

# Branch Dueling Deep Q-Networks for Robotics Applications

*Master's Thesis*

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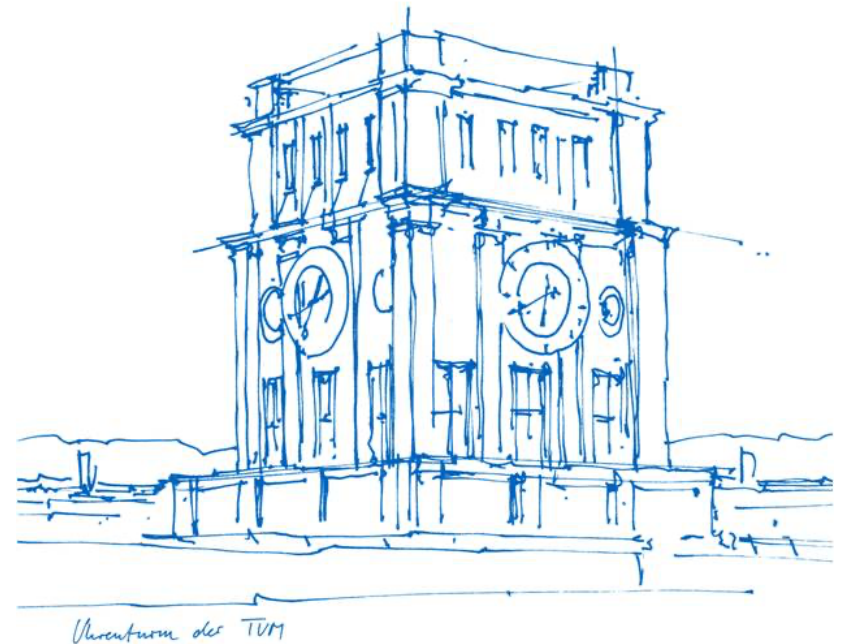
Technical University of Munich

Computer Science Faculty

Chair for Robotics, Artificial Intelligence

and Realtime Systems

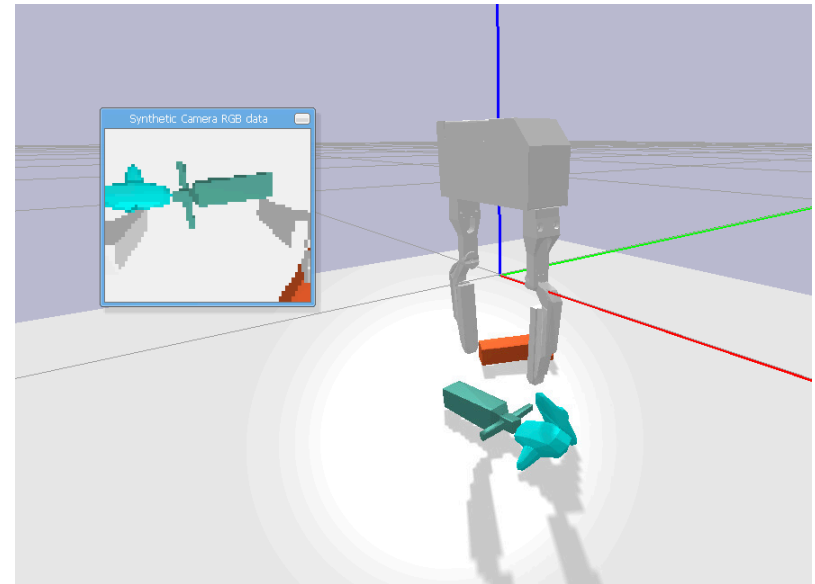
Munich, 22.09.2020



# OpenAI Gym-based Grasping Environment

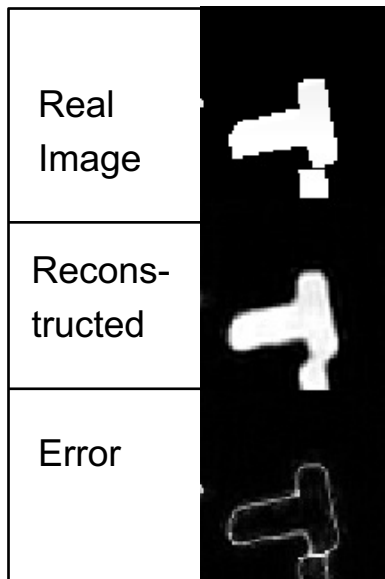
Training with different modules:

- Curriculum Strategy
- Input and Reward Normalization
- Shaped Reward
- Encoder, depth and RGB-D perception

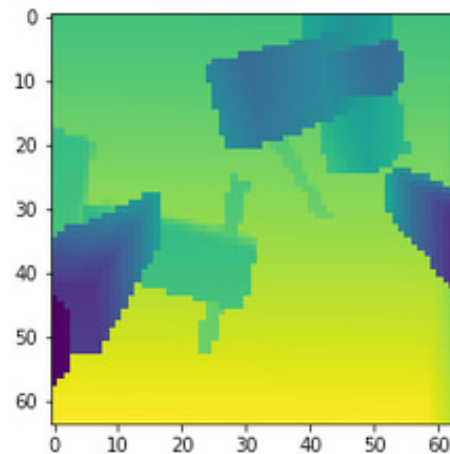


# Experiments with Different Perception Layers

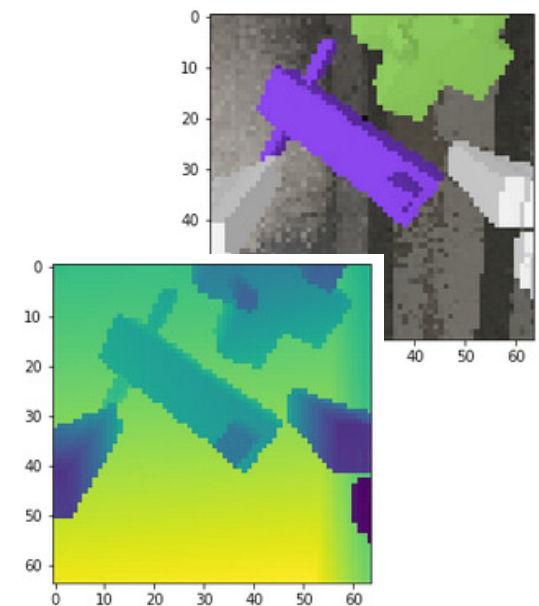
Auto-encoder



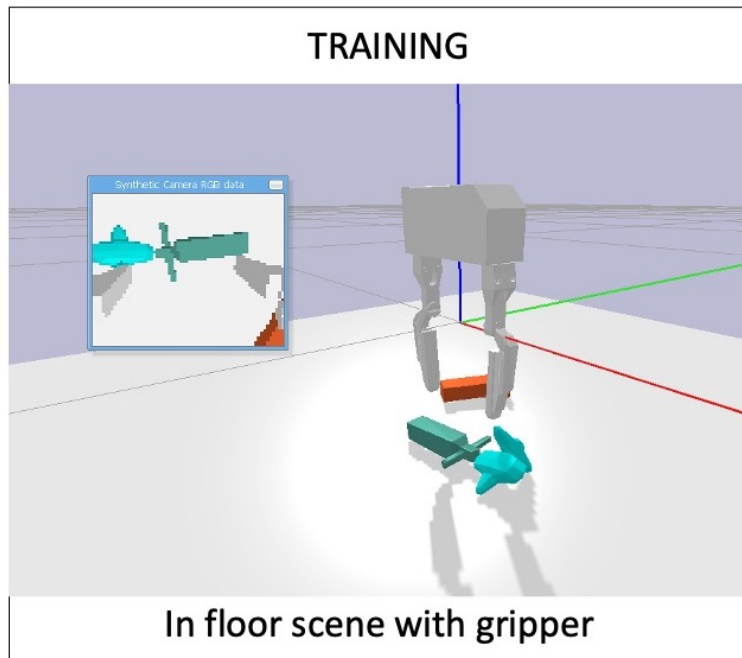
Depth



RGB-D

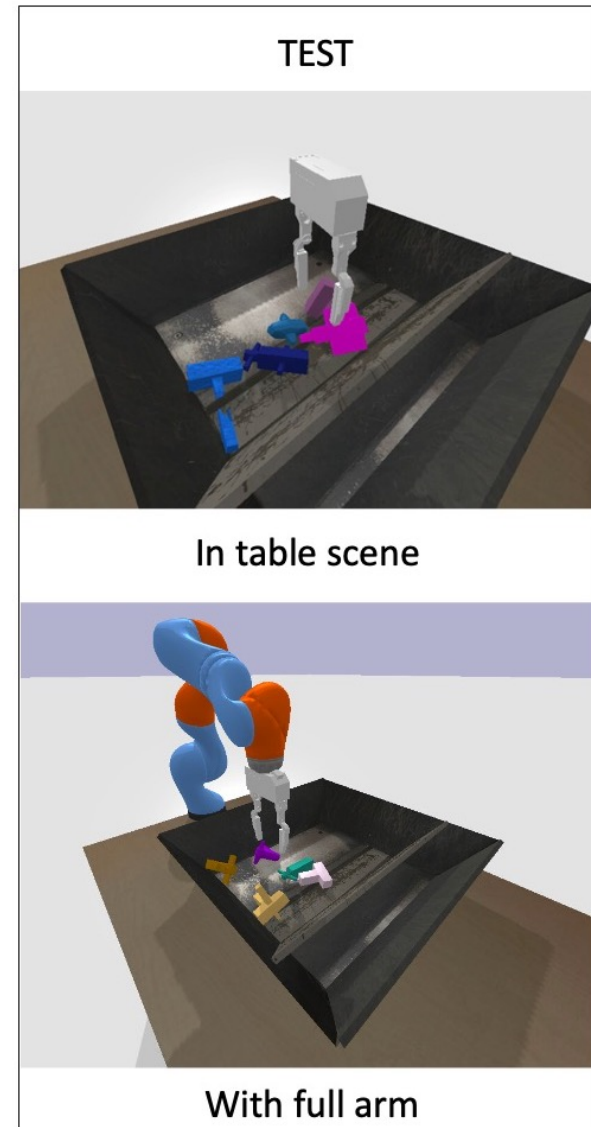


# Training and Test Pipeline



New scene

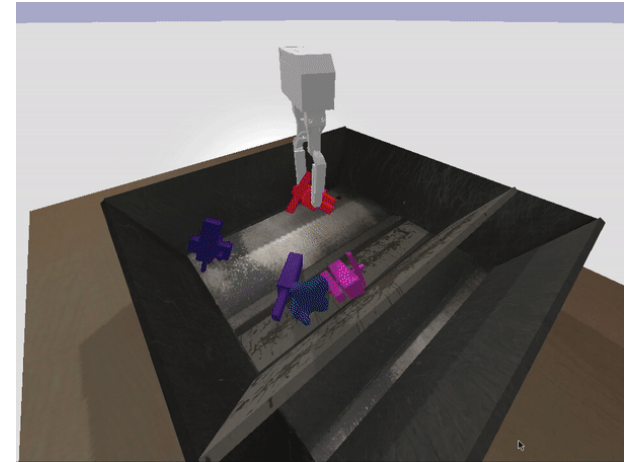
New Domain



# SAC Test Results on Gripper Environment

Models	SAC Gripper Environment			
	Floor Scene		Table Scene	
	Random Objects (%)	Wooden Blocks (%)	Random Objects (%)	Wooden Blocks (%)
SAC_encoder_50k	65	62	63	59
SAC_encoder_1m	100	95	99	82
SAC_depth	100	95	95	23
SAC_rgb	91	95	46	17
SAC_depth_no_curr	100	97	97	64
SAC_depth_sparse	99	97	100	72
SAC_depth_no_act	95	75	84	24

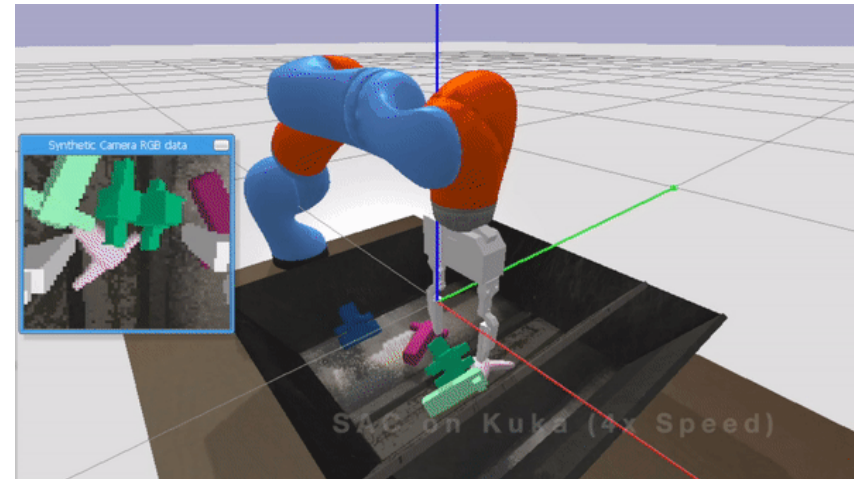
Table 1: SAC test results on gripper environment with new scene and objects set



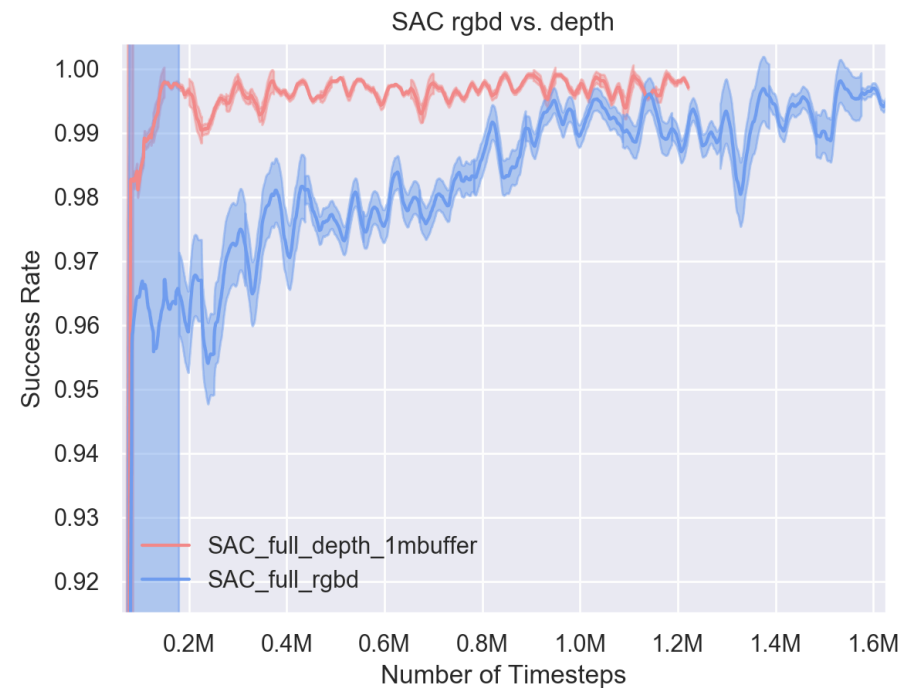
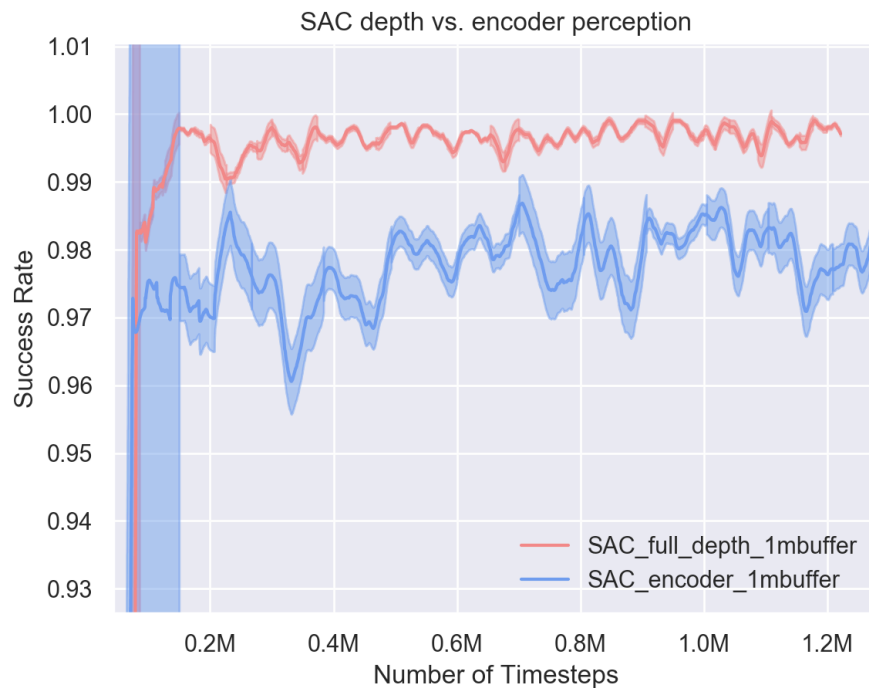
# SAC Model Domain Transfer to Kuka

Models	SAC on Kuka	
	Floor Scene (%)	Table Scene (%)
<b>SAC_encoder_50k</b>	62	66
<b>SAC_encoder_1m</b>	84	87
<b>SAC_depth</b>	97	97
<b>SAC_rgbd</b>	77	38
<b>SAC_depth_no_curr</b>	97	90
<b>SAC_depth_sparse</b>	66	28
<b>SAC_depth_no_act</b>	95	48

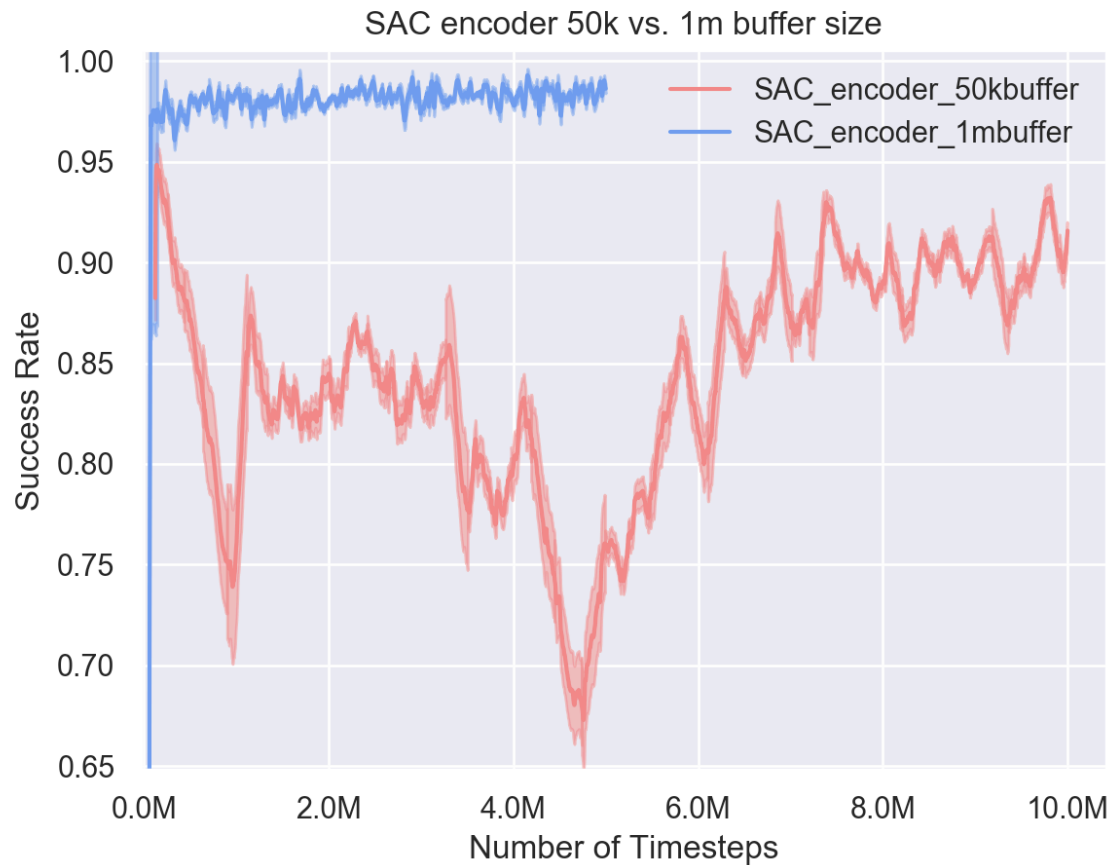
Table 2: SAC model transfer to Kuka domain



# SAC Plots— Perception Comparison

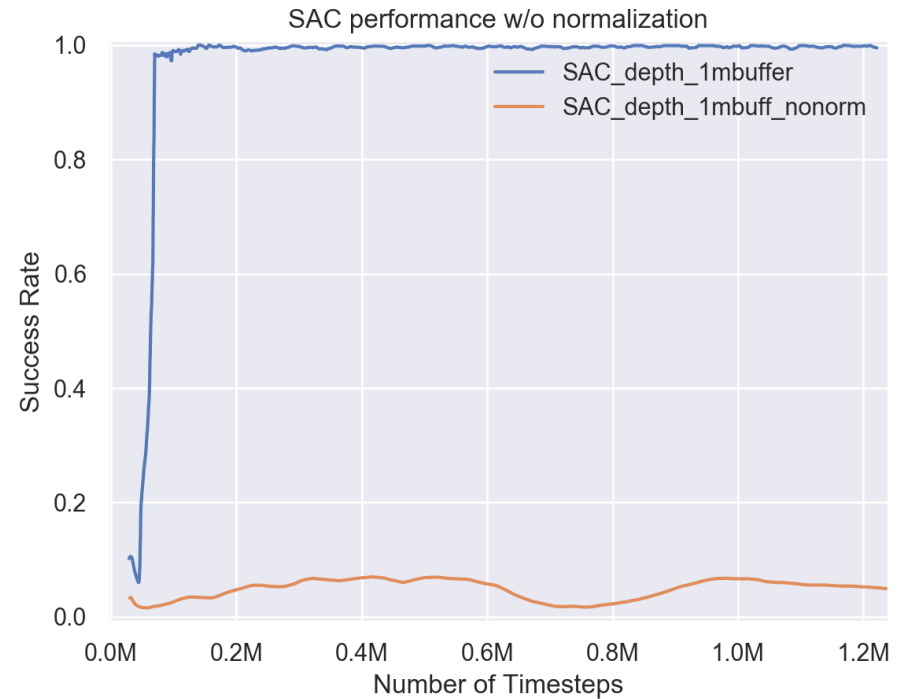
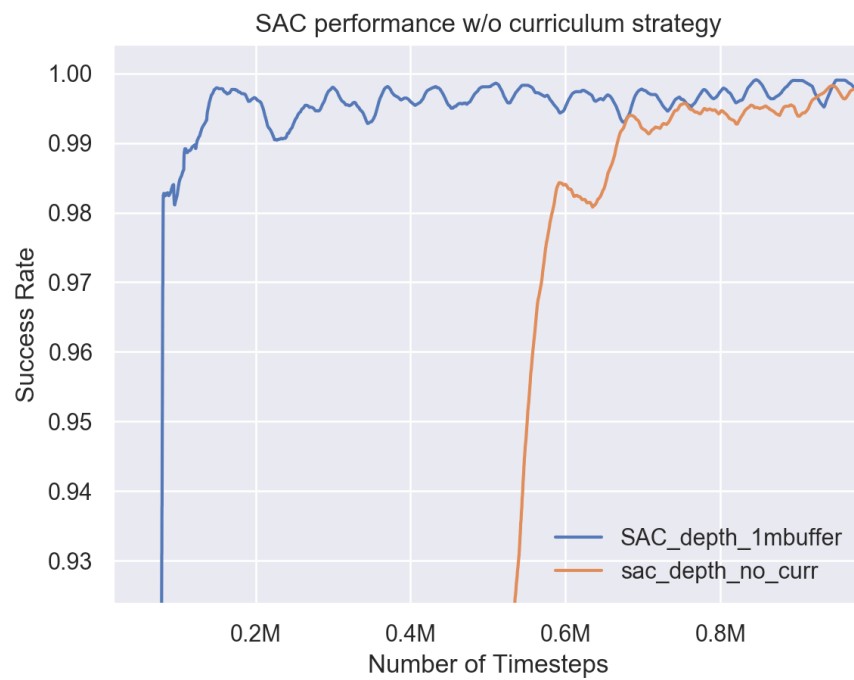


# SAC Encoder Result



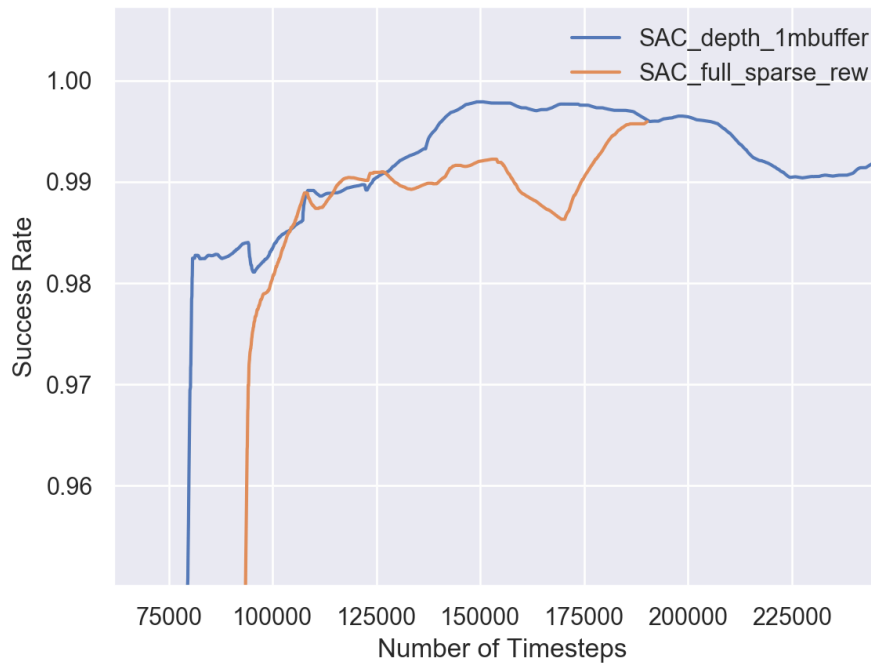


# SAC Ablation Studies



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SAC performance shaped reward vs. sparse reward



SAC performance w/o actuator width

