

# Knowledge-free domain-independent automated planning for games

## Results on the Atari video game

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# Introduction

## Motivation



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# Motivation

- Building classical planning models using symbolic languages represents a knowledge acquisition bottleneck;
- Describing a video game as a symbolic domain is a hard task for a human to perform;
- Agents for Atari games usually rely on reinforcement learning algorithms or running look-ahead techniques for playing;
- We wanted to evaluate a technique to do automated planning using the knowledge we obtain using deep learning.



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# Introduction

## Theoretical foundation



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# Automated Planning

- Introduces symbolic language to generalize search;
- The model is a 4-tuple  $\Sigma = (S, A, E, \gamma)$ , where:
  - $S = \langle s_1, s_2, \dots, s_n \rangle$  is a set of states;
  - $A = \langle a_1, a_2, \dots, a_n \rangle$  is a set of actions.
  - $\gamma = S \times A \times E \rightarrow 2^S$  is a state-transition function.
- Given a representation of the domain finds a sequence of actions to go from an initial state to a goal state;



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# Deep Learning

- Machine learning algorithms to extract patterns from data and make predictions about it;
- Uses processing units and connections between them to approximate functions which represent the patterns we are interested in;
- Learn by adjusting parameters and validating the output of the neural network – using a loss function;
- Deep: multiple hidden layers connecting the input to the output.



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- Proposes to bridge the gap between subsymbolic-symbolic boundary using deep learning to obtain a categorical representation from domain's images;
- Successful planning on puzzles: 8-puzzle, Towers of Hanoi and LightsOut;
- Uses a reparameterization trick to make the latent layer of the encoders converge into a categorical representation;
- Extracts PDDL directly from the categorical representation of domains' images.





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# Game Latplan

## Architecture and dataflow



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# Overview

- Our solution adds to the Latplan's architecture:
  - A framework to extract frames and transitions from Atari games;
  - An autoencoder to extract a latent representation from those frames;
  - A neural network to obtain a sequence of commands from a sequence of states' latent representations.
- Three core components:
  - Dataset acquisition
  - Knowledge acquisition
  - Automated planner
- Two phases:
  - Learning
  - Planning



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# Game Latplan

## Dataset acquisition



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# Dataset acquisition

- We use the Arcade Learning Environment;
- Two methods to obtain the dataset:
  - Random agent;
  - Human agent;
- We store frames as grayscale images (210x160 pixels);
- We store the transitions we observe, including commands and rewards.



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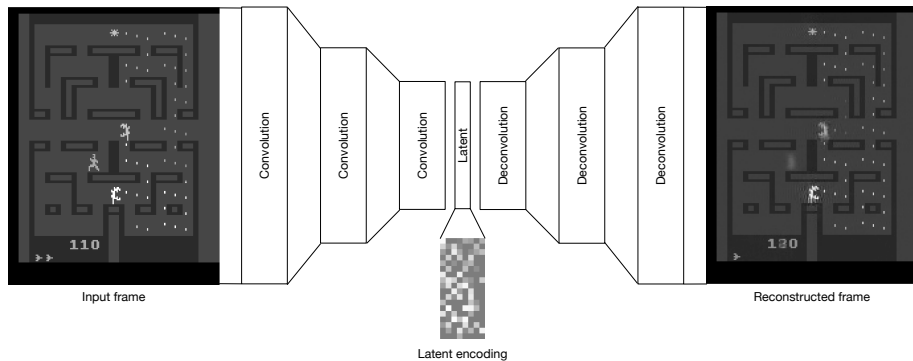
# Game Latplan

## Knowledge acquisition



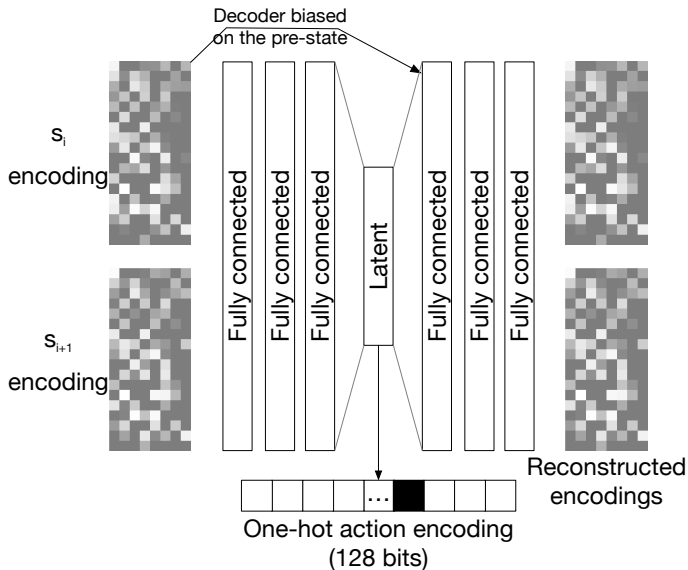
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# State Autoencoder



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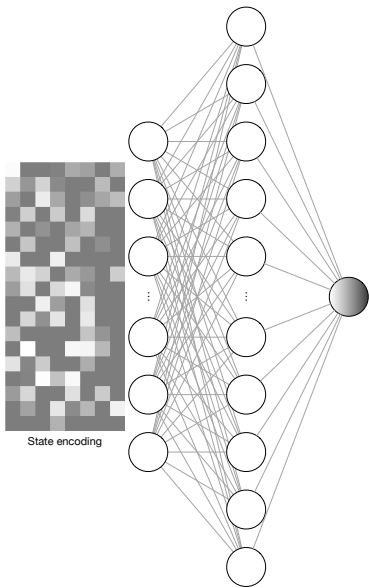
# Action Autoencoder



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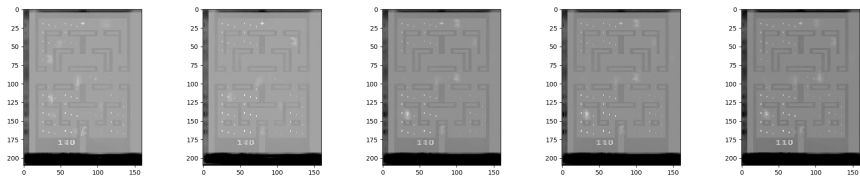


## State Discriminator



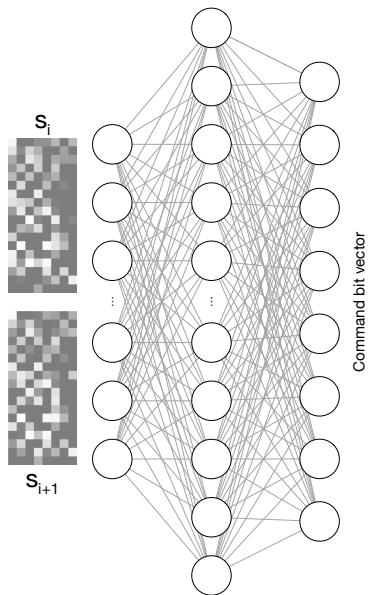
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# State Discriminator - Fake States



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# Command Categorizer



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# Game Latplan

## Automatic planning



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# Automatic planning

- Use a search algorithm to find a plan to go from the initial state to the goal state;
- Use the Action Autoencoder to expand the current state;
- Use the State Discriminator to prune out invalid states;
- Use the Command Categorizer to convert the plan – a sequence of frames' latent representations – into a sequence of commands.



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# Experiments and results

## Implementation details



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# Implementation details

- We implemented the solution using Python, Numpy, and Keras;
- We load all of our datasets on-demand using dataset generators;
- We obtain all the hyperparameters for our artificial neural network using the following steps:
  - ① Manually obtain an estimation for hyperparameters' lower and upper bounds;
  - ② Input intermediate values between the lower and upper bounds and run a grid search on all combinations;
  - ③ Manually adjust the best set of hyperparameters to reduce the number of weights in the neural network.



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# Hyperparameter influence on training

Batch size	Training epochs	Loss	Validation loss
2000	1200	6.0820e-04	0.0106
1000	600	5.8458e-04	0.0015
500	300	5.7769e-04	0.0014
250	150	5.2938e-04	5.1800e-04
120	70	5.0823e-04	5.8021e-04

Using smaller batch sizes makes the neural network to train faster and overfit less.



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# Hyperparameter influence on training

Batch Normalization	Frame Cropping	Training loss	Validation loss
Yes	Yes	0.0027	0.1137
Yes	No	5.5038e-04	0.0324
No	Yes	0.0025	0.0027
No	No	4.1907e-04	5.5773e-04

Removing Batch Normalization and using full frames makes the StateAutoencoder obtain smaller reconstruction loss.



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# Hyperparameter influence on training

Gaussian noise	Training loss	Validation loss
0	2.3350e-04	2.3169e-04
0.2	3.1260e-04	4.3848e-04
0.4	5.0859e-04	5.5853e-04

Adding Gaussian noise to the input causes the neural network to overfit less at the expense of larger reconstruction losses.



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# Experiments and results

## Experiments



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# Categorical State Autoencoder

- We tested three architectures:
  - Fully connected autoencoder;
  - Mixed autoencoder;
  - Fully convolutional autoencoder.
- We were not able to make the autoencoder's latent layer converge into a categorical representation;
- As a result we could not extract PDDL directly from the game's frames.



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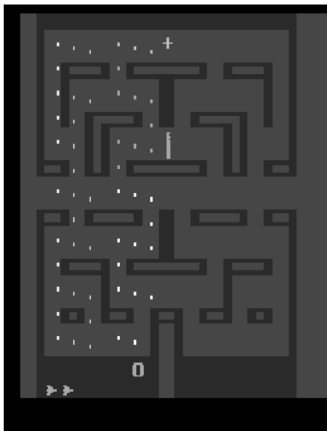
# Planning with Game Latplan

- Run training using the Alien game: 400 thousand frames, 500 thousand transitions;
- Select a pair of states from the transitions we observe during dataset acquisition;
- 97% of the transitions the Action Autoencoder generates are invalid;
- The State Discriminator marks less than 15% of the states as invalid;
- After the expansion of the fifth state, we had over six billion states to analyze.



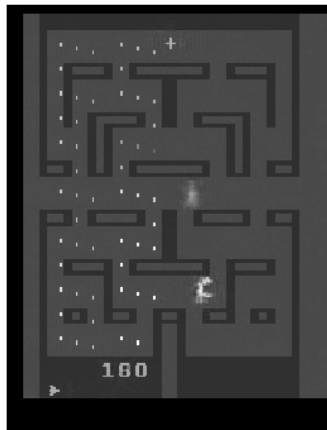
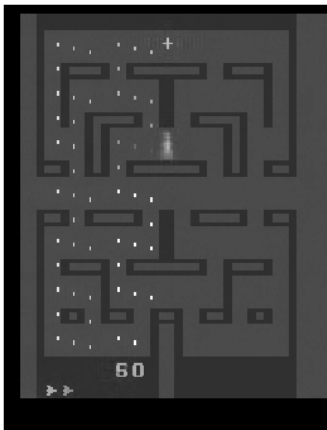
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# Planning with Game Latplan - Initial/Goal State



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# Planning with Game Latplan - Initial/Goal Reconstruction



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# Planning with Game Latplan - Initial/Goal Reconstruction

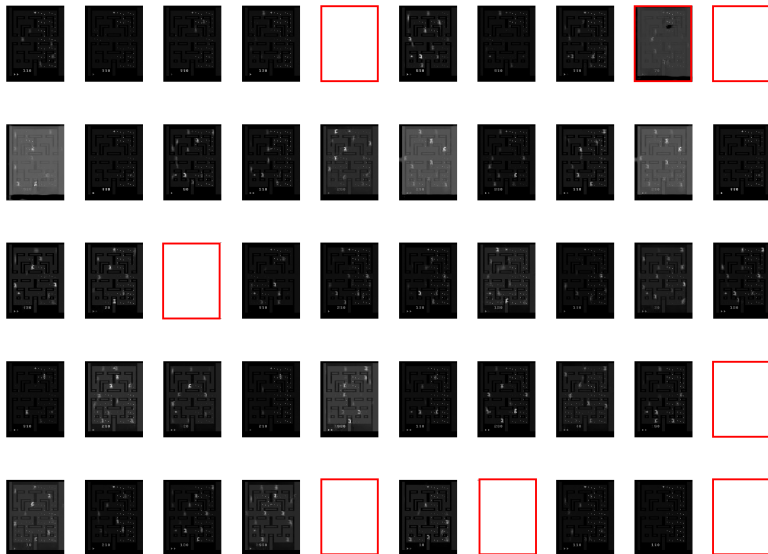
Metric	Initial state reconstruction loss	Goal state reconstruction loss
Mean absolute error	0.00447	0.00521
Binary cross-entropy	0.44695	0.44788
Mean squared error	2.78381	3.61213

Reconstruction loss for the initial and goal states.



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# Planning with Game Latplan - State expansion



# Experiments and results

## Discussion



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- The categorical autoencoder could not converge due to the high number and low variability of the game's frames;
- Most of the frame is static data. We reward the neural network for reconstructing and categorizing irrelevant areas;



- Since we are not pruning enough states, the branching factor becomes a bottleneck;
- The reconstruction loss we observe is still too high for the planner to know when it is at the goal state;
- Without an Action Discriminator, the planner is trying to reconstruct the goal from the initial state.
- The Command Categorizer has a low accuracy to allow us to construct useful command sequences.



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# Conclusion

- Latplan could not plan effectively on the domain of Atari games;
- We were able to understand how to organize a deep learning project, and how to conduct scientific research to obtain a neural network architecture for a given problem;
- We reached a better understanding of the difficulties to obtain a symbolic representation for complex – and large – domains.



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# Future work

- Combine our neural networks into a single architecture to reduce the reconstruction loss accumulation;
- Experiment with Generative Adversarial Networks to obtain fake states to train the State Discriminator;
- Research methods to obtain an Action Discriminator for Atari games;



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# Future work

- Research frameworks to run hyperparameter optimization sessions in parallel;
- Test our State Autoencoder with other Atari games, and use it as part of a game streaming solution (video compression);
- Keep on learning and researching!



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Thank you!



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