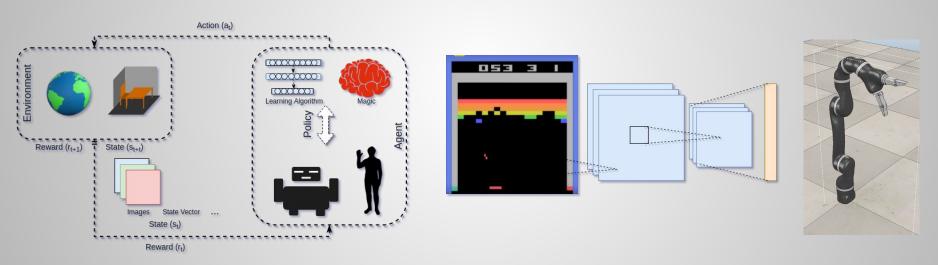
Deep Reinforcement Learning on Robots

An Evaluation of Models, Demonstration and Rewards

Deep Reinforcement Learning



Reinforcement Learning

DRL learns to play Atari Games

Mico Robot Arm

DRL on Robotics: Challenges

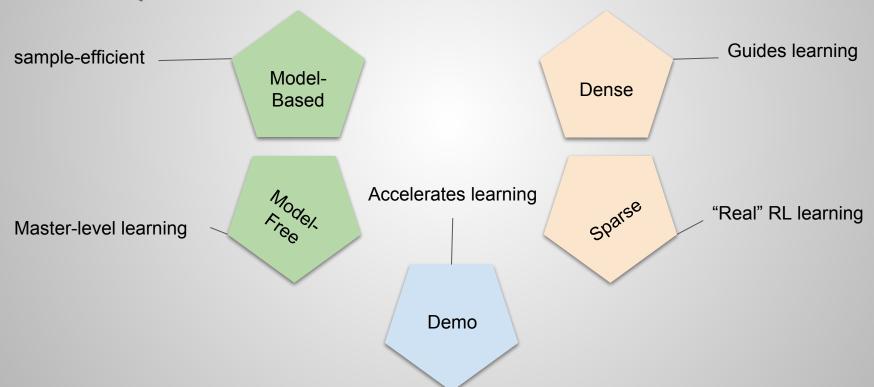
Training on real robots

Training in simulation

- Safety
- Interaction time/Sample efficiency

 Transferring from simulation to real-world. Reality Gap.

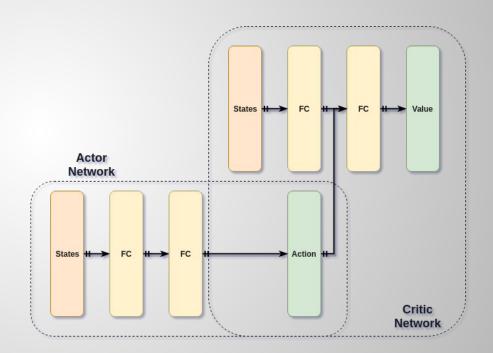
Models, Rewards and Demonstrations



Agents: Model-Free

DDPGfD

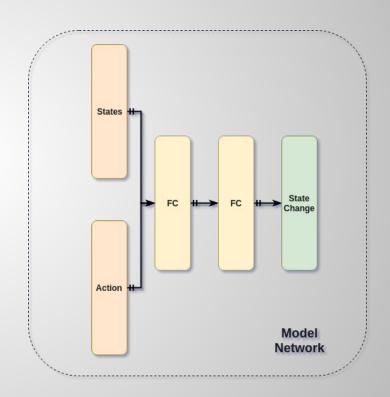
- Actor-Critic
- Demonstration loaded to agent's experience replay



Agents: Model-Based

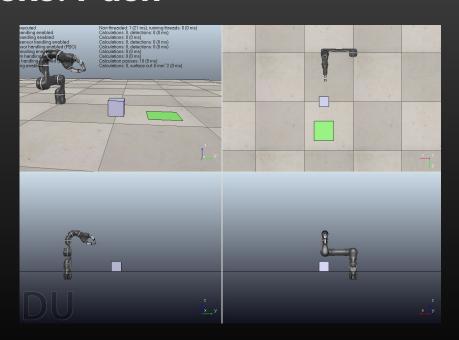
Neural Network Dynamics Model with Model Predictive Control(MPC)

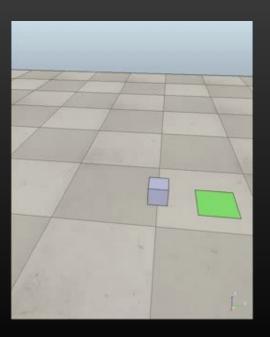
- Only Model Networks
- Sampling-based MPC
- Demonstration loaded to agent's experience replay



Tasks

Tasks: Push



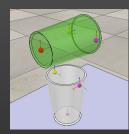


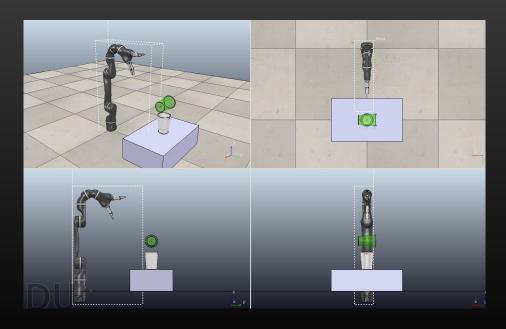
Initial State

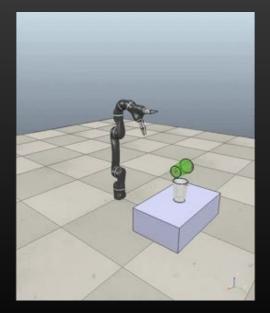
Demonstration Collection

Task: Grasp









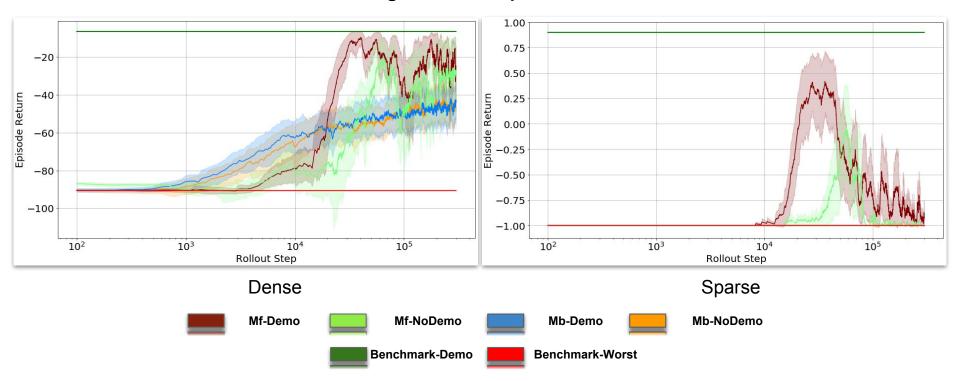
Initial State

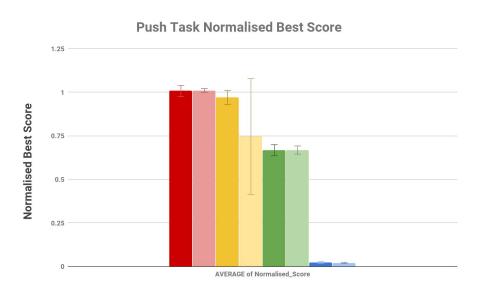
Demonstration Collection

Experiments and Evaluation

Push Task

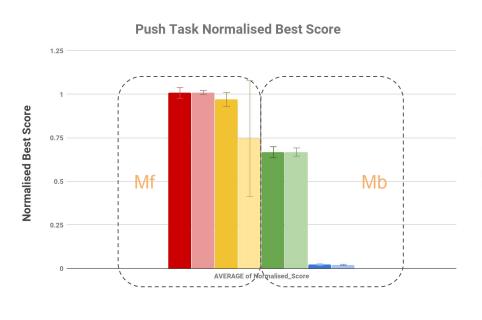
Training Statistics: Episode Return







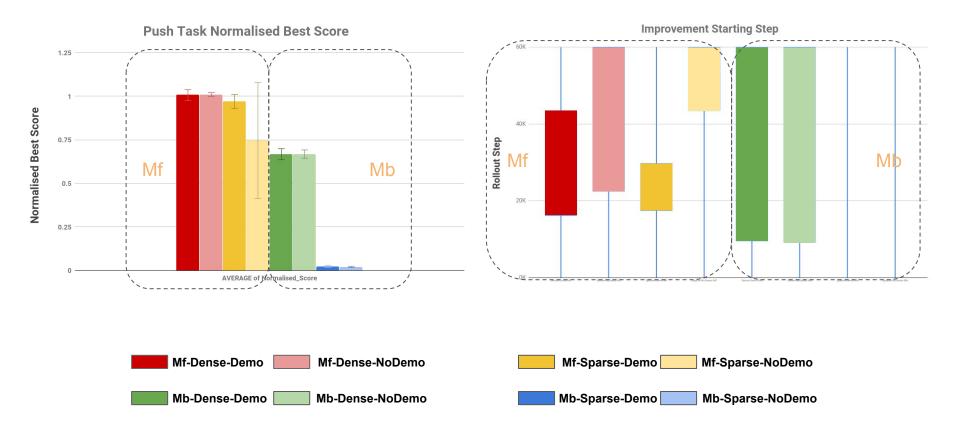


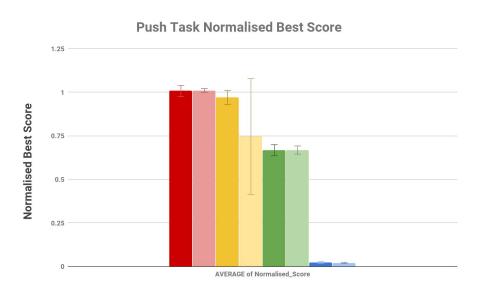






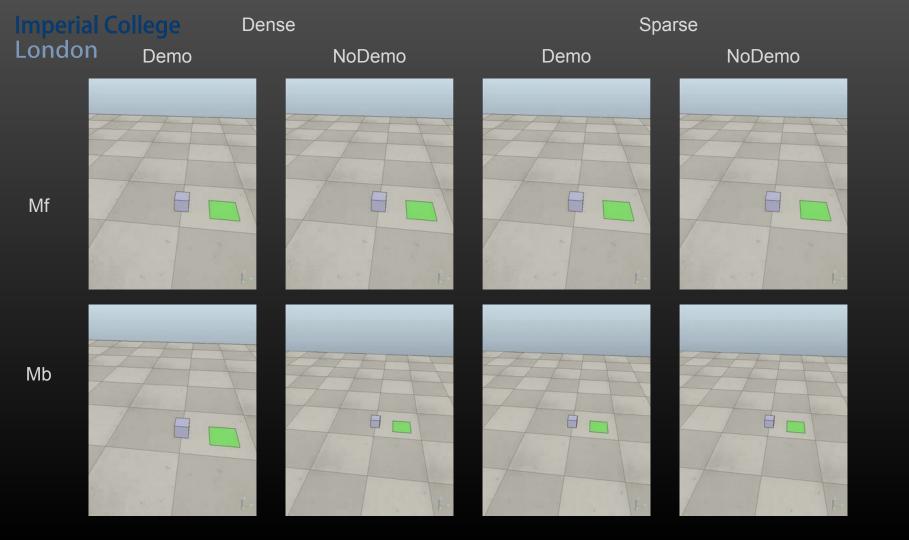




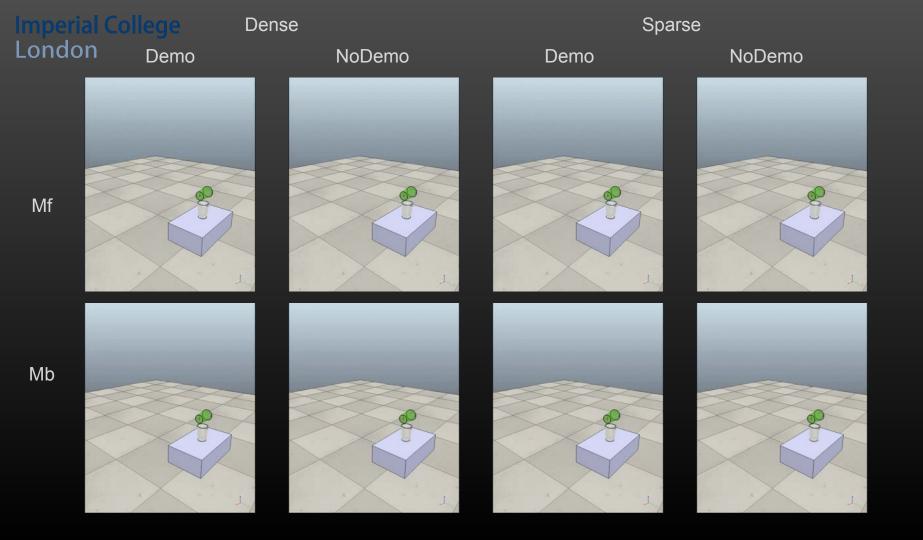




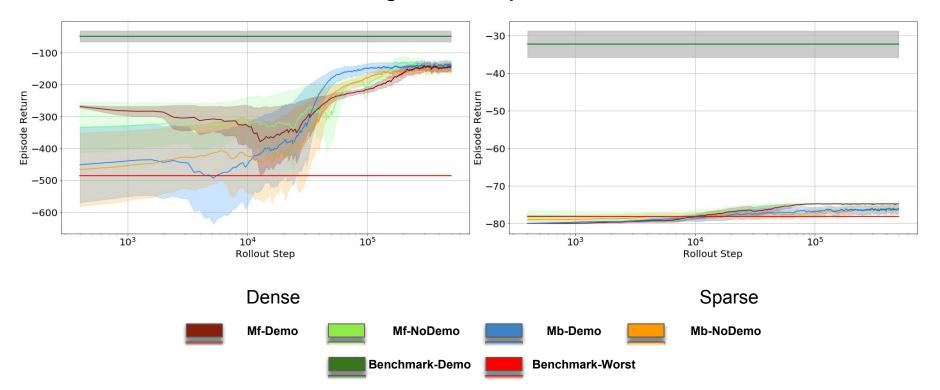




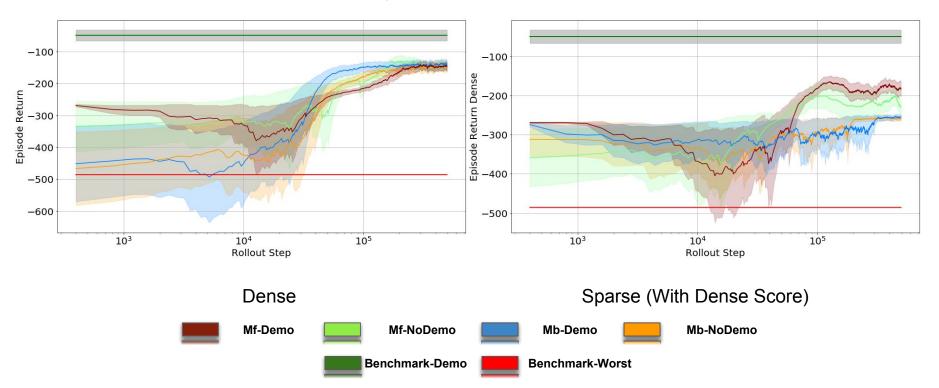
Grasp Task

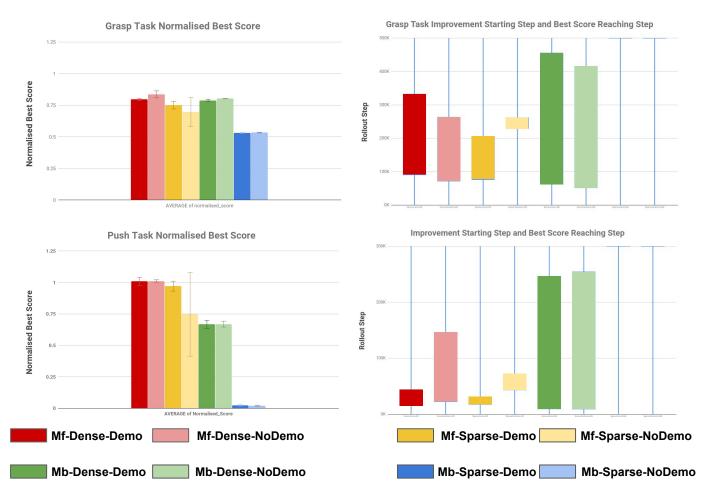


Training Statistics: Episode Return

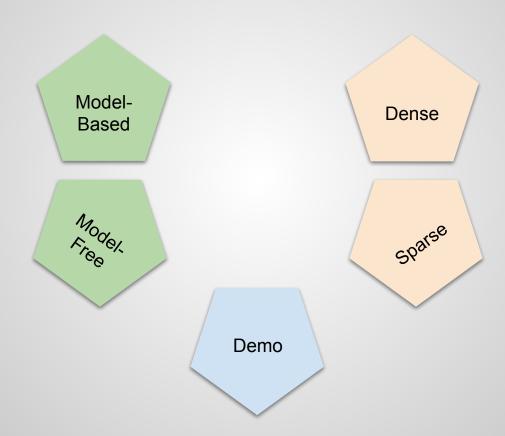


Training Statistics: Episode Return





Conclusion



Future Work



Thank you very much!

Appendix

Model

Model-Based	Model-Free
+ Sample-efficient + Stable training process	+ Master-level learning+ Operates under sparse rewards
 Typically worse asymptotic performance Requires dense reward function 	 Needs a lot more training data Training can be unstable

Rewards

Den	se Reward	Sparse Reward
+	Provides a strong reward signal	+ Intuitive to define+ Real autonomous learning
-	May be impractical to define in complex tasks May lead to sub-optimal solutions	- Hard to learn

Demonstration

+ Accelerates learning

- May be hard to collect