Machine learning in robotic manipulation

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How far are we from robots being ubiquitous and superhuman?

Atlas robot from Boston Dynamics

DARPA Robotics Challenge

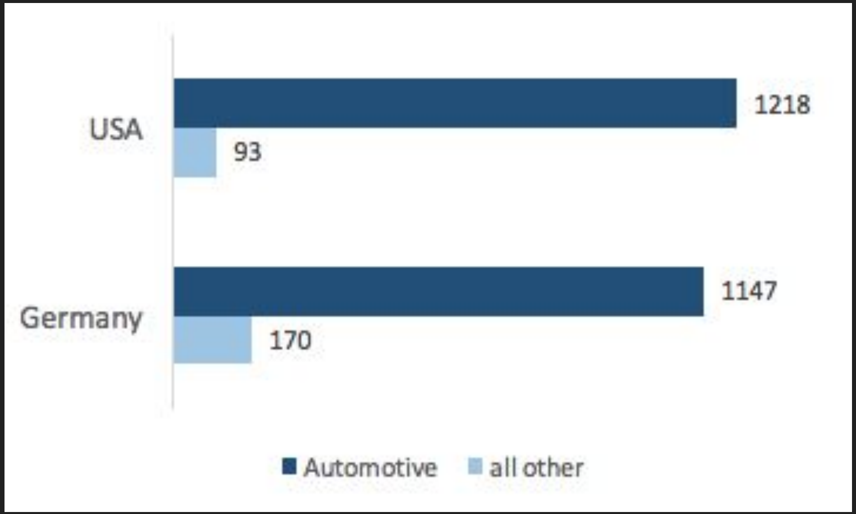
Automation today

Number of robots per 10,000 workers in manufacturing:

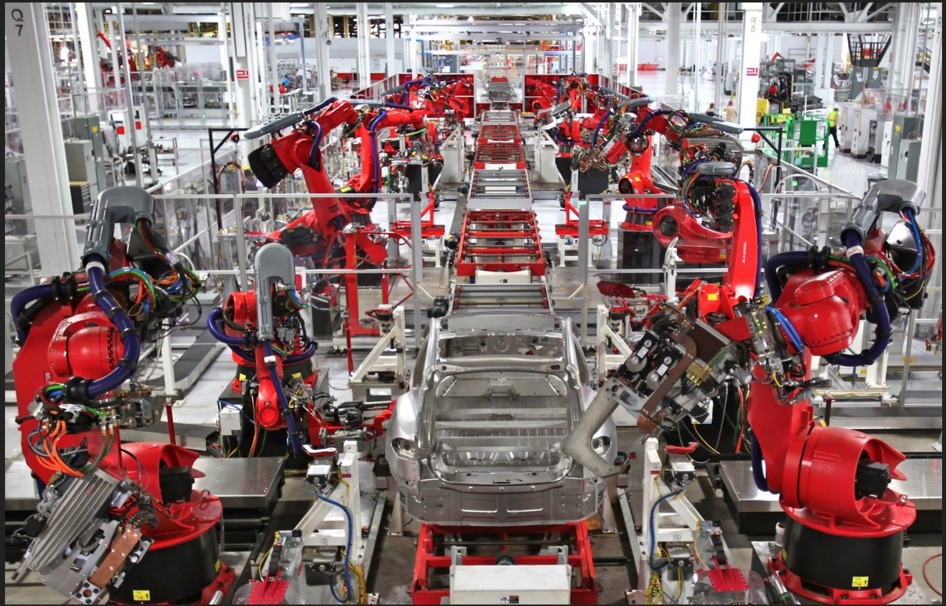
- Korea, Singapore - 700
- Germany, Japan - 300
- United States - 200
- China - 100
- World average - 85

Source: International Federation of Robotics, 2018

Number of robots per 10000 workers



Source: International Federation of Robotics, 2016



"A logistics robot would need to handle a wide array of different parts in an infinite number of combinations. It would help if the robot could ***see, move, and react to its environment****. "*

Source: DHL, Robotics in logistics

Nomagic

- Startup focused on robotic manipulation, Warsaw based.
- Started: June 2017, now 20 people, always hiring.
- First robot in production: Oct 2018.

Deep learning revolution

2010: Speech Recognition

Audio → Acoustic Model → Phonetic Model → Language Model → Text

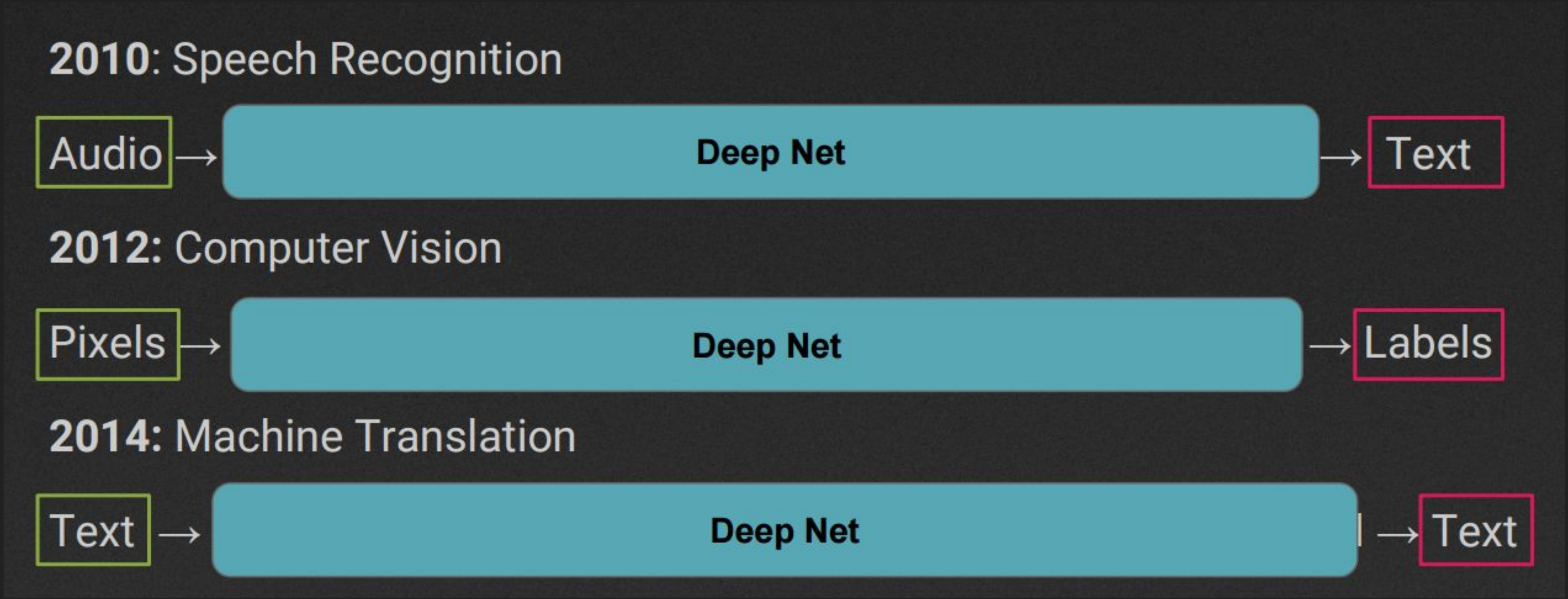
2012: Computer Vision

Pixels → Key Points → SIFT features → Deformable Part Model → Labels

2014: Machine Translation

Text → Reordering → Phrase Table/Dictionary → Language Model → Text

Slide by V. Vanhoucke



Slide by V. Vanhoucke

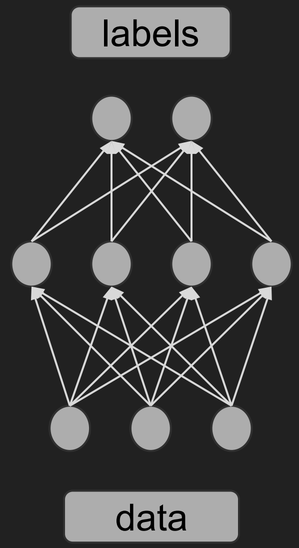
Supervised learning

Success stories in machine learning are mostly based on supervised learning, where the goal is to learn a mapping from data to labels.

Speech recognition: speech ⟶ text

Computer vision: image ⟶ label

Machine translation: text ⟶ text



Is robotics next?

Classic robotics:

Sensors → Perception → World Model → Planning → Actuation

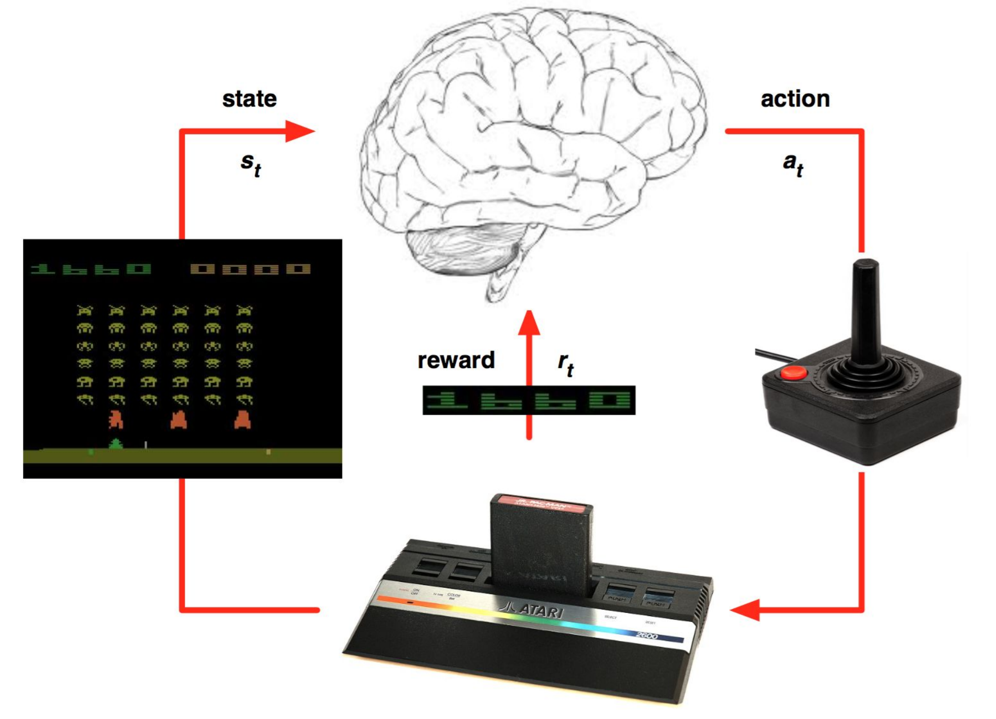
Future?

Sensors → Deep Neural Network → Actuation

What's the problem?

Robotics is different:

- What a robot sees depends on actions it takes.
- Credit assignment problem.
- Reinforcement learning has large sample complexity.



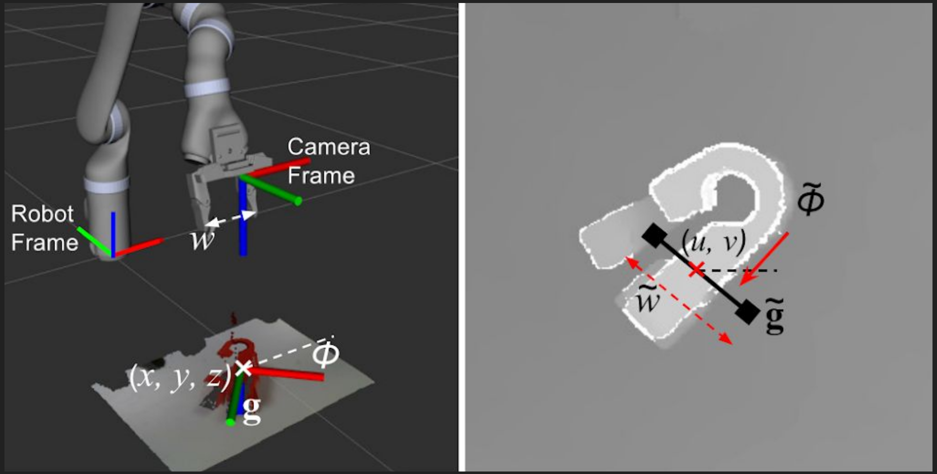
Robotic manipulation

Grasping

Back to supervised learning

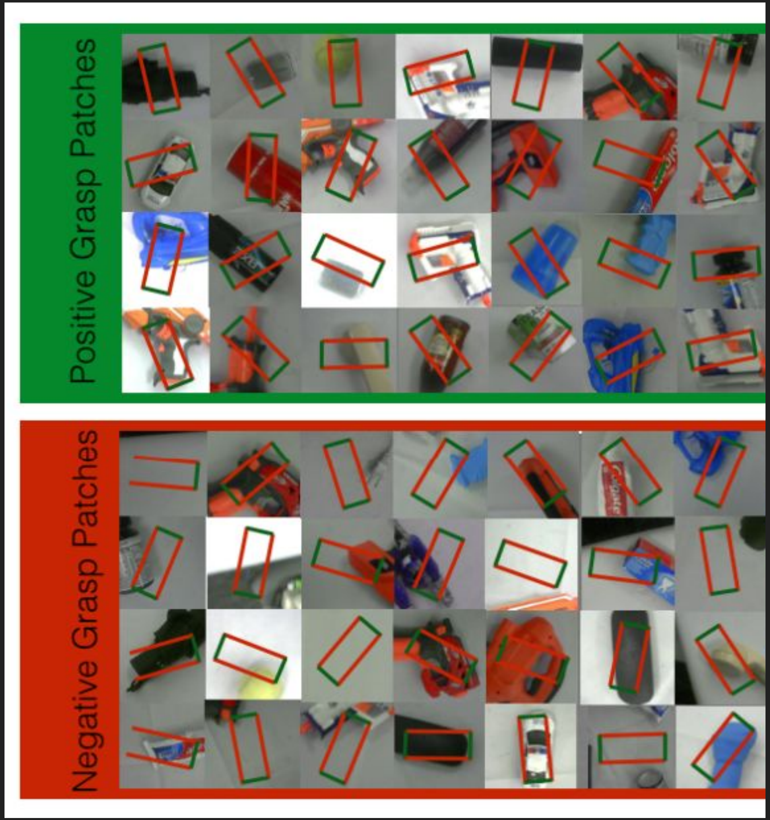
Simplifying assumptions

- Grasping from top:
  - Move the robot above the grasp point
  - Go vertically down with open fingers
  - Close fingers
  - Go up
- Note the open loop control (no feedback during the action).



- Specify grasping action by only few parameters:
  - Pixel coordinates of grasp center.
  - Gripper rotation.
- Input-output mapping:
  - Input: image, grasp parameters.
  - Output: is grasp successful.

Source: Morrison et al. RSS'18



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Where to take data from?

1. Human labelling
    - Cornell Grasp Dataset - 1k images, each with several positive and negative grasps).

2. Self-supervision (real robot experience).

3. Simulation.

Lerrel Pinto, Abhinav Gupta (ICRA’16):

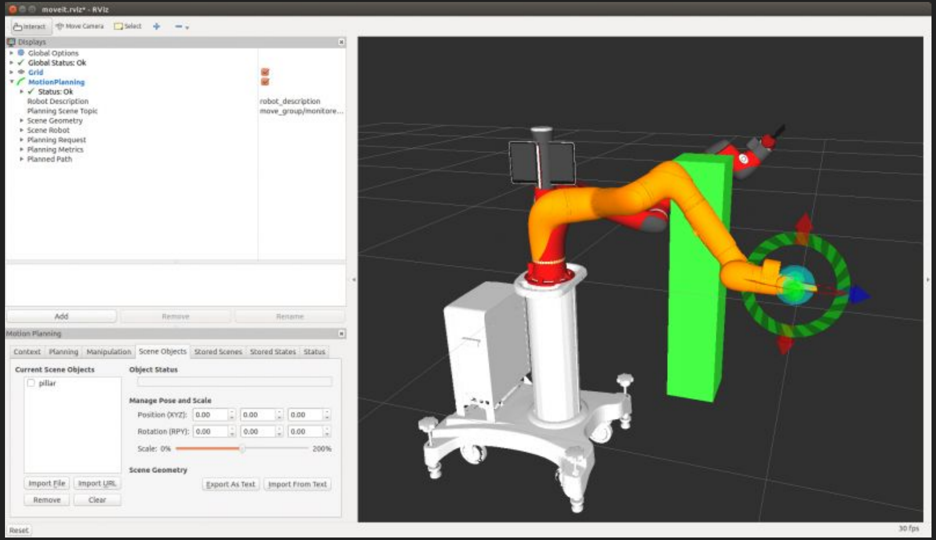
Supersizing self-supervision: Learning to grasp from ***50K tries*** *and* ***700 robot hours****.*

Levine, Pastor, Krizhevsky, Quillen (ISER'16):

Learning Hand-Eye Coordination for Robotic Grasping with Large-Scale Data Collection.

- **800k** grasp attempts
- 14 robots
- **2 months**

Learning in simulation



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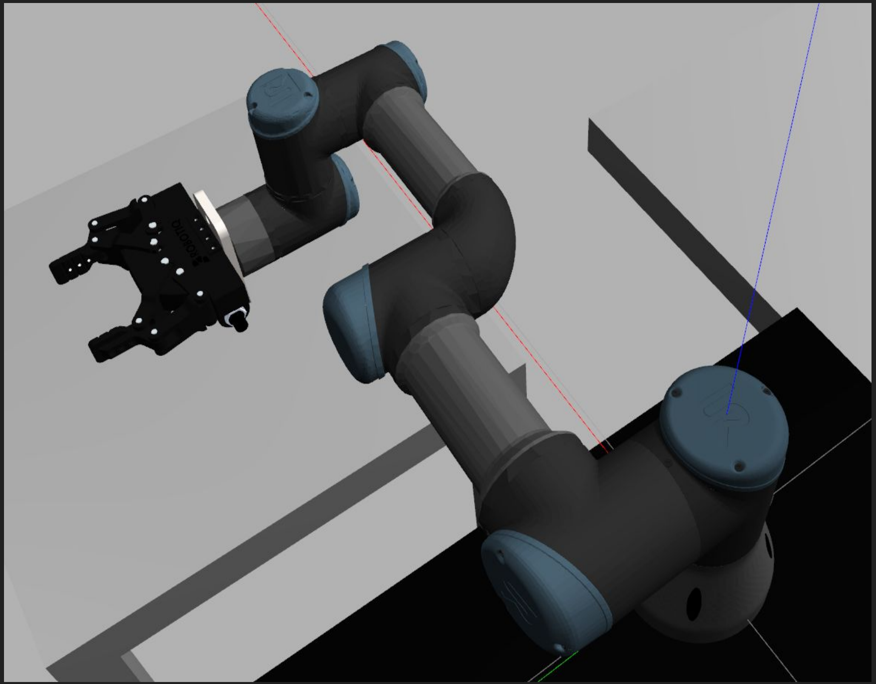
amazon web services™

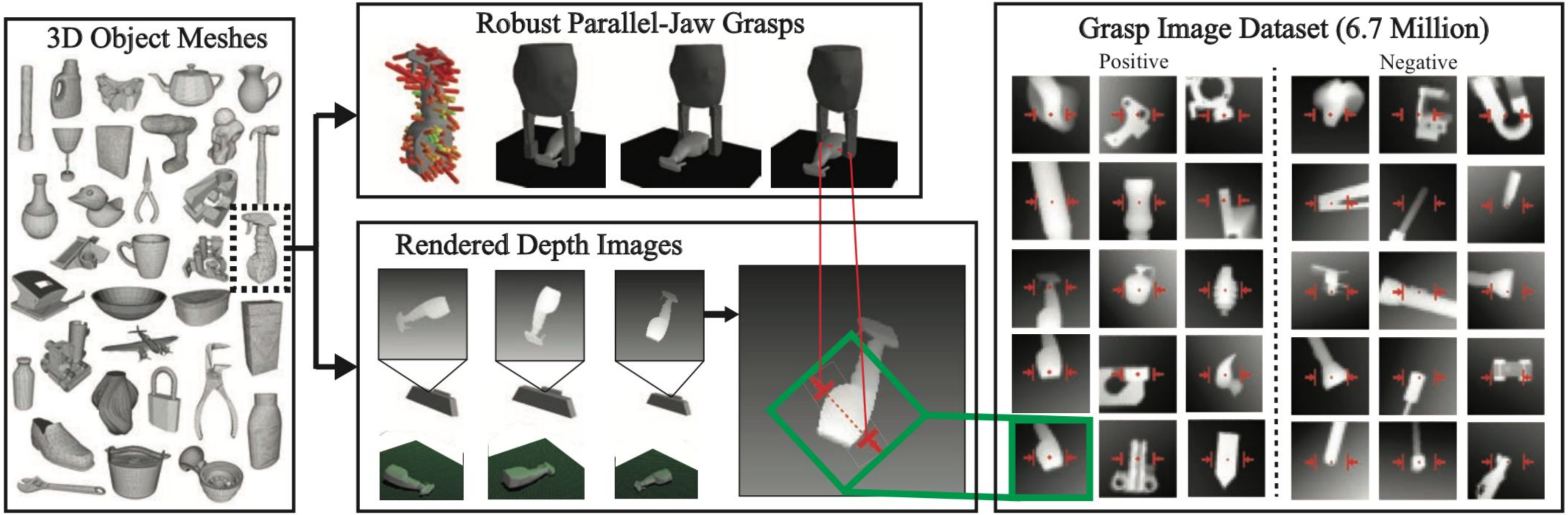
Google Cloud Platform

Microsoft Azure

Problem - reality gap

- Low fidelity images
- Hard to simulate inter-objects contacts





References:

- Mahler et al. *Dex-Net 2.0: Deep Learning to Plan Robust Grasps with Synthetic Point Clouds and Analytic Grasp Metrics*
- Jaśkowski, Świątkowski, Zając et al. *Improved GQ-CNN: Deep Learning Model for Planning Robust Grasps*

Data - summary

1. Human labelling - hard to scale.

2. Self-supervision (real robot experience) - effective if one has a lot of robot time.

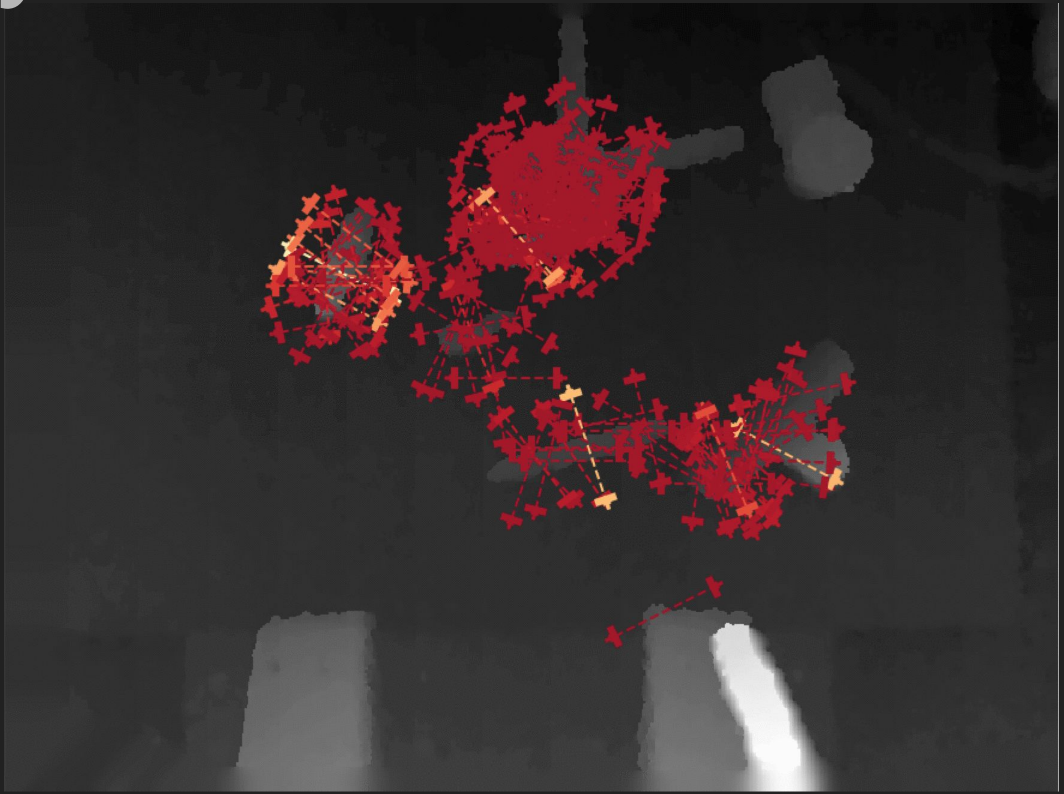
3. Simulation - risk of biased data.

But where to grasp?

Cross-entropy method

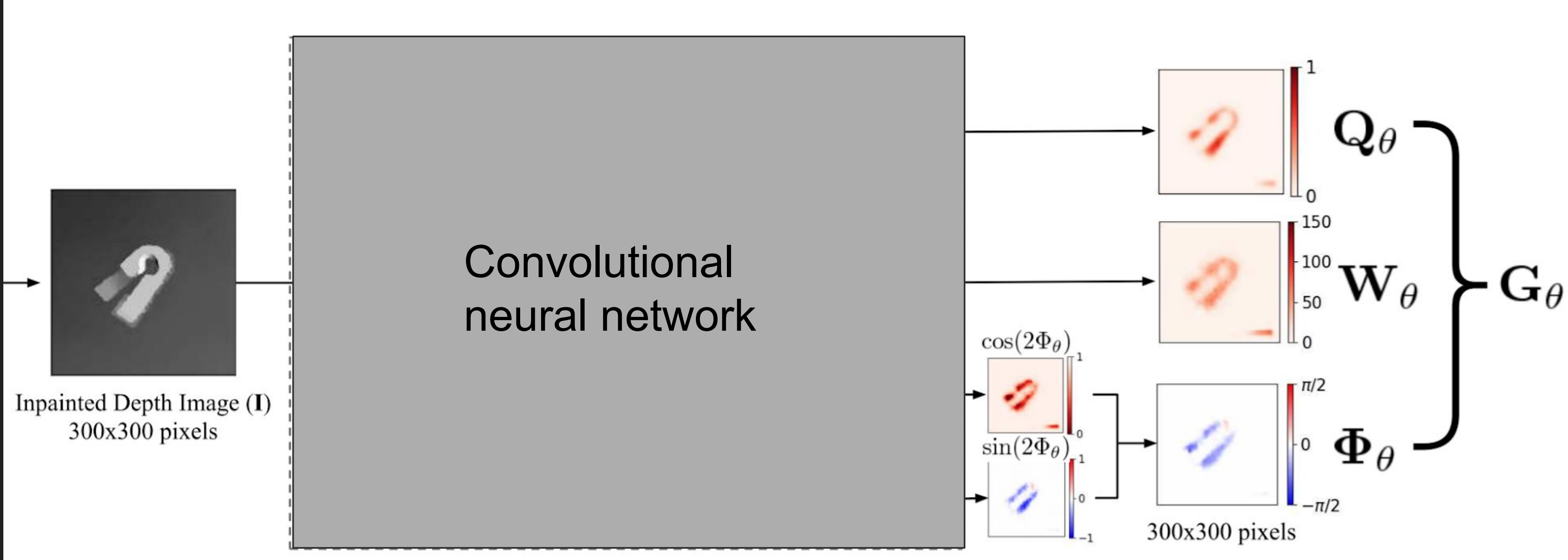
1. Train a model that rates a single grasp candidate

2. Iteratively sample and optimize using the cross-entropy method.



Source: Mahler et al. RSS'16

Model rates multiple grasps



Source: Morrison et al. RSS'18

Bridging the visual reality gap

ISAAC simulator by NVIDIA

Use randomization!

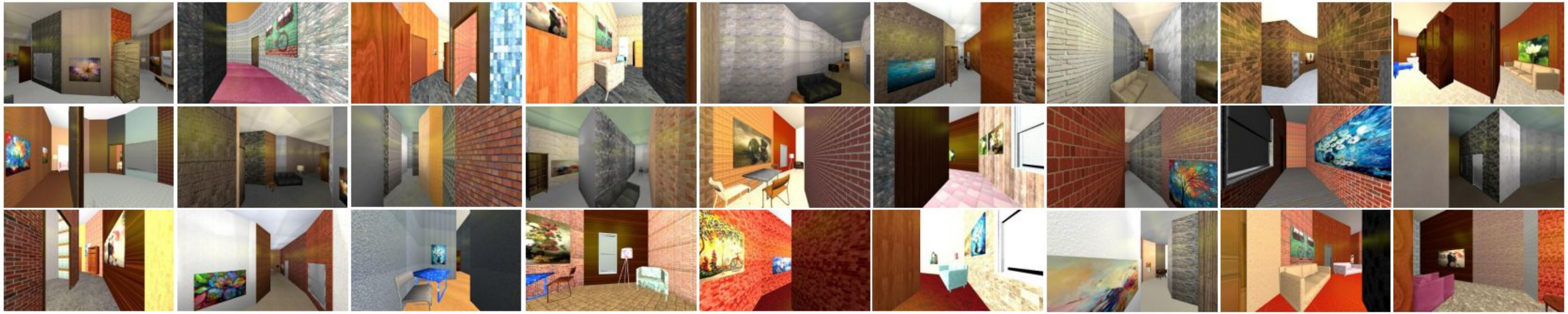
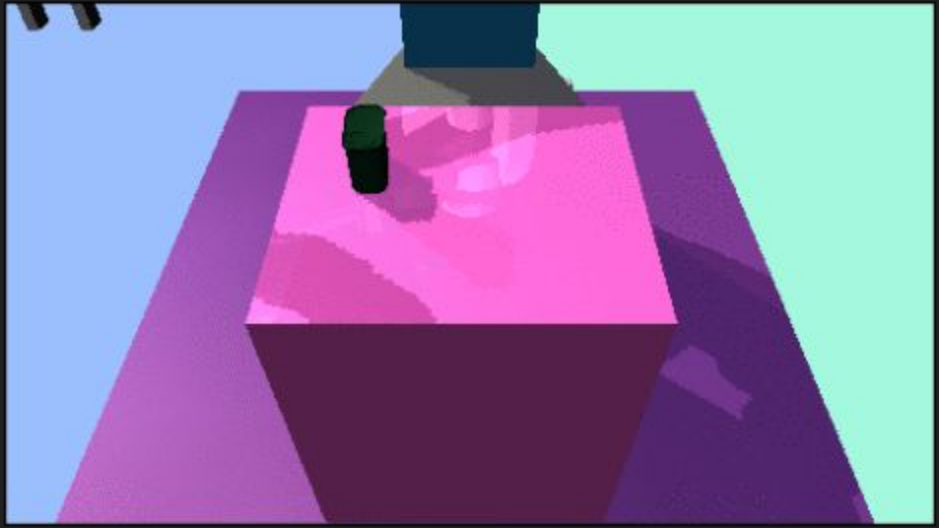
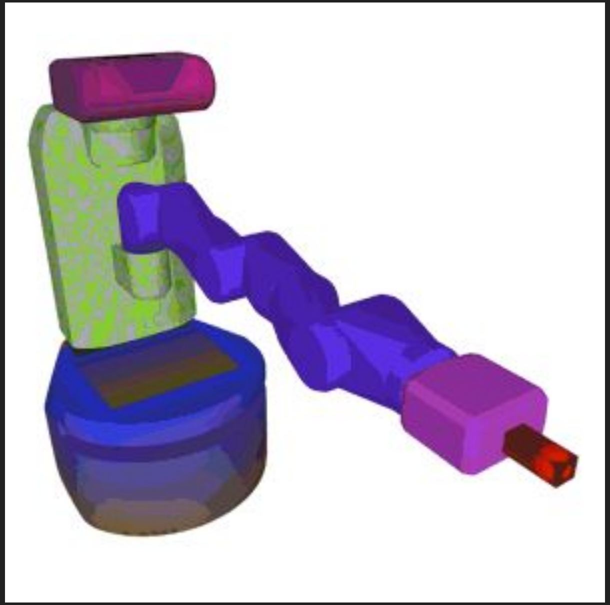


Fig. 2. Examples of rendered images using our simulator. We randomize textures, lighting and furniture placement to create a visually diverse set of scene

Sadeghi, Levine, *CAD2RL: Real Single-Image Flight without a Single Real Image*

Use randomization!





Tobin et al., [*Domain Randomization for Transferring Deep Neural Networks from Simulation to the Real World*]

Summary

- Deep learning has a great chance to revolutionize robotics, but there are still major challenges for end-to-end learning.

- Casting a subproblem in the supervised learning setting helps a lot.

- One can train models on different regimes of data:
  - Hand labelling
  - Self-supervision, i.e., robot experience
  - Simulation (domain randomization)

Thank you!