Hochschule
Bonn-Rhein-Sieg
University of Applied Sciences

b-it Bonn-Aachen International Center for Information Technology

Institute for AI and Autonomous Systems

Sim-to-Real Transfer

Making Simulation-Based Knowledge Useful in Reality

Dr. Alex Mitrevski
Master of Autonomous Systems

Structure

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Crossing the Reality Gap: A Survey on Sim-to-Real Transferability of Robot Controllers in Reinforcement Learning

ERICA SALVATO, GIANFRANCO FENU, ERIC MEDVET, AND FELICE ANDREA PELLEGRINO, (Member, IEEE)

Sim-to-Real Transfer in Deep Reinforcement Learning for Robotics: a Survey

Wenshuai Zhao[1], Jorge Peña Queralta[1], Tomi Westerlund[1]

2019 International Conference on Robotics and Automation (ICRA)
Palais des congres de Montreal, Montreal, Canada, May 20-24, 2019

Quantifying the Reality Gap in Robotic Manipulation Tasks

Jack Collins[1,2], David Howard[2] and Jürgen Leitner[1,3]

- Sim-to-real motivation
- Sim-to-real methods

Sim-to-Real Motivation

What is Sim-to-Real?

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- For this reason, data collection for learning is often done in a **simulated environment that models the target real-world environment** as closely as possible

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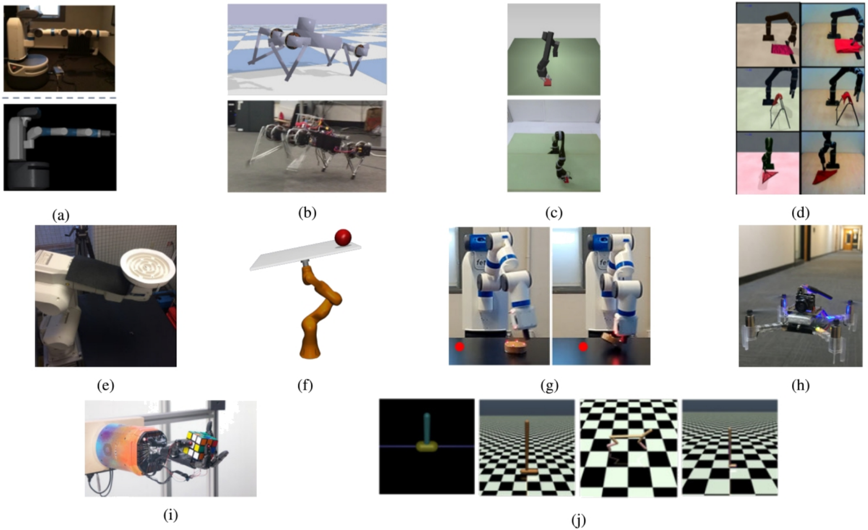
- In many learning scenarios in robotics, **collecting real-world for learning data can be impractical or dangerous**
- For this reason, data collection for learning is often done in a **simulated environment that models the target real-world environment** as closely as possible
- Sim-to-real transfer is the problem of **adapting a simulation-based model to the real world**

Sim-to-real transfer is the process of making a model that was trained in a simulated environment suitable for use in the real, target environment

Sim-to-Real Applications



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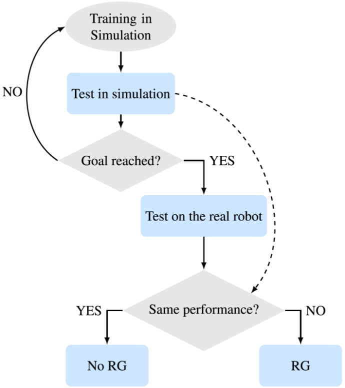

- A simulation is never a completely faithful model, but merely **an approximation of physical entities and phenomena**
  - For instance, object are often modelled as meshes, so object interactions are expressed on the mesh elements
  - Physical phenomena are expressed through (partial) differential equation models

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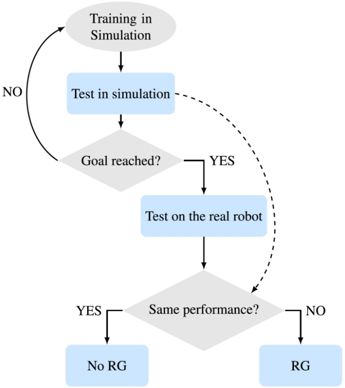

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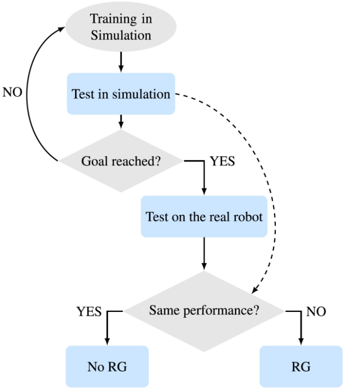

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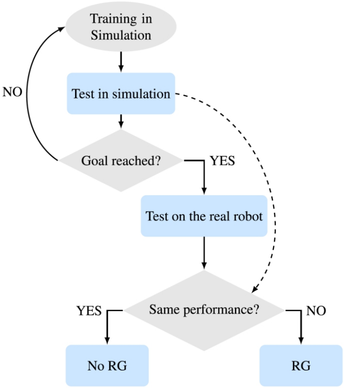

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- The reality gap refers to the **difference in performance when a model learned in simulation is applied in the real world**
- Sim-to-real is thus the problem of **reducing this gap** so that models acquired in simulation can be transferred to the corresponding real system with reasonable accuracy

Sim-to-Real Challenge Cases

Perceptual models

Models trained in simulation (e.g. for object recognition) may overfit on artificially looking objects

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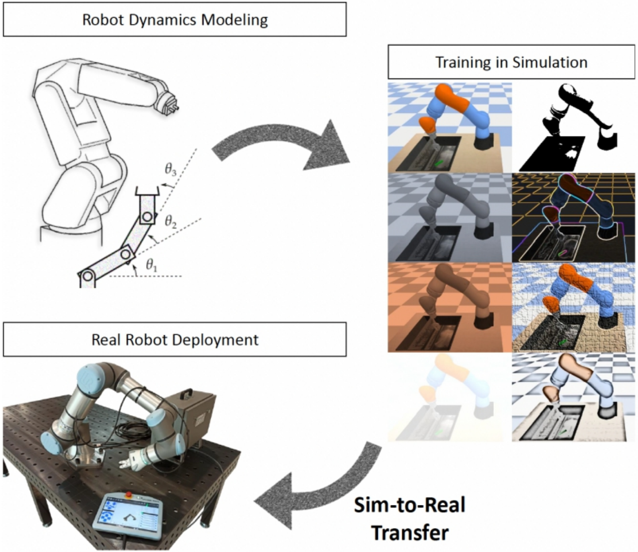
Human-robot interaction

Simulated human models may not be able to capture important intricacies of how human-robot interaction is performed

Typical Sim-to-Real Workfklow



Simulation Errors Without Object Interaction

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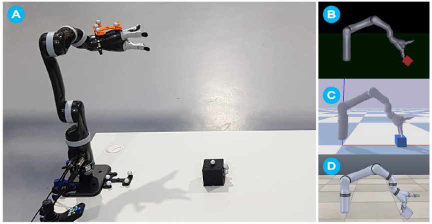
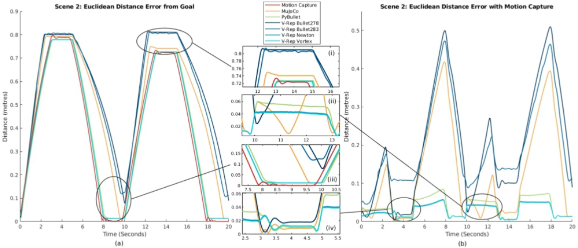
Quantifying the Reality Gap in Robotic Manipulation Tasks

Jack Collins[1,2], David Howard[2] and Jürgen Leitner[1,3]





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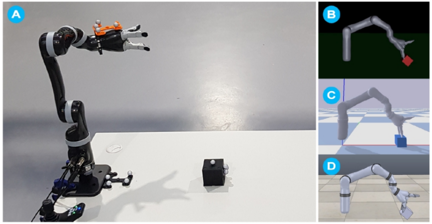

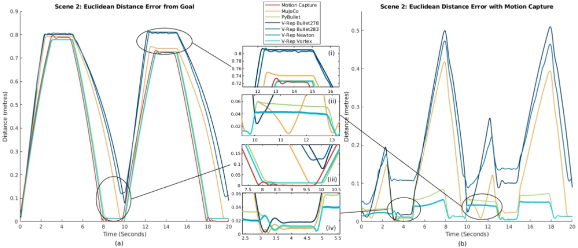

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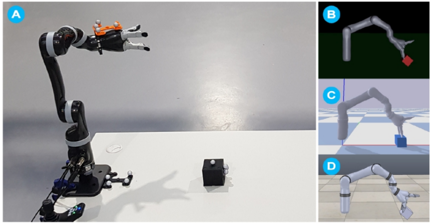

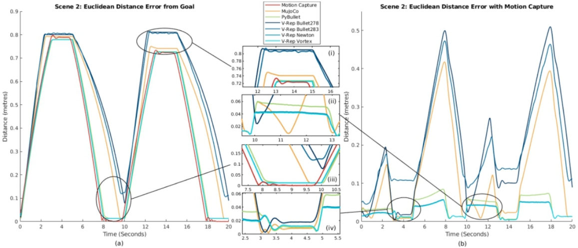

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- **Errors are particularly visible when the joint goal orientation changes significantly** — some physics engines are too slow in correcting the error
- From this evaluation, it can also be seen that **the error accumulates visibly for some physics engines**

Simulation Errors During Object Interaction

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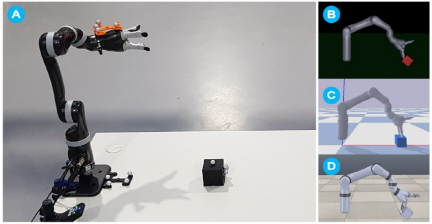

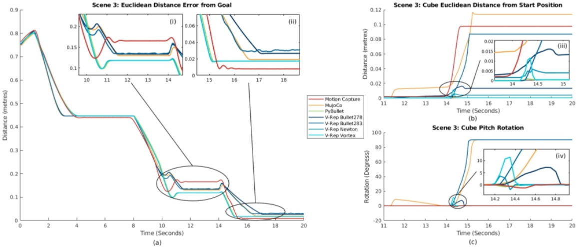

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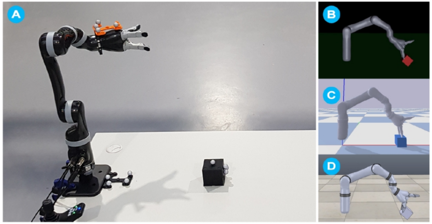

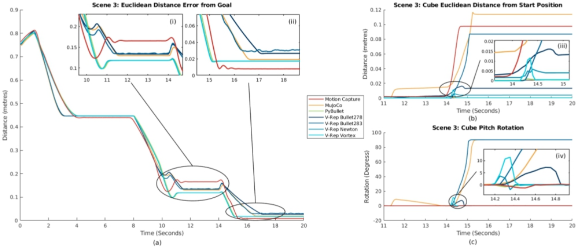

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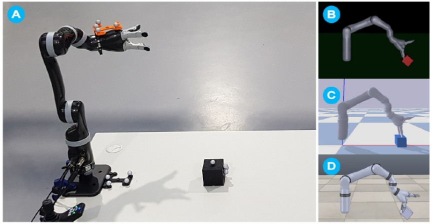

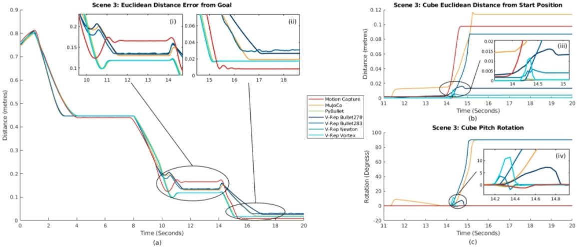

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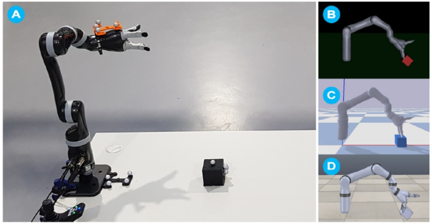

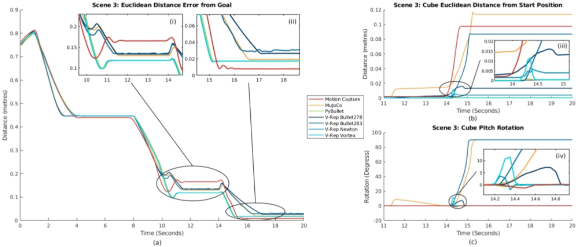

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- It can also be seen that the cube's position error is large for all engines, which means that **none of the simulators are able to accurately represent the actual cube interaction**
- This is visible for the rotational motion, where **some engines are shown to lead to a large orientation error due to knocking the cube**

Sim-to-Real in Reinforcement Learning

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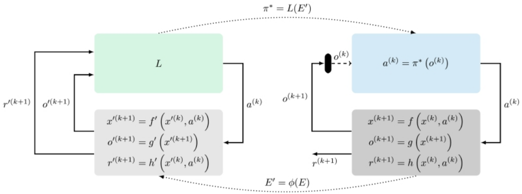
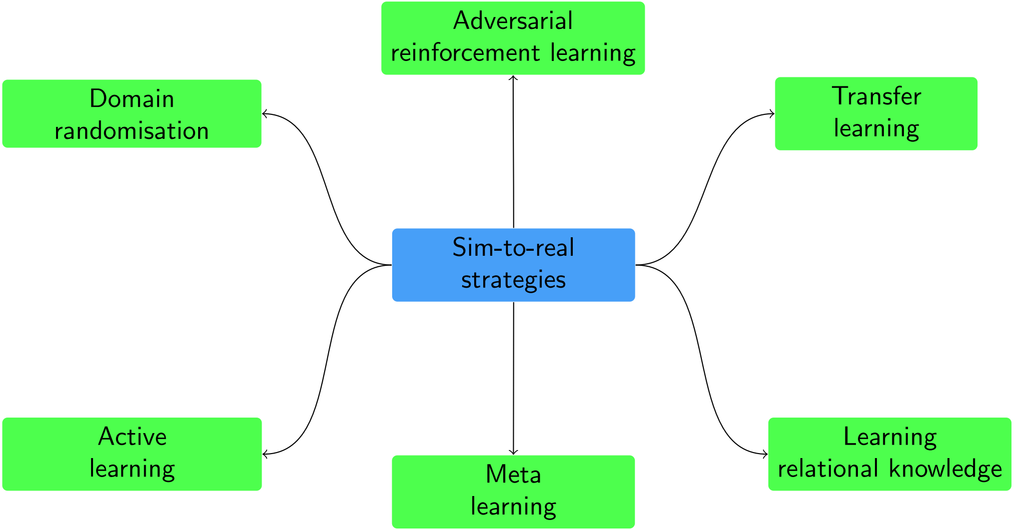
- Sim-to-real is a particularly relevant problem when learning **continuous robotics policies**, namely policies with continuous state and/or action spaces
- Here, the real system is governed by **a transition model** $f : S \times A \to S$, **an observation model** $g : S \to O$, and **a reward function** $h : S \times A \to \mathbb{R}$
- The policy π^* is, however, learned in **a simulated environment** E**, which has an approximate transition model** f', **observation model** g', and **reward model** h'



- The transfer problem can be simplified by either **improving the simulated model** (typically difficult) or **designing and learning the policy so that model discrepancies are less detrimental**

Sim-to-Real Methods

Methods for Enabling Sim-to-Real Transfer



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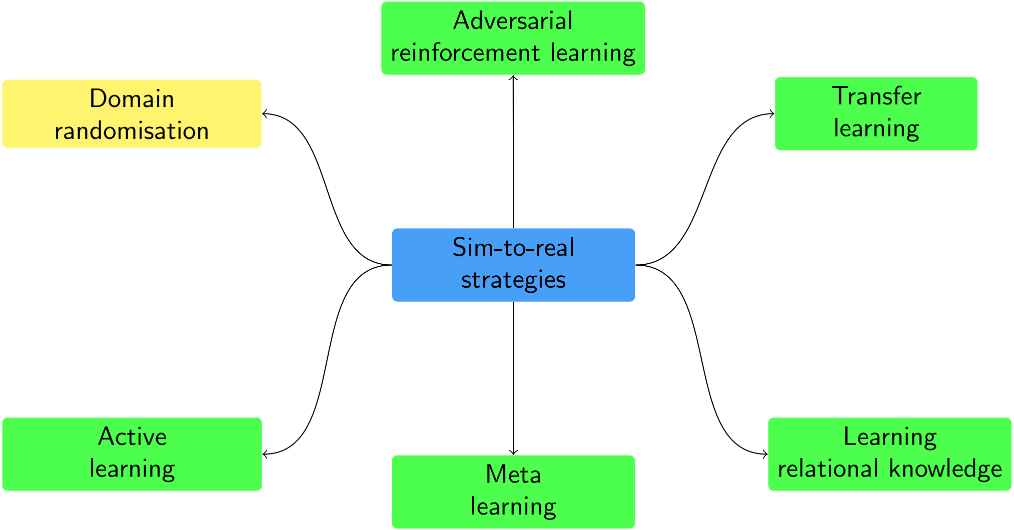

Domain Randomisation

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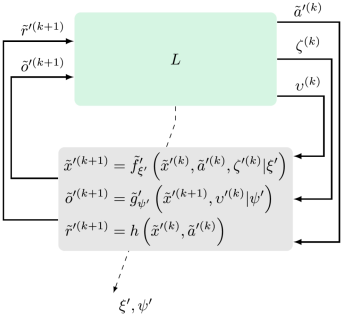

- In domain randomisation, the simulated environment is observed as a **corrupted model** E' with parameters ξ and ψ governing the disturbances of the transition and observation function, respectively

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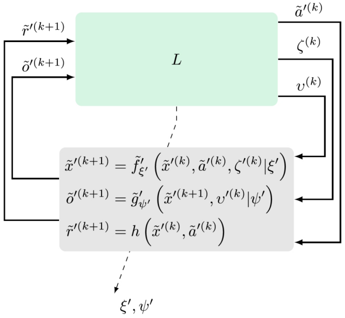

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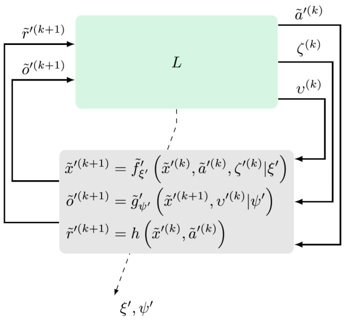

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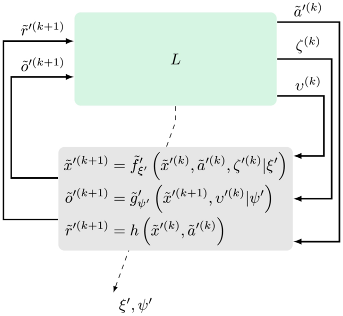

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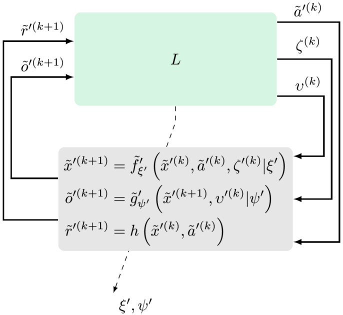

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- A randomisation-based learning process may result in a **collection of candidate policies** from which π^* can be selected — for instance, by evaluation over different simulations

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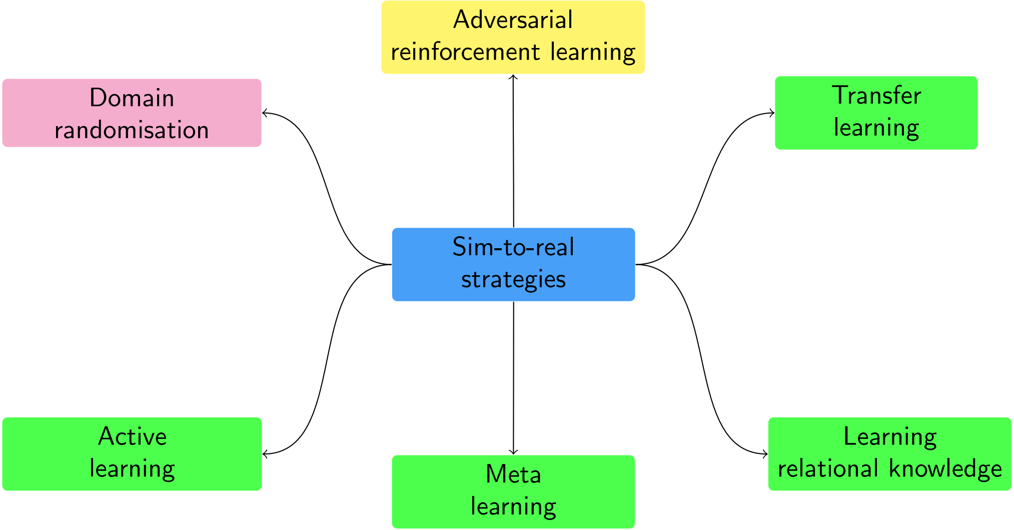
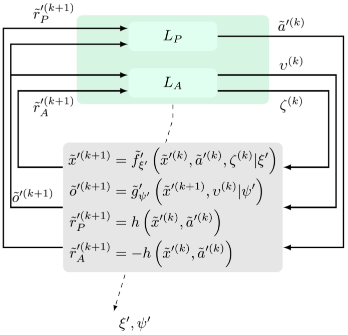


Adversarial Reinforcement Learning



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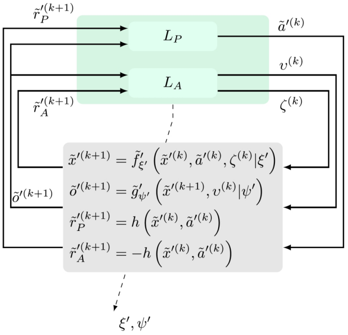

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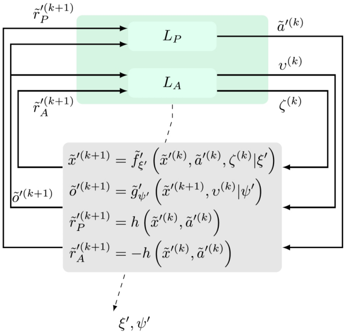

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- The policy π_A of L_A is to **select parameters for variying E'**, such that **the policy is trained with the negative of the reward of L_P** (i.e. $\tilde{r}_{L_A} = -\tilde{r}_{L_P}$)

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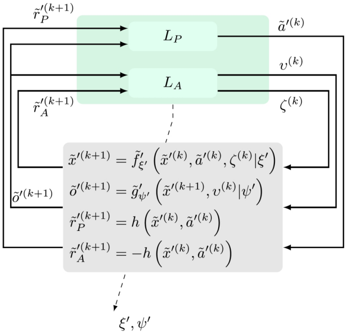

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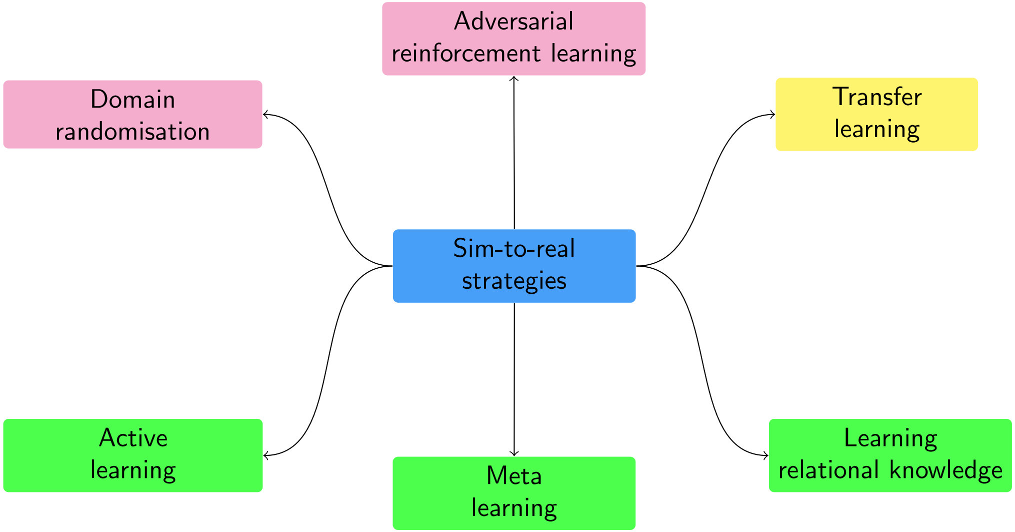
- As in domain randomisation, **training is done on a collection of environments**, but these are **selected by an adversarial model L_A** that is **trained in parallel with the agent L_P** and which **aims to generate challenging environments** (which lead to a low return)
- The policy π_A of L_A is to **select parameters for variying E'**, such that **the policy is trained with the negative of the reward of L_P** (i.e. $\tilde{r}_{L_A} = -\tilde{r}_{L_P}$)
- Denoting the joint return over L_P and L_A as J_{π_P,π_A}, the overall policy learning objective can be expressed as

$$\pi^* = \arg\max_{\pi_P} \arg\min_{\pi_A} J_{\pi_P,\pi_A}$$

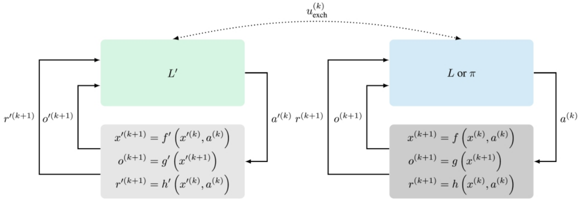
Methods for Enabling Sim-to-Real Transfer



Transfer Learning

Crossing the Reality Gap: A Survey on Sim-to-Real Transferability of Robot Controllers in Reinforcement Learning

ERICA SALVATO, GIANFRANCO FENU, ERIC MEDVET, AND FELICE ANDREA PELLEGRINO, (Member, IEEE)



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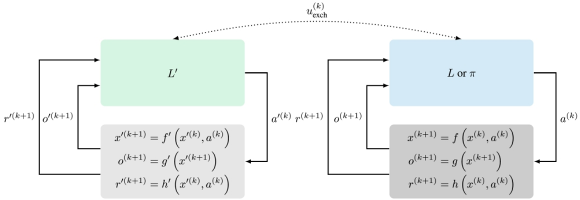

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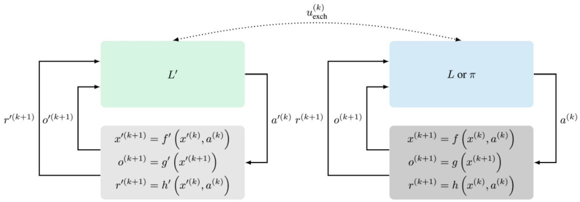

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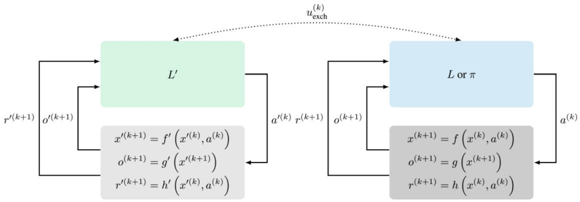

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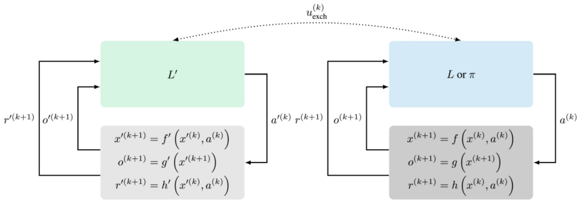

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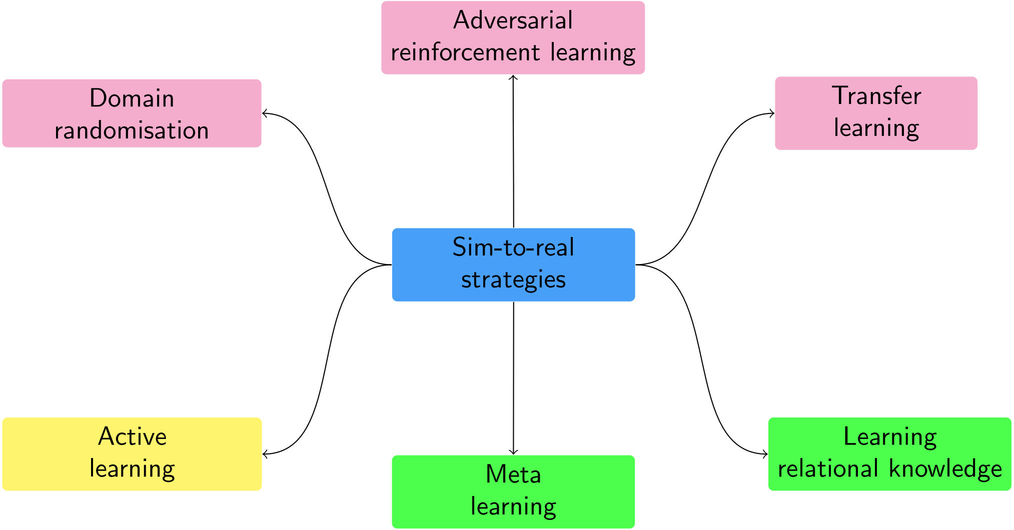
Methods for Enabling Sim-to-Real Transfer



Active Learning

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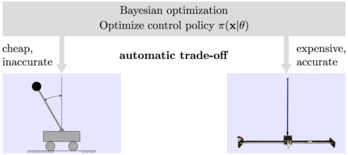

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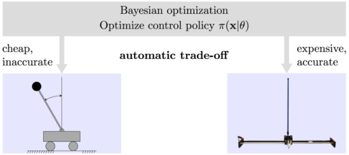

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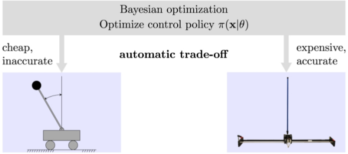

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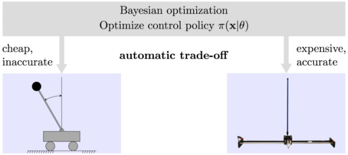

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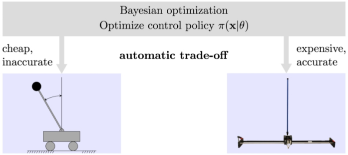

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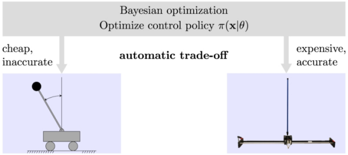

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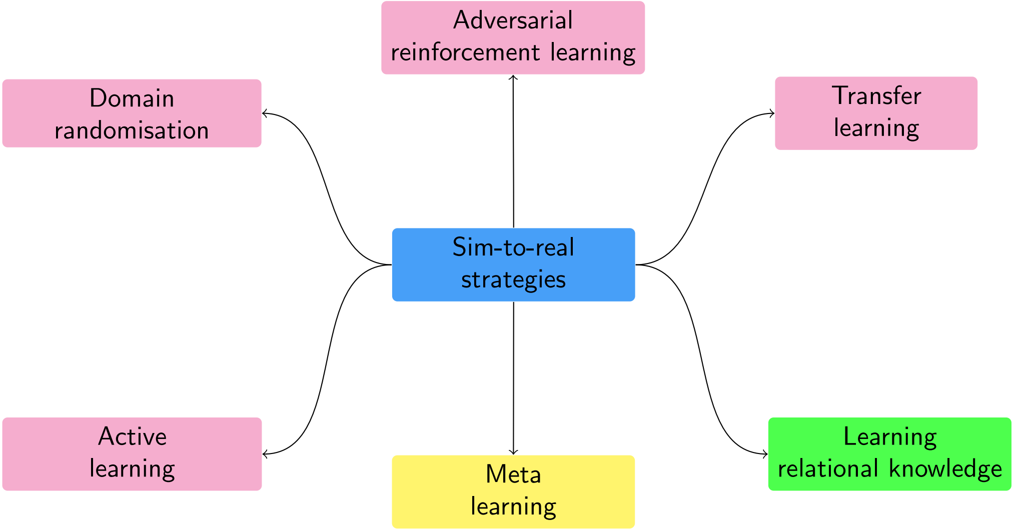
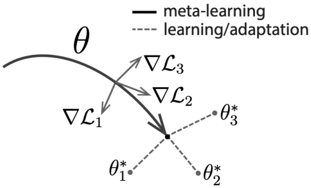
- In Bayesian optimisation, this is achieved by **modelling $J(\theta)$ as a combination** of
  - **the cost estimate in simulation $J_{\text{sim}}(\theta)$** and
  - **an estimate $J_{\text{err}}(\theta)$ of the cost error between the real system and the simulation**

Methods for Enabling Sim-to-Real Transfer



Meta Learning



Algorithm 3 MAML for Reinforcement Learning

Require: $p(\mathcal{T})$: distribution over tasks
Require: α, β: step size hyperparameters

```
randomly initialize θ
while not done do
    Sample batch of tasks T_i ~ p(T)
    for all T_i do
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C. Finn, P. Abbeel, and S. Levine, "Model-Agnostic Meta-Learning for Fast Adaptation of Deep Networks", in *Proc. 34th Int. Conf. Machine Learning*, vol. 70, 2017, pp. 1126–1135.

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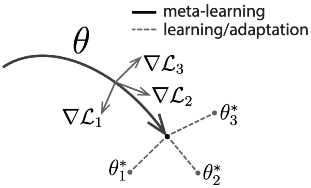

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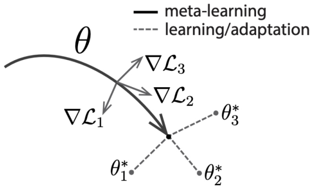

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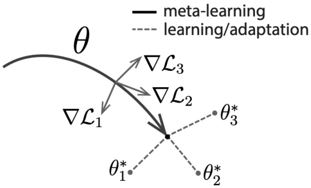

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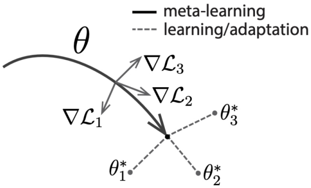

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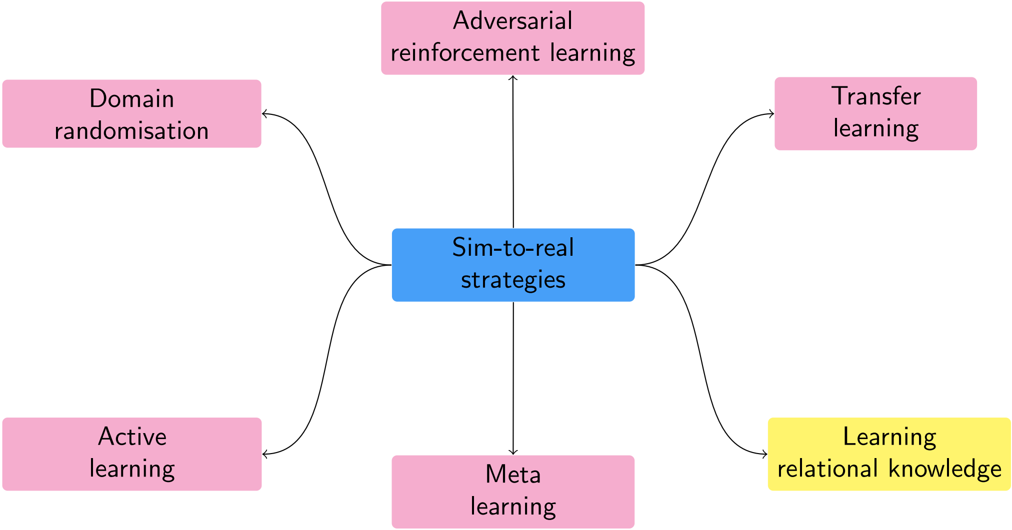
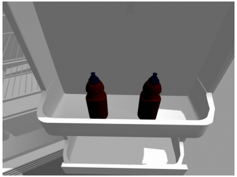
- Meta-learning is conceptually related to transfer learning, but **uses a different (meta-)learning objective** that aims to optimise the hyperparameters of the learning process

Methods for Enabling Sim-to-Real Transfer



Learning Relational Knowledge



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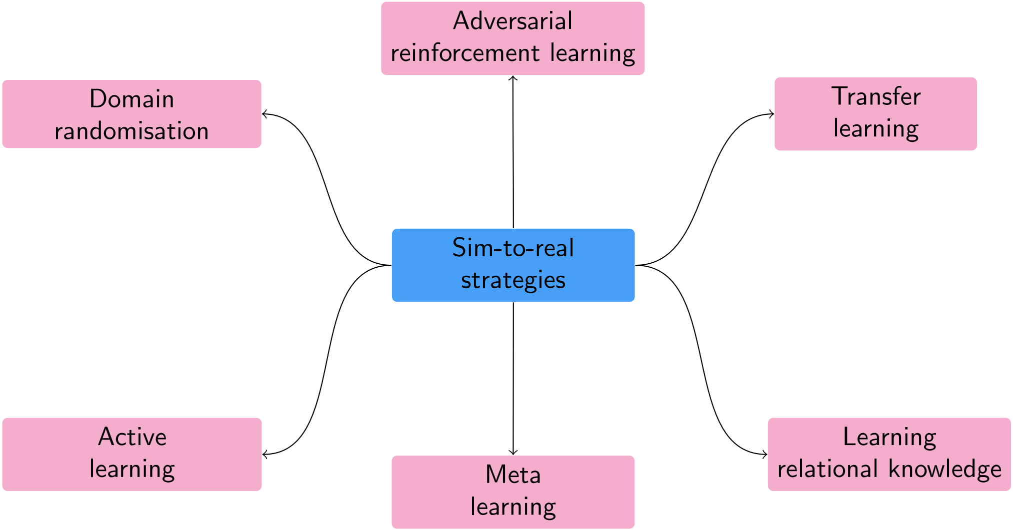
- Learning relational knowledge does, however, require:
  - **a definition of symbols to learn** or **a procedure to extract new symbols**
  - **explicit state estimation** for estimating the values of the symbols

Methods for Enabling Sim-to-Real Transfer



Methods for Enabling Sim-to-Real Transfer

Sim-to-real strategies

- Adversarial reinforcement learning
- Domain randomisation
- Transfer learning
- Active learning
- Meta learning
- Learning relational knowledge

All of these have their own merits and limitations

Summary

- Sim-to-real transfer refers to the problem of using knowledge that was acquired in simulation in the corresponding real-world environment
- The problem exists because of the reality gap, namely the inevitable discrepancy between simulated and real environments, which stems from the fact that simulations are simplified models of real environments
- There is a variety of methods that can be used for performing sim-to-real transfer — we particularly looked at domain randomisation, adversarial learning, transfer learning, active learning, meta-learning, as well as learning relational knowledge
- There is no clear winner among the existing sim-to-real methods in terms of quality and applicability
    - Which method is best to apply can depend on what is and is not known about the real environment