

Deep Reinforcement Learning Lecture 10: Sim2real RL (succinct ver.)

Huazhe Xu Tsinghua University

Al This Week



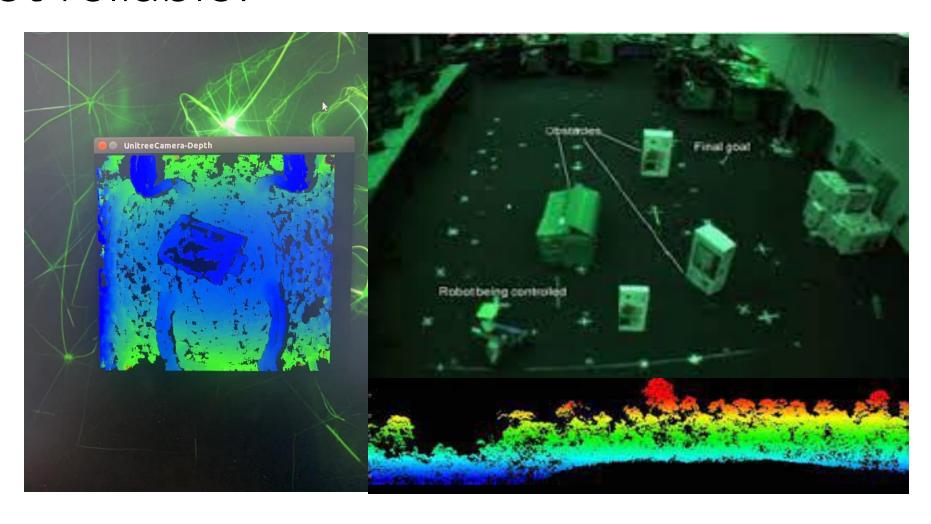
In Lec10

- 1 Why sim2real?
- 2 Domain Adaptation
- 3 Domain Randomization

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Real robot tasks are hard: the sensors are not reliable!



Real robot tasks are hard: What else?

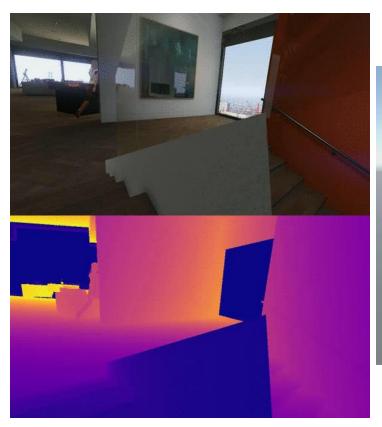
- Reward function is hard to extract
- The hardware is easily broken.

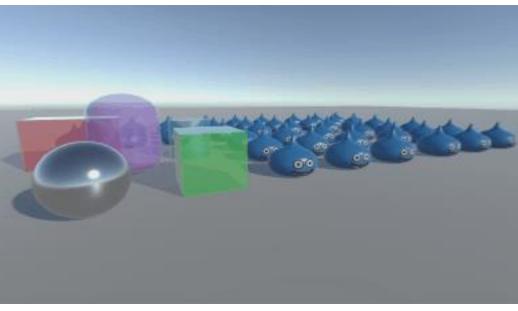
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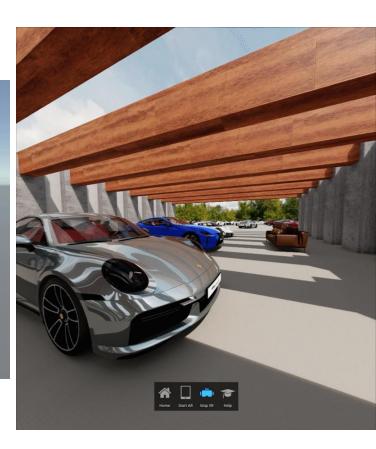
Traditional robotics methods fail···

"Manipulation breaks all the rigorous/reliable approaches I know for control." --- Russ Tedrake, MIT

Simulators are amazing!





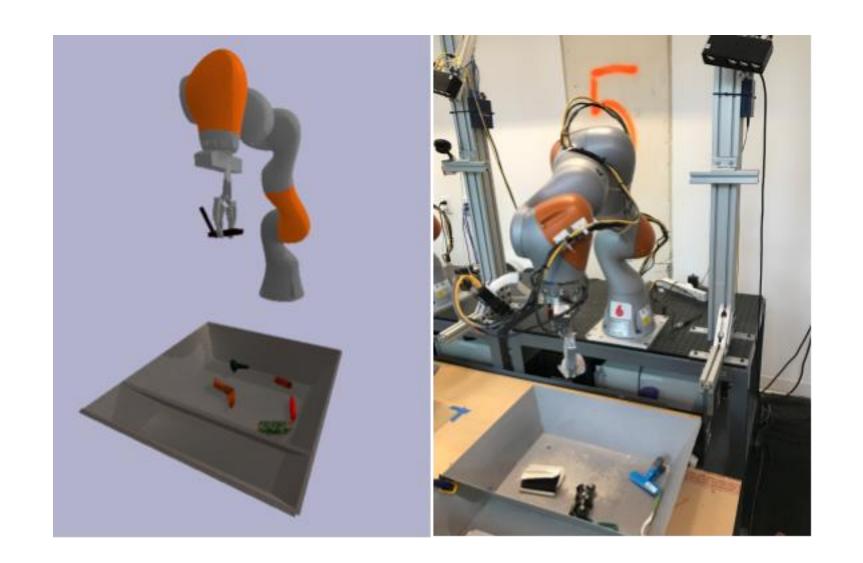


Is everything solved by learn in sim and deploy in real?

• "There is a real danger (in fact, a near certainty) that programs which work well on simulated robots will completely fail on real robots because of the differences in real world sensing and actuation - it is very hard to simulate the actual dynamics of the real world."

Artificial Life and Real Robots [Rodney Brooks, 1992]

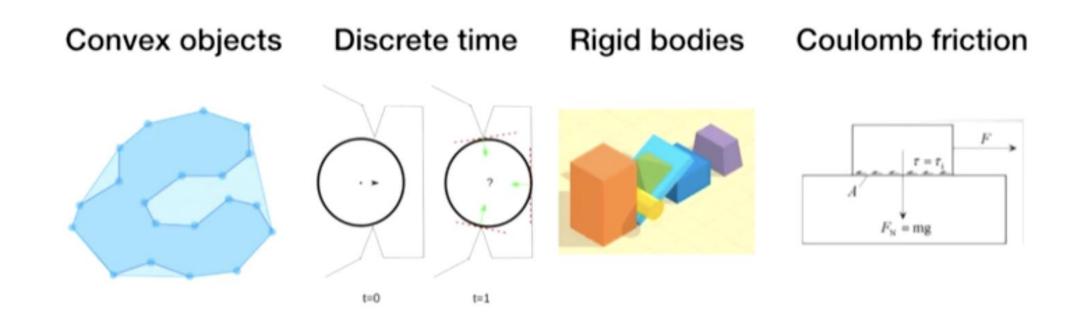
The reality gap are sometimes huge!



Why the gap exists?

- Sensors and physical systems are hard to model
- (Small) error accumulation

Physics simulators make big assumption



Source: Josh Tobin Talk

Photorealistic sensor simulation is expensive

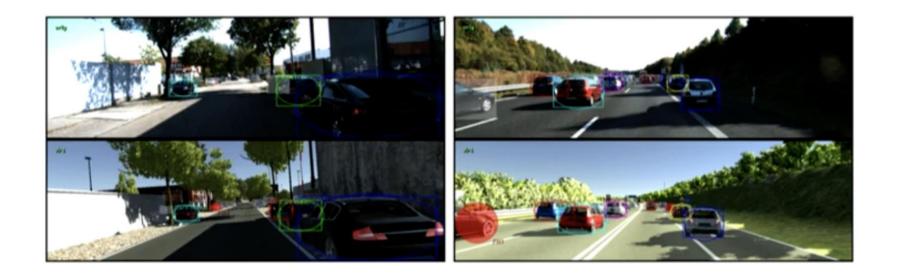


Why the gap exists?

- Sensors and physical systems are hard to model
- (Small) error accumulation

Neural network overfits to tiny differences

- Neural network are very lazy
- Sim ~63% Real ~78%



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Domain Adaptation

• Domain Adaptation is a technique to improve the performance of a model on a target domain containing insufficient annotated data by using the knowledge learned by the model from another related domain with adequate labeled data.

Domain Adaptation Examples

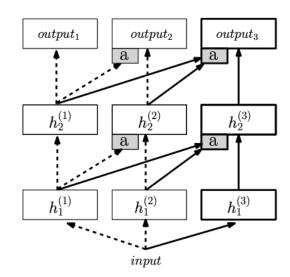
Progressive Neural Networks

Andrei A. Rusu*, Neil C. Rabinowitz*, Guillaume Desjardins*, Hubert Soyer, James Kirkpatrick, Koray Kavukcuoglu, Razvan Pascanu, Raia Hadsell

* These authors contributed equally to this work

Google DeepMind London, UK

{andreirusu, ncr, gdesjardins, soyer, kirkpatrick, korayk, razp, raia}@google.com



Domain Adaptation Examples

CyCADA: Cycle-Consistent Adversarial Domain Adaptation

Judy Hoffman ¹ Eric Tzeng ¹ Taesung Park ¹ Jun-Yan Zhu ¹ Phillip Isola ¹² Kate Saenko ³ Alexei A. Efros ¹ Trevor Darrell ¹



Source image (GTA5)



Source images (SVHN)



Adapted source image (Ours)



Adapted source images (Ours)



Target image (CityScapes)

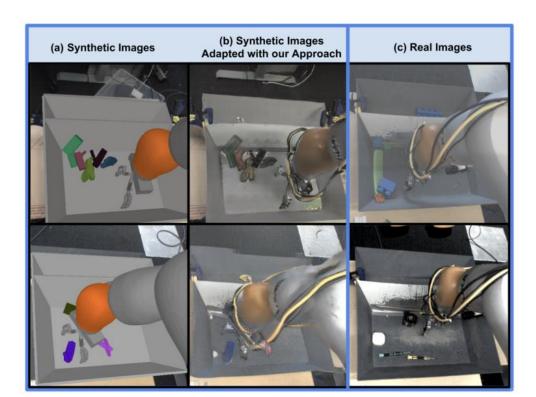


Accuracy on target Source-only: 67.1% Adapted (ours):90.4%

Target images (MNIST)

Using Simulation and Domain Adaptation to Improve Efficiency of Deep Robotic Grasping

Konstantinos Bousmalis*,¹, Alex Irpan*,¹, Paul Wohlhart*,², Yunfei Bai², Matthew Kelcey¹, Mrinal Kalakrishnan², Laura Downs¹, Julian Ibarz¹, Peter Pastor², Kurt Konolige², Sergey Levine¹, Vincent Vanhoucke¹



Domain Adaptation Examples

LEARNING CROSS-DOMAIN CORRESPONDENCE FOR CONTROL WITH DYNAMICS CYCLE-CONSISTENCY

Qiang Zhang

Shanghai Jiao Tong University zhangqiang2016@sjtu.edu.cn

Tete Xiao

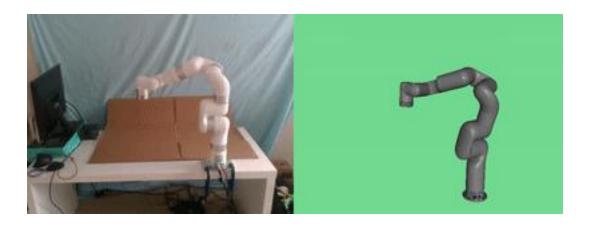
UC Berkeley

txiao@eecs.berkeley.edu

Alexei A. Efros
UC Berkeley
efros@eecs.berkeley.edu

Lerrel Pinto
New York University
lerrel@cs.nyu.edu

Xiaolong Wang
UC San Diego
xiw012@ucsd.edu



In Lec9

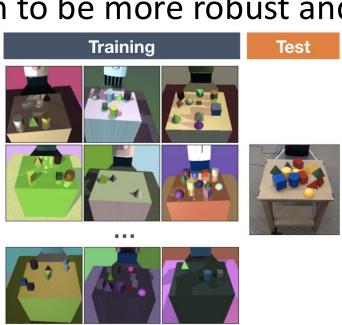
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Domain Randomization --- World is just another simulator ©

 Applying random transformations or perturbations, such as changes in lighting conditions, camera angles, object textures, or background noise, among others.

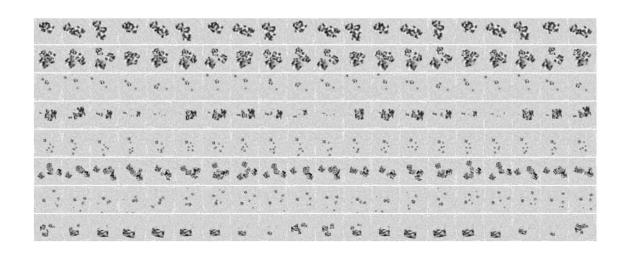
 These modifications introduce variability and complexity into the training data, which can help the model learn to be more robust and

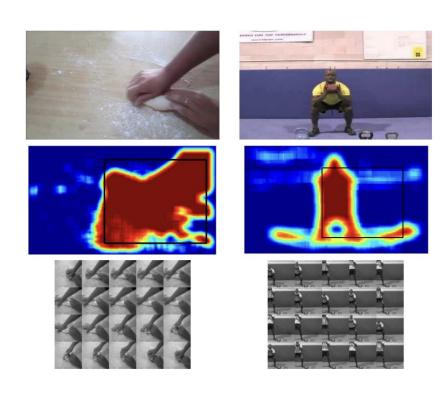
adaptable to different environments.



History: Live Repetitive Counting

- Train on repetitive random images
- Test on repetitive real images





You randomize anything that should be ignored.

DR in dexterous manipulation



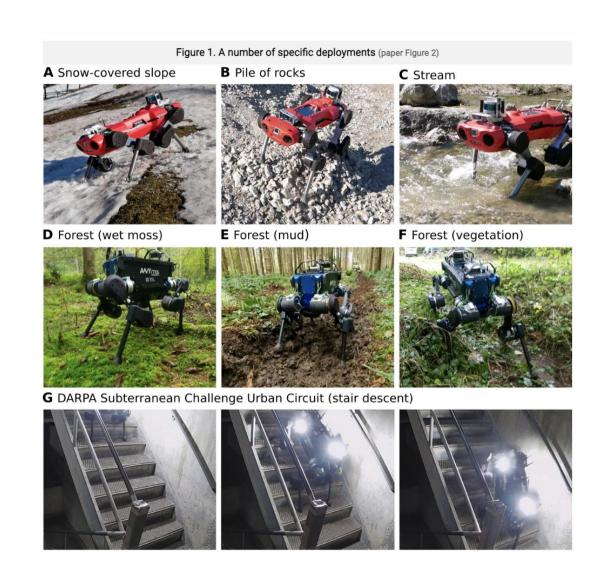
DR in dexterous manipulation

- Deep RL training (PPO)
- Automatic Domain Randomization
 - Physical parameters
 - Noise to policy inputs
 - Sensor dropout
 - Physics discretization steps
 - Backlash
 - Force
 - Visual appearance



DR in locomotion

- Randomized terrain
- Teacher-student architecture



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