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Vision-based Navigation Using Deep Reinforcement Learning

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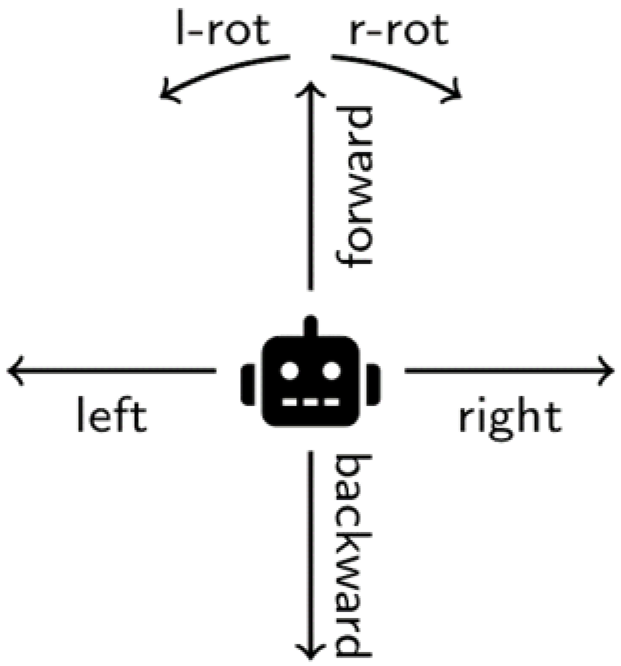
Introduction

- Navigating using camera only
- Goal is given by an image
- At discrete time an action is sampled from a discrete set
- Agent does not have an explicit representation of the environment
- Deep neural network is used to represent the agent



Outline

Network architecture

Auxiliary tasks

Training

Experiments

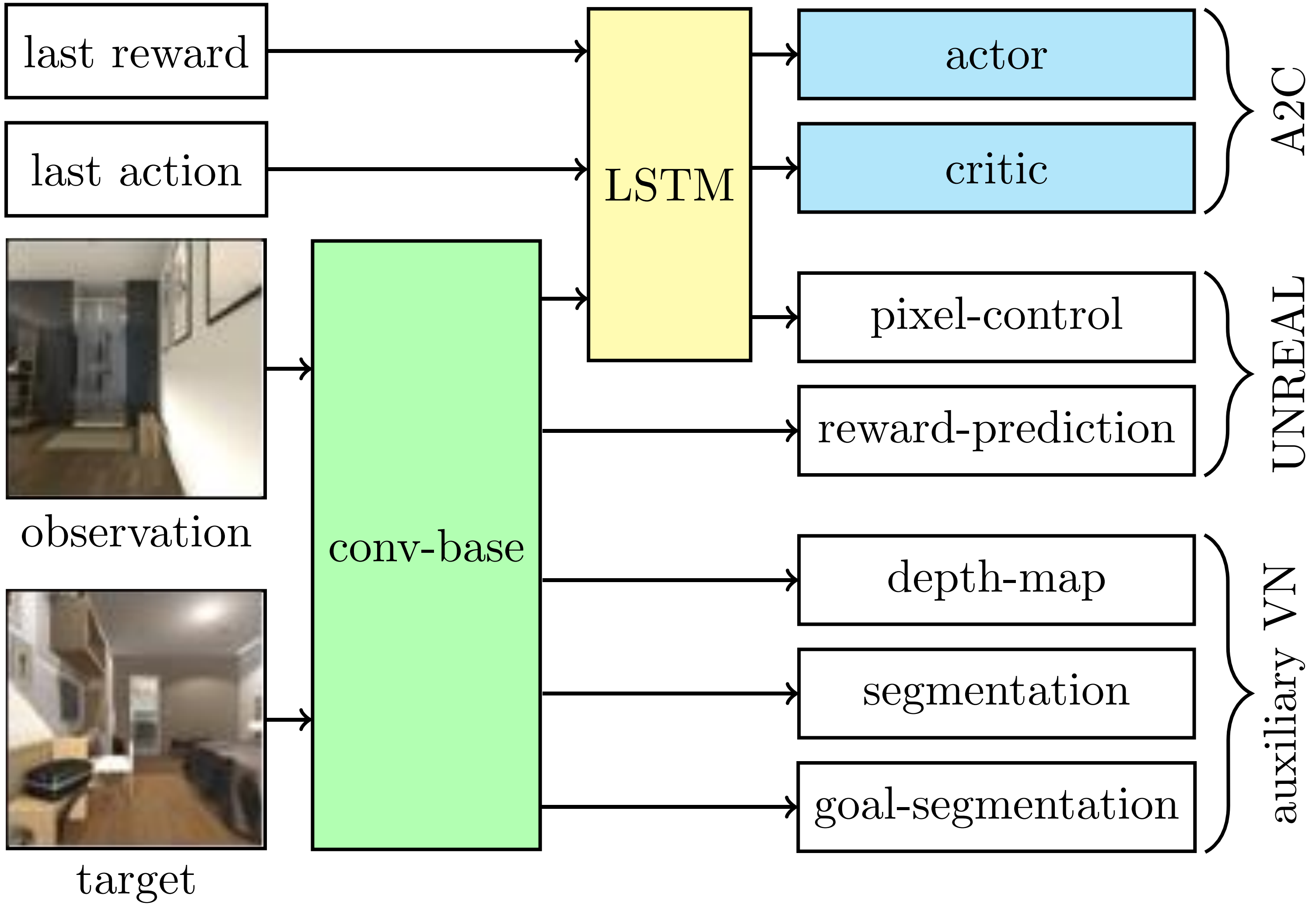
Conclusions

Network architecture

Convolutional-base shares layers for observation and target images

LSTM to resolve partial observability problem

Outputs policy (actor) and the RL state-value function (critic)



Auxiliary Tasks

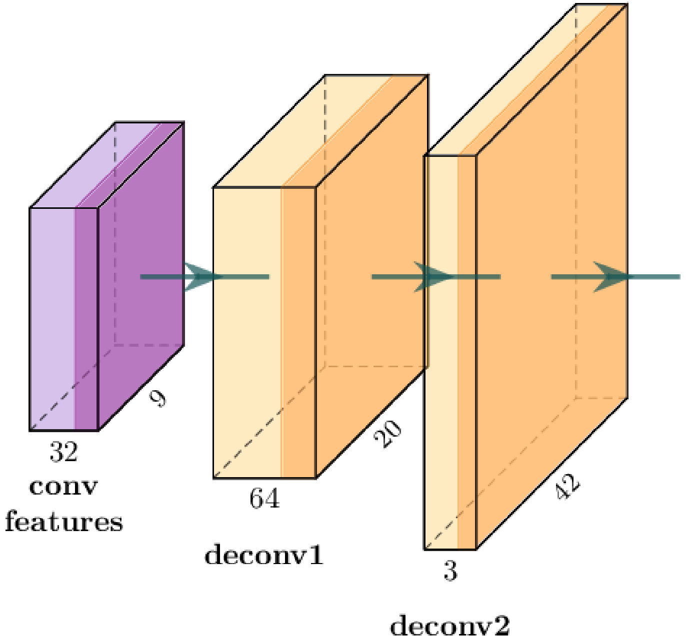
Using pixel control and reward prediction from UNREAL (Jaderberg, et al., 2016)

Depth-map prediction, segmentations projected to RGB space prediction

Auxiliary tasks help build useful features in shared part of the network

Gradient from auxiliary tasks is added to the total gradient used for optimization

Network can be pretrained using auxiliary VN tasks



Training

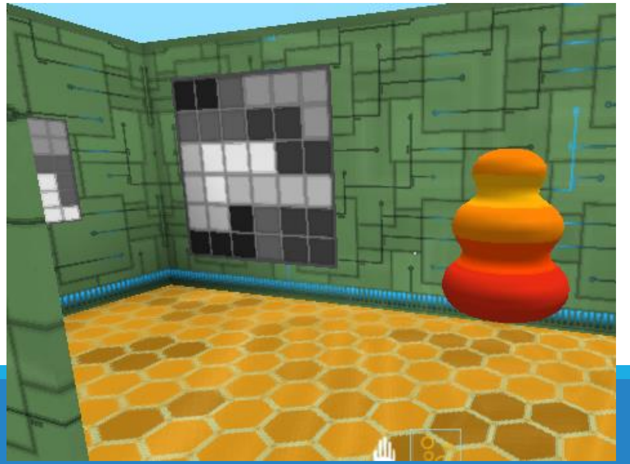
Trained using batched A2C algorithm

Maximizing entropy to ensure exploration

Fairly robust to change of hyperparameters

Training takes ~1 day to converge

Applied to multiple environments from multiple environment simulators (AI2-THOR, SUNCG, DM-Lab)



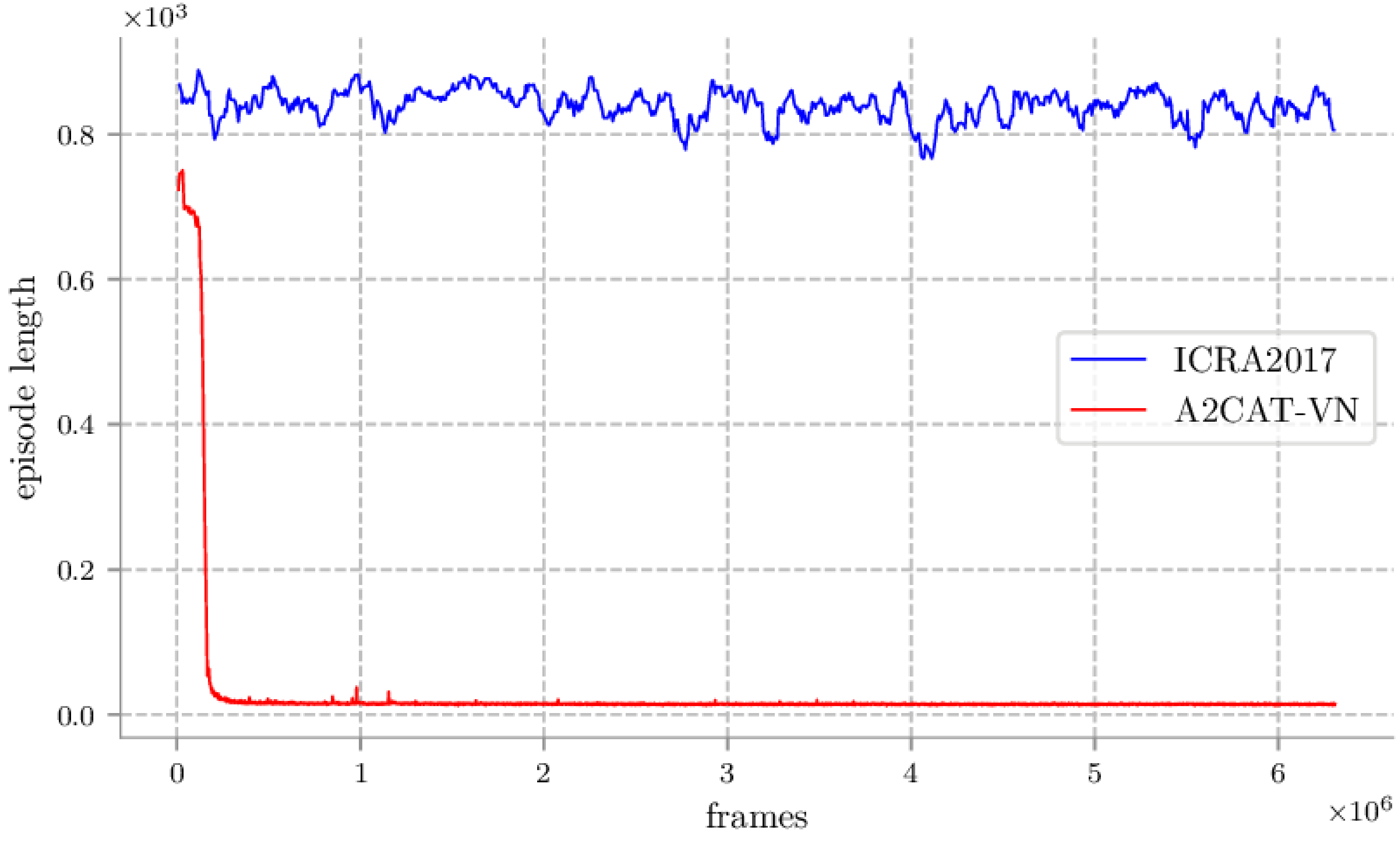
AI2-THOR Experiment

Compared to other method applied to AI2-THOR

Uses discretized space (grid-world)

Shows average episode length during training

Significantly outperforms the other method in terms of learning speed and stability



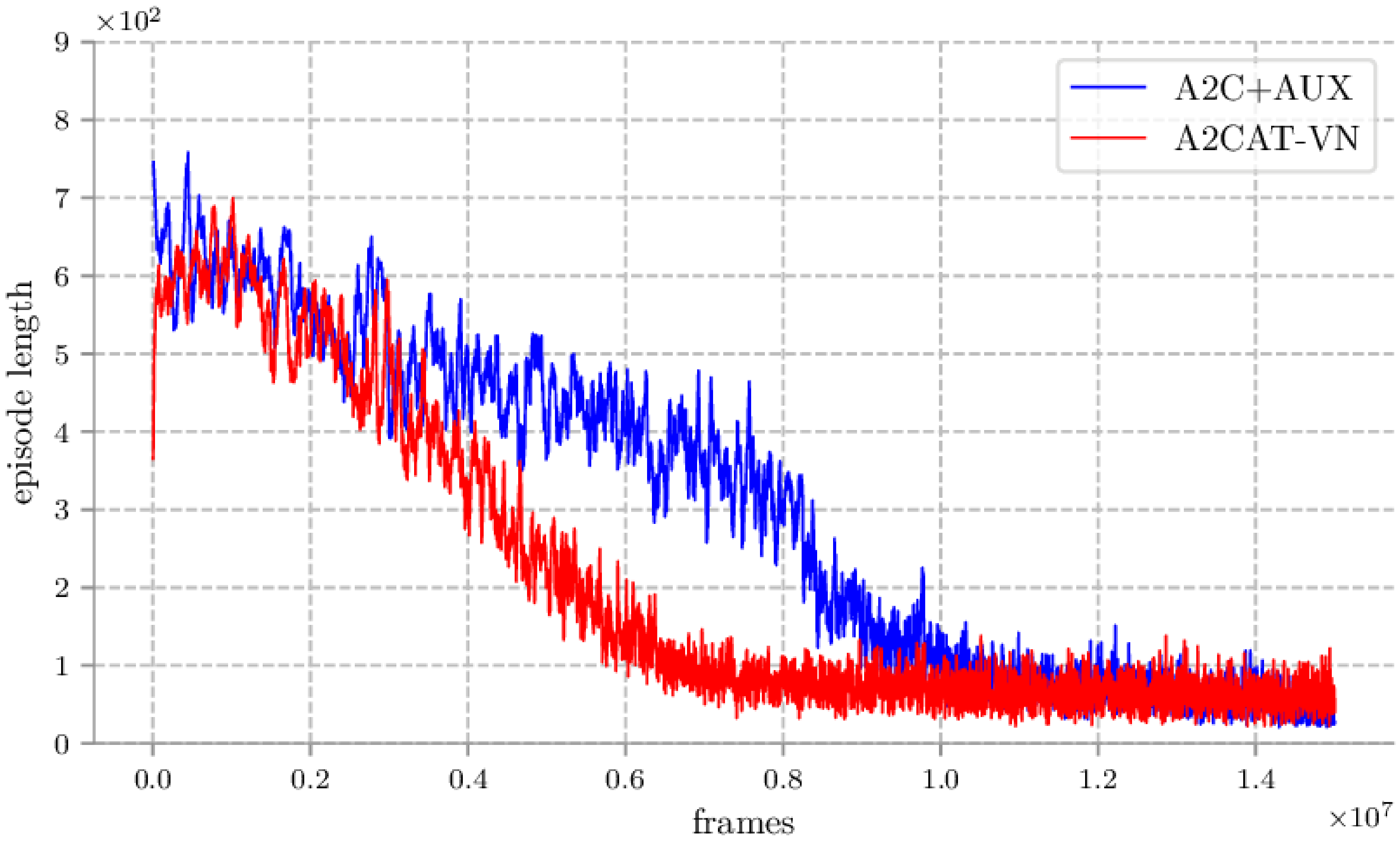
VN-CAT Experiment

Compared versions with VN-auxiliary tasks turned on or off (VN-CAT, UNREAL respectively)

Uses noisy actions in continuous space

Shows average episode length during training

VN-auxiliary tasks improve the training performance



Conclusions & future research

Novel auxiliary tasks to speed up the training

Single agent is able to navigate to multiple targets in multiple environments

Achieving better performance than other methods on AI2-THOR

Trade-off between realistic and fast environments

Future research should evaluate the impact of using pretraining to the training performance

Real-world applications shall be investigated

https://github.com/jkulhanek/deep-rl-pytorch https://github.com/jkulhanek/a2cat-vn-pytorch

Thank you for your attention

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