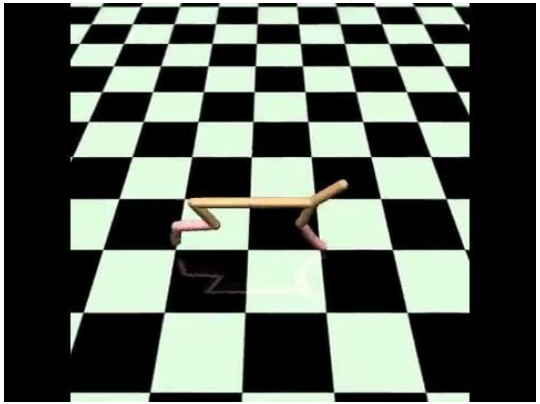

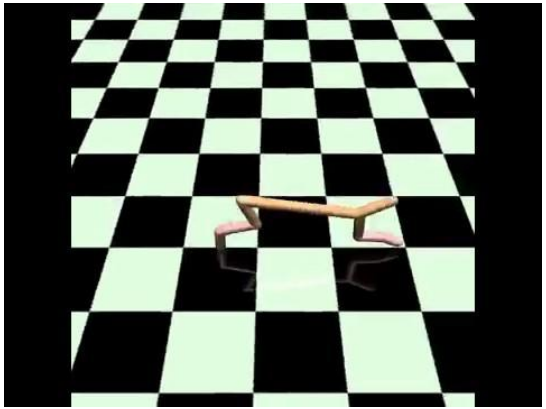

Humanoid

High-dimensional problems like Humanoid:

- All learned behaviors were on the ground, none of them get humanoid to get up and run
- Maybe something more is needed beyond the MI objective...

Summary: Representation Learning in Reinforcement Learning

- Auxiliary losses
- State representation
- Exploration
- Unsupervised skill discovery

Some recommended readings we didn't cover

- **Temporal Difference Variational Auto-Encoder**
  Karol Gregor, George Papamakarios, Frederic Besse, Lars Buesing, Theophane Weber
  https://arxiv.org/abs/1806.03107
- **Model-Based Reinforcement Learning for Atari**
  Lukasz Kaiser, Mohammad Babaeizadeh, Piotr Milos, Blazej Osinski, Roy H Campbell, Konrad Czechowski, Dumitru Erhan, Chelsea Finn, Piotr Kozakowski, Sergey Levine, Ryan Sepassi, George Tucker, Henryk Michalewski
  https://arxiv.org/abs/1903.00374
- **Time-Contrastive Networks: Self-Supervised Learning from Video**
  Pierre Sermanet, Corey Lynch, Yevgen Chebotar, Jasmine Hsu, Eric Jang, Stefan Schaal, Sergey Levine
  https://arxiv.org/abs/1704.06888
- **Learning Actionable Representations with Goal-Conditioned Policies**
  Dibya Ghosh, Abhishek Gupta, Sergey Levine
  https://arxiv.org/abs/1811.07819
- **Deep Object-Centric Representations for Generalizable Robot Learning**
  Coline Devin, Pieter Abbeel, Trevor Darrell, Sergey Levine
  https://arxiv.org/abs/1708.04225
- **Decoupling Dynamics and Reward for Transfer Learning**
  Amy Zhang, Harsh Satija, Joelle Pineau
  https://arxiv.org/abs/1804.10689