Hochschule
Bonn-Rhein-Sieg
University of Applied Sciences

b-it Bonn-Aachen International Center for Information Technology

Institute for AI and Autonomous Systems

Learning for Robot Manipulation

An Overview

Dr. Alex Mitrevski
Master of Autonomous Systems

Structure

Journal of Machine Learning Research 22 (2021) 1-82 Submitted 9/19; Revised 8/20; Published 1/21

A Review of Robot Learning for Manipulation: Challenges, Representations, and Algorithms

Oliver Kroemer* Scott Niekum George Konidaris

Reinforcement learning in robotics: A survey

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Jens Kober[1,2], J. Andrew Bagnell[3] and Jan Peters[4,5]

Robotics and Autonomous Systems 156 (2022) 104224

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Robotics and Autonomous Systems

journal homepage: www.elsevier.com/locate/robot

A survey of robot manipulation in contact

Markku Suomalainen[a,*], Yiannis Karayiannidis[b], Ville Kyrki[c]

- Why learning for robot manipulation
- Overview of learning for manipulation
- State representation
- Manipulation policy learning
- Transition model learning

Why Learning for Robot Manipulation

Manipulation Skill Examples

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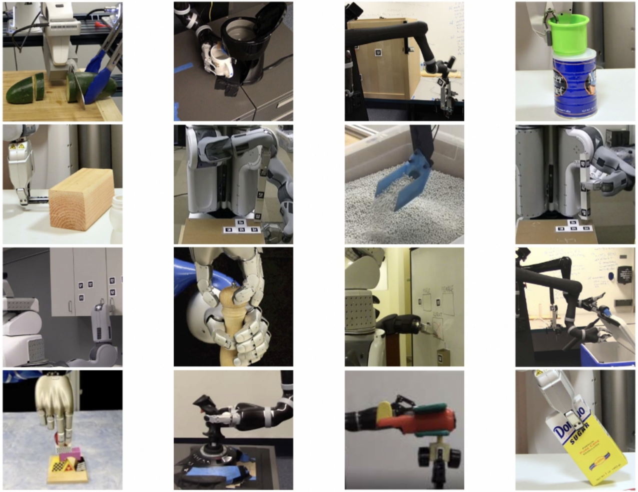

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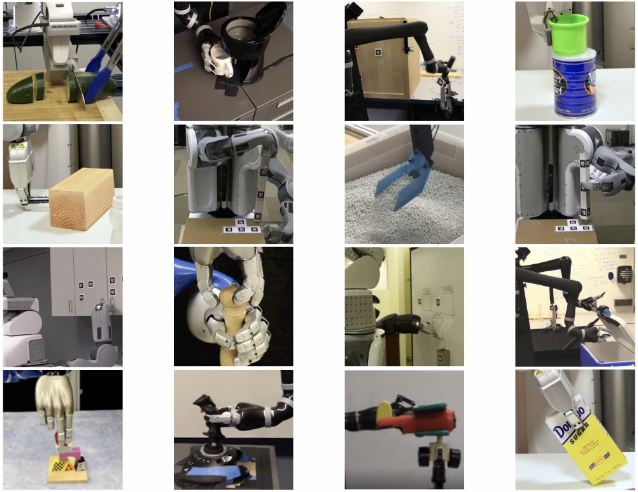

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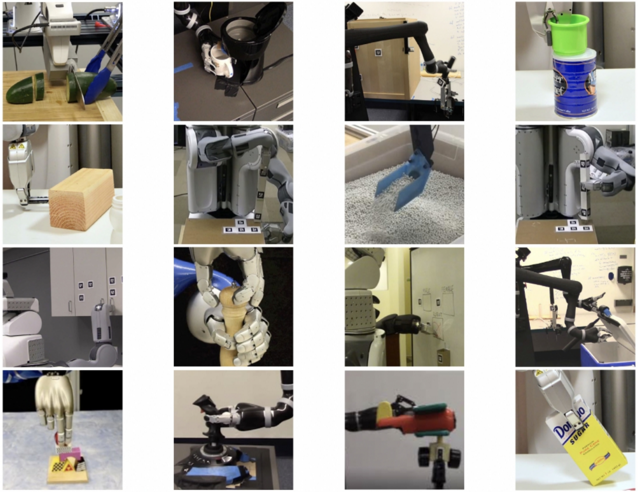

- In everyday environments, there is a large variety of useful manipulation skills, which require varying degrees of dexterity
- Many such skills can be designed using model-based techniques, but many others require flexibility that can be tricky to model explicitly
- An alternative approach is to allow a robot to acquire such skills (semi-)autonomously

Learning for Contact-Heavy Interactions


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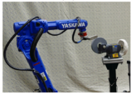

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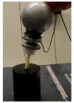
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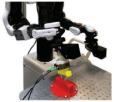
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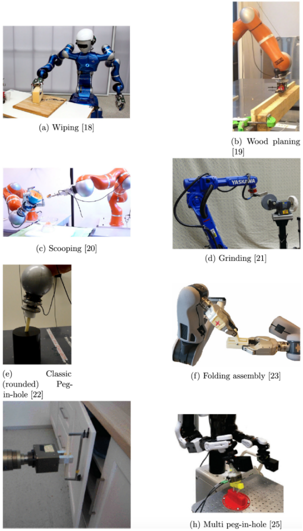
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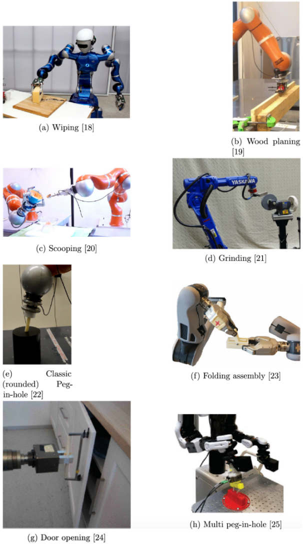
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- Learning can be particularly useful to consider for manipulation tasks that involve prolonged or precise contacts with the environment
- This is because, in principle, **contact-heavy interactions can be challenging to model in sufficient detail**
- Instead, it is sensible to **allow a robot to learn an appropriate interaction policy**

Learning and Robot Control

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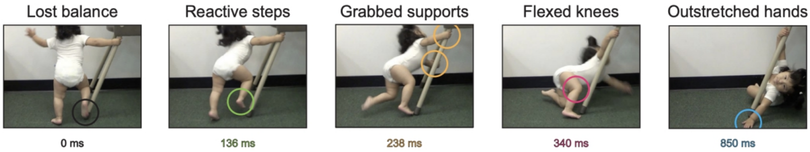
- The approaches are, however, conceptually different:
  - Control theory **models systems and controllers explicitly**
  - Learning enables robots to **optimise controllers through direct experience**
- Depending on the nature of the learning problem, **a combination of control theory and learning is both possible and reasonable** (e.g. learning can be used to optimise the parameters of an explicitly modelled controller)

Lessons from Natural Systems

- **The perspective on the previous slides is a practical one** — explicitly programming robot skills is often challenging or inflexible, so we use learning techniques instead
- **Learning is also interesting to look at from a cognitive developmental point of view** — after all, biological creatures acquire most of their skills via learning
- Robots that have learning and adaptation capabilities that are similar to those of biological creatures are likely to be **most useful in our complex, regularly changing environments**



D. Han and K. E. Adolph, "The impact of errors in infant development: Falling like a baby," *Developmental Science*, vol. 24, no. 5, pp. e13069:1–14, 2020.

Overview of Learning for Manipulation

What to Learn for Manipulation?

Learning in the manipulation context can be concerned with multiple aspects, for instance:

Object models

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Skill hierarchies

When multiple (primitive) skills are available, it can be useful to learn how the skills can be combined for solving complex tasks

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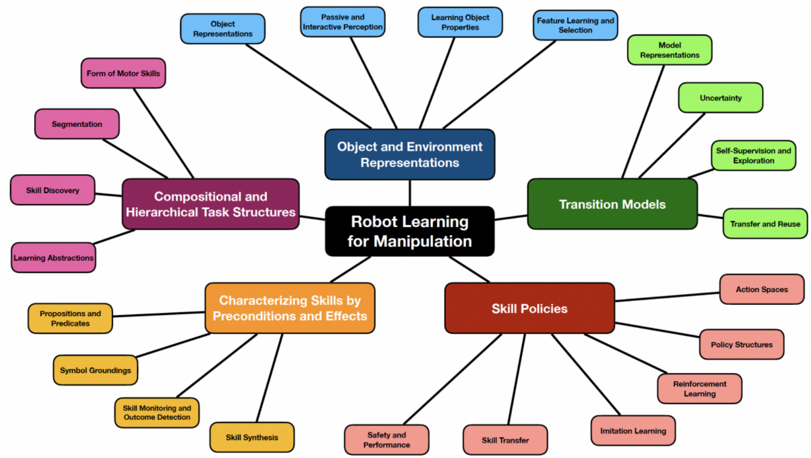

State Representation

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- **The manner in which the environment changes based on a robot's actions can be captured by a change of state**; thus, the state representation should be able to capture **relevant changes in the environment**
- In addition, an appropriate state representation is often responsible for **simplifying otherwise intractable learning problems**

Robot and Environment State

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- **Robot actions have an effect both on the robot itself and on the robot's environment**
- A general state representation thus has to capture both of these aspects and has the following form:

$$S = S_r \cup S_e$$

where

- S_r is a representation of the robot's internal state
- S_e represents the state of the task environment

Object-Centric Environment Representation

- As manipulation is typically concerned with handling objects, **the environment state is typically modelled through the states of individual objects of interest**

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- Let O_j represent the state of some object o_j and n be the number of objects of interest for a task; then

$$S_o = \bigcup_{j=1}^{n} O_j$$

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- In many cases, it can also be useful to capture some general information S_w about the environment; thus, **the complete environment state can be seen as a combination of the general environment state and the object-specific states**:

$$S_e = S_w \cup S_o = S_w \cup \left(\bigcup_{j=1}^{n} O_j \right)$$

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- The dependence on such parameters can be made explicit by representing them as an **execution context vector** $\boldsymbol{\tau} \in C$
- The execution context can then serve as information that **conditions the execution policy**:

$$\pi : S \times C \rightarrow A$$

Task Family

- When modelling learning problems, we can often define a **task family**, which is a collection of tasks $T_i, 1 \leq i \leq \mathrm{t}$ that
  - have the same action space A
  - but each of them has its own state space S_i, context space C_i, a transition function $\mathcal{T}_i$, as well as a reward function R_i

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- **The relation between tasks of a task family can be expressed through the reward function** R_i, which can be modelled as

$$R_i = G_i - E$$

where G_i **represents a task-specific goal** and E **is a common cost function**

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- Overall, a task family of t tasks can be represented as **a collection of Markov Decision Processes (MDPs)**:

$$P(\mathcal{M}) = \{(S_i, A, \mathcal{T}_i, R_i, C_i, \gamma) \mid 1 \leq i \leq \mathrm{t}\}$$

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- Ideally, **the hierarchical levels are used by different skills that can be composed** to solve a specific task

Passive vs. Interactive Perception

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- **Many aspects of the environment are not observable using passive perception only** (e.g. the mass of an object), so interactive perception is often essential for successful task completion

Manipulation Policy Learning

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Reinforcement learning	Imitation learning
A policy is learned using direct interactions with the world	Learning is done based on expert observations

Execution Policies Revisited

- In the last lecture, we defined a skill by an execution policy together with initiation and termination conditions
- A policy $\pi : S \rightarrow A$ models a robot's behaviour, and **a particularly large effort in robot learning is put on how to actually acquire such a policy**
- There are a few general ways in which this can be done:

Reinforcement learning	Imitation learning	Transfer learning
A policy is learned using direct interactions with the world	Learning is done based on expert observations	Previously learned policies are used to guide the learning process

Journal of Machine Learning Research 22 (2021) 1-82 Submitted 9/19; Revised 8/20; Published 1/21
A Review of Robot Learning for Manipulation:
Challenges, Representations, and Algorithms
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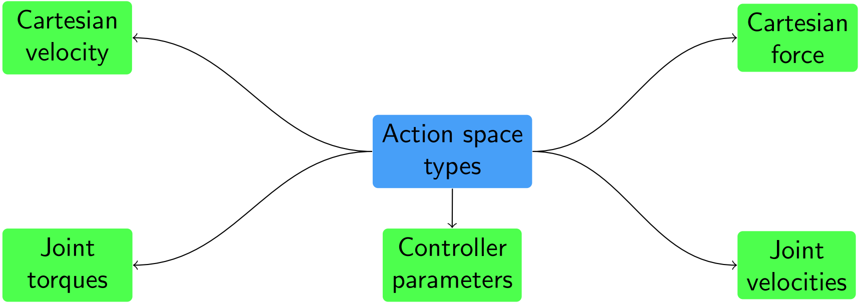
Action Spaces

- Execution policies can have a variety of action spaces, which are illustrated below:



- Note that policy outputs are typically not directly used as actuator commands, but are **processed by a low-level robot controller**

Policy Representations

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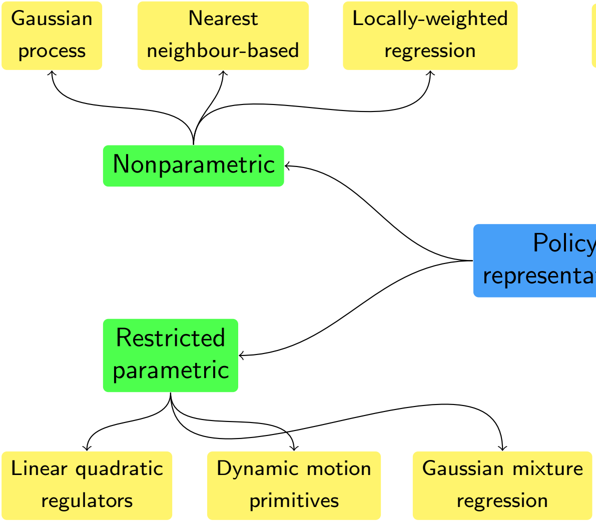

Deterministic vs. Stochastic Policies

- Regarding how actions are selected from a policy, we can distinguish between **deterministic and stochastic policies**

Deterministic vs. Stochastic Policies

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Stochastic policy

Actions are selected by sampling from the distribution of actions given a state

$$\boldsymbol{a}_t \sim \pi(\boldsymbol{a}|\boldsymbol{s}_t)$$

Deterministic vs. Stochastic Policies

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Stochastic policy

Actions are selected by sampling from the distribution of actions given a state

$$\boldsymbol{a}_t \sim \pi(\boldsymbol{a}|\boldsymbol{s}_t)$$

Deterministic policy

Actions are selected by a deterministic function of the current state

$$\boldsymbol{a}_t = \pi(\boldsymbol{s}_t)$$

Parameterised Policies and Trajectories


Reinforcement learning in robotics: A survey

Jens Kober[1,2], J. Andrew Bagnell[3] and Jan Peters[4,5]

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- In robotics, **policies are often represented by parameters $\boldsymbol{\theta}$**, so we denote the policy as $\pi_{\boldsymbol{\theta}}$

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- In robotics, **policies are often represented by parameters θ**, so we denote the policy as $\pi_{\boldsymbol{\theta}}$
- A policy is used to define a **trajectory (also called episode or rollout)**

$$\tau = (\boldsymbol{s}_0, \boldsymbol{a}_0, \boldsymbol{s}_1, ..., \boldsymbol{a}_n, \boldsymbol{s}_{n+1})$$

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$$\tau = (\boldsymbol{s}_0, \boldsymbol{a}_0, \boldsymbol{s}_1, ..., \boldsymbol{a}_n, \boldsymbol{s}_{n+1})$$

- Given a policy π, the probability of a trajectory can be found to be

$$P_\pi(\boldsymbol{s}_0, \boldsymbol{a}_0, \boldsymbol{s}_1, ..., \boldsymbol{a}_n, \boldsymbol{s}_{n+1}) = P(s_0) \prod_{i=0}^{n} P_\pi(\boldsymbol{a}_i | \boldsymbol{s}_i) P(\boldsymbol{s}_{i+1} | \boldsymbol{s}_i, \boldsymbol{a}_i)$$

Reinforcement Learning Objective

- When using reinforcement learning for acquiring a policy, the objective is to find a policy π^* that maximises the robot's expected return:

$$\pi^* = \arg\max_{\pi} \underset{\tau \sim \pi}{E}\left[\sum_t r(\boldsymbol{s}_t, \boldsymbol{a}_t)\right] = \arg\max_{\pi} \int P(\tau|\pi) R(\tau) d\tau$$

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- If we are given a parameterised policy $\pi_{\boldsymbol{\theta}}$, the learning objective is that of finding a set of parameters θ^* that maximise the expected return

$$\theta^* = \arg\max_{\boldsymbol{\theta}} \mathop{E}_{\tau \sim \pi_{\boldsymbol{\theta}}} \left[\sum_t r(\boldsymbol{s}_t, \boldsymbol{a}_t) \right] = \arg\max_{\boldsymbol{\theta}} \int P(\tau|\pi_{\boldsymbol{\theta}}) R(\tau) d\tau$$

Exploration vs. Exploitation

Reinforcement Learning

- During learning, a robot has to balance **exploration and exploitation**

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Acting according to the best policy available to the robot (so far)

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Exploration

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- There is always a trade-off between exploitation and exploration:
  - if the robot exploits too much too early, it risks converging to a suboptimal policy
  - the robot's policy should eventually converge however; too much exploration can prevent that from happening

Model-Free Learning

Reinforcement Learning

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Temporal difference learning

Performs value / policy updates at every step (i.e. after the execution of every action)

Hochschule Bonn-Rhein-Sieg University of Applied Sciences

b-it Bonn-Aachen International Center for Information Technology

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Temporal difference learning	Monte Carlo learning
Performs value / policy updates at every step (i.e. after the execution of every action)	Estimates the return from complete trajectories and then performs value / policy updates

Temporal Difference — TD(λ) — Learning and Q-Learning

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Reinforcement Learning

- **The TD(λ) learning algorithm attempts to bring the value function $V(s_t)$ closer to the reward function, while preventing myopic updates**

Temporal Difference — TD(λ) — Learning and Q-Learning

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$$V(\boldsymbol{s}_t) = V(\boldsymbol{s}_t) + \alpha \left(r(\boldsymbol{s}_t, \boldsymbol{a}_t) + \gamma V(\boldsymbol{s}_{t+1}) - V(\boldsymbol{s}_t) \right)$$

Temporal Difference — TD(λ) — Learning and Q-Learning

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Temporal Difference — TD(λ) — Learning and Q-Learning


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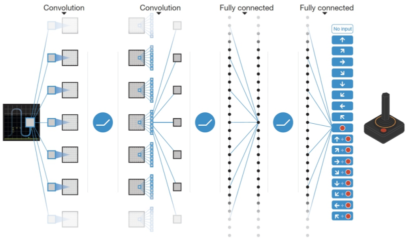
- The Q-learning update rule is given by

$$Q(\boldsymbol{s}_t, \boldsymbol{a}_t) = Q(\boldsymbol{s}_t, \boldsymbol{a}_t) + \alpha\left(r(\boldsymbol{s}_t, \boldsymbol{a}_t) + \gamma \max_{\boldsymbol{a}} Q(\boldsymbol{s}_{t+1}, \boldsymbol{a}) - Q(\boldsymbol{s}_t, \boldsymbol{a}_t)\right)$$

Deep Q-Learning

Reinforcement Learning



V. Mnih et al. "Human-level Control Through Deep Reinforcement Learning," *Nature*, vol. 518, no. 7540, pp. 529–533, 2015.

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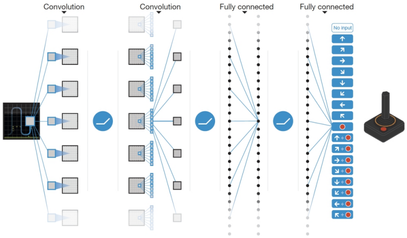

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- In deep Q-learning, Q-function is represented using a deep neural network, and the objective function that is being minimised here is often of the form

$$\mathcal{L}(\boldsymbol{\theta}) = E\left[Q(\boldsymbol{s}_t, \boldsymbol{a}_t) - \left(r(\boldsymbol{s}_t, \boldsymbol{a}_t) + \gamma \max_{\boldsymbol{a}} Q(\boldsymbol{s}_{t+1}, \boldsymbol{a})\right)\right]$$

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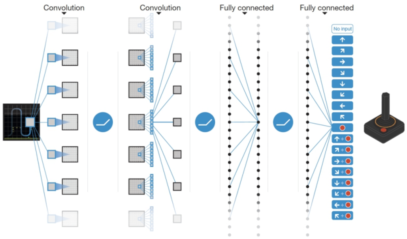

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- Q-learning can be fairly unstable when a neural network is used to represent the value function (and may not even converge) — but there are practical tricks to improve the convergence

- Value-based algorithms, such as TD(λ) and Q-learning, derive the policy from the value function

Policy Search

Reinforcement Learning

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Policy Search

- Value-based algorithms, such as TD(λ) and Q-learning, derive the policy from the value function
- Policy search circumvents the need for the value function by **optimising in the policy space directly**
- **Policy search algorithms are useful in robotics since they allow incorporating prior knowledge about the policy**

Policy Gradients

Reinforcement Learning

- Policy gradient methods represent one popular family of policy search

Policy Gradients

Reinforcement Learning

- Policy gradient methods represent one popular family of policy search
- Given a parameterised policy $\pi_{\boldsymbol{\theta}}$, a **policy gradient algorithm estimates the gradient of the expected return and modifies the parameters $\boldsymbol{\theta}$** using the update rule

$$\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} + \nabla J(\boldsymbol{\theta}) = \boldsymbol{\theta} + \nabla \int R(\tau) P(\tau | \boldsymbol{\theta}) d\tau$$

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Reinforcement Learning

- Policy gradient methods represent one popular family of policy search
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$$\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} + \nabla J(\boldsymbol{\theta}) = \boldsymbol{\theta} + \nabla \int R(\tau) P(\tau|\boldsymbol{\theta}) d\tau$$

- Policy gradient algorithms often make use of the so-called likelihood ratio trick

$$\nabla_{\boldsymbol{\theta}} P(\tau|\boldsymbol{\theta}) = P(\tau|\boldsymbol{\theta}) \nabla_{\boldsymbol{\theta}} \log P(\tau|\boldsymbol{\theta})$$

while estimating the gradient of J

REINFORCE Algorithm

Reinforcement Learning

- REINFORCE is an algorithm that forms the backbone of many practically used policy gradient algorithms
- The algorithm was originally formulated for neural network-based policies, but its general formulation is applicable to any differentiable policy
- A high-level overview of the algorithm is shown on the right

```
Initialise θ randomly
for i ← 1 to N do
    𝒯 ← {}
    for j ← 1 to M do
        τ ← sample(π_θ)
        𝒯 ← 𝒯 ∪ τ
    J_θ ← (1/M) Σ_{j=1}^{M} Σ_t r_t^j
    θ ← θ + ∇J_θ
```

Initialise $\boldsymbol{\theta}$ randomly
for $i \leftarrow 1$ **to** N **do**
  $\mathcal{T} \leftarrow \{\}$
  for $j \leftarrow 1$ **to** M **do**
    $\tau \leftarrow \texttt{sample}(\pi_{\boldsymbol{\theta}})$
    $\mathcal{T} \leftarrow \mathcal{T} \cup \tau$
  $J_{\boldsymbol{\theta}} \leftarrow \frac{1}{M} \sum_{j=1}^{M} \sum_t r_t^j$
  $\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} + \nabla J_{\boldsymbol{\theta}}$

Actor-Critic Learning

Reinforcement Learning

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- A combination of the two also exists — this forms the so-called **actor-critic family of RL algorithms, which estimate the value function and maintain a policy at the same time**
- Actor-critic algorithms make use of a **baseline b when estimating the gradient of J**

$$\nabla_{\boldsymbol{\theta}} J(\theta) = E\left[\sum_{i=0}^{T} \nabla_{\boldsymbol{\theta}} \log P_{\boldsymbol{\theta}}(\boldsymbol{a}_t|\boldsymbol{s}_t)(R_t - b_t)\right]$$

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- The benefit of actor-critic algorithms is that the variance of policy updates is reduced

Proximal Policy Optimisation (PPO)

Reinforcement Learning

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$$\mathcal{L}(\boldsymbol{\theta}) = E\left[\min\left(q_t(\boldsymbol{\theta})A_{\boldsymbol{\theta}}(\boldsymbol{s},\boldsymbol{a}), \text{clip}\left(q_t(\boldsymbol{\theta}), 1-\epsilon, 1+\epsilon\right)A_{\boldsymbol{\theta}}(\boldsymbol{s},\boldsymbol{a})\right)\right]$$

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for a small ϵ where $A_{\boldsymbol{\theta}}$ is called the **advantage function**

$$A(\boldsymbol{s}, \boldsymbol{a}) = Q(\boldsymbol{s}, \boldsymbol{a}) - V(\boldsymbol{s})$$

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for a small ϵ where $A_{\boldsymbol{\theta}}$ is called the **advantage function**

$$A(\boldsymbol{s}, \boldsymbol{a}) = Q(\boldsymbol{s}, \boldsymbol{a}) - V(\boldsymbol{s})$$

and

$$q_t(\theta) = \frac{\pi_{\boldsymbol{\theta}}(\boldsymbol{a}|\boldsymbol{s})}{\pi_{\boldsymbol{\theta}_{old}}(\boldsymbol{a}|\boldsymbol{s})}$$

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for a small ϵ where $A_{\boldsymbol{\theta}}$ is called the **advantage function**

$$A(\boldsymbol{s}, \boldsymbol{a}) = Q(\boldsymbol{s}, \boldsymbol{a}) - V(\boldsymbol{s})$$

and

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Proximal Policy Optimisation (PPO)

Reinforcement Learning

- PPO is a policy gradient algorithm that is often used as a baseline method in learning problems
- The optimisation objective of PPO is maximising

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- PPO maintains a (deep) policy network (thus it is considered a deep RL algorithm) and tries to limit the amount by which the policy is updated

Imitation Learning

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Behaviour cloning	Inverse reinforcement learning	Learning from observation
An expert policy is mimicked directly based on observed states and actions	Expert demonstrations are used for extracting a reward function	A policy is learned from raw observations, without explicit state and action labels

Behaviour Cloning

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- Given such a dataset, supervised learning can be used to acquire a policy
- A policy learned using behaviour cloning can be **further improved using reinforcement learning, but also using corrective demonstrations**

Inverse Reinforcement Learning

Imitation Learning

- Another way in which expert demonstrations can be utilised is for **extracting a reward function** — this is the approach taken by inverse reinforcement learning (aka reward inference)

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  - Inverse RL is usually performed as an iterative process that has **an outer loop for reward extraction** (based on some optimisation metric) and **an inner loop for policy learning**
- Inverse RL is challenging because **the problem is ill-defined** — there can be many possible reward functions that optimise the metric

Policy Transfer

- One additional strategy in which a policy π for a new task T_j can be acquired is to **reuse a policy $\pi^{T_i^*}$ that has already been learned for a different task $T_i, i \neq j$**

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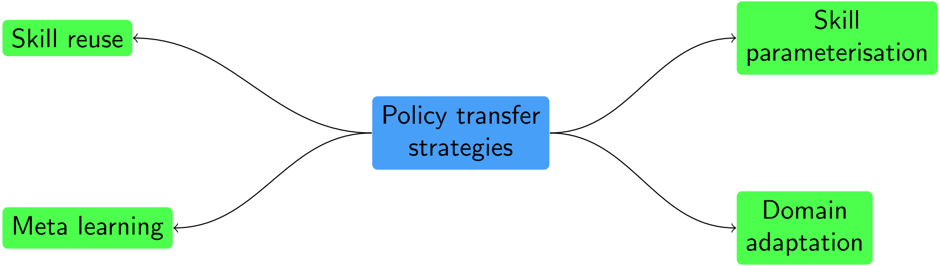

Skill Learning

- In this section, we only discussed the aspect of learning a policy
- In the previous lecture, we defined a complete skill as $\mathcal{S} = (\mathcal{S}_{\mathcal{I}}, \mathcal{S}_{\mathcal{T}}, \pi)$, namely a skill also has initiation and termination conditions — what about those, you might ask?
- The aspect of learning the initiation conditions (preconditions) and the termination condition is left out on purpose; this will be discussed in a dedicated session later in the course

Transition Model Learning

Transition Models for State Prediction

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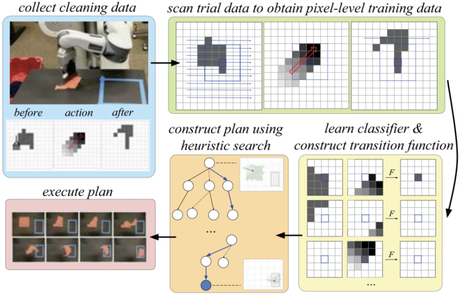

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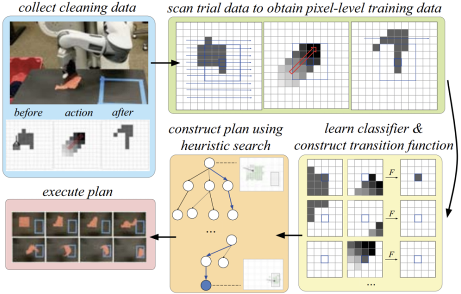

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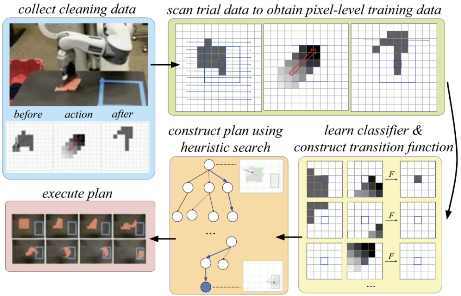

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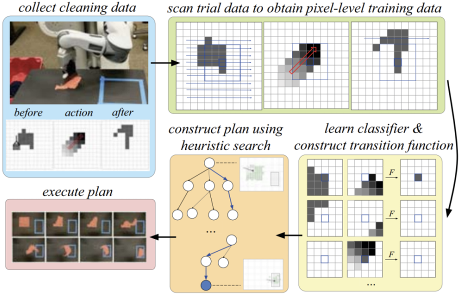

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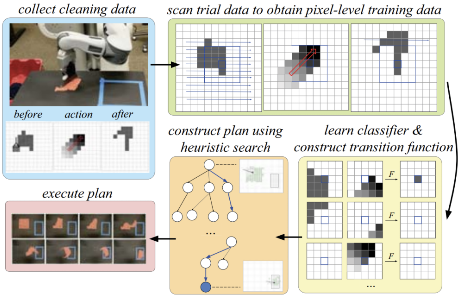

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Deterministic transition model

$$\mathcal{T} : S \times A \to S$$

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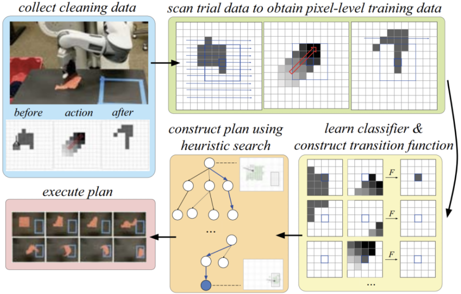

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Deterministic transition model	Probabilistic transition model
$\mathcal{T} : S \times A \rightarrow S$	$\mathcal{T} : S \times A \times S \rightarrow \mathbb{R}$

Discrete and Continuous Transition Models

- There are two types of predictive models based on the nature of the state variables to be predicted:

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- Discrete and continuous transition models can be combined in a **hybrid model** to enable the representation of different **manipulation modes**
  - Here, a discrete model is used to predict mode transitions
  - A continuous model is used to predict state variables within a mode

Model Uncertainty

- Probabilistic transition models have an associated uncertainty that stems from the fact that **a robot does not have perfect knowledge about the process to be predicted**

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Aleatoric uncertainty	Epistemic uncertainty
Inherent uncertainty in the process	Uncertainty due to a lack of process knowledge

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Aleatoric uncertainty

Inherent uncertainty in the process

Epistemic uncertainty

Uncertainty due to a lack of process knowledge

- Epistemic uncertainty can be **minimised with more training data (or with interactive perception)**; this is not the case with aleatoric uncertainty, **where more data cannot help**

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- Inverse models can be learned similarly to predictive models