# Improving sample-efficiency of model-free reinforcement learning algorithms on image inputs with representation learning

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# Presentation structure

# Project overview

# Hypothesis

- state (feature) extraction
- dynamics modelling
- reward dynamics modelling

**Joint training hypothesis**

Joint training is better than pretraining.

# Hypotheses

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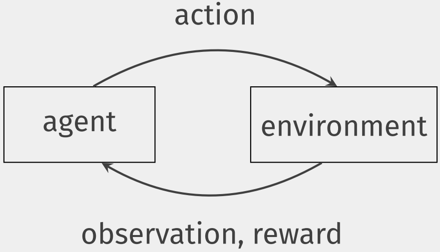
**Regularization hypothesis.**

Proper regularization helps when learning different objectives.

# Reinforcement learning

# What is reinforcement learning?

- formalized “trial-and-error” learning
- needs a **reward function**
- trade-off between exploration and exploitation



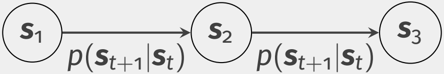



**Figure:** Schematic of a Markov chain.

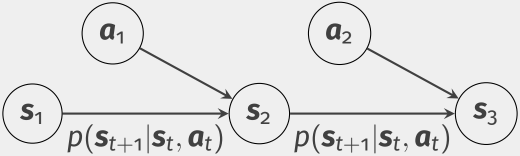



**Figure:** Schematic of a Markov decision process.

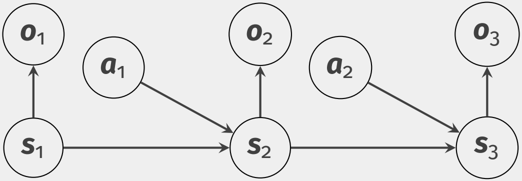



**Figure:** Schematic of a partially observable Markov decision process.

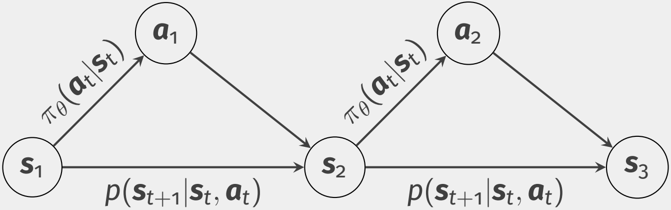



**Figure:** Schematic of a Markov decision process with a policy $\pi$.

# Markov decision process in equation form

$$\underbrace{p_\theta(\mathbf{s}_1, \mathbf{a}_1, \ldots, \mathbf{s}_T, \mathbf{a}_T)}_{p_\theta(\tau)} = p(\mathbf{s}_1) \prod_{t=1}^{T} \underbrace{\pi_\theta(\mathbf{a}_t|\mathbf{s}_t) p(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t)}_{\text{Markov chain on } (\mathbf{s},\mathbf{a})}$$

Find policy parameters $\theta^\star$ such that:

$$\begin{aligned}\theta^\star &= \operatorname*{argmax}_\theta \mathbb{E}_{\tau\sim p_\theta(\tau)}\left[\sum_t r(\boldsymbol{s}_t, \boldsymbol{a}_t)\right] \\ &= \operatorname*{argmax}_\theta \sum_t^T \mathbb{E}_{(\boldsymbol{s}_t,\boldsymbol{a}_t)\sim p_\theta(\boldsymbol{s}_t,\boldsymbol{a}_t)}\left[r(\boldsymbol{s}_t, \boldsymbol{a}_t)\right]\end{aligned}$$

Q-function:

$$Q^{\pi}(\boldsymbol{s}_t, \boldsymbol{a}_t) = \sum_{t'=t}^{T} \mathbb{E}_{\pi_\theta}\left[r(\boldsymbol{s}_{t'}, \boldsymbol{a}_{t'}) | \boldsymbol{s}_t, \boldsymbol{a}_t\right]$$

State value function:

$$V^{\pi}(\boldsymbol{s}_t) = \sum_{t'=t}^{T} \mathbb{E}_{\pi_\theta}\left[r(\boldsymbol{s}_{t'}, \boldsymbol{a}_{t'} | \boldsymbol{s}_t)\right]$$

Their connection:

$$V^{\pi}(\boldsymbol{s}_t) = \mathbb{E}_{\boldsymbol{a}_t \sim \pi(\boldsymbol{s}_t, \boldsymbol{a}_t)}\left[Q^{\pi}(\boldsymbol{s}_t, \boldsymbol{a}_t)\right]$$

Based on objective:

- policy gradient algorithms
- actor-critic algorithms
- value iteration algorithms

Based on sampling strategy:

- on-policy
- off-policy

REINFORCE algorithm:

1. sample $\{\tau^i\}$ from $\pi_\theta(\boldsymbol{a}_t|\boldsymbol{s}_t)$ by running the policy
2. use the samples to estimate the gradient of the objective:
   $\nabla_\theta J(\theta) \approx \sum_i \left(\sum_t^T \nabla_\theta \log \pi_\theta(\boldsymbol{a}_{i,t}|\boldsymbol{s}_{i,t})\right) \left(\sum_t r(\boldsymbol{s}_{i,t}, \boldsymbol{a}_{i,t})\right)$
3. update the policy function by performing a step of gradient ascent:
   $\theta \leftarrow \theta + \alpha \nabla_\theta J(\theta)$

Actor-critic algorithm template

1. take action $\boldsymbol{a} \sim \pi_\theta(\boldsymbol{a}|\boldsymbol{s})$, observe transition $(\boldsymbol{s}, \boldsymbol{a}, \boldsymbol{s'}, r)$ and store it in the replay buffer $\mathcal{R}$
2. sample a batch $\{(\boldsymbol{s}_i, \boldsymbol{a}_i, \boldsymbol{s}'_i, r_i)\}$ from buffer $\mathcal{R}$
3. update the Q-value estimator $\hat{Q}^\pi_\theta$ by using the target: $y_i = r_i + \gamma \hat{Q}^\pi_\theta(\boldsymbol{s}'_i, \boldsymbol{a}'_i) \forall \boldsymbol{s}_i, \boldsymbol{a}_i$
4. compute the policy gradient estimate with: $\nabla_\theta J(\theta) \approx \frac{1}{N} \sum_i \nabla_\theta \log \pi_\theta(\boldsymbol{a}^\pi_i|\boldsymbol{s}_i) \hat{Q}^\pi(\boldsymbol{s}_i, \boldsymbol{a}^\pi_i)$, where $\boldsymbol{a}^\pi_i \sim \pi_\theta(\boldsymbol{a}|\boldsymbol{s}_i)$
5. update the policy function by performing a gradient step: $\theta \leftarrow \theta + \alpha \nabla_\theta J(\theta)$

$$\pi_{\text{greedy}}(\boldsymbol{s}_t|\boldsymbol{a}_t) = \begin{cases} 1 & \text{if } \boldsymbol{a}_t = \text{argmax}_{\boldsymbol{a}_t} A^{\pi}(\boldsymbol{s}_t, \boldsymbol{a}_t) \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

Bootstrap update for the value function:

$$V^{\pi}(\mathbf{s}) \leftarrow E_{\mathbf{a}\sim\pi(\mathbf{a}|\mathbf{s})}\left[r(\mathbf{s},\mathbf{a}) + \gamma E_{\mathbf{s}'\sim p(\mathbf{s}'|\mathbf{a},\mathbf{s})}[V^{\pi}(\mathbf{s}')]\right] \tag{2}$$

Value iteration

1. set $Q(\mathbf{s},\mathbf{a}) \leftarrow r(\mathbf{s},\mathbf{a}) + \gamma E[V(\mathbf{s}')]$
2. set $V(\mathbf{s}) \leftarrow \max_{\mathbf{a}} Q(\mathbf{s},\mathbf{a})$

"Classic" DQN

1. take some action $\mathbf{a}_i$, observe $(\mathbf{s}_i, \mathbf{a}_i, \mathbf{s}'_i, r_i)$ and add it to $\mathcal{B}$
2. sample a mini-batch $\left(\mathbf{s}_j, \mathbf{a}_j, \mathbf{s}'_j, r_j\right)$ from $\mathcal{B}$ uniformly
3. compute $y_j = r_j + \gamma \max_{\mathbf{a}'_j} Q_{\phi'}(\mathbf{s}'_j, \mathbf{a}'_j)$ using the *target* network $Q_{\phi'}$
4. $\phi \leftarrow \phi - \alpha \sum_j \frac{dQ_\phi}{d\phi}(\mathbf{s}_j, \mathbf{a}_j)\left(Q_\phi(\mathbf{s}_i, \mathbf{a}_i) - y_j\right)$
5. update $\phi'$: copy $\phi$ every $N$ steps

# Rainbow

DQN with the following improvements:

- double Q-networks
- multi-step returns
- prioritized replay buffer
- dueling network
- noisy networks

# Representation learning

- goal is to learn a parametric mapping from raw input data to a feature vector in order to capture and extract useful abstract information
- works with unsupervised learning
- generative and discriminative models

- deterministic:
  - autoencoders (AEs)
- probabilistic:
  - variational autoencoders (VAEs)
  - generative adversarial networks (GANs)

# Discriminative models

- have only encoders
- trained with:
  - contrastive learning
  - bootstrapping

Known from [BCV13], [Gho+19] and others:

- on input:
  - denoising autoencoders
- on bottleneck:
  - noise injection
  - Tikhonov regularization (L2 regularization)
- other:
  - gradient penalty (weight decay)
  - spectral normalization

# Representation learning for control

# Desirable properties

On top of general desirable properties for representations:

- having the Markov property
- represent states well enough for policy improvement
- generalize in the stateful sense

- autoencoders
- forward models
- inverse models
- hybrid models

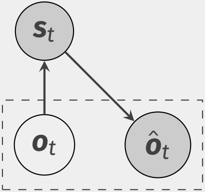



**Figure:** Auto-encoder: learned by reconstructing the observation (one-to-one). The observation is the input and the computed state is the vector at the auto-encoder's bottleneck layer.

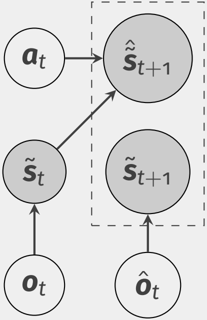



**Figure:** Forward model: predicting the future state from the state-action pair.

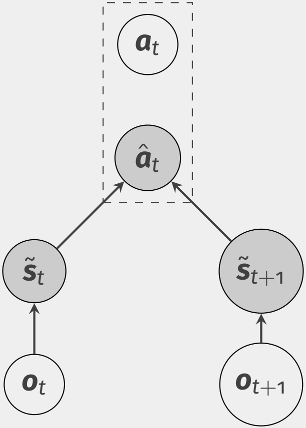



**Figure:** Inverse model: predicting the action between two consecutive states.

# Related work

- started with DQN [Mni+13]
- many improvements:
  - algorithm fundamentals, combination in [Hes+18]
  - exploration schemes: [Pat+17], [Eco+21]
  - better sampling: [And+17], [Kap+18]
- model based algorithms: [Sch+20a]
- all solved on human level in [Bad+20]

# Reinforcement learning on Atari games

- started with DQN [Mni+13]
- many improvements:
  - algorithm fundamentals, combination in [Hes+18]
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**Next challenge**

Making reinforcement learning more sample-efficient.

# Using data augmentation for regularization

- simply adding data augmentation to RL: [Las+20]
- using it to regularize RL: [KYF20], [Yar+21]

# Leveraging unsupervised representation learning

- early efforts for state representation learning did not work well
- initially used to help exploration: [She+16], [Jad+16] or [Pat+17]
- recent efforts use both deterministic and stochastic generative models (mostly stochastic)
- most recent works focus on using discriminative models
- ideally obtained solely via pretrainining; recent efforts include [Seo+22]

Idea introduced in [LR10]. Most importantly used in [Yar+19]. Authors identify the following for success:

- only value function gradients update the encoder
- same update rate for autoencoder and RL updates
- using L2 regularization

Possible improvements:

- prediction architecture from [Oh+15]
- optical or latent flow: [Sha+21]

Theoretically more interesting because:

- can be integrated into the underlying Markov chain: [Lee+20]
- can be used as models in model-based RL

Despite large interest they are hard to get to work due to their stochasticity (elaborated and tested in [Yar+19]).

# Discriminative models

More practical as there is no decoder (which is unnecessary for the purpose). Trained using different objectives:

- contrastive loss: [LSA20]
- mutual information: [Rak+21], [Ana+19], [Maz+20]
- bisimulation metrics: [Zha+20]
- bootstrapped self-predictions (introduced in [Gri+20]): [Sch+20b], and in [Mer+22]

# Methods

# Our hypotheses

We want to test the following claims:

1. joint representation and reinforcement training performs better than pretraining
2. representation better incentivised to learn stateful information will yield better features
3. regularization is important for joint training stabilization and final effectiveness

# Implicit feature spaces hypothesis

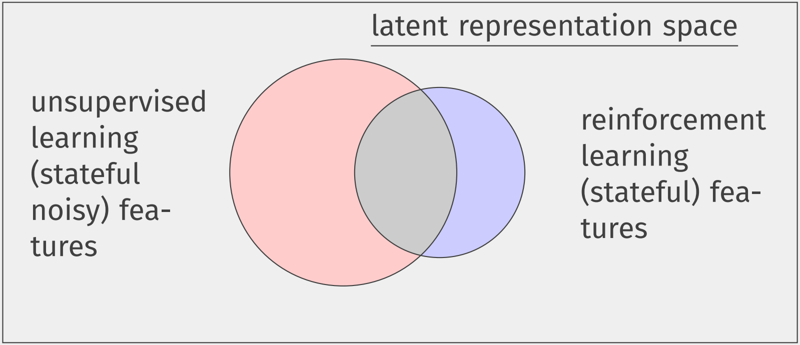



**Figure:** Schematic of the latent representation space.

We can only indirectly test the hypothesis by observing the obtained returns on different games. We run the following experiments and observe the results:

1. only RL
2. only RL, but on encoders from a finished RL run
3. only RL, but on encoders pretrained with pixel reconstruction loss
4. joint training from scratch

# Testing hypothesis 2

1. joint training where unsupervised learning task is only compression
2. joint training where unsupervised learning task is compression and one-step forward prediction in pixel space

# Testing hypothesis 3

1. joint training with no regularization
2. joint training with L2 regularization
3. joint training with L2 regularization and data augmentation

# Module implementation

We really implement our add-on module as an add-on module in the reinforcement learning library Tianshou.
This is possible because Tianshou abstract different parts of reinforcement learning.
We implement our module as a policy wrapper.

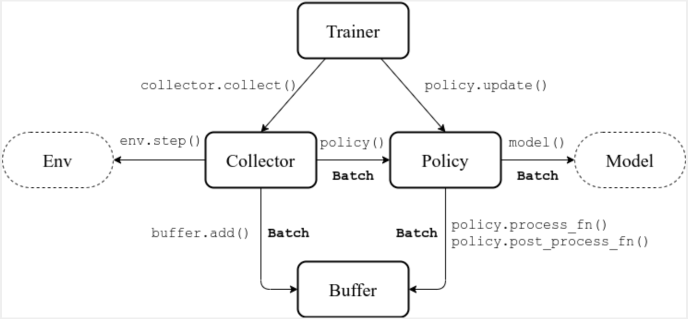



**Figure:** Tianshou abstractions.

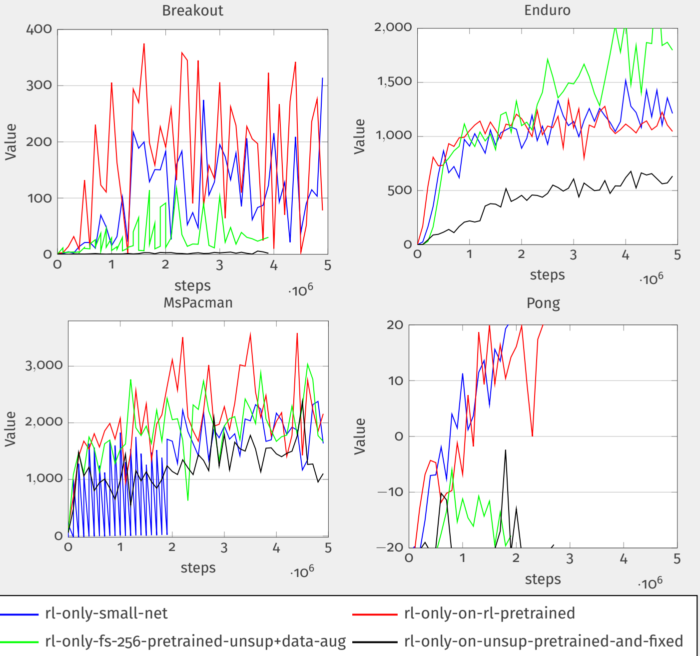
# Network architectures and hyperparameters

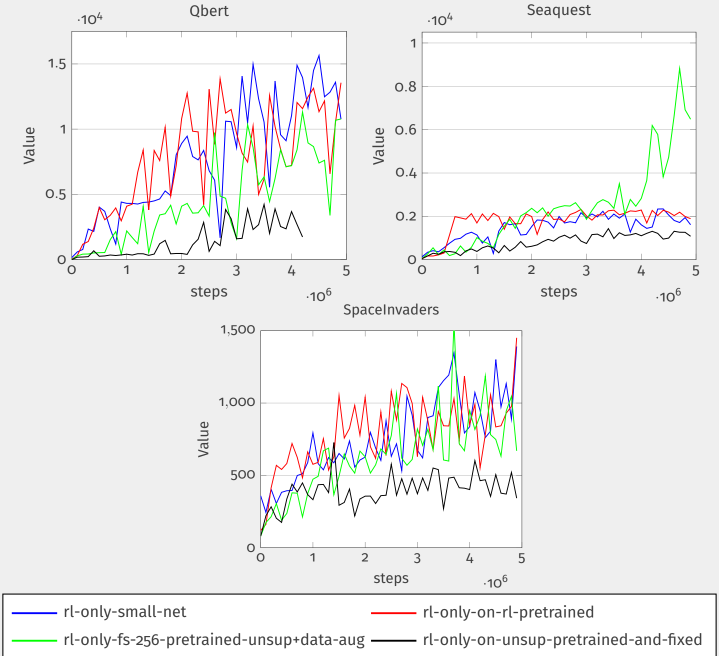
- all reinforcement learning parameters are kept equal and correspond to those in [Hes+18]
- two sized encoders, 2-D convolutional layers specified as (number of input channels, number of output channels, kernel size, stride, padding):
  - smaller, same as in [Mni+15]:
    (number of stacked frames, 32, 8, 4, 0), (32, 64, 4, 2, 0), (64, 64, 3, 1, 0)
  - bigger, same as in [Yar+19]:
    (number of stacked frames, 32, 3, 2, 0), (32, 32, 3, 2, 0), (32, 32, 3, 2, 0), (32, 32, 3, 2, 0)
    followed by a linear layer of shape ($32 \times 35 \times 35$, features dimension)

# Results

# Games

1. Breakout
2. Enduro
3. Ms Pacman
4. Pong
5. Qbert
6. Seaquest
7. Space Invaders


Breakout
Value
steps
$\cdot 10^6$
Enduro
Value
steps
$\cdot 10^6$
MsPacman
Value
steps
$\cdot 10^6$
Pong
Value
steps
$\cdot 10^6$
rl-only-small-net
rl-only-on-rl-pretrained
rl-only-fs-256-pretrained-unsup+data-aug
rl-only-on-unsup-pretrained-and-fixed



Qbert
$\cdot 10^4$
1.5
1
0.5
0
Value
0
1
2
3
4
5
steps
$\cdot 10^6$
Seaquest
$\cdot 10^4$
1
0.8
0.6
0.4
0.2
0
Value
0
1
2
3
4
5
steps
$\cdot 10^6$
SpaceInvaders
1,500
1,000
500
0
Value
0
1
2
3
4
5
steps
$\cdot 10^6$
rl-only-small-net
rl-only-on-rl-pretrained
rl-only-fs-256-pretrained-unsup+data-aug
rl-only-on-unsup-pretrained-and-fixed

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# No Slide Numbering

This slide is not numbered and is citing reference [**knuth74**].

The packages `inputenc` and `FiraSans`[1,2] are used to properly set the main fonts.

This theme provides styling commands to typeset *emphasized*, alerted, **bold**, example text, …

`FiraSans` also provides support for mathematical symbols:

$$e^{i\pi} + 1 = 0.$$

[1] https://fonts.google.com/specimen/Fira+Sans
[2] http://mozilla.github.io/Fira/

# Section 2

# Blocks

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### Block

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**Block**

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# Blocks

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### Block

Text.

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Alert text.

### Example block

Example text.

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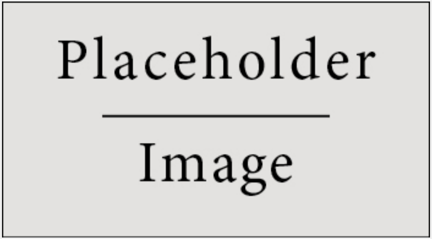

# Lists

Items:

- Item 1
  - Subitem 1.1
  - Subitem 1.2
- Item 2
- Item 3

Enumerations:

1. First
2. Second
   - 2.1 Sub-first
   - 2.2 Sub-second
3. Third

Descriptions:

**First** Yes.

**Second** No.

| Discipline | Avg. Salary |
|---|---|
| **Engineering** | **\$66,521** |
| Computer Sciences | \$60,005 |
| Mathematics and Sciences | \$61,867 |
| Business | \$56,720 |
| Humanities & Social Sciences | \$56,669 |
| Agriculture and Natural Resources | \$53,565 |
| Communications | \$51,448 |
| **Average for All Disciplines** | **\$58,114** |

**Table:** Table caption

# Thank you for your attention!