

Evaluating Learned State Representations for Atari

Adam Tupper¹ and Kourosh Neshatian

Department of Computer Science and Software Engineering
University of Canterbury

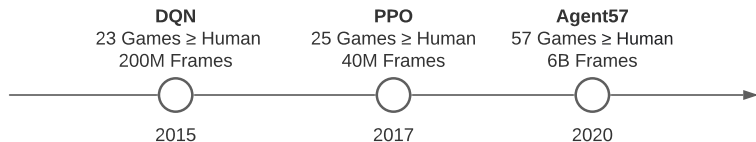
IVCNZ 2020

¹adam.tupper@pg.canterbury.ac.nz

State Representation Learning

Goal: Learn to extract the important features (“state variables”) from raw observations (e.g. images).

Why? Poor sample efficiency limits the applicability of deep reinforcement learning to real world problems (e.g. robotics).



To address this inefficiency, there has been a renewed focus on separated state representation and policy learning.

Our Research

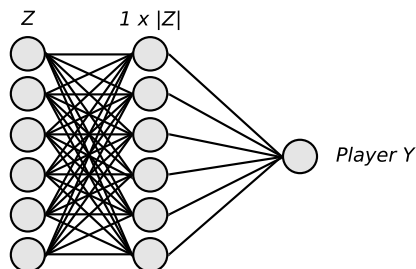
Autoencoders are a popular method for state representation learning, but the evaluations of the learned representations tend to be primitive.

Our research:

1. presented a new method for evaluating learned state representations by probing their contents.
2. investigated the quality of state representations learned by undercomplete, variational, and disentangled variational autoencoders for a range of representation sizes.

Evaluating Representation Quality via Probing

The state representations were evaluated by training non-linear regression and classification “probes” to predict important state variables from them.

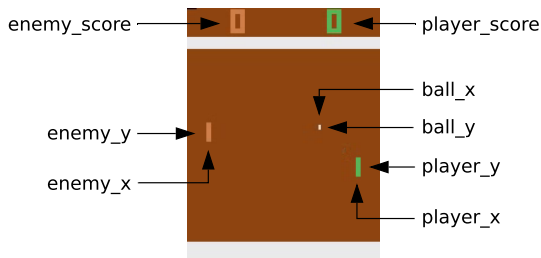


This extended a probing method that was proposed alongside the Atari Annotate RAM Interface¹, which provided the target values.

¹Anand et al., 'Unsupervised State Representation Learning in Atari', in Advances in Neural Information Processing Systems 32, Dec. 2019.

Evaluating Representation Quality via Probing

- ▶ The Atari Annotated RAM Interface identifies the RAM values of important state variables for each game.



- ▶ The previous probing method did not take into account the nature of each state variable (i.e. numeric or categorical).

Probing vs. Reconstructions: Regression

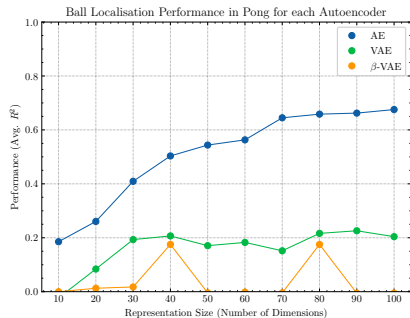
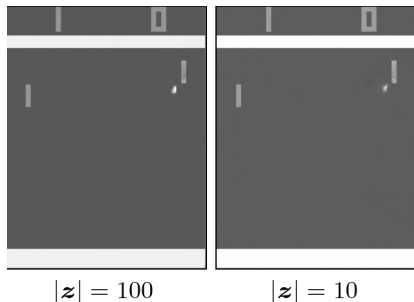


$|z| = 100$



$|z| = 10$

Probing vs. Reconstructions: Regression



Probing vs. Reconstructions: Classification

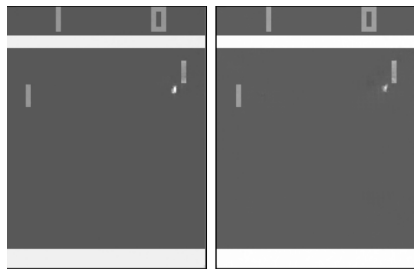


$|z| = 100$



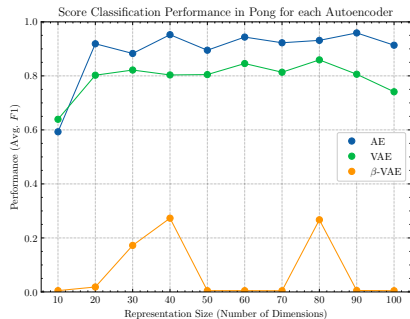
$|z| = 10$

Probing vs. Reconstructions: Classification



$|z| = 100$

$|z| = 10$



Key Findings and Future Work

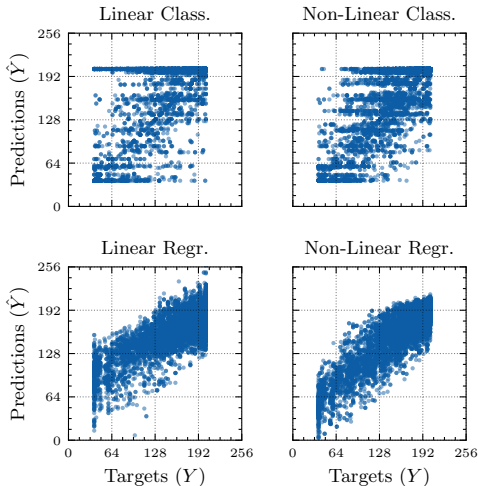
Our results:

- ▶ demonstrate the differences in representations learned by different types of autoencoders, and assess their robustness to representation size.
- ▶ highlight the discrepancies between evaluations using reconstruction quality vs. probing.

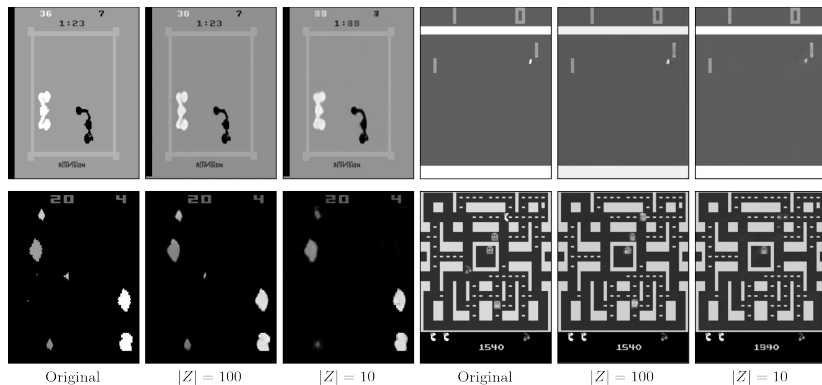
Avenues for future work:

- ▶ Investigate why the differences in performance between the types of autoencoders exist.
- ▶ Create a broader benchmark that contains both a wider set of games and extends to other domains to more comprehensively evaluate state representation learners.

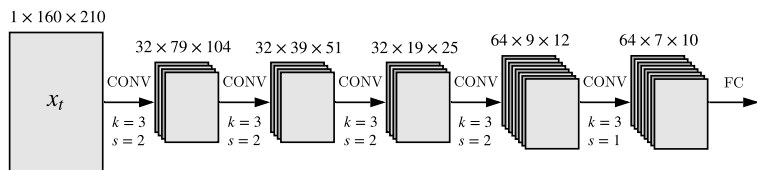
Extra: A Comparison Between Probing Techniques for Assessing the Encoding Quality of *Player Y* in Pong



Extra: Reconstructions for all Games



Extra: Autoencoder Architecture



- ▶ Fully convolutional encoder/decoder with five layers.
- ▶ Only difference between autoencoders was the bottleneck layer(s).
- ▶ Learnt compact representations of full size (160×210 px), greyscale images.