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 represent 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 learn.

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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 $\Sigma = (\mathtt{S}, \mathtt{A}, \mathtt{E}, \gamma)$, where:
  - $\mathtt{S} = \langle s_1, s_2, \ldots, s_n \rangle$ is a set of states;
  - $\mathtt{A} = \langle a_1, a_2, \ldots, a_n \rangle$ is a set of actions.
  - $\gamma = \mathtt{S} \times \mathtt{A} \times \mathtt{E} \rightarrow 2^{\mathtt{S}}$ 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.

Latplan

- 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 the 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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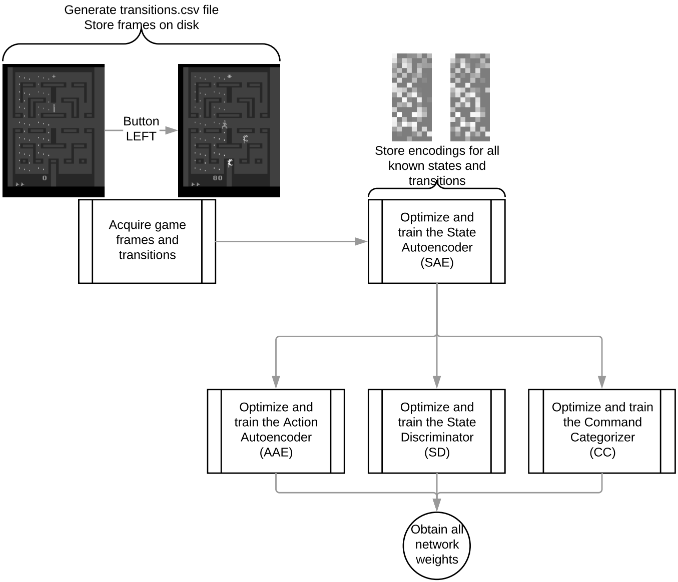
Learning phase



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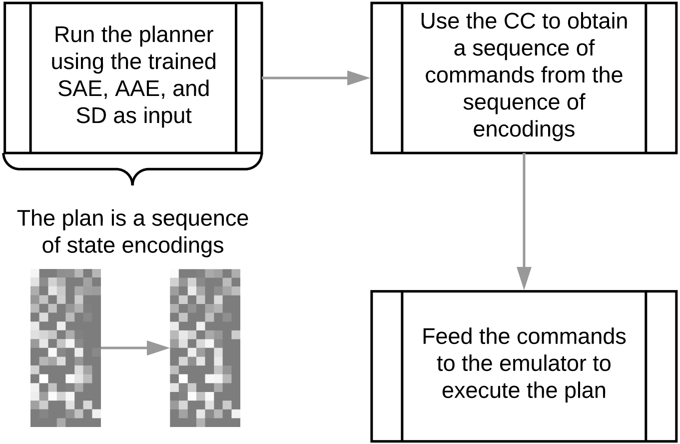
Planning phase



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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;
- We store the transitions we observe, including commands and rewards.

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Game Latplan

Knowledge acqusition

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Overview

- Four artificial neural networks:
  - State Autoencoder
  - Action Autoencoder
  - State Discriminator
  - Command Categorizer
- We first train the State Autoencoder;
- We use the frames' latent representations to train the other three artificial neural networks.

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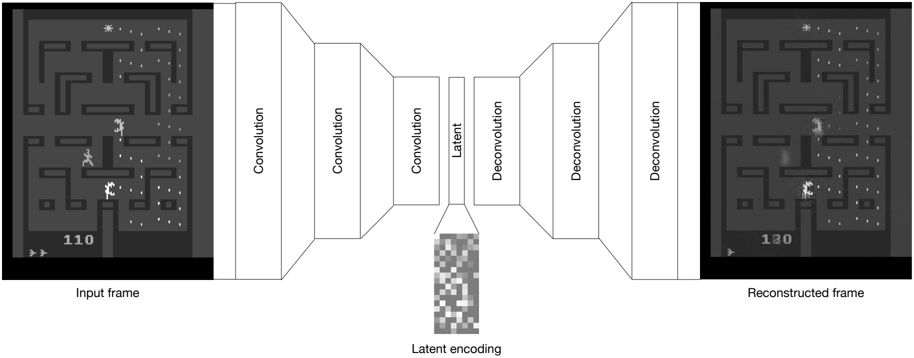
State Autoencoder



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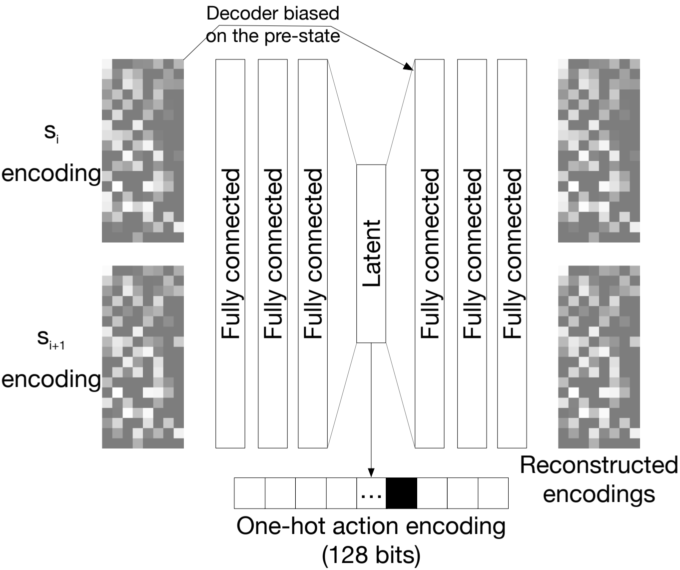
Action Autoencoder



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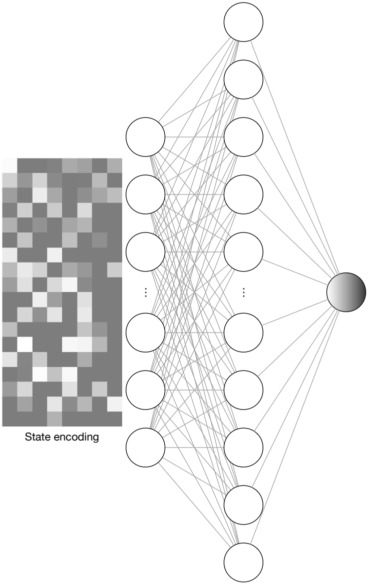
State Discriminator



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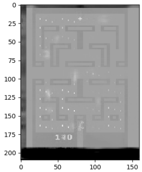
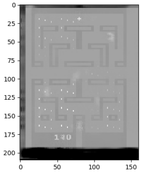
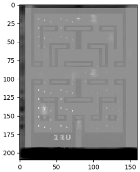
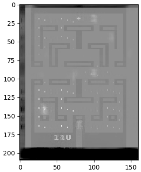
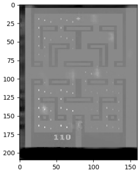
State Discriminator - Fake States











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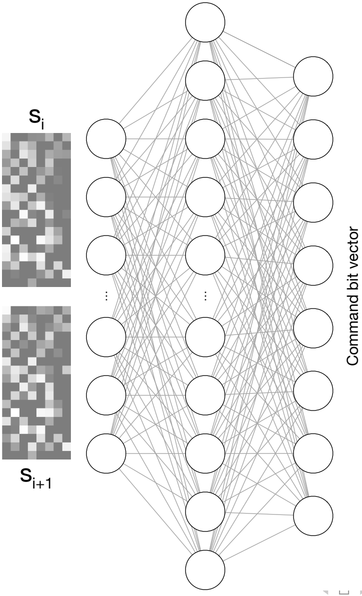
Command Categorizer



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

- Using smaller batch sizes makes the neural network to train faster and overfit less;
- Removing Batch Normalization and using full frames makes the State Autoencoder obtain smaller reconstruction loss;
- Adding Gaussian noise to the input makes the neural network to overfit less at the expense of larger reconstruction losses.

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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

Impact of batch size in reconstruction loss.

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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

Impact of batch normalization and frame cropping in 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

Impact of adding Gaussian noise to the input in reconstruction loss.

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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 to converge into a categorical representation;
- As a result we could not extract PDDL directly from 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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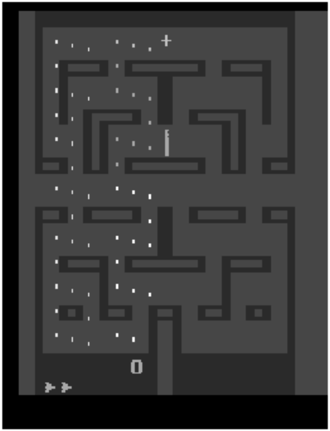
Planning with Game Latplan - Initial/Goal State



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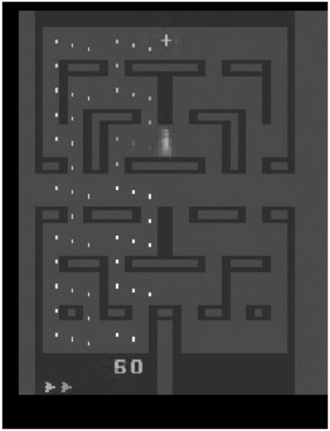

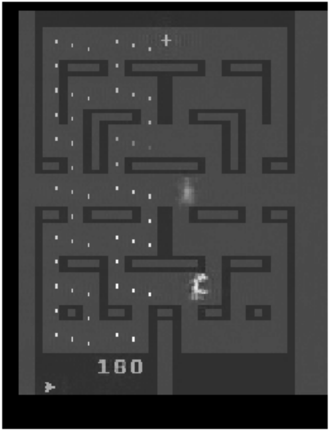

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Planning with Game Latplan - Initial/Goal Reconstruction

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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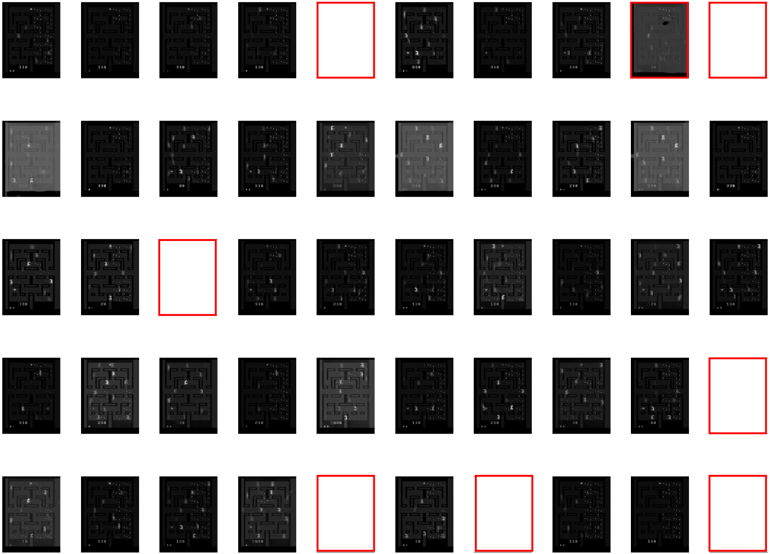
Planning with Game Latplan - State expansion



Experiments and results

Discussion

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Discussion

- 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;

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Discussion

- 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 – or implement one – to allow for hyperparameter optimization to run multiple 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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