



Aalto University
School of Electrical
Engineering

ELEC-E8126: Robotic Manipulation Learning

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18.3.2019

Learning goals

- Understand application areas of learning in robotics.
- Understand challenges of learning in robotics.

Applications of learning in robotics

- What can you think of?

Applications of learning in robotics

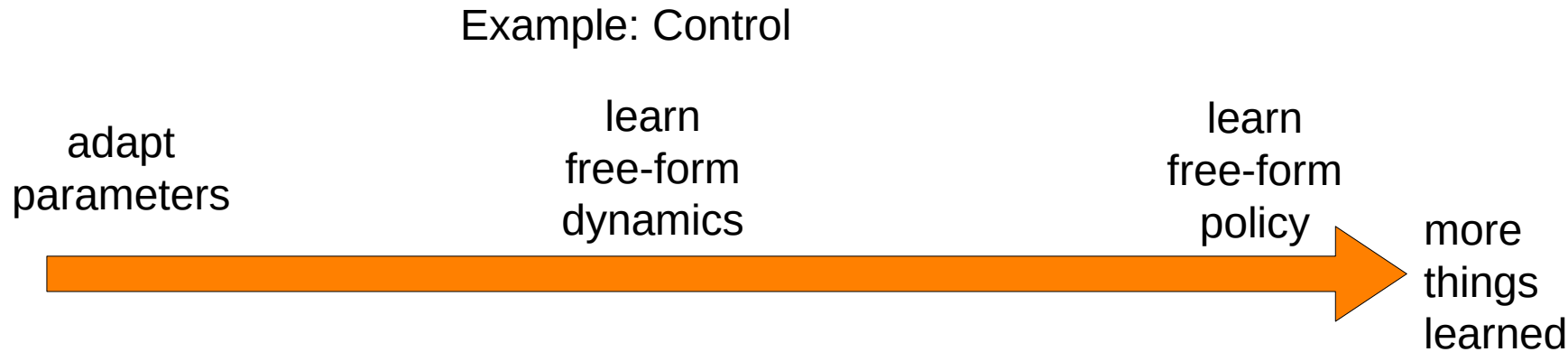
- Learn how world works
 - Robot and/or environment dynamics
- Learn what to do (and how)
 - Learn a control policy, skill, task
- Learn to understand environment / situation
 - Learn to perceive
- *Learn how to interact, ...*

Types of machine learning

- Supervised learning
 - Learn input-output mappings from examples
 - Give some examples!
- Reinforcement learning
 - Learn by acting and observing rewards
 - Give some examples!
- Unsupervised learning
 - Cluster inputs without outputs
 - Give some examples!

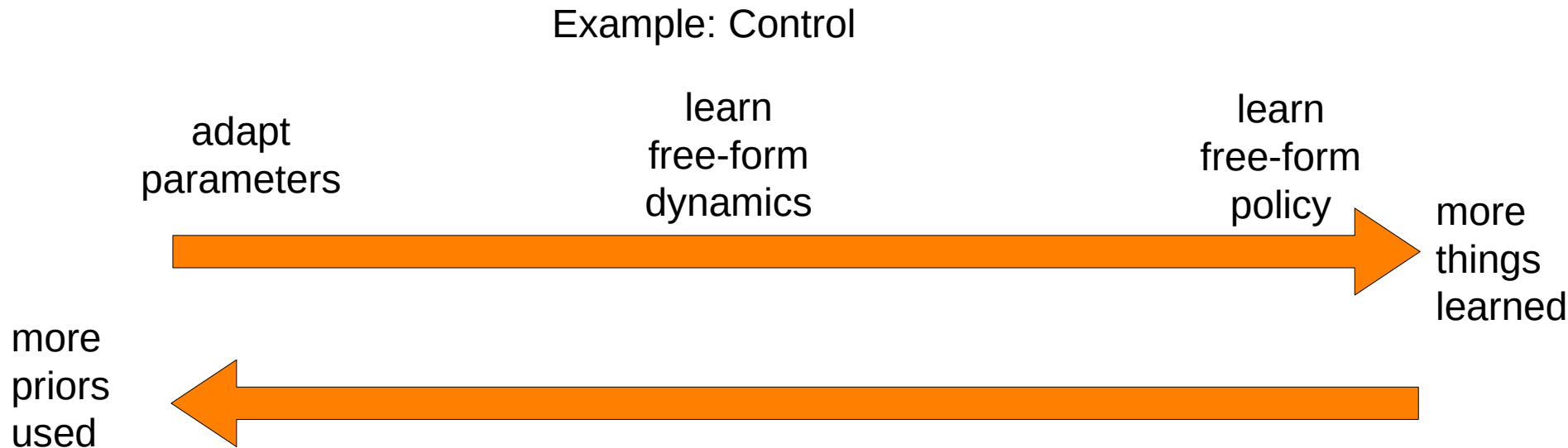
Scope of learning

Scope can vary from e.g. adapting physical parameters to learning “everything”.



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Effect of priors

- When are priors useful?
- What's their meaning in learning?
- When are they harmful?

Challenges of learning in robotics

- Data cost is usually high.
 - Physical experiments time consuming and potentially unsafe.
- Desired operation not always easy to define.
 - For reinforcement learning.
- Safety and performance of learning difficult to guarantee.
 - Depends on data and method used.
 - Possibly weak transparency – internal operation often difficult to characterize.

Some solutions

- Data cost
 - Simulation may provide training data.
 - Reality gap between simulation and real world a challenge.
- Safety and transparency
 - Explainable learning currently a topic of major interest.

Let's watch a video

<https://www.youtube.com/watch?v=jwSbzNHGfIM>

Example: Dextrous manipulation

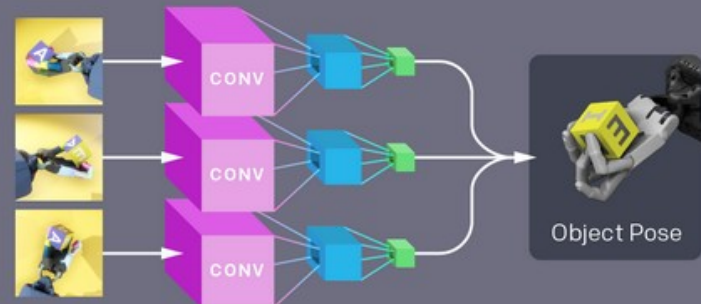
A Distributed workers collect experience on randomized environments at large scale.



B We train a control policy using reinforcement learning. It chooses the next action based on fingertip positions and the object pose.



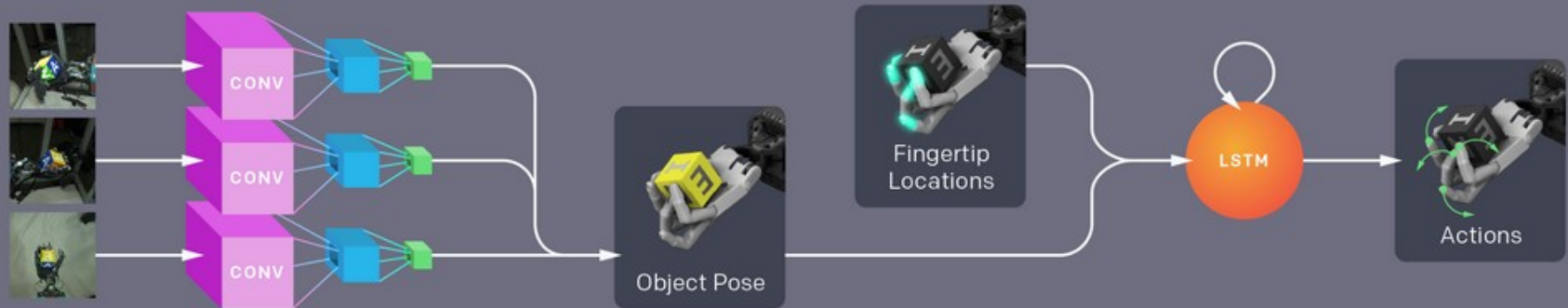
C We train a convolutional neural network to predict the object pose given three simulated camera images.



Example: Dextrous manipulation

Transfer to the Real World

D We combine the pose estimation network and the control policy to transfer to the real world.



Example: Dextrous manipulation

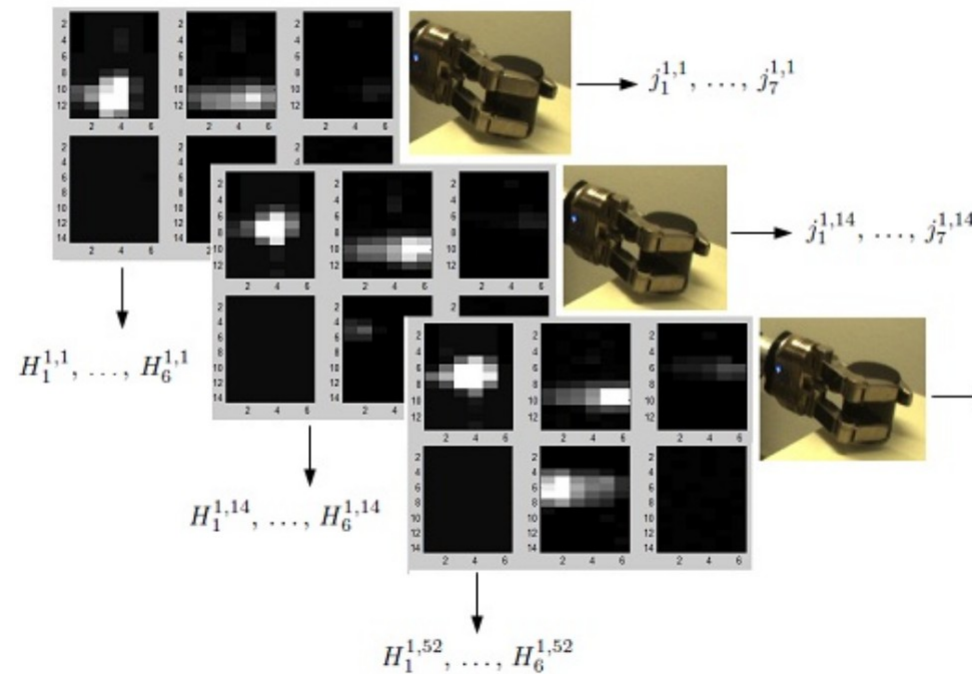


Analyze!

- Could this approach be used in practice?
- In which cases?
- Why or why not? Which constraints are there for use?
- Any other notes?

Example: Learning grasp stability

- Learn to predict if a grasp is stable based on tactile sensor measurements.
- Simple simulation and analytic grasp quality measures to generate training data.
- Statistical ML.

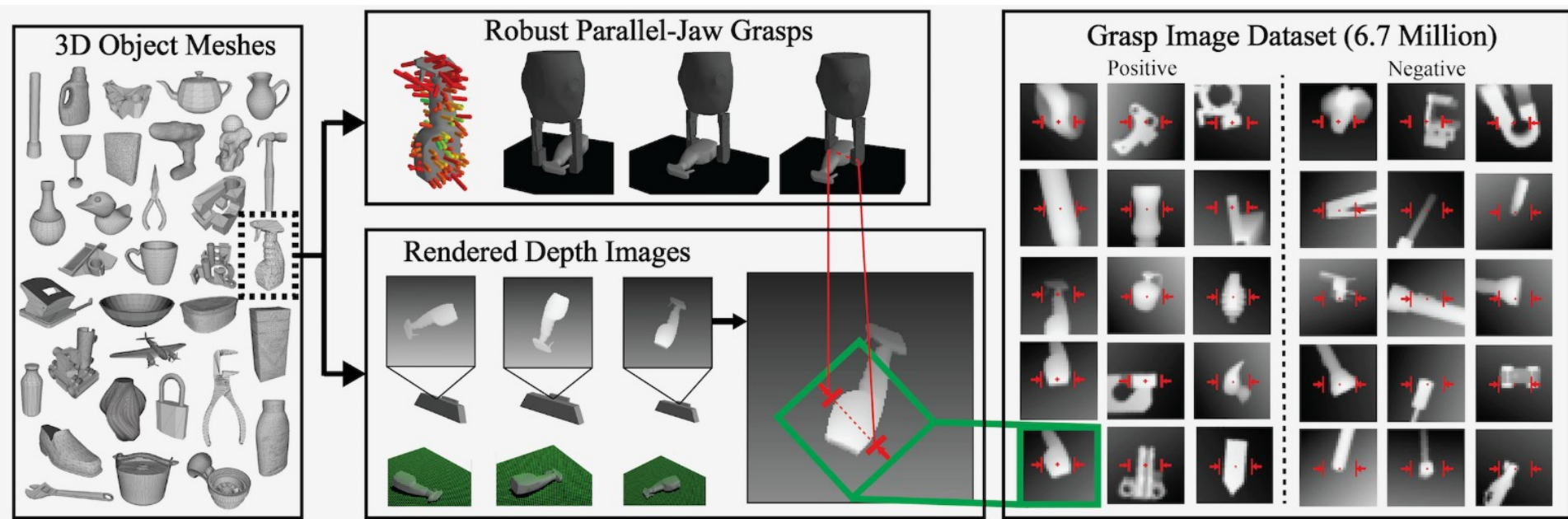


Bekiroglu et al. 2011

Example: Learning where to grasp

Dex-Net 2.0

- Simulated pointcloud training data creation.

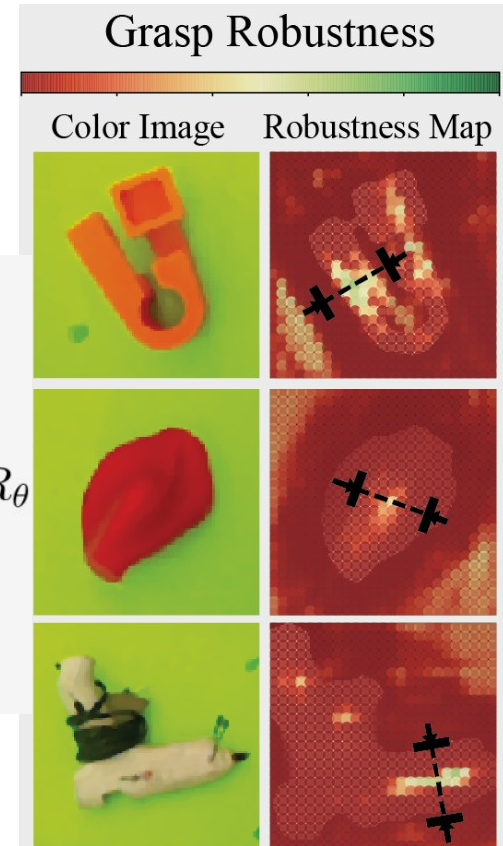
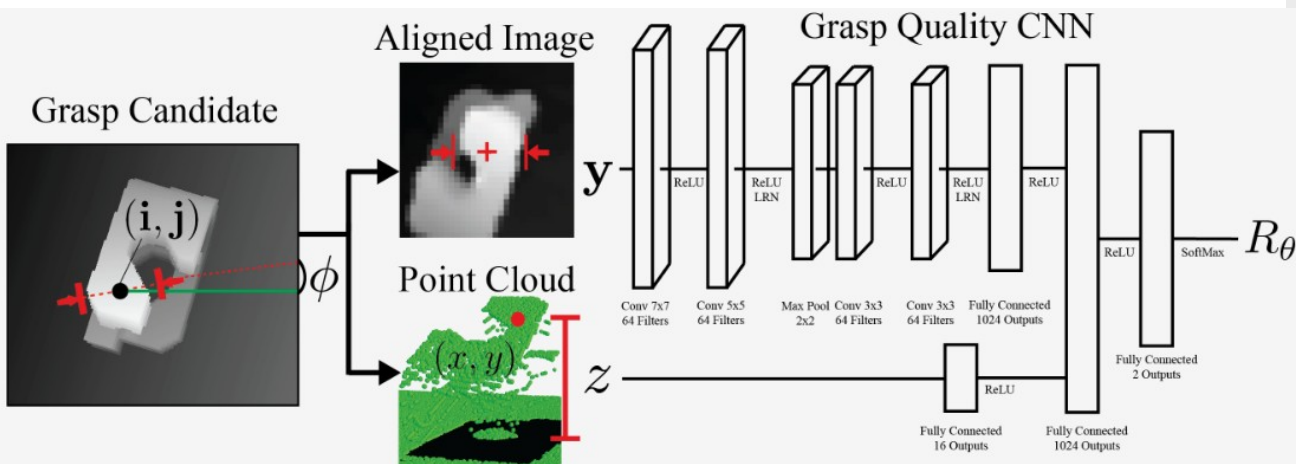


Mahler et al., 2017

Example: Learning where to grasp

Dex-Net 2.0

- Learn to predict quality metric from image using convolutional NN.



Example: Learning movements

Movement primitives

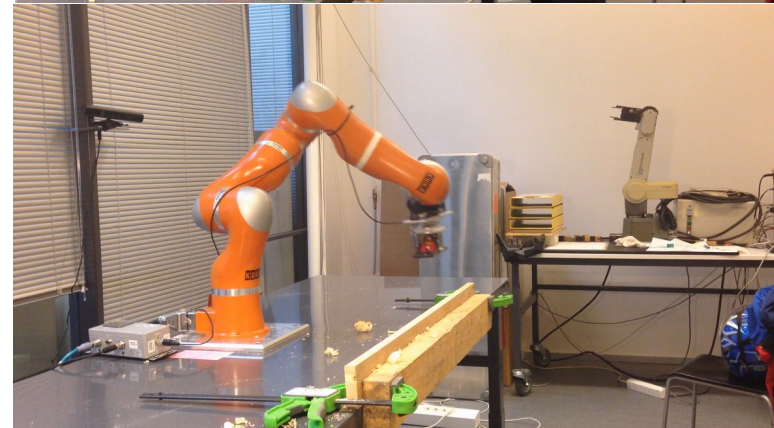
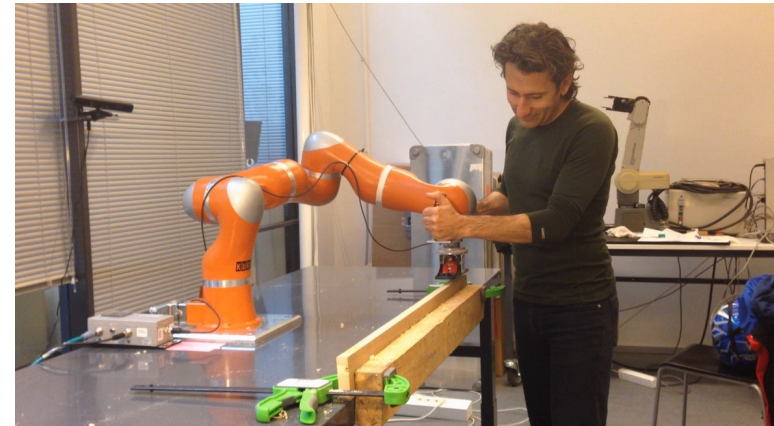
- General idea: Learn trajectories (trajectory primitives).
 - Can be modulated, e.g. end-point or speed change.
 - Learned from e.g. human demonstration.
 - May be improved by reinforcement learning.
 - Sequencing can also be learned.



Muelling et al. 2013

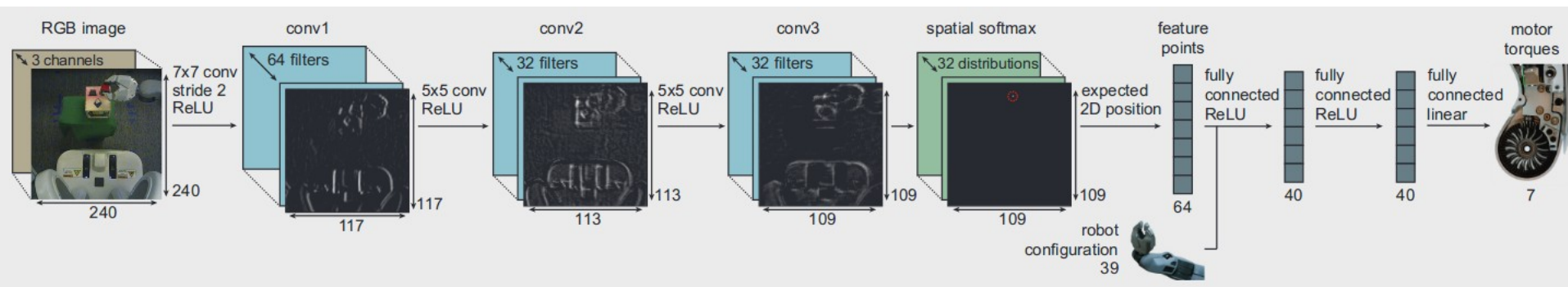
Example: Learning in-contact skills

- Learn position and force trajectories from human demonstration.
- Impedance control with force feed-forward.
- Can be improved by reinforcement learning.



Example: End-to-end learning of deep visuomotor policies

- Learn a NN controller from vision to torques.
- Training: Learn first individual trajectories using reinforcement learning, train NN using supervised learning.



Levine et al. 2015

Summary

- Machine learning provides tools for subproblems in robotic manipulation.
- Data availability is often a challenge.
- At the moment, robot learning still primarily only in research labs because of lack of robustness.

Next time: Task level planning

- Readings:
 - Springer Handbook of Robotics, 2nd ed., secs. 14.3-14.3.2, 36.3-36.3.3
 - Handbook freely available through library webpage lib.aalto.fi. Log-in first and then search for “Springer Handbook of Robotics”.