

Learning Visual Embeddings for Reinforcement Learning

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Objectives

To learn meaningful embedding representations for visual tasks entirely from a small number of unlabeled expert demonstration videos by constructing a self-supervised vision task, and use these representations to improve the training in reinforcement learning tasks.

Introduction

- Deep Reinforcement Learning (RL) methods struggle in tasks with sparse reward environments
- We use the approach proposed in [1]:

1. Self-Supervised Computer Vision:

Classify time misalignment between frame pairs sampled from a video to generate embeddings and get an understanding of the environment

2. Imitation Learning:

Use these embeddings to extract dense rewards for improving the training of an agent

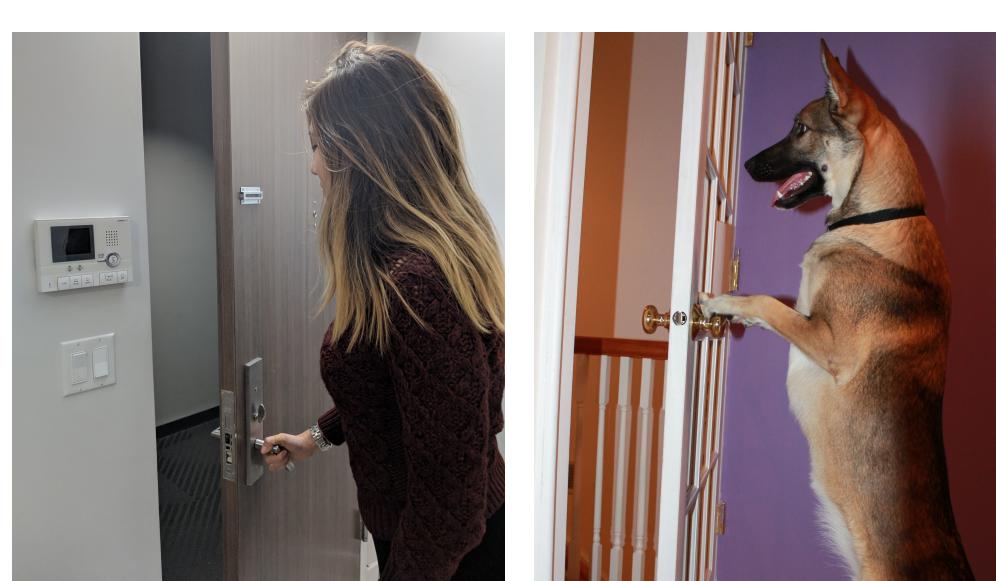


Figure 1: Dog Learns to Open Door by Watching Human

- We study the algorithm described in [1] and re-implement it for a maze environment constructed using [2] where the original rewards are extremely sparse, and demonstrate the effectiveness of this method, identifying potential problems, and proposing possible solutions.

- **Assumption:** Expert trajectory is *optimal* – demonstrations encode distance between frames, i.e., closer frames have lesser distance in some abstract space (which we extract via embeddings)

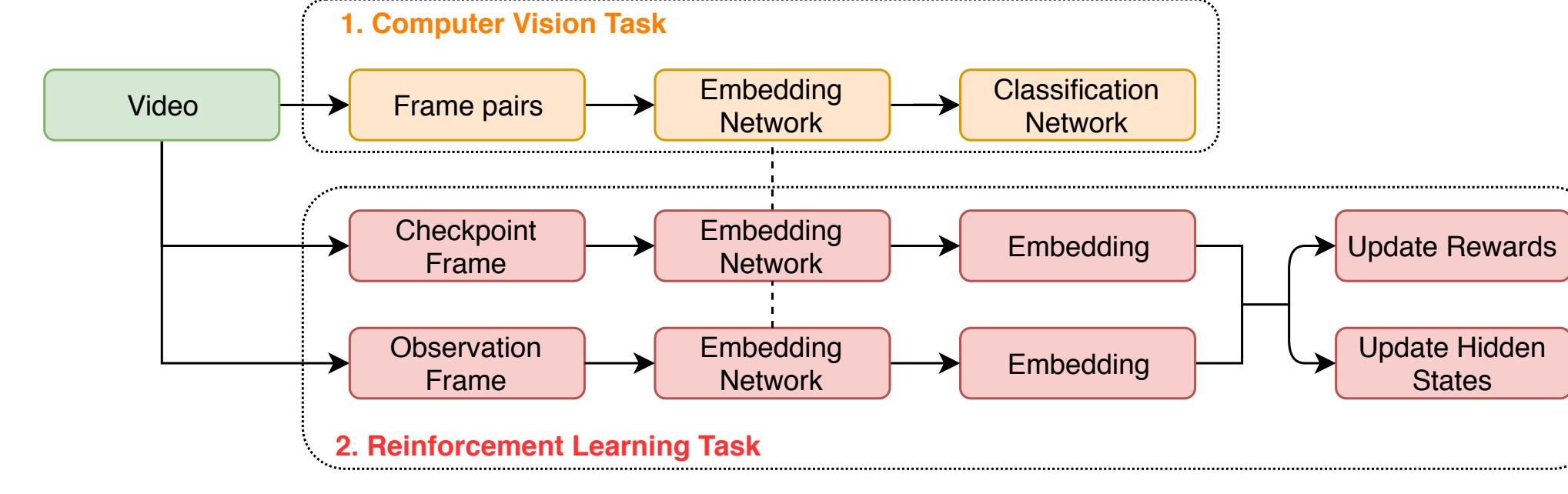


Figure 2: Overall Methodology

Data

The dataset is constructed using [2] and comprises unlabelled demonstration videos of an expert navigating through (i) 1000 and (ii) 10000 mazes of grid sizes 8×8 and 16×16 each, with obstacles such as closed doors:

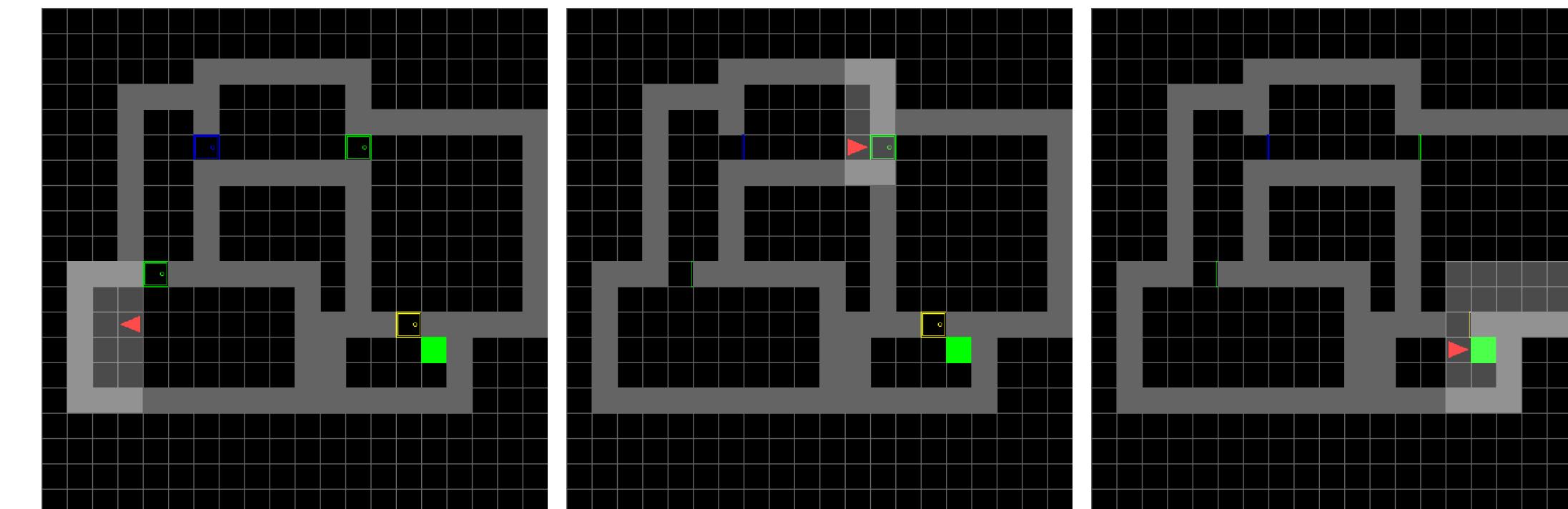


Figure 3: Different Agent Positions in 16×16 Maze

The paired frame data for the classification task is generated using the following procedure till 500000 (train), 100000 (val), and 100000 (test) frame pairs are obtained:

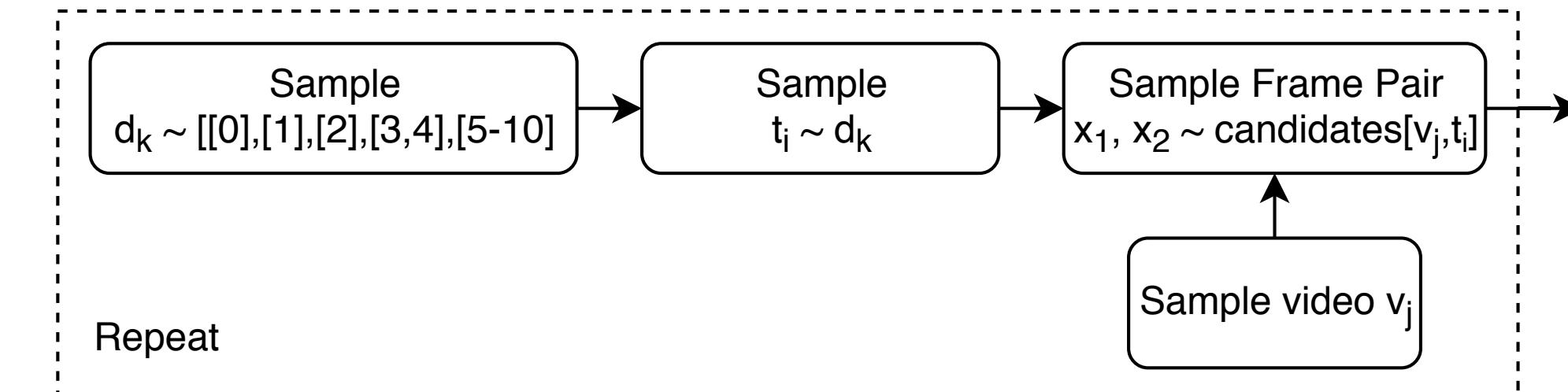


Figure 4: Data Generation Process
 d_k = time bucket, t_i = time difference

Embedding Generation

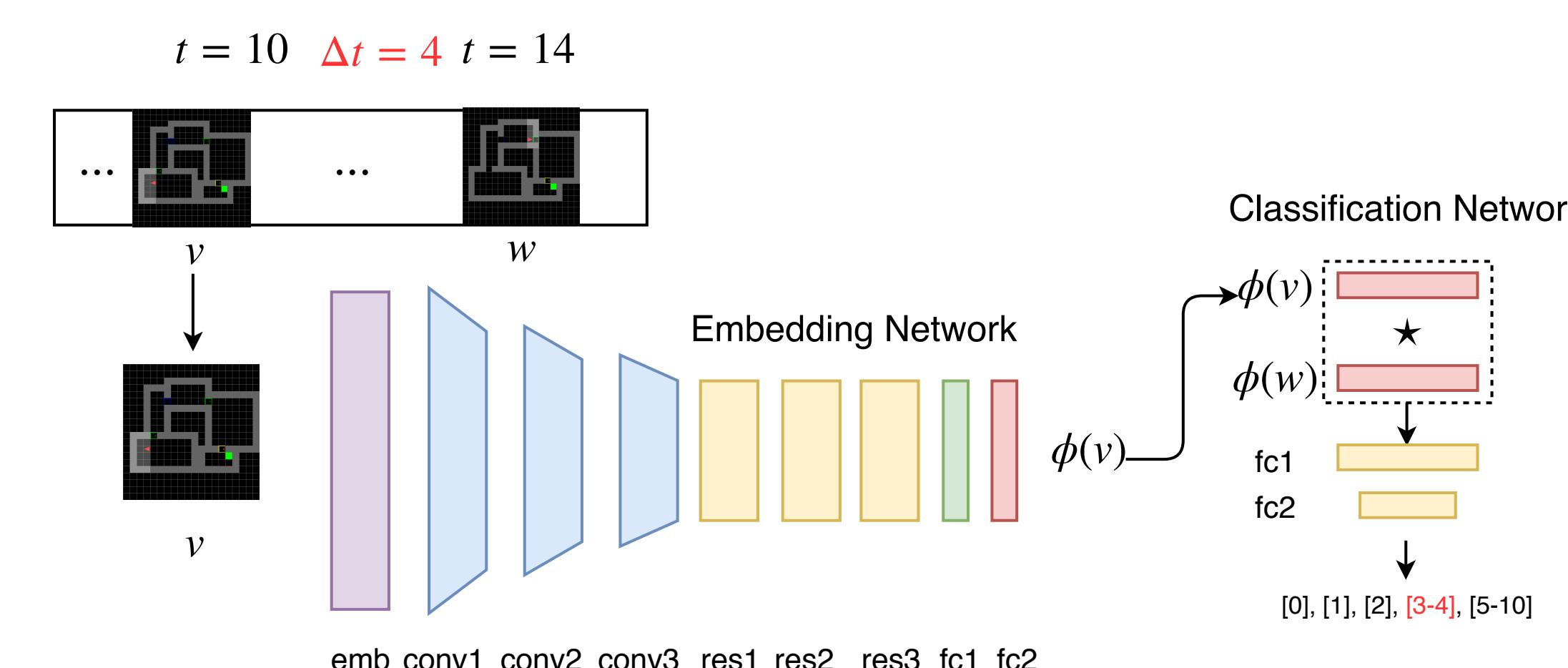


Figure 5: Embedding and Classification Networks.
Architecture from [1] with added initial Embedding (*emb*) layer

Classification Results

Grid Size	k	$\rho_{emb,bfs}$	$\rho_{raw,bfs}$
8×8	1.0	0.739	0.314
16×16	0.99	0.856	0.640

Table 1:

k : Fraction of Triplets with Valid Triangle Inequality
 $\rho_{emb,bfs}$: Pearson Correlation of (BFS, Embeddings+Cosine)
 $\rho_{raw,bfs}$: Pearson Correlation of (BFS, Raw Obs+Cosine)

Grid Size	Mazes	Accuracy
8×8	1000	84%
8×8	10000	88%
16×16	1000	90%
16×16	10000	96%

Table 2: Classification Test Accuracy for Different Configurations

Imitation Results

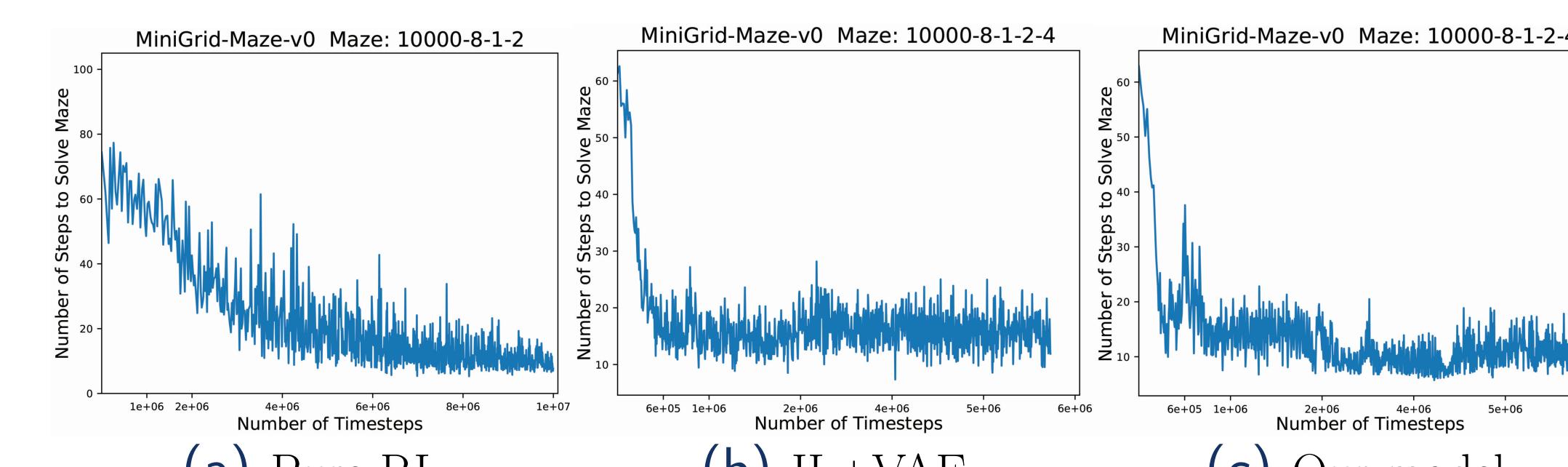


Figure 6: Avg. Steps to Solve 8×8 Maze vs. Timesteps
(Checkpoints every 4 frames)

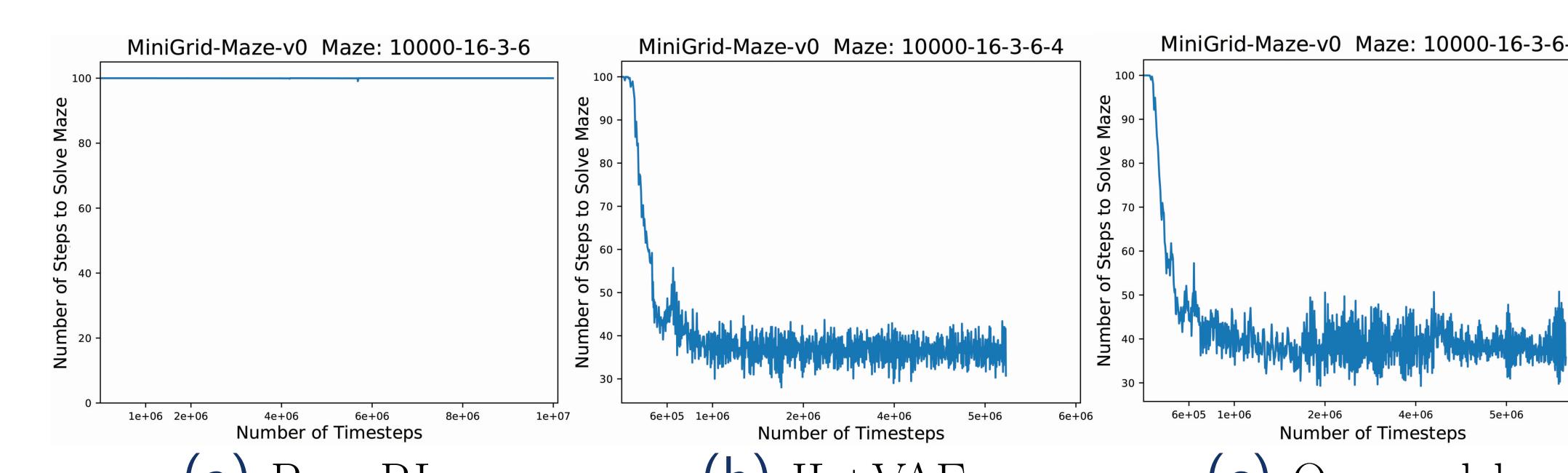


Figure 7: Avg. Steps to Solve 16×16 Maze vs. Timesteps
(Checkpoints every 4 frames)

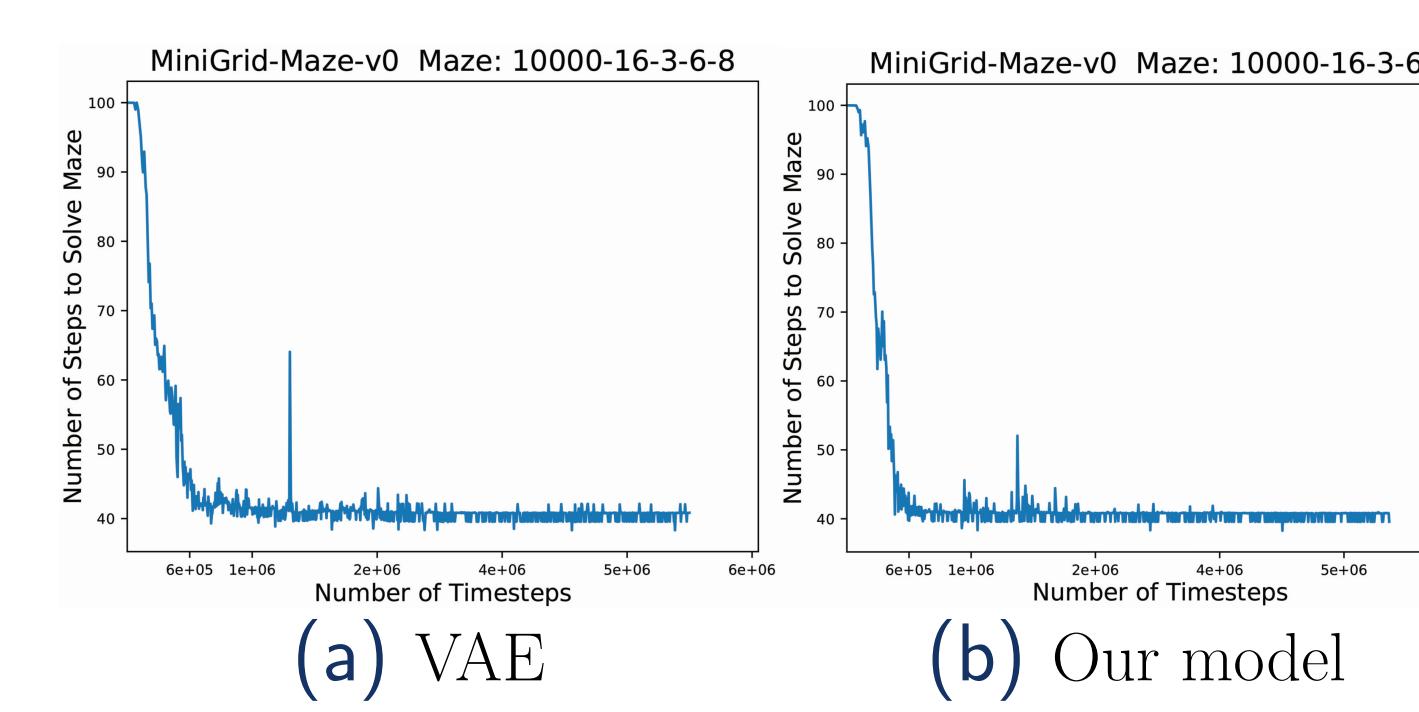


Figure 8: Avg. Steps to Solve 16×16 Maze vs. Timesteps
(Checkpoints every 8 frames)

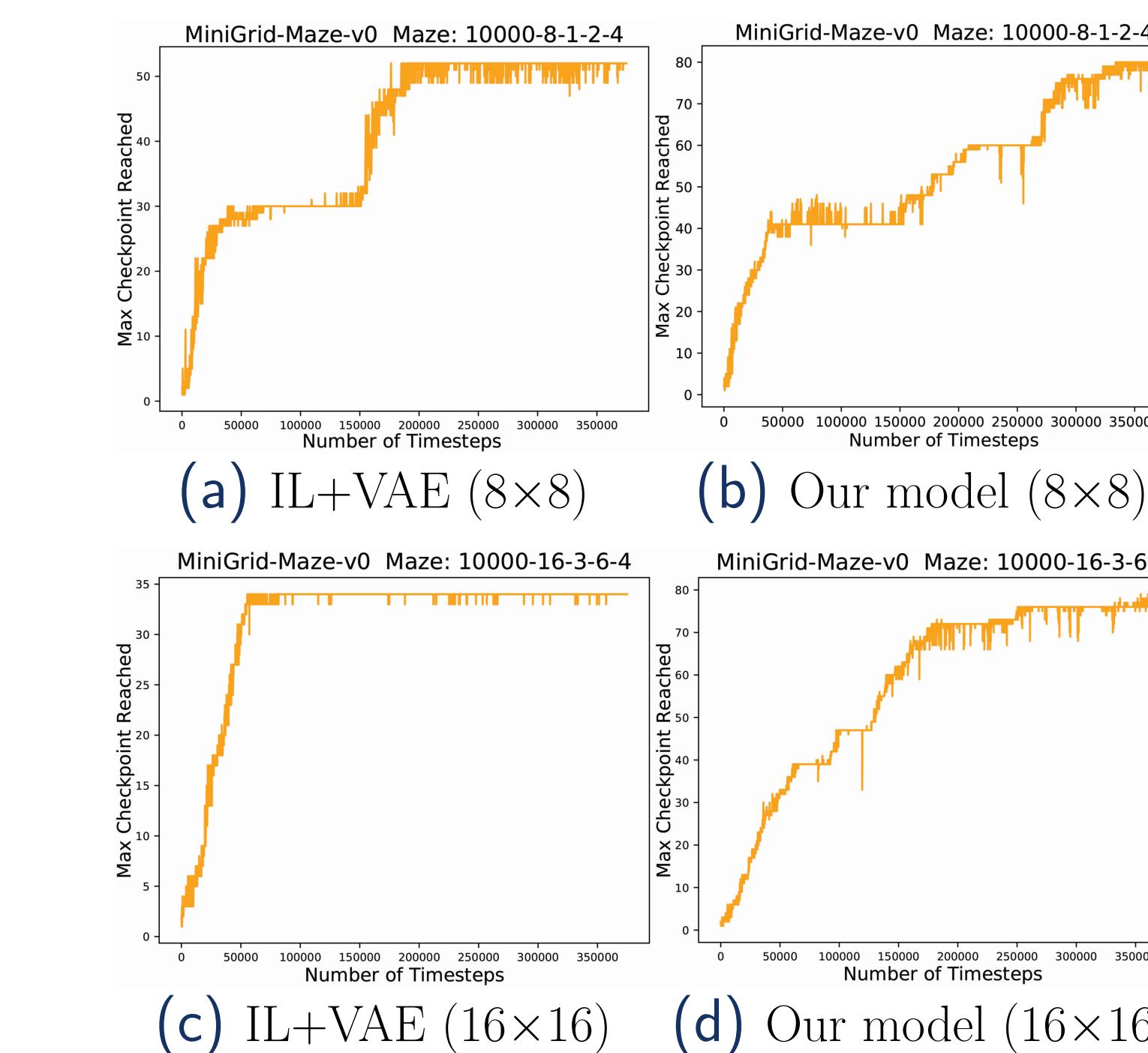


Figure 9: Max. Checkpoint Crossed vs. Timesteps in Different Mazes
(Checkpoints every 4 frames)

Conclusions

- Embeddings lead to faster, better convergence especially in bigger mazes where pure RL fails
- Embedding space captures true Manhattan distance well, indicating it might be linear

Contributions

- Reversible environments necessary for [1], otherwise some checkpoints may be skipped
 - We set time limits for reaching checkpoints to avoid wasting whole episode
- [1] requires setting first checkpoint as initial state and same training and test environments to allow for checkpoints during testing
 - We propose to set closest starting state from other demonstrations to current one

Future Work

- Address domain gap with more variations in environment and extend to real-world settings
- Extend to partially observable environments

References

- [1] Yusuf Aytar, Tobias Pfaff, David Budden, Thomas Paine, Ziyu Wang, and Nando de Freitas.
Playing hard exploration games by watching youtube.
In *Advances in Neural Information Processing Systems 31*, pages 2935–2945. 2018.

- [2] Maxime Chevalier-Boisvert and Lucas Willems.
Minimalistic gridworld environment for openai gym.
<https://github.com/maximecb/gym-minigrid>, 2018.

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