ME336 Collaborative Robot Learning

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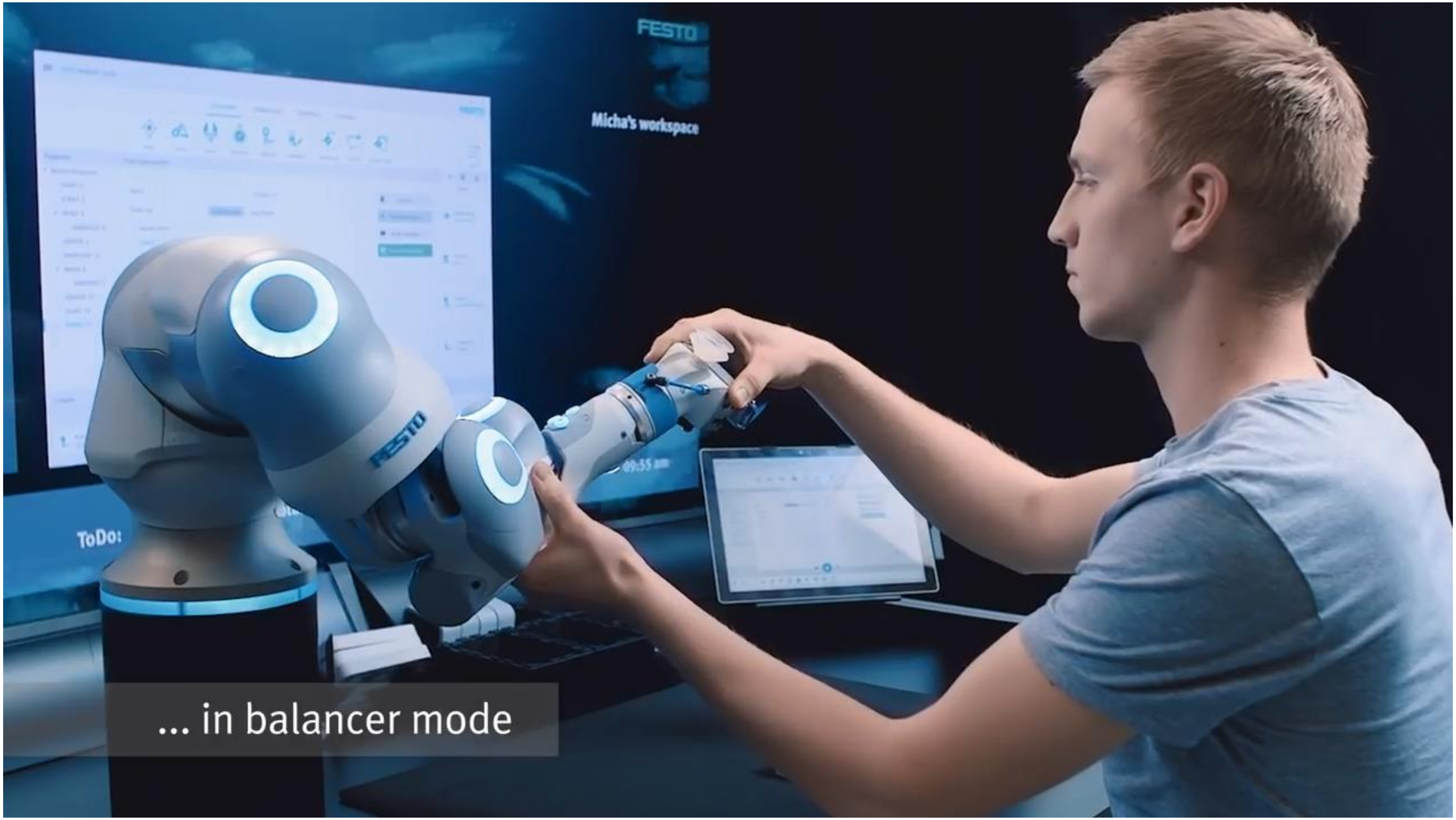
A Future of Human-Robot Collaboration?



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Agenda

Week 01, Wednesday, February 20

- The Goal of This Course
- Course Introduction
- The Rise of Robotics & AI
- Why Making Robots Collaborative?
  - Scenarios of Human-Robot Collaboration | Safety vs. Risk
- Why Teaching the Robots to Learn?
  - Challenges in Robotics | Computation vs. Algorithm vs. Data
- Learning to Pick
  - A Typical Picking Pipeline | Current Trends | Future Directions

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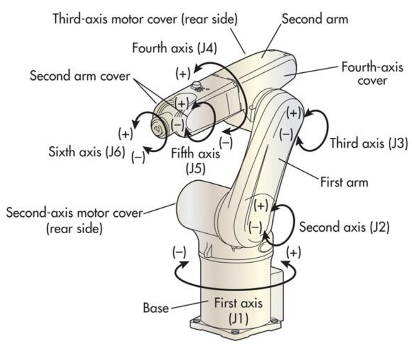
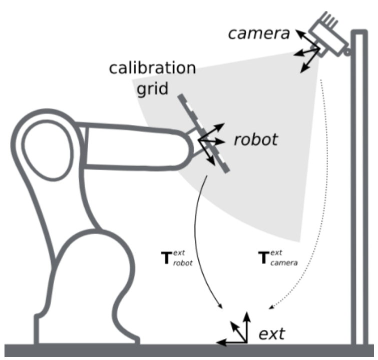
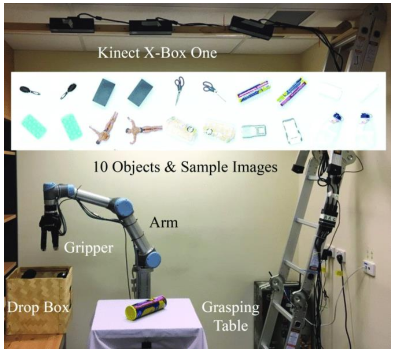
The Goal of This Course

A *Gentle* Introduction to Modern Robotic Picking

- Understand the theoretical fundamentals of robotics
- Implement robotic vision for programmable picking
- Integrate rational agents for interactive robot picking
- Practice deep learning for autonomous robot picking
- Use collaborative robots to start using robotics





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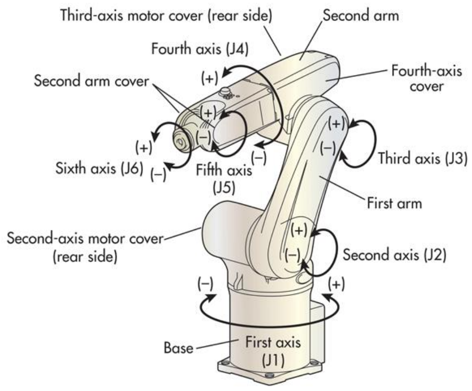
Project 1: Simulate Picking Using Kinematics

Understand the theoretical fundamentals of robotics

Week	Lecture	Lab
	Part I Robot Foundations	**Project I Simulate A Picking Robot**
02	Mathematical Foundations	ROS Basics
03	Kinematics & Jacobian	ROS Simulation
04	Dynamics & Control	ROS Picking



- **Simulate a robot arm picking fixed objects and placing them in a bin.**
  - Similar to Amazon Picking Challenge, but much simplified in ROS;
  - Without using any image data, focus mainly on the kinematics for planning;
  - Focus on the understanding of analytical method for common robotic grasping;
  - To be completed using the students' own laptop.

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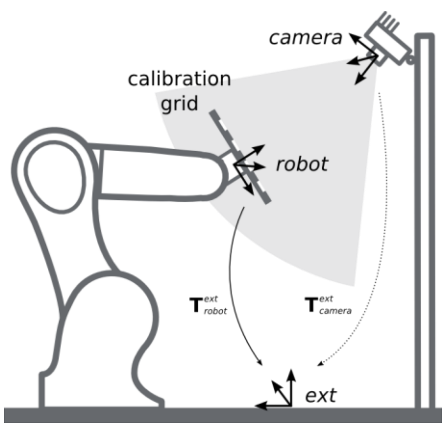
Project 2: Simulate Picking Using Robotic Vision

Implement robotic vision for programmable picking

Week	Lecture	Lab
	Part II Robotic Vision	**Project II Picking Robot with Vision**
05	Camera & Images	RealSense with ROS
06	Features & Filters	OpenCV & PCL
07	Calibration & Servoing	Hand-Eye Calibration and integration



- **Simulate a robot arm processing RGB-D images to grasp objects from a bin.**
  - Similar to industrial bin-picking scenario, but much simplified in ROS;
  - Process simulated images in ROS to pick up simple object autonomously;
  - Focus on the use of robotic vision techniques for common robotic grasping;
  - To be completed using the students' own laptop.

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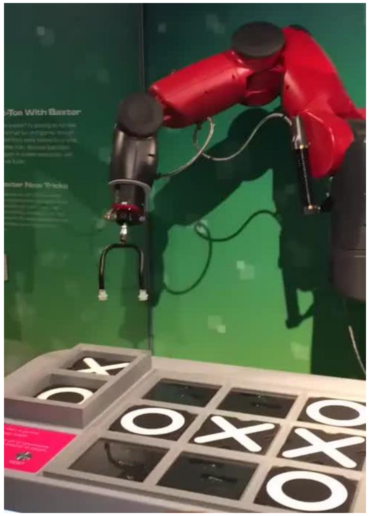
Project 3: Program an AI robot to play Tic-Tac-Toe

Integrate rational agents for interactive robot picking

Week	Lecture	Lab
	Part III Artificial Intelligence	**Project III Program a Tic-Tac-Toe Robot**
08	Introduction and Intelligent Agents	Coding Agents
09	Solving Problem by Searching	Tic-Tac-Toe
10	Game Problem	Robot Player



- **Use AI to control a real robot to play tic-tac-toe with a human player.**
  - Similar to the Alpha-Go scenario, but much simplified using a real desktop robot;
  - Design and implement an AI algorithm on a robot for tic-tac-toe;
  - Focus on the design of AI algorithms to control a real robot arm autonomously;
  - To be completed using a real desktop robot hardware

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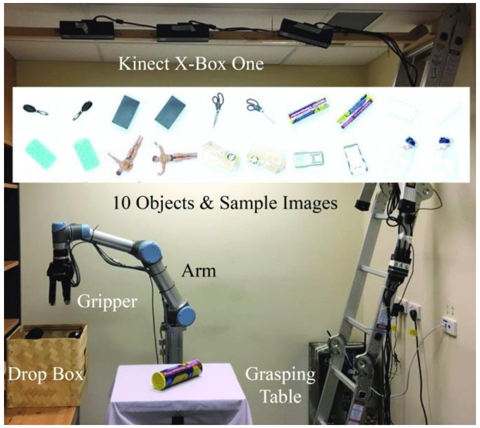
Project 4: Program a DL robot to play arcade claw game

Practice deep learning for autonomous robot picking

Week	Lecture	Lab
	Part IV Deep Learning	**Project IV Program an Arcade Claw Robot**
11	Neural Networks	TensorFlow Basics
12	Autonomous Picking	Learning Picking
13	Robot Learning	Arcade Claw



- **Use Deep Learning to control a real robot to play arcade claw machine game.**
  - Similar to the DeepClaw scenario, but much simplified using a real desktop robot;
  - Design and implement a deep neural network to play the game for data acquisition;
  - Focus on the use of DL techniques on a real robot for data-driven robotics;
  - To be completed using a real desktop robot hardware.

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Project 5: Autonomous Robot Manipulation Competition

Use collaborative robots to start using robotics

Week	Lecture	Lab
	Part V Special Topics	**Project V Collaborative Robot Learning**
14	Shareability & Reproducibility	Competitive Picking
15	Industrial vs. Collaborative	Final Presentation

- **Design a competitive and autonomous picking robot**
  - Design a robot system to autonomously play a board game competitively;
  - In the final class, each team will present your robot system design in details by
    - Writing a full paper describing your robot system in technical details;
    - Submit a video demo of your robot system design;
    - Submit a poster and present your robot system design;
    - Open-source your codes by uploading on GitHub;
    - Compete live and win! (*Good luck*)
  - To be completed using a real desktop robot hardware.

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Week	**Lecture Session Every Week** Wednesday 10:20-12:10 #208, 2 Lychee Park	**Lab Session Every Week** Friday 10:20-12:10 #607, 7 Innovation Park
01	Course Introduction	Programming Basics
	Part I Robot Foundations	**Project I Simulate Picking Kinematics**
02	Mathematical Foundations	ROS Basics
03	Kinematics & Jacobian	ROS Simulation
04	Dynamics & Control	ROS Picking
	Part II Robotic Vision	**Project II Simulate Picking with Vision**
05	Camera & Images	RealSense with ROS
06	Features & Filters	OpenCV & PCL
07	Calibration & Servoing	Hand-Eye Calibration and integration
	Part III Artificial Intelligence	**Project III Program a Tic-Tac-Toe Robot**
08	Rational Agents	Coding Agents
09	Game Problems	Tic-Tac-Toe
10	Robotic AI	Robot Player
	Part IV Deep Learning	**Project IV Program an Arcade Claw Robot**
11	Neural Networks	TensorFlow Basics
12	Autonomous Picking	Learning Picking
13	Robot Learning	Arcade Claw
	Part V Special Topics	**Project V Collaborative Robot Learning**
14	Shareability & Reproducibility	Competitive Picking
15	Industrial vs. Collaborative	Final Presentation

Teaching Team

songcy@sustc.edu.cn

- Course Instructor
  Prof. Song Chaoyang

- Invited Instructor
  Dr. Wan Fang

Every Week	Time	Location
1 Lecture	10:20~12:10, Wednesday	#208, 2 Lychee Park
1 Lab	10:20~12:10, Friday	#607, 7 Innovation Park

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Course Content

Will be posted on the Instructor's website

THE BIONICDL LAB
Bionic Design + Robot Learning

HOME NEWS RESEARCH PUBLICATIONS PEOPLE LABORATORY TEACHING RESOURCES

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WELCOME TO THE BIONICDL LAB @ SIR GROUP

The **Bionic Design + Learning Lab** is led by **Dr. Song Chaoyang** at Southern University of Science and Technology (SUSTech) with research interests in Bionic Design, Robot Learning, and Design Science. Dr. Song completed his undergraduate degree at Tongji University, Shanghai, China in 2009, and Ph.D. degree at the Robotics Research Center at Nanyang Technological University, Singapore in 2014. His doctoral research focuses on the theoretical kinematics of a class of overconstrained linkages, dealing with the fundamental mechanism theory in robotics and mechanical engineering. During post-doc research, Dr. Song joined the newly founded Singapore University of Technology and Design. His post-doc research moves towards the application end of research and development, investigating the factor of technological and design innovation in the successful translation of lab results into commercial products. He continued his post-doc research topic at Massachusetts Institute of Technology. Before joining SUSTech, Dr. Song was appointed as a Lecturer (Assistant Professor) in the Department of Mechanical Engineering at Monash University, where **the Sustainable + Intelligent Robotics Group**, or **the SIR Group**, was originally formed. We updated the lab name as the newly formed **SUSTech Institute of Robotics** shares the same acronym.

TEACHING

Southern University of Science and Technology

- ME303 Introduction to Mechanical Design
  - Autumn 2018
- ME336 Collaborative Robot Learning
  - Spring 2019

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ME336 COLLABORATIVE ROBOT LEARNING, SPRING 2019

Spring 2019 | Selective Core Course for Final Year Undergrad

Please fill out this form if you have registered this course. You will be invited to the Tower discussion forum later.

Time and Place

- **Lecture**: Every Wednesday 10:20-12:10, Location @ #206, 2 Lychee Park
- **Lab**: Every Friday 10:20-12:10, Location @ #607, 7 Innovation Park

Instructor Team

- Lead Instructor: Prof. Song Chaoyang, Dr. Wan Fang (Invited)
- Teaching Assistant: Mr. Liu Xiaobo
- Office: Room 606, 7 Innovation Park

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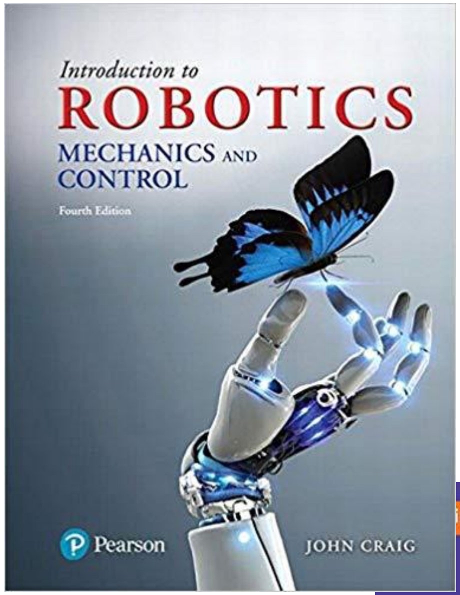
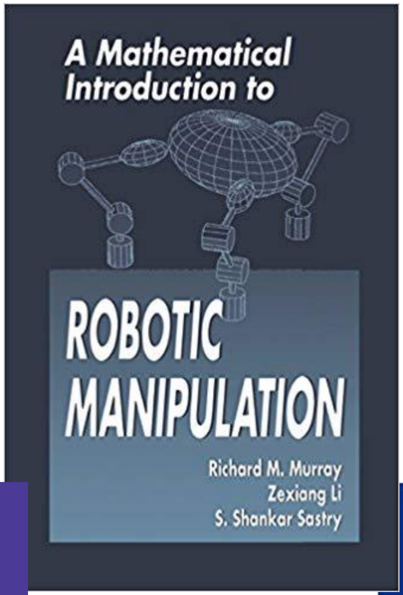
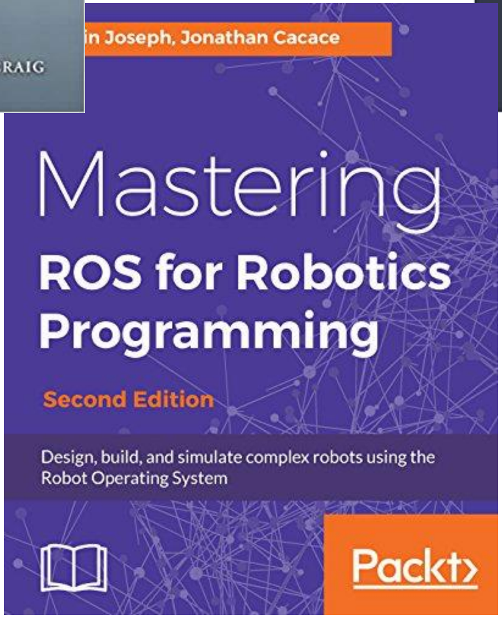
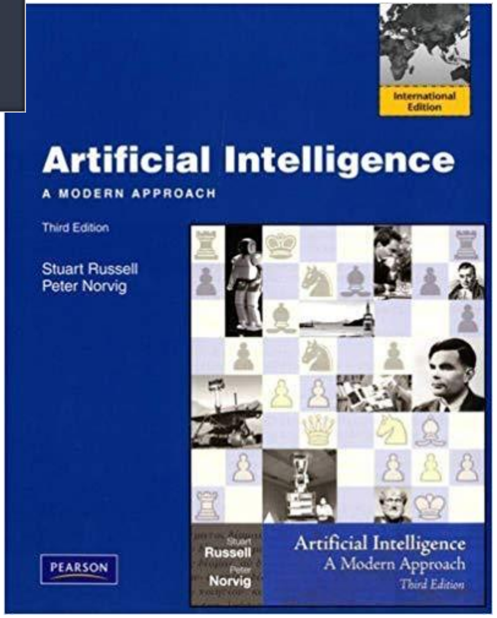
Recommended Textbooks









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Other (Important) Things

You should always keep in mind.

- **Grading**
  - 60%: project marking
    - 15% for each of the first 4 projects, including 10% code submission and 5% video presentation.
  - 10%: individual marking
  - 30%: final project marking, including
    - 10% final paper + 10% final video demo + 5% final poster + 5% code submission

- **Late Assignment Policy**
  - Each student is granted four unpenalized late days for the semester. Assignments can be submitted in no more than four days late and will receive a 25% penalty for each day late (excluding unpenalized late days used). Homework are due at 3 PM on the due date, and each late day extends the deadline by exactly 24 hours. All assignments, labs and presentations must be done to pass the course.

- **Academic Integrity**
  - This course follows the SUSTech Code of Academic Integrity. Each student in this course is expected to abide by the SUSTech Code of Academic Integrity. Any work submitted by a student in this course for academic credit will be the student's own work. Violations of the rules (e.g., cheating, copying, non-approved collaborations) will not be tolerated.

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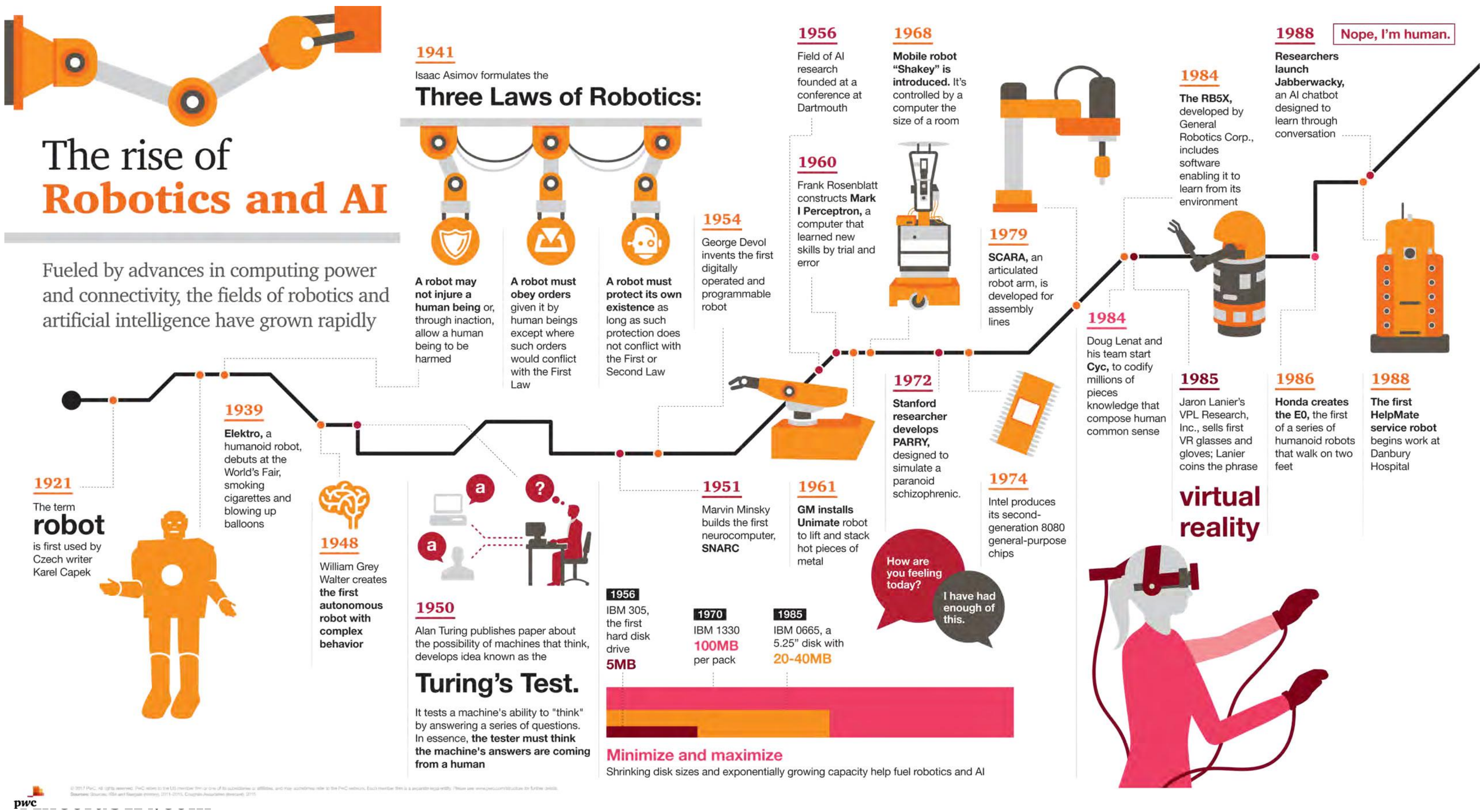
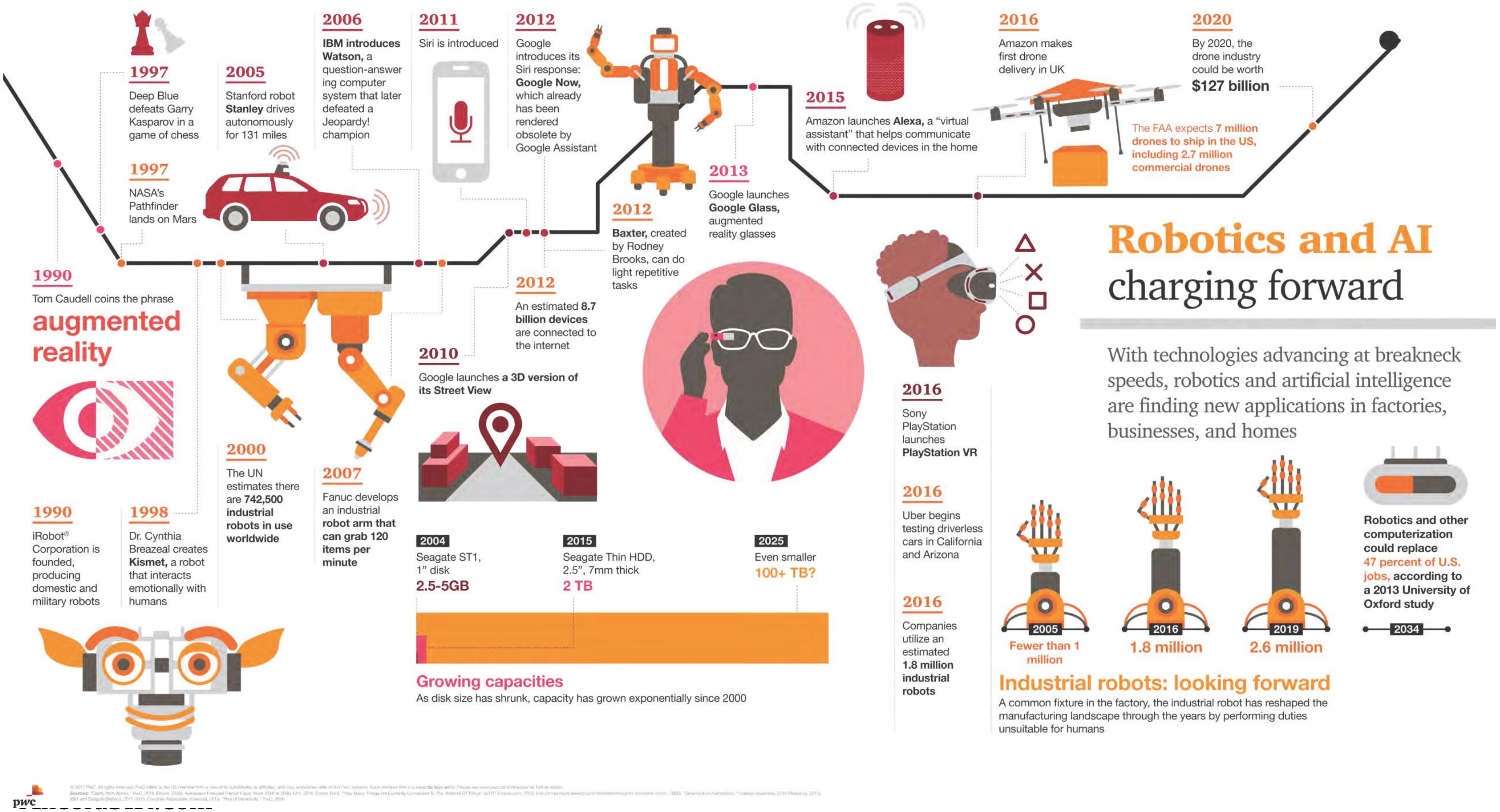
The Rise of Robotics & AI

A Brief History – Part I



Robotics & AI Charging Forward

A Brief History – Part II



A look at *robots ready for work*

At a glance

Robots once were viewed as expensive, limited in their abilities, and applicable only in manufacturing. Now, THEY are more capable, easier to use, and less COSTLY, making the technology more desirable and accessible. But competing operating systems, form factors, and interfaces make for a fragmented robotics marketplace. We believe widespread adoption will accelerate when dominant vendors and platforms begin to emerge.

Five ways robots are going mainstream

They're not restricted to structured environments.

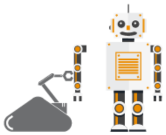
They can now handle dynamic, less predictable settings. In hospitals, robots can safely roam halls and deliver medications. In hotels, they can deliver towels, toiletries, and minibar items to guest rooms.

They can work with humans.

Thanks to sensors and smart technology, new-generation robots are much safer around humans.

They can learn.

The new robots can "learn" skills through trial and error, mimicking the way humans learn new tasks.



They are no longer single-task machines.

Robots are being designed with modularity in mind, beginning with a platform upon which a customized solution can be built.

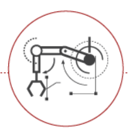
They're moving beyond the factory floor.

Robots are engaged in functions across the enterprise, including positions where they interact directly with customers and employees.

Benefits of robotics

Robots are not just for manufacturing anymore. No matter the industry, they can:

- Automate business operations
- Boost efficiency, quality, and repeatability
- Free up humans for higher-value tasks
- Replace or augment humans in jobs where there are labor shortages

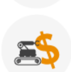


Potential challenges

Lack of expertise and support — Your company may not have the knowledge or the resources to buy and maintain robots.

Fallout from job losses — Robots could displace workers, which could lower morale and create conflict with labor unions.

Regulatory compliance — Safety rules and monitoring and reporting requirements can create burdens, particularly for smaller companies.

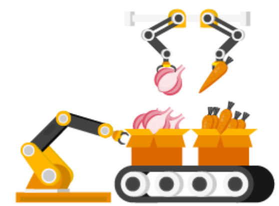


Costs — Prices for robots are dropping, but the cost of engineering the system, installing it, and managing the change can be prohibitive.

Potential new applications

Collaboration

Robots can replace or work as "cobots," in tandem with humans.



Handling more complex tasks

Robots can be instrumental in warehousing and fulfillment by fetching, monitoring inventory, moving pallets, picking, packing, screening, and inspecting. They can also greet, direct, and assist customers.

Mitigating labor shortages

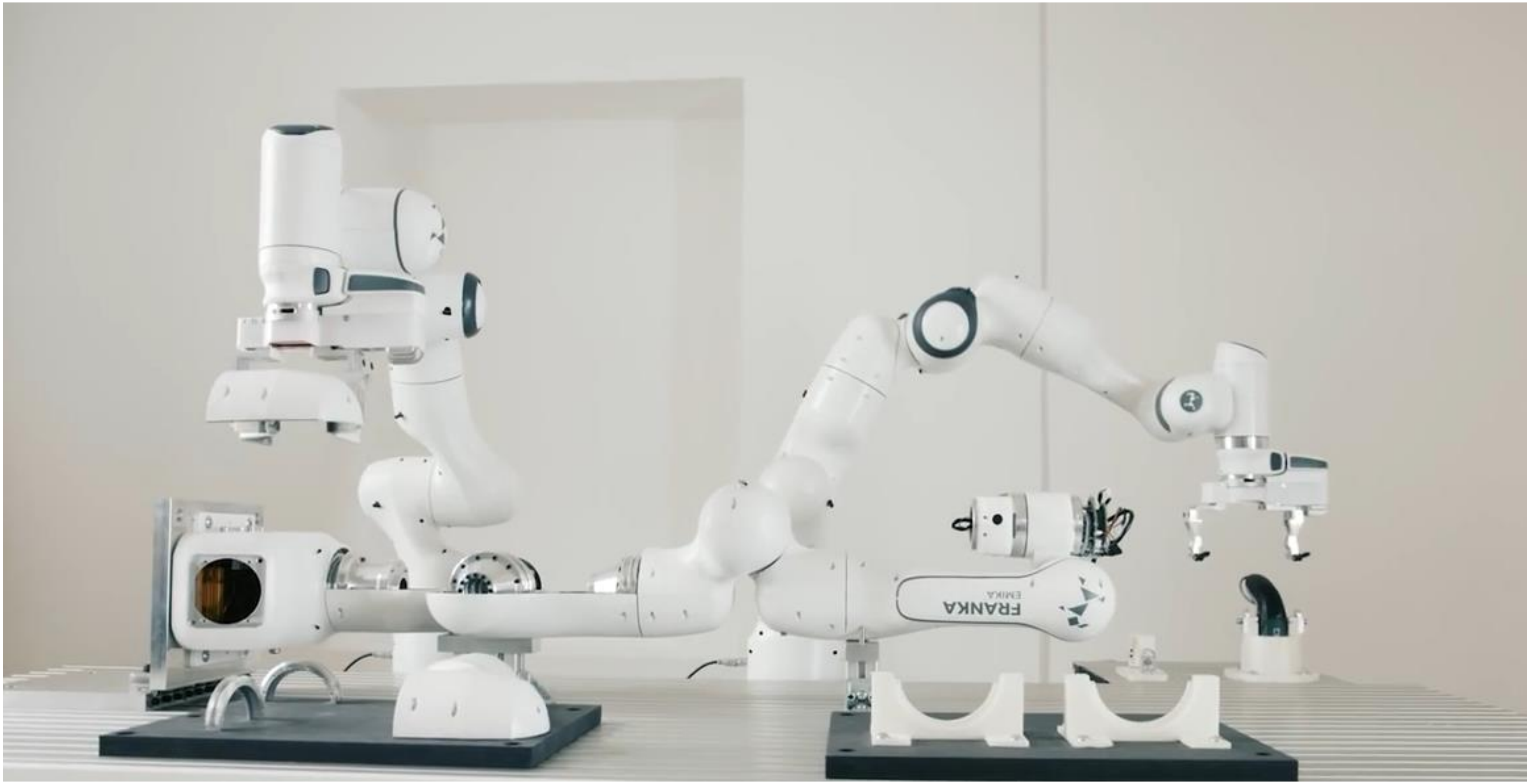
Robots can be used to automate tasks too difficult and expensive for human manual labor. For example, robots won't just plant and harvest crops; they'll also monitor their health, size, and maturity, and target-spray fertilizer, herbicides, and fungicides where most needed.

Source: PwC, 2017

pwc.com/NextinTech

Why Making a Robot Collaborative?

"The action of working with someone to produce or create something"



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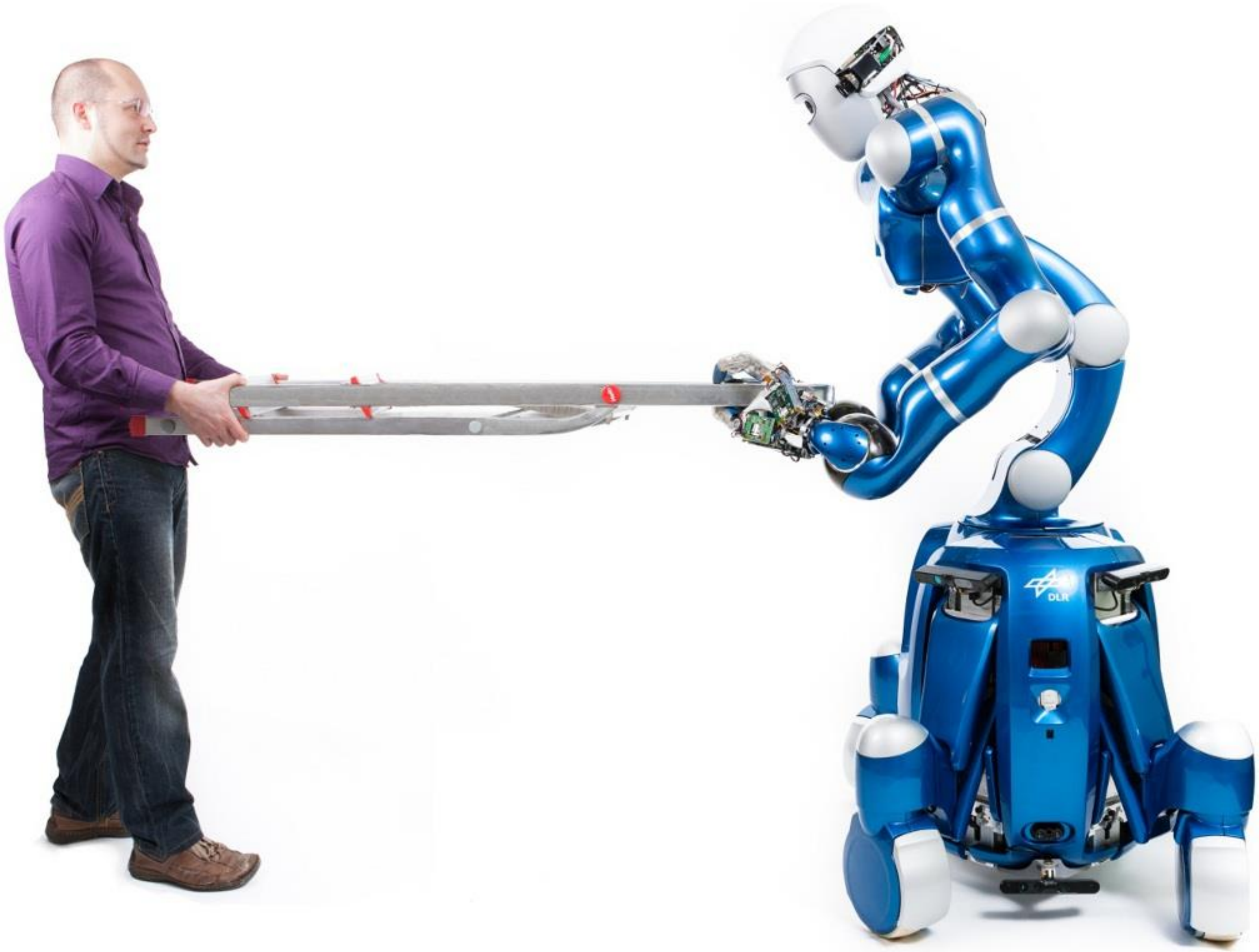
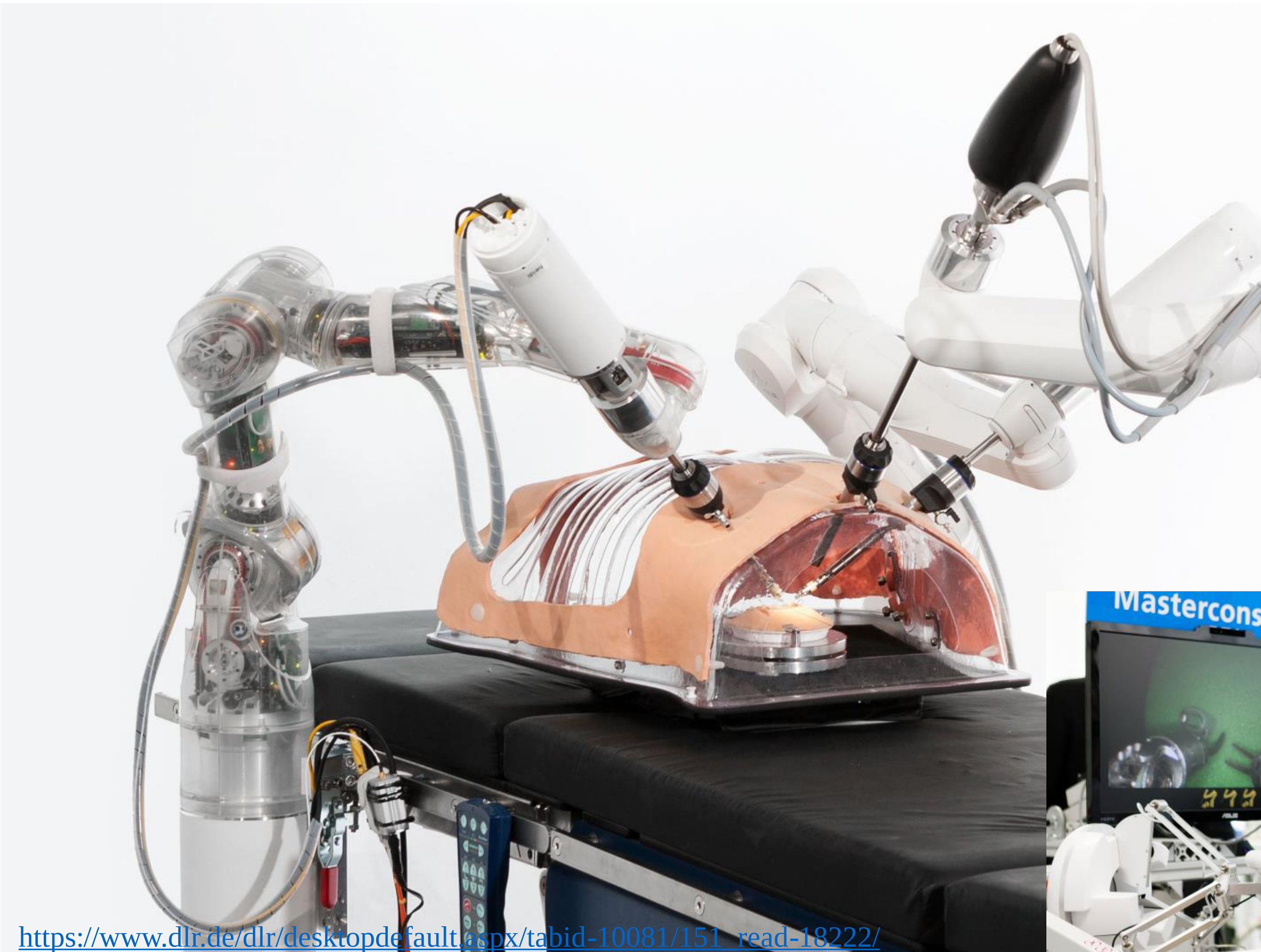
Possible Ways of Collaboration

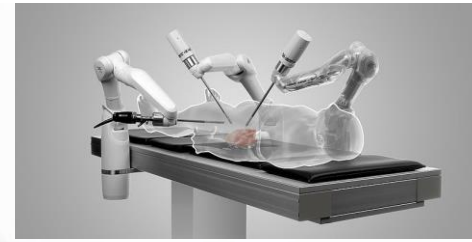
Passing a Ladder?



Robot-Assisted Surgery

DLR Institute for Robotics and Mechatronics – MIRO Robot





https://www.dlr.de/dlr/desktopdefault.aspx/tabid-10081/151_read-18222/

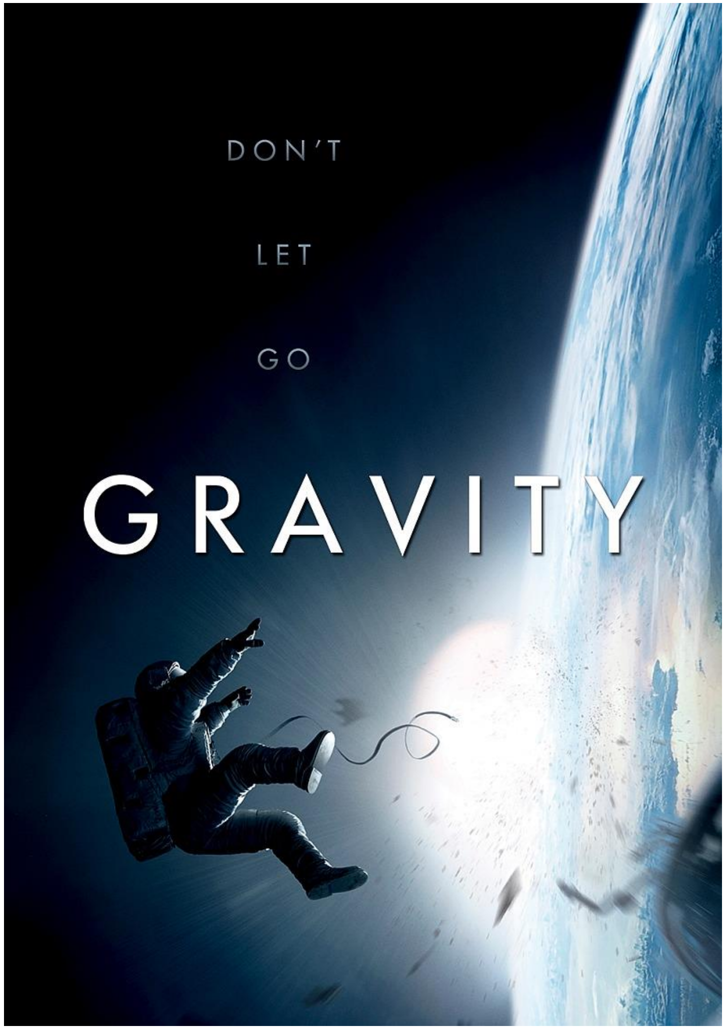
Radiation Therapy

Heidelberg Ion-Beam Therapy Center/Heidelberg University Hospital

https://bioengineeringtoday.org/therapy/future-carbon-therapy

Film Production

Bot'n'Dolly



Cost-effective Collaboration

Key Features

- Small payload
  - Force limiting for safe interaction
- Small footprint
  - Less disruption to the existing automation line
- Highly repetitive
  - Labor replacement for added value
- Ease of integration
  - Flexible implementation for the changing demand

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Common Applications of Cobot in Automation

Highly repetitive tasks that requires different levels of dexterity

- **Object Relocation**
  - Handling object from one location to another
  - Pick & Place | Machine Tending | Packing and Palletizing
- **Material Releasing**
  - Releasing material from the robot to the target location
  - Gluing | Dispensing | Welding | Screwdriving
- **Material Removal**
  - Removing material from the target object using the robot
  - Polishing | Grinding | Deburring
- **Information Gathering**
  - Collecting information using sensors attached to the robot
  - Quality Inspection

Robot Movement

- Fixed
- Patterned
- Continuous
- Changing
- Random

Critical Components

- End-Effector
- Vision System
- I/O Interfacing
- Conveyor Tracking
- Force-Torque Sensor
- External Jig
- Protective Suit

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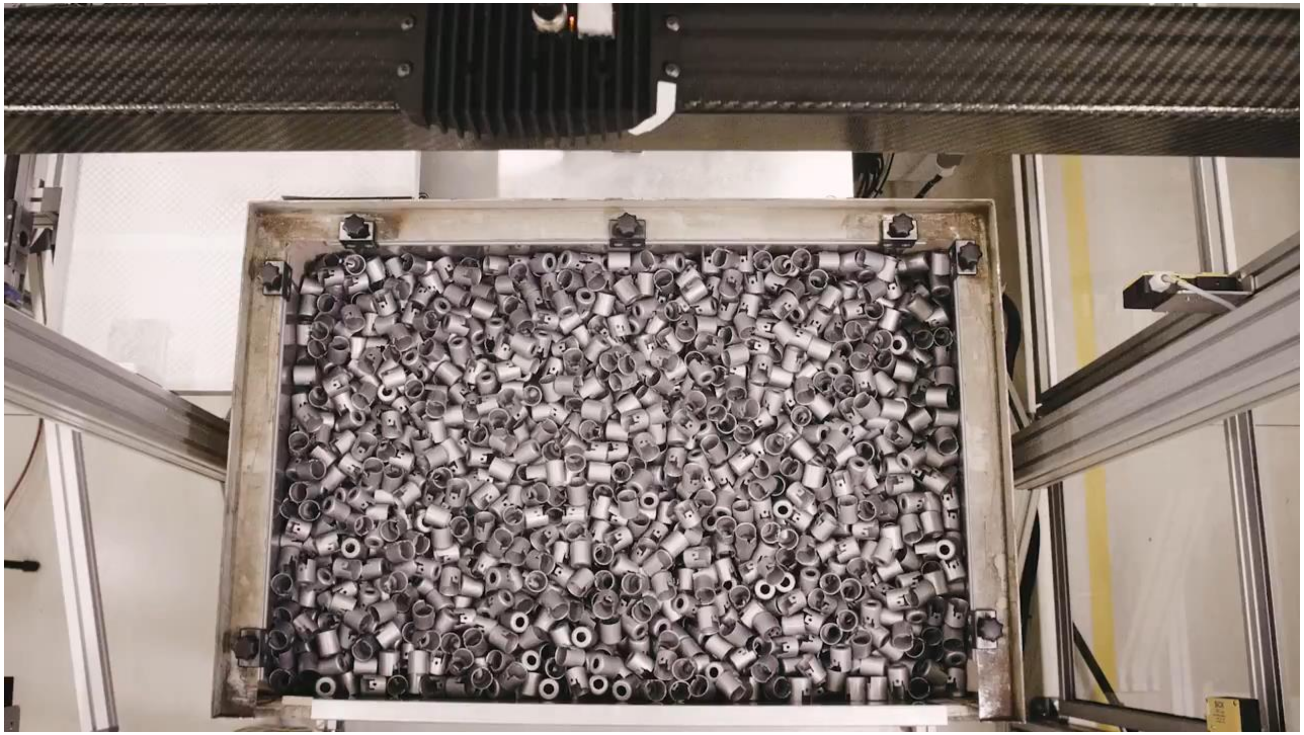
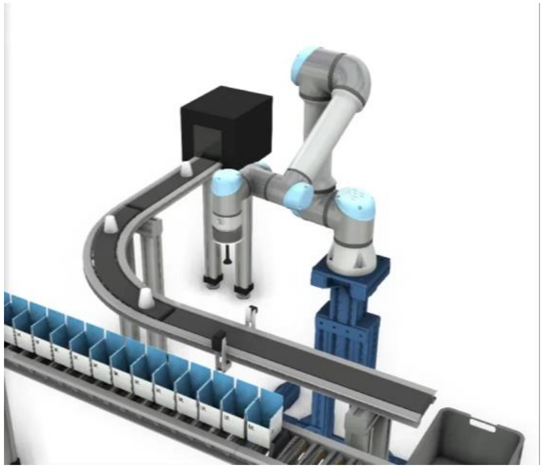
Examples of Object Relocation

Handling object from one location to another





- Bin-Picking using 3D Vision (Photoneo)
- Machine Tending & Packaging without Vision Sensor (Universal Robots)

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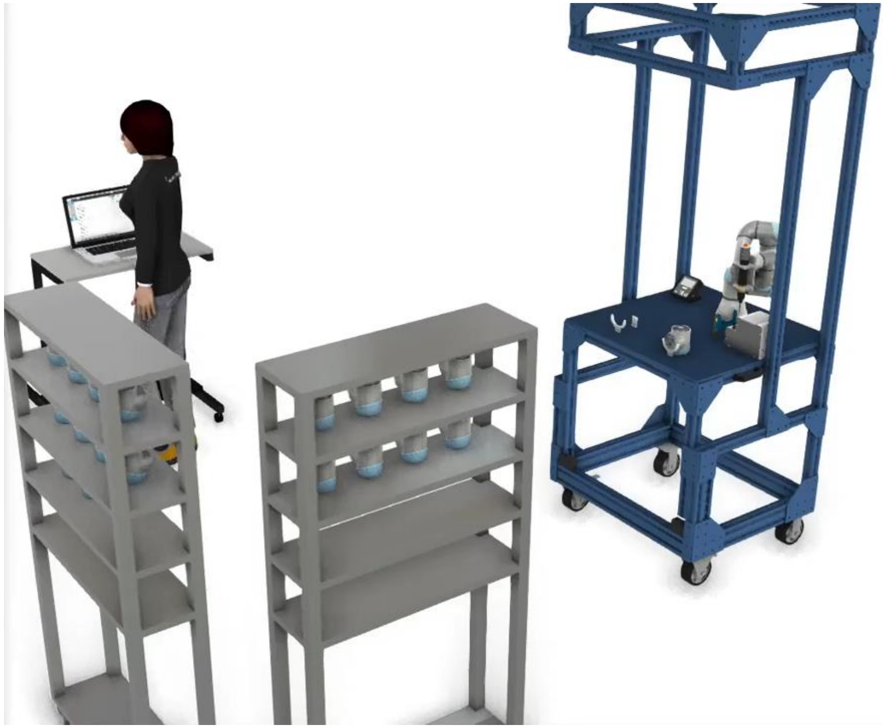
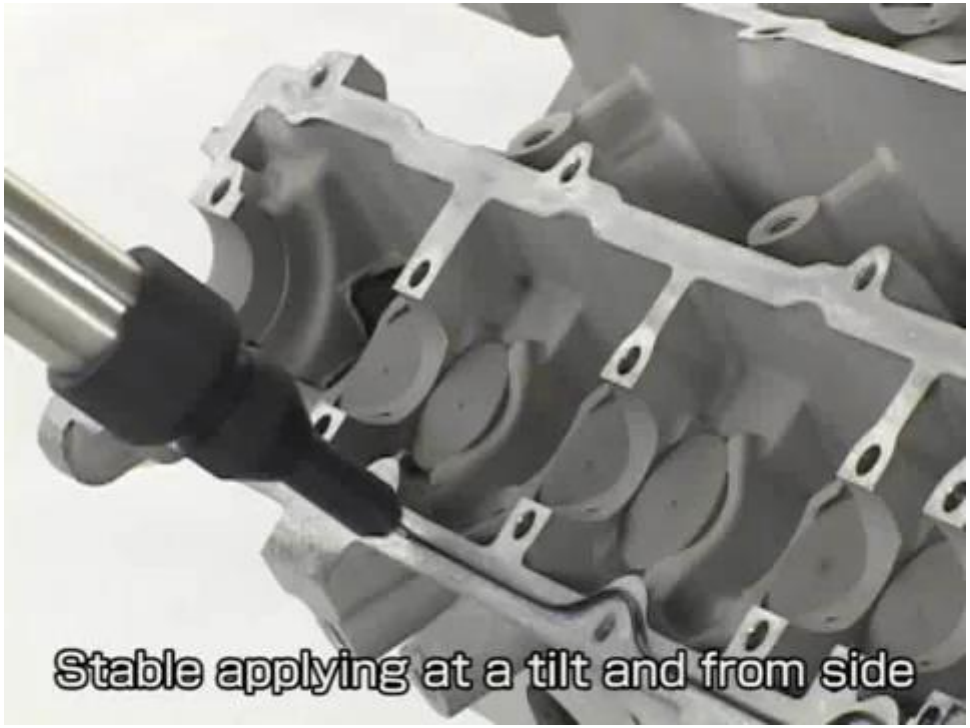
Examples of Material Releasing

Releasing material from the robot to the target location





- Screwdriving (Universal Robots)
- Dispensing (NETZSCH)

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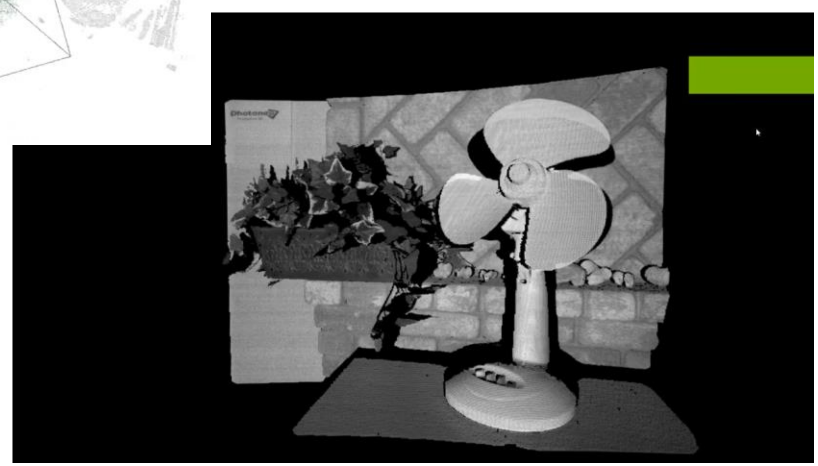
Example of Information Gathering

Collecting information using sensors attached to the robot

Quality Inspection
(Photoneo)



Realtime 3D Sensing
(Photoneo)

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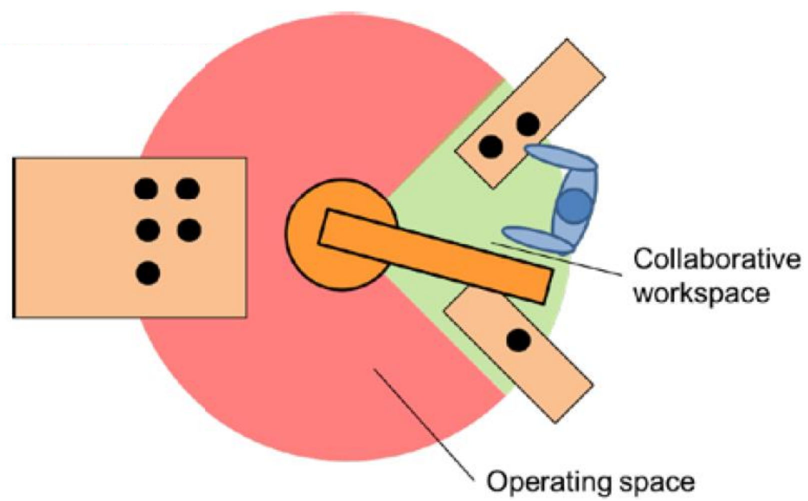
Features of Collaborative Robots

Collaborative Robot Technical Specification ISO/TS 15066

- A collaborative robot is a robot that **CAN** (capable) for use in a collaborative operation
  - **Collaborative Operation** - where *purposely designed robot systems* work in **direct cooperation with a human** within **a defined workspace**

Specified Task ***Specified Space***



Collaborative Workspace: space within the operating space where the robot system (including the workpiece) and a human can perform tasks concurrently during production operation.

- *Robot*: Robot arm & robot control
- *Robot System*: Robot, end-effector & workpiece

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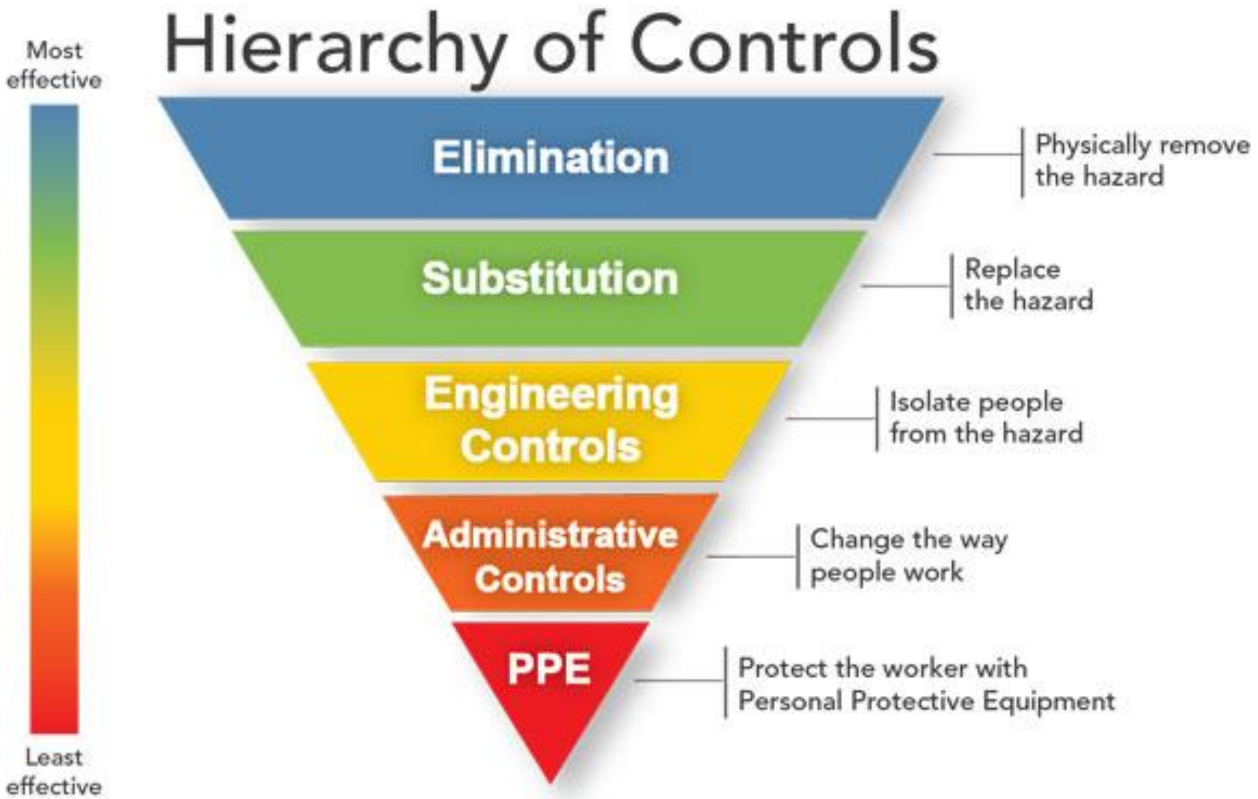
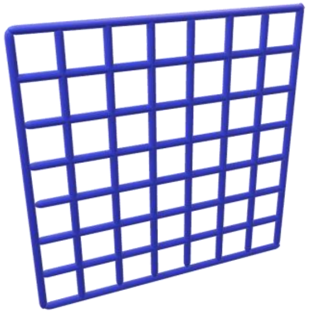
Risk = Likelihood x Consequence

Risk Assessment + Risk Reduction = Safety Assurance



Hazard



Exposure

Vulnerability

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4 Techniques of Collaborative Operation

The **APPLICATION** determines whether the robot system can be collaborative

- Safety-rated monitored stop
  - *Allows for direct operator interaction with the robot system under specific circumstances*
- Hand guiding
  - *Operator uses a hand-operated device to transmit motion commands*
- Speed and separation monitoring
  - *Operator and robot system may move concurrently in the collaborative workspace*
- Power and force limiting
  - *Physical contact between the robot system (including the workpiece) and an operator can occur either intentionally or unintentionally*

While in AUTOMATIC mode (ISO/TS 15066)

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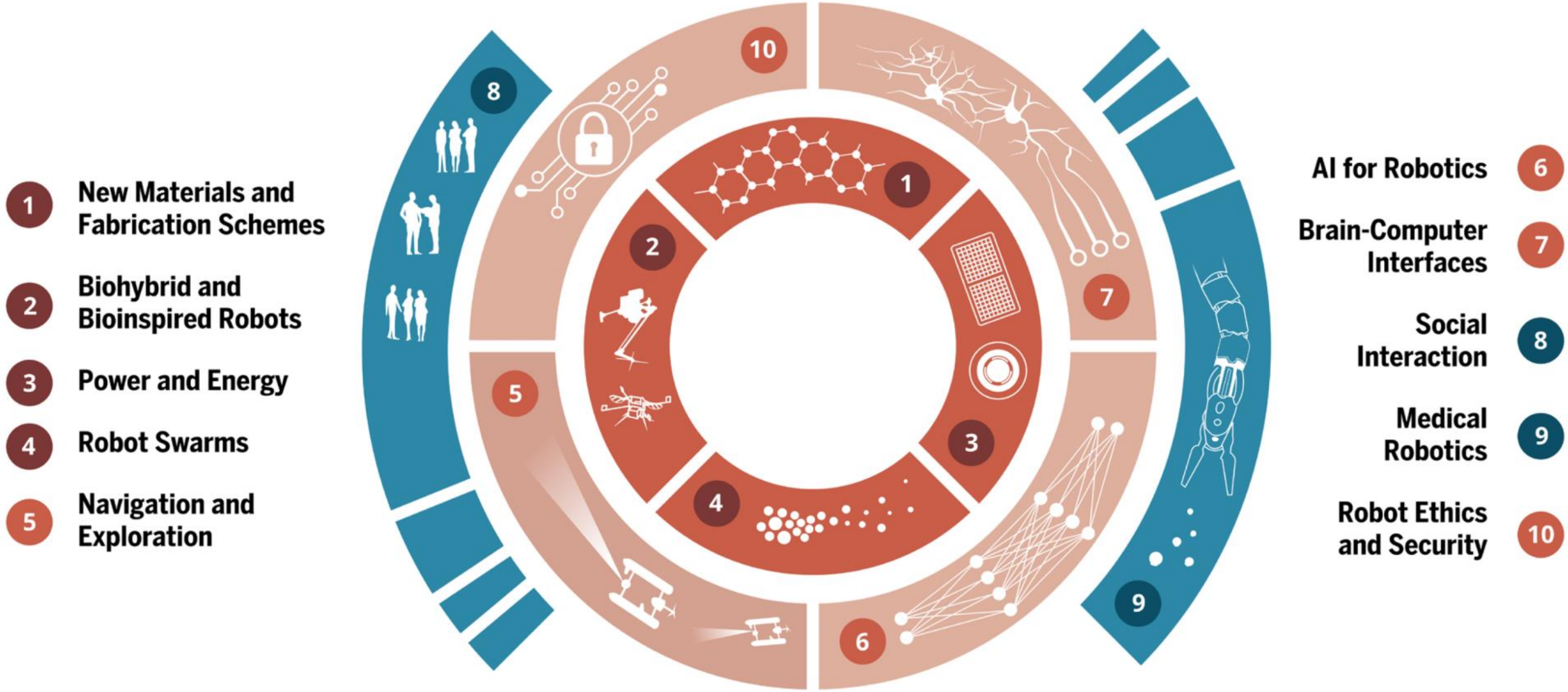
The Grand Challenges in Robotic Science

There remains a wide range of problems to be solved in robotics



Yang, G.-Z., Dupont, P. E., Fischer, P., Floridi, L., Bellingham, J., Full, R., … Wood, R. (2018). The grand challenges of Science Robotics. Science Robotics, 3(14), eaar7650.

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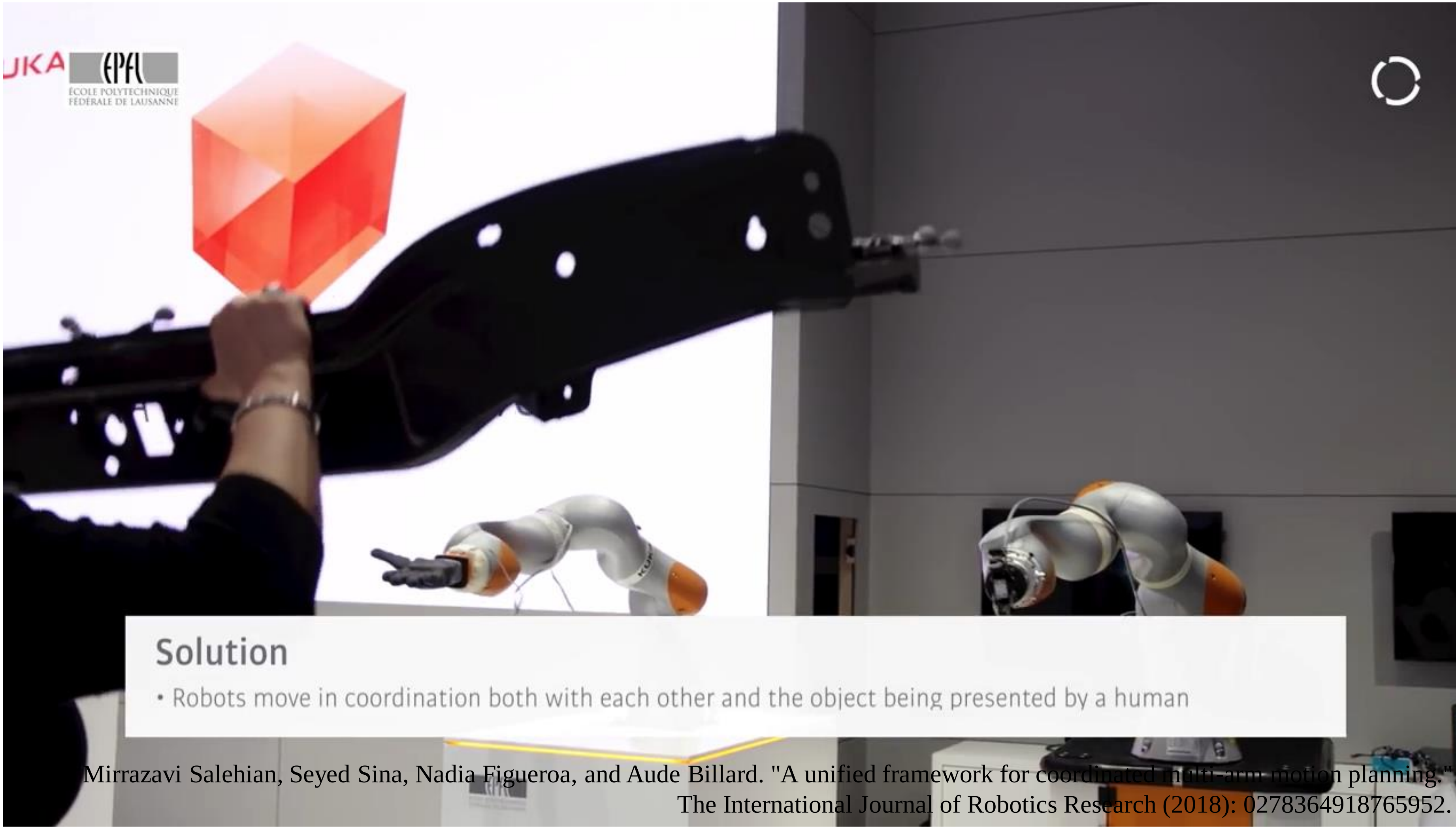
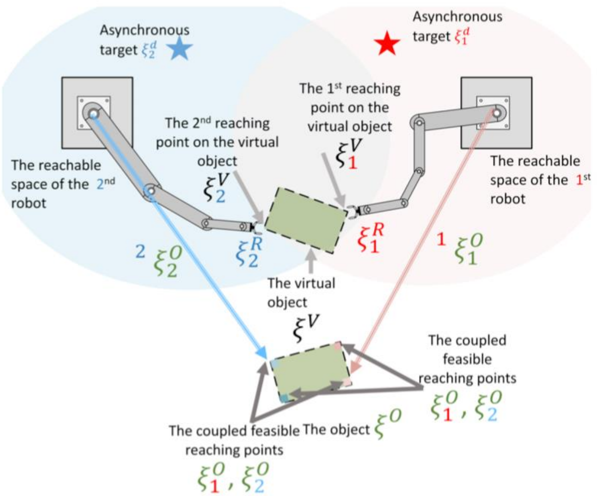
Multi-Robot Human Collaboration

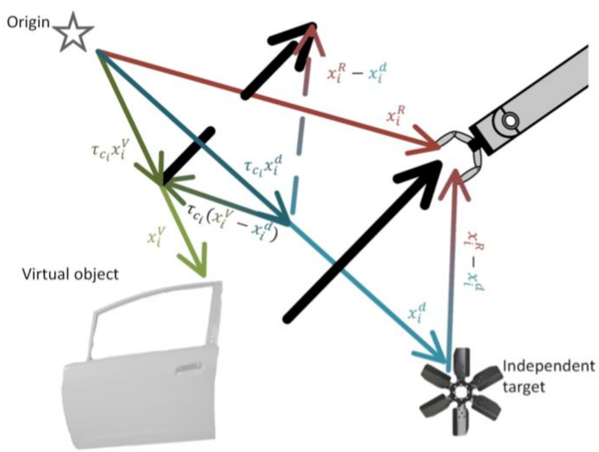
Collaborative Handling of Heavy Load

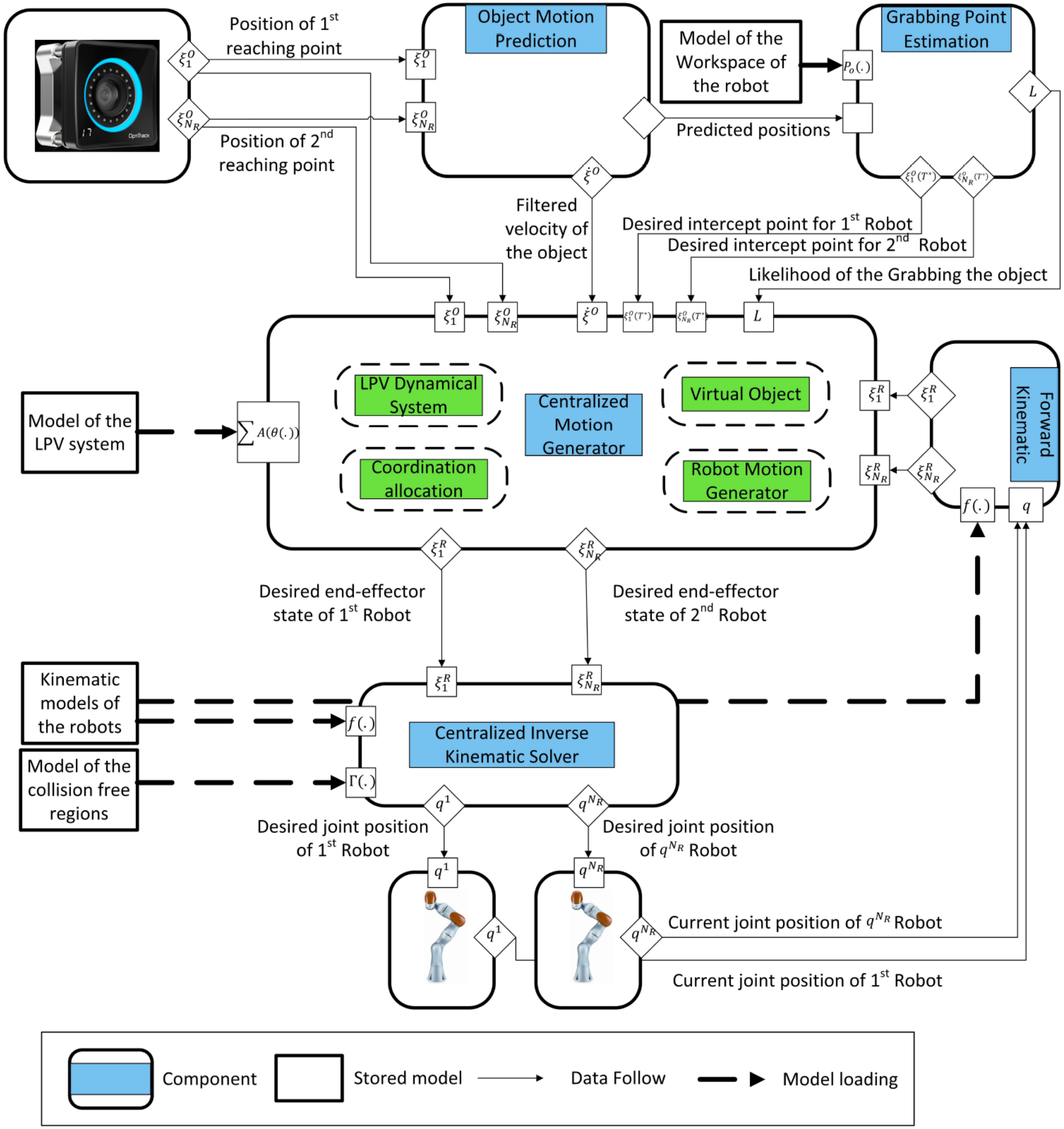


Mirrazavi Salehian, Seyed Sina, Nadia Figueroa, and Aude Billard. "A unified framework for coordinated multi-arm motion planning." The International Journal of Robotics Research (2018): 0278364918765952.

Classical Model Based Method







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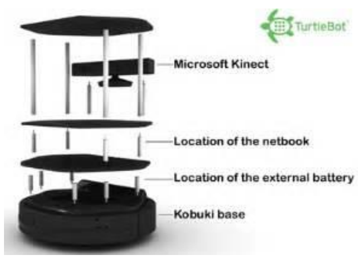
Success Examples in Robot Learning

Autonomous Vehicles | Autonomous Drones | Arm-Type Robots

Research Challenge (Science 1st)

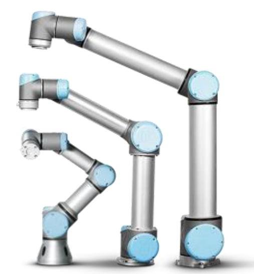
Industry Need

Consumer Electronics (Cost 1st)



?

Service Integration (App 1st)



Service Penetration

Still **Expensive** to buy/integrate,
Difficult to use/learn,
Un-safe to work with,
…

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Why Making the Robots to Learn?

Translating Success in Machine Learning for Robotics

- Computing Unit ✓
- Advanced Algorithms ✓..
- Big Data ✘

How to cost-effectively acquire large, quality, robotic data for learning?

Data-Driven Grasp Synthesis - A Survey, Jeannette Bohg, Antonio Morales, Tamim Asfour, Danica Kragic (https://arxiv.org/pdf/1309.2660.pdf)

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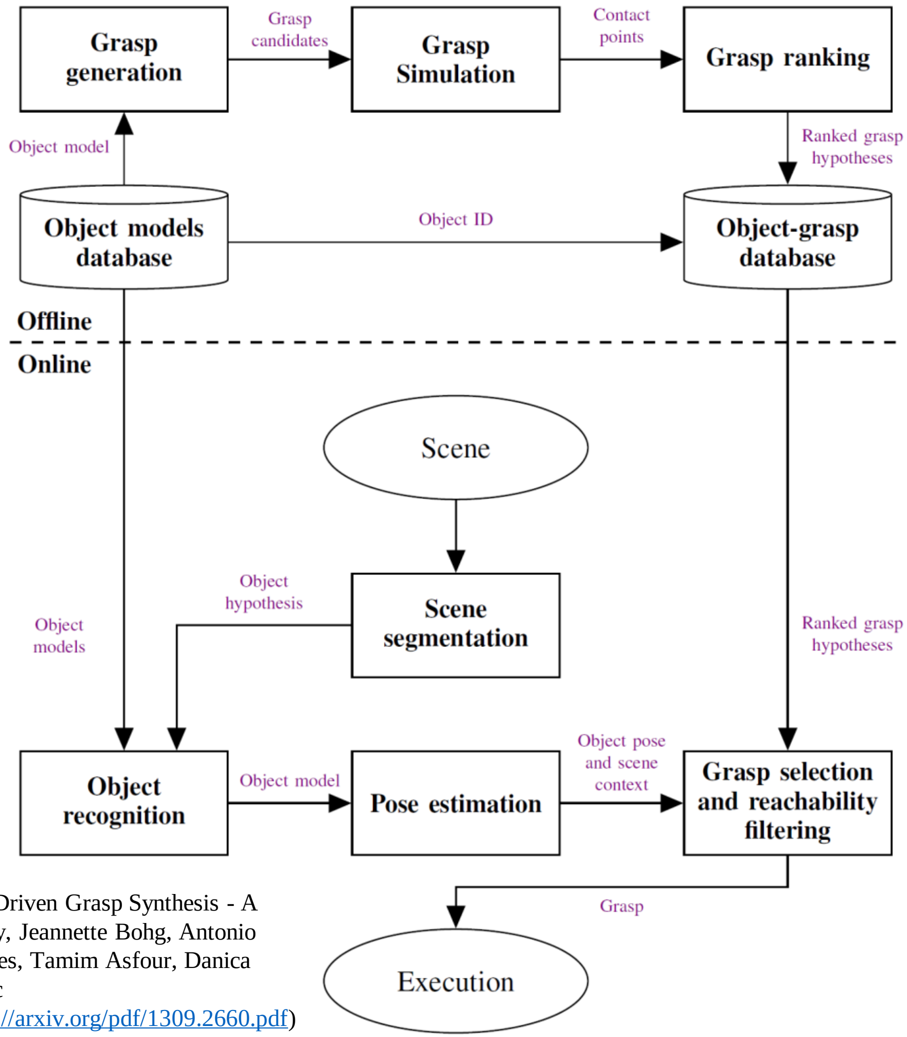
Adapted Functional Flow-chart of Image-based Picking



Data-Driven Grasp Synthesis - A Survey, Jeannette Bohg, Antonio Morales, Tamim Asfour, Danica Kragic (https://arxiv.org/pdf/1309.2660.pdf)

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Scene Segmentation
- What we are going to interact with …

Object Recognition
- Representation & Classification

Pose Estimation
- Object & Picker

Pick Planning
- Picker & Arm

Pick Execution
- MoveIt & PickIt

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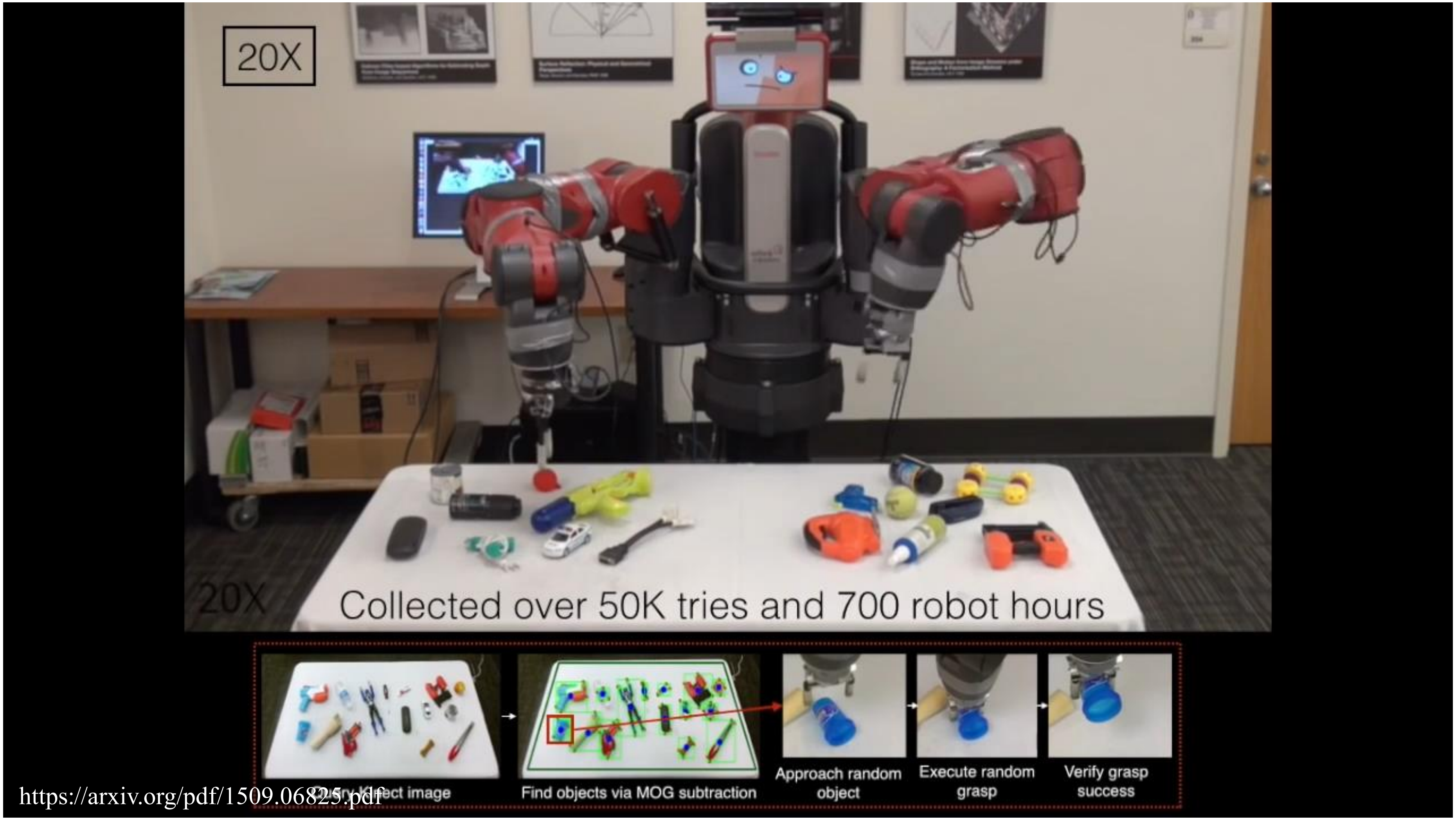
Supersizing self-supervision: Learning to grasp from 50k tries and 700 robot hours

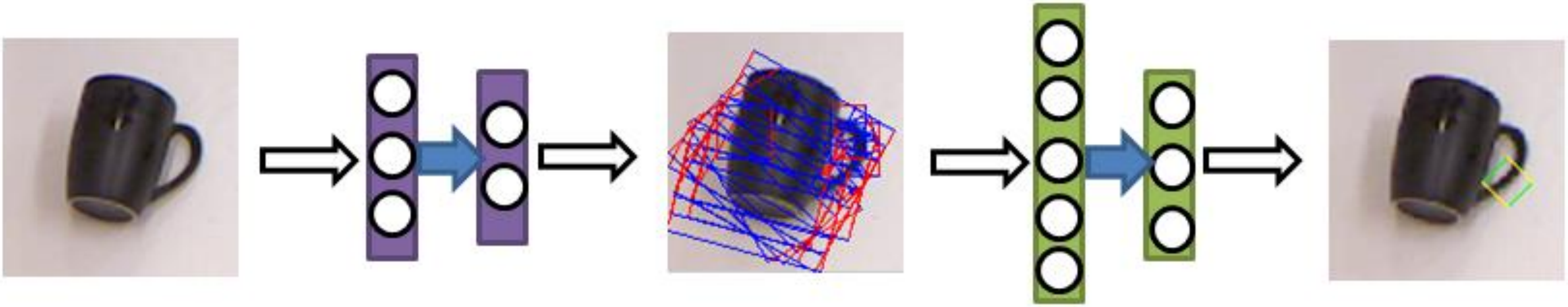
By Pinto, Lerrel, and Abhinav Gupta @ CMU

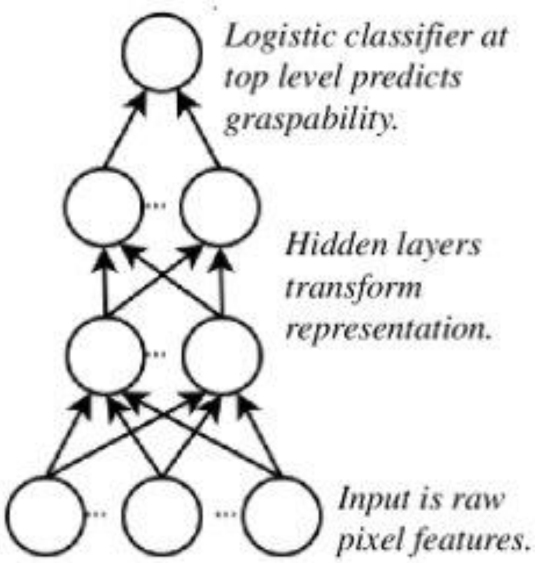


https://arxiv.org/pdf/1509.06825.pdf

Deep Learning for Detecting Robotic Grasps

By Ian Lenz, Honglak Lee, and Ashutosh Saxena @ Cornell





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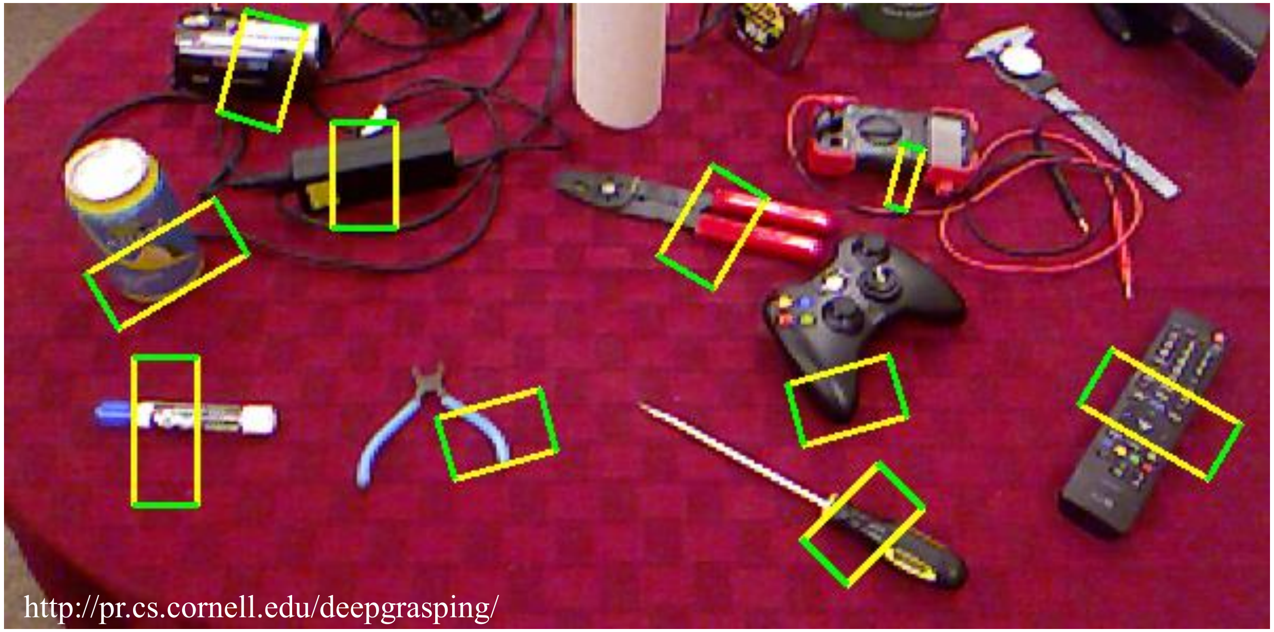
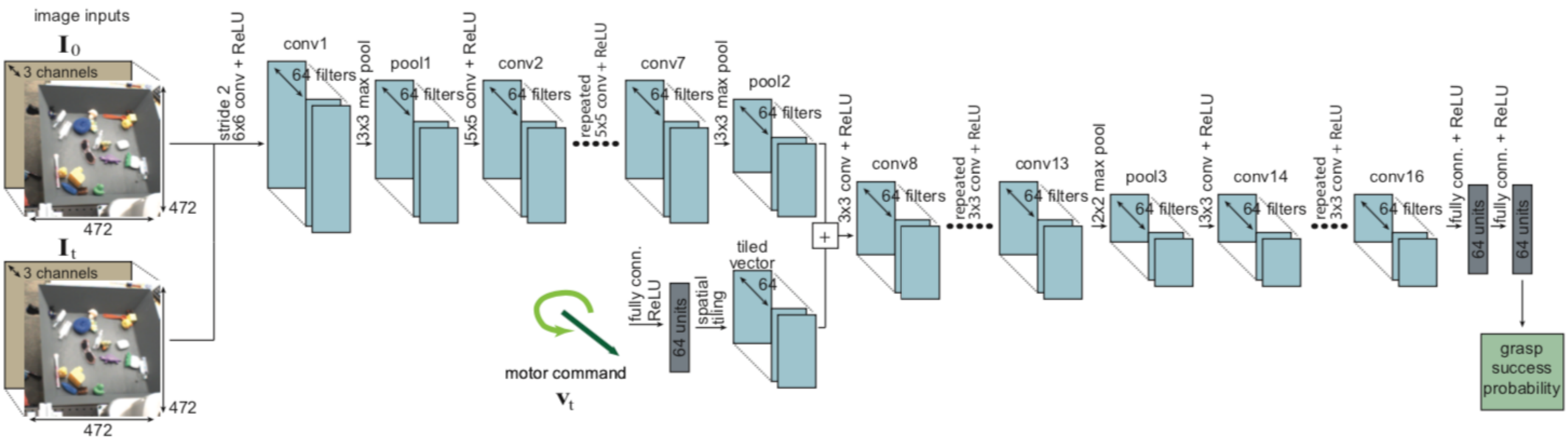


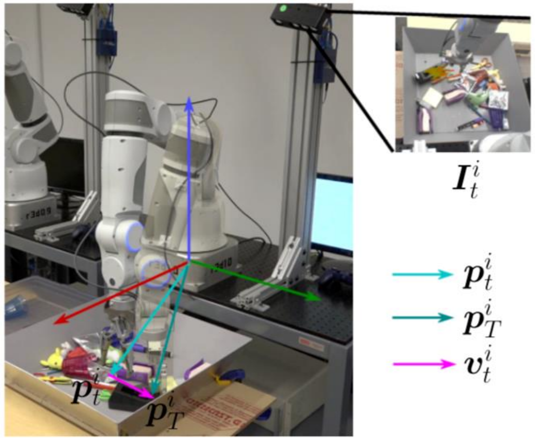
Learning Hand-Eye Coordination for Robotic Grasping with Deep Learning and Large-Scale Data Collection

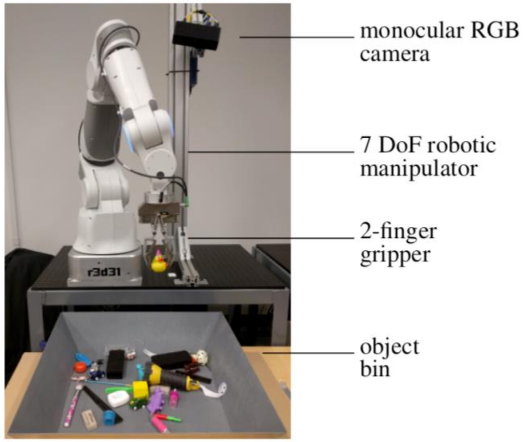
By Sergey Levine, Peter Pastor, Alex Krizhevsky, Deirdre Quillen @ Google



Algorithm 1 Servoing mechanism $f(\boldsymbol{I}_t)$

Given current image $\boldsymbol{I}_t$ and network g.
Infer $\boldsymbol{v}_t^\star$ using g and CEM.
Evaluate $p = g(\boldsymbol{I}_t, \emptyset)/g(\boldsymbol{I}_t, \boldsymbol{v}_t^\star)$.
if $p = 0.9$ **then**
  Output $\emptyset$, close gripper.
else if $p \leq 0.5$ **then**
  Modify $\boldsymbol{v}_t^\star$ to raise gripper height and execute $\boldsymbol{v}_t^\star$.
else
  Execute $\boldsymbol{v}_t^\star$.
end if





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https://arxiv.org/pdf/1603.02199v1.pdf

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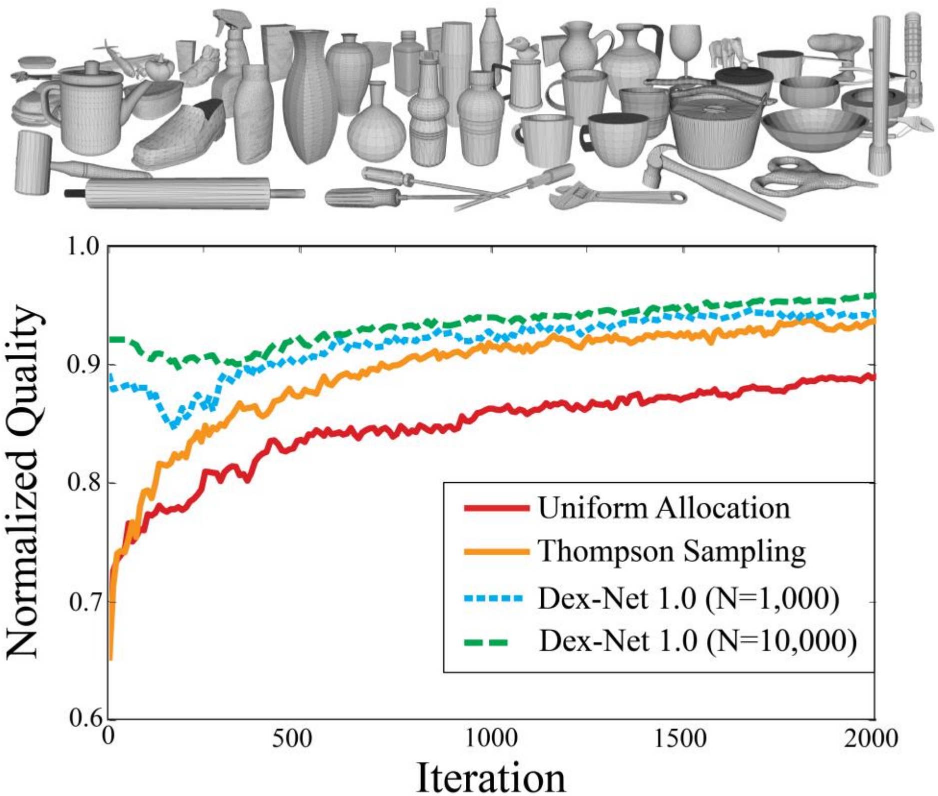
Dex-Net 1.0: A Cloud-Based Network of 3D Objects for Robust Grasp Planning Using a Multi-Armed Bandit Model with Correlated Rewards

By Jeff Mahler, Florian Pokorny, Brian Hou, Melrose Roderick, Michael Laskey, Mathieu Aubry, Kai Kohlhoff, Torsten Kroeger, James Kuffner, Ken Goldberg @ UC Berkley

Normalized Quality vs Iteration Averaged Over Test Objects



Input: Object $\mathcal{O}$, Number of Candidate Grasps N_g, Number of Nearest Neighbors N_n, Dex-Net 1.0 Database $\mathcal{D}$, Features maps ψ and η, Maximum Iterations T, Prior beta shape α_0, β_0, Lower Bound Confidence p, Random Variables ν, ξ, and γ
Result: Estimate of the grasp with highest P_F, $\hat{\mathbf{g}}^*$

`// Generate candidate grasps and priors`
Γ = AntipodalGraspSample($\mathcal{O}$, N_g) ;
$\mathcal{A}_0 = \varnothing, \mathcal{B}_0 = \varnothing$;
for $\mathbf{g}_k \in \Gamma$ **do**
  `// Equations VI.1 and VI.2`
  $\alpha_{k,0}, \beta_{k,0}$ = ComputePriors($\mathcal{O}, \mathbf{g}_k, \mathcal{D}, N_n, \psi$);
  $\mathcal{A}_0 = \mathcal{A}_0 \cup \{\alpha_{k,0}\}, \mathcal{B}_0 = \mathcal{B}_0 \cup \{\beta_{k,0}\}$;
end
`// Run MAB to Evaluate Grasps`
for $t = 1, .., T$ **do**
  j = ThompsonSample($\mathcal{A}_{t-1}, \mathcal{B}_{t-1}$);
  $\hat{\nu}, \hat{\xi}, \hat{\gamma}$ = SampleRandomVariables(ν, ξ, γ);
  F_j = EvaluateForceClosure($\mathbf{g}_j, \mathcal{O}, \hat{\nu}, \hat{\xi}, \hat{\gamma}$);
  `// Equations VI.3 and VI.4`
  $\mathcal{A}_t, \mathcal{B}_t$ = UpdateBeta(j, F_j, Γ);
  $\mathbf{g}_t^*$ =MaxLowerConfidence($\mathcal{A}_t, \mathcal{B}_t, p$);
end
return $\mathbf{g}_T^*$;

Dex-Net 1.0 Algorithm: Robust Grasp Planning Using Multi-Armed Bandits with Correlated Rewards

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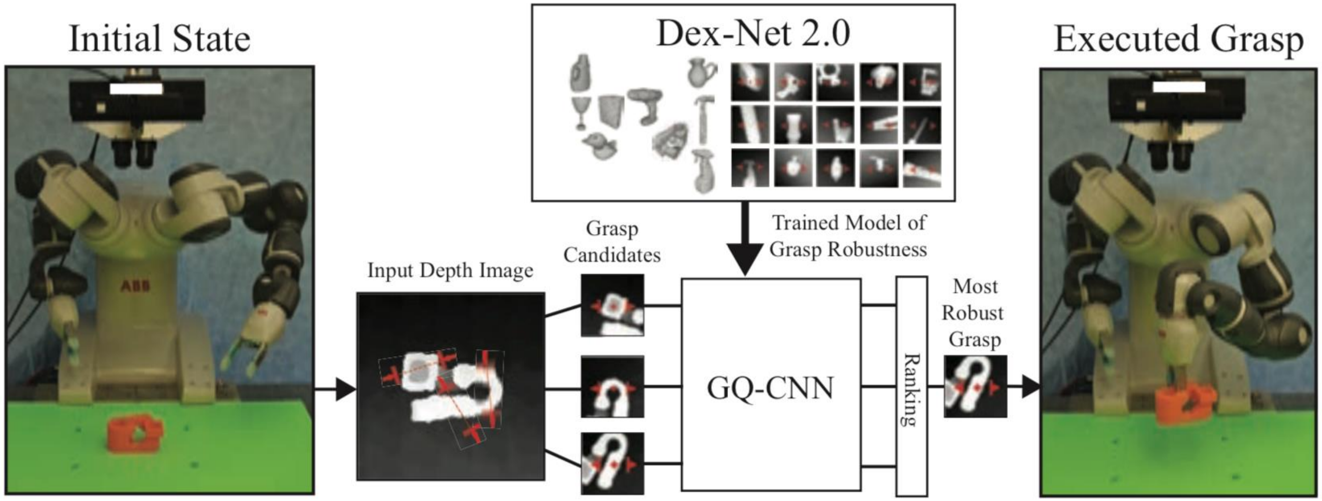
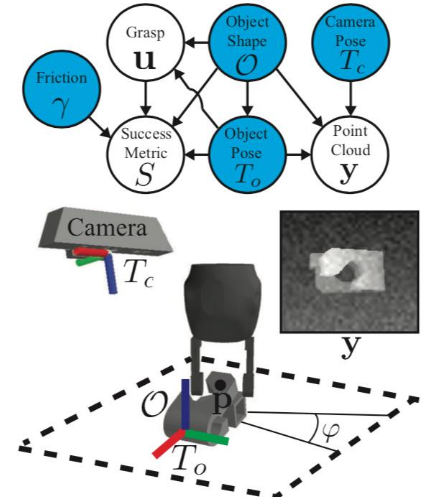
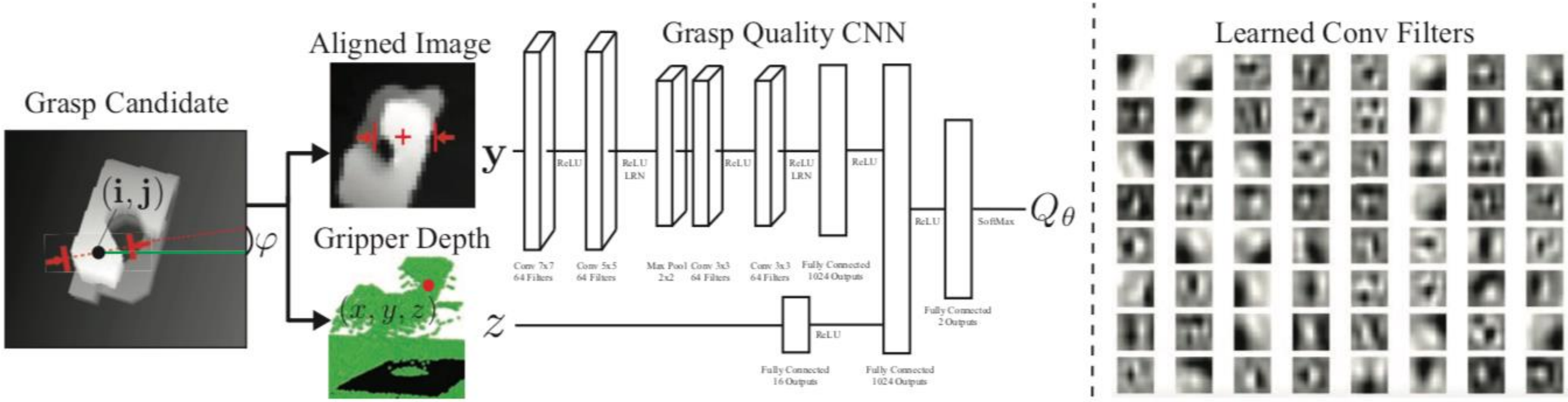
https://berkeleyautomation.github.io/dex-net/#dexnet_1

Dex-Net 2.0: Deep Learning to Plan Robust Grasps with Synthetic Point Clouds and Analytic Grasp Metrics

By Jeffrey Mahler, Jacky Liang, Sherdil Niyaz, Michael Laskey, Richard Doan, Xinyu Liu, Juan Ojea, Ken Goldberg @ UC Berkley







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https://berkeleyautomation.github.io/dex-net/#dexnet_2

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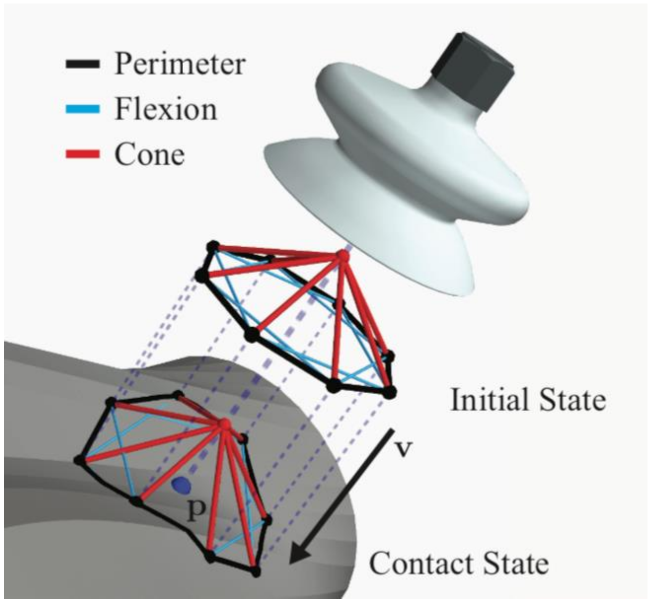
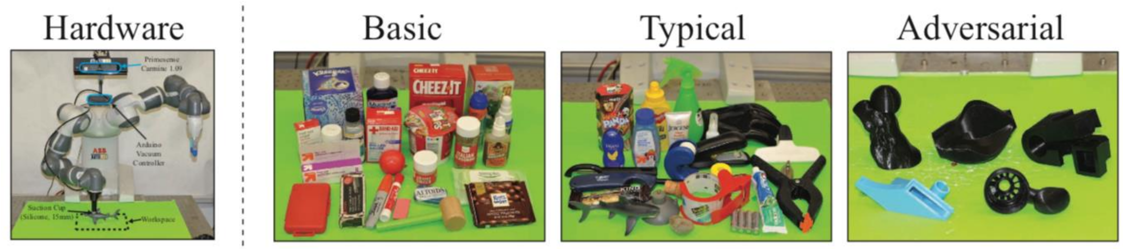
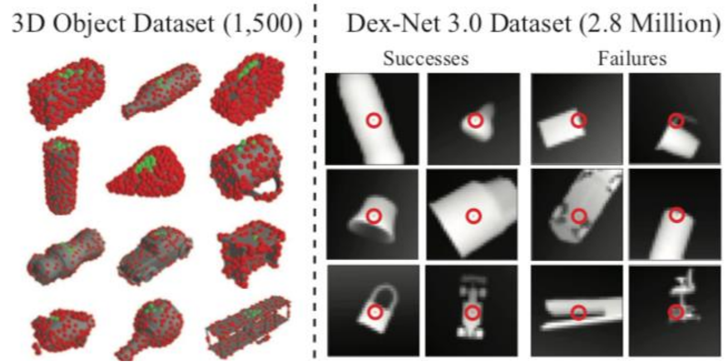
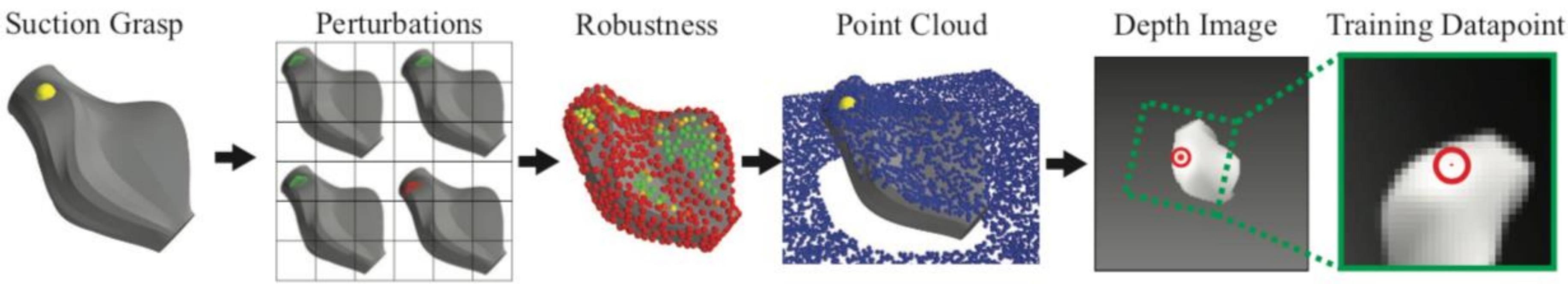
Dex-Net 3.0: Computing Robust Vacuum Suction Grasp Targets in Point Clouds using a New Analytic Model and Deep Learning

By Jeffrey Mahler, Matthew Matl, Xinyu Liu, Albert Li, David Gealy, Ken Goldberg @ UC Berkley









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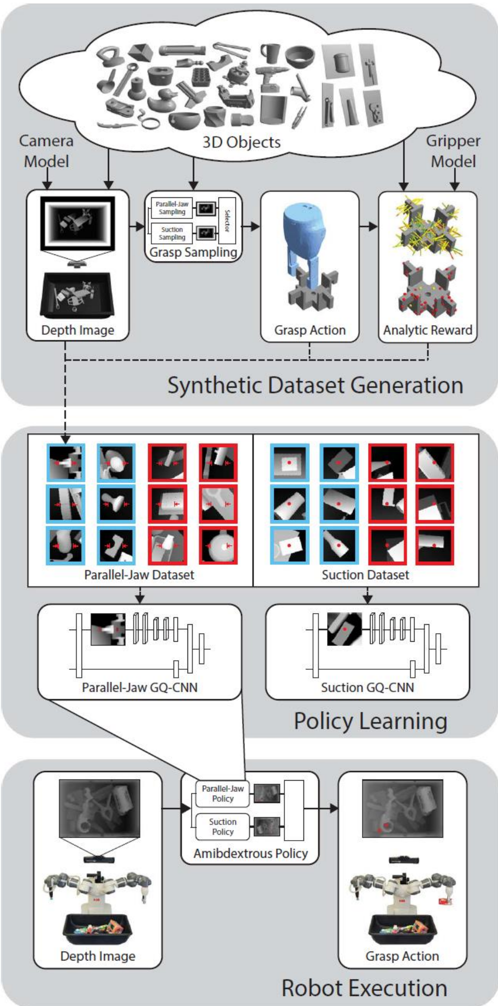
https://berkeleyautomation.github.io/dex-net/#dexnet_3

Learning Ambidextrous Robot Grasping Policies

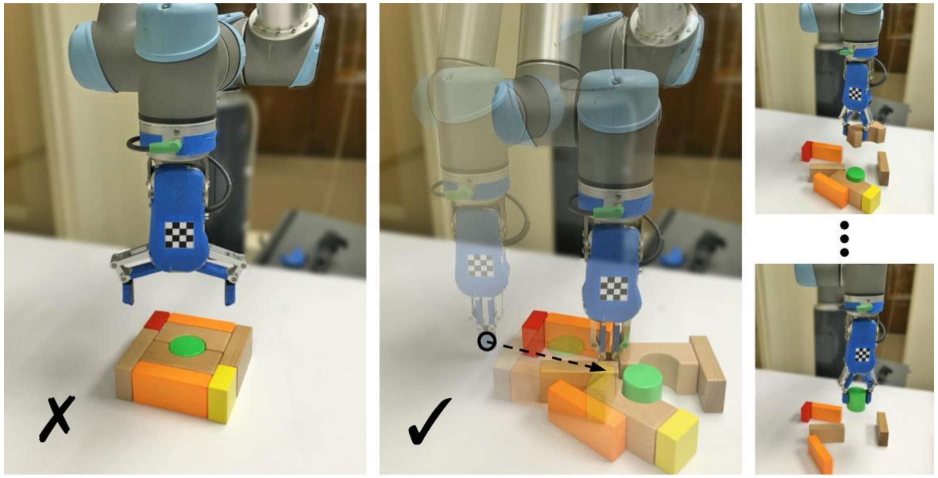
By Jeffrey Mahler, Matthew Matl, Vishal Satish, Michael Danielczuk, Bill DeRose, Stephen McKinley and Ken Goldberg @ UC Berkley

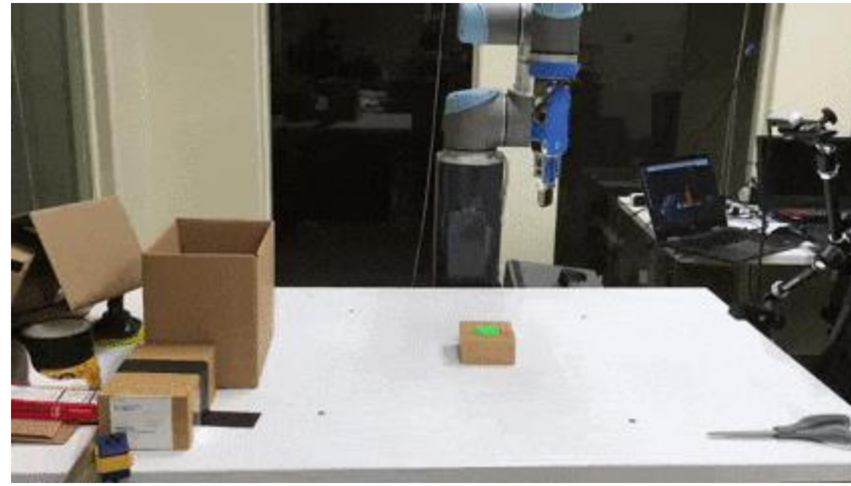


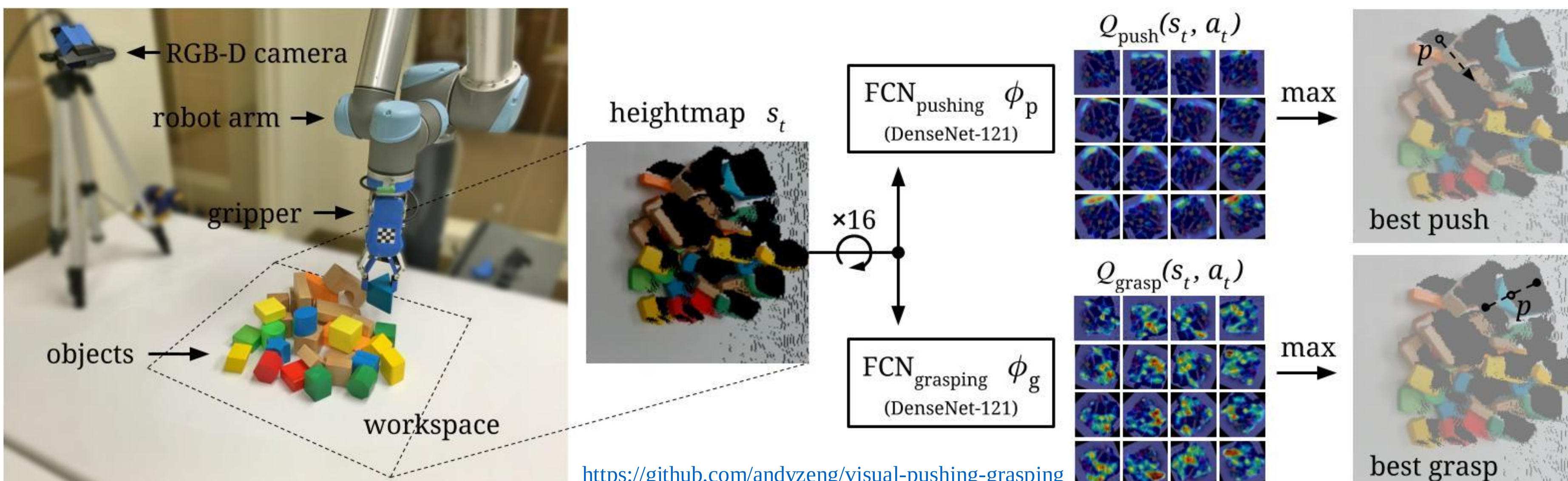
http://robotics.sciencemag.org/content/4/26/eaau4984

Learning Synergies between Pushing and Grasping with Self-supervised Deep Reinforcement Learning

By Andy Zeng, Shuran Song, Stefan Welker, Johnny Lee, Alberto Rodriguez, Thomas Funkhouser @ MIT & Princeton

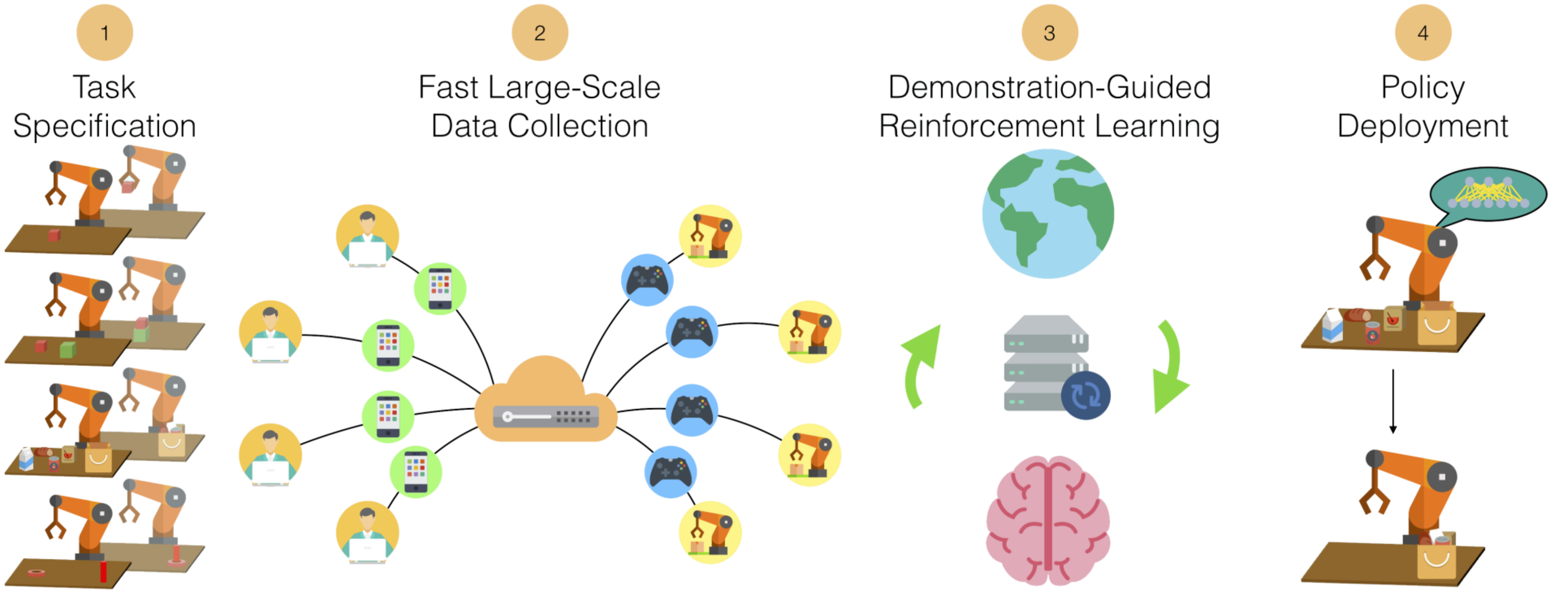


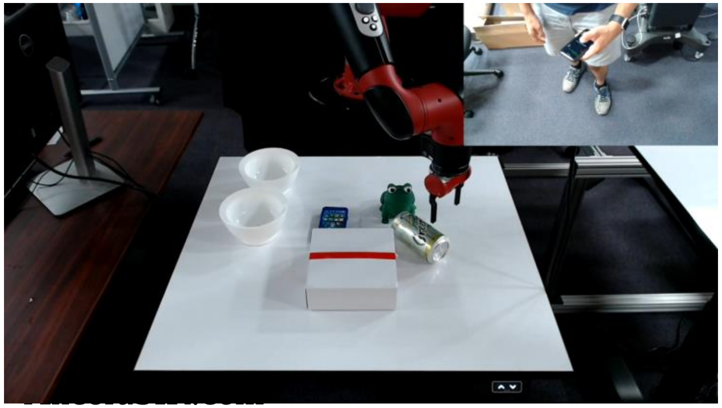




https://github.com/andyzeng/visual-pushing-grasping

RoboTurk: A Crowdsourcing Platform For Robotic Skill Learning Through Imitation





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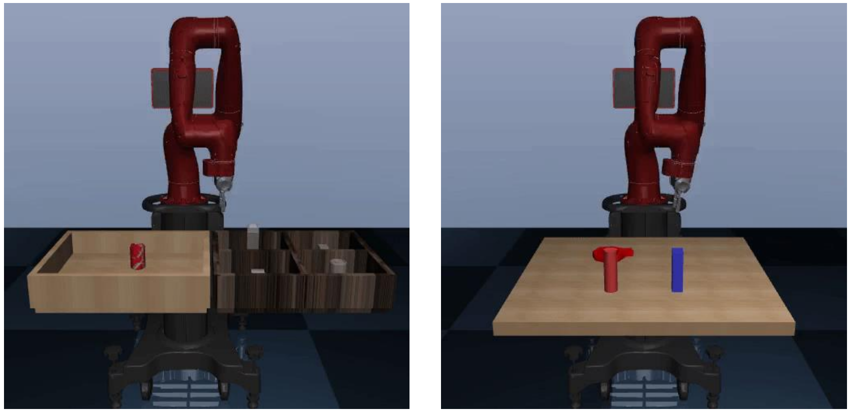
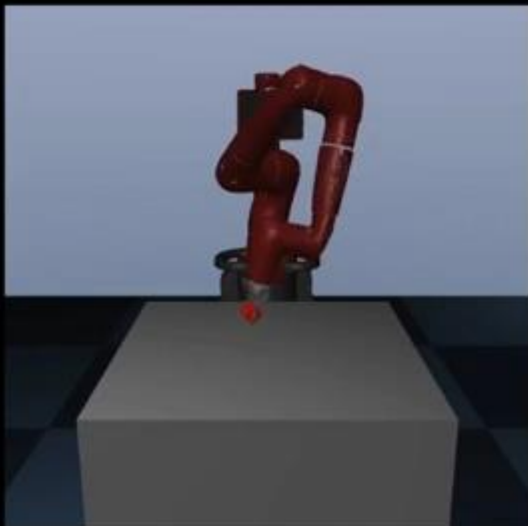
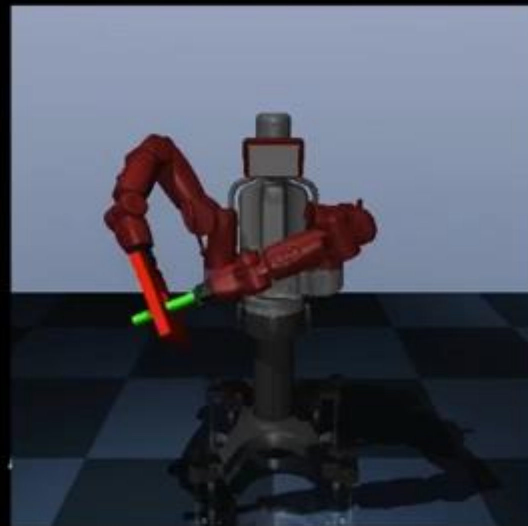


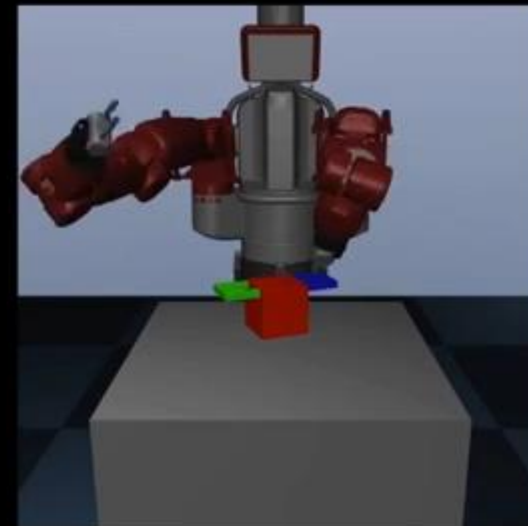
Surreal Robotics Suite Tasks: Surreal-PPO Agents



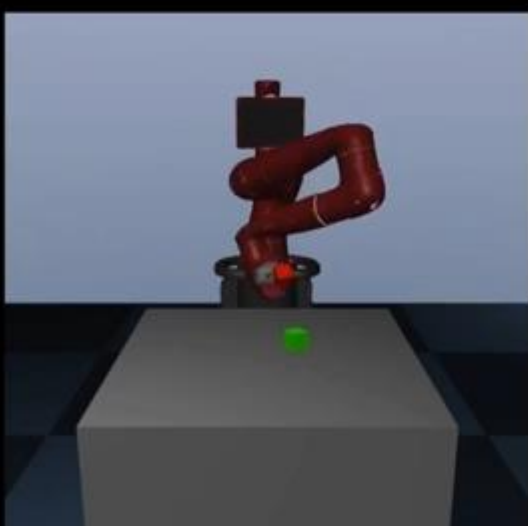
Block Lifting



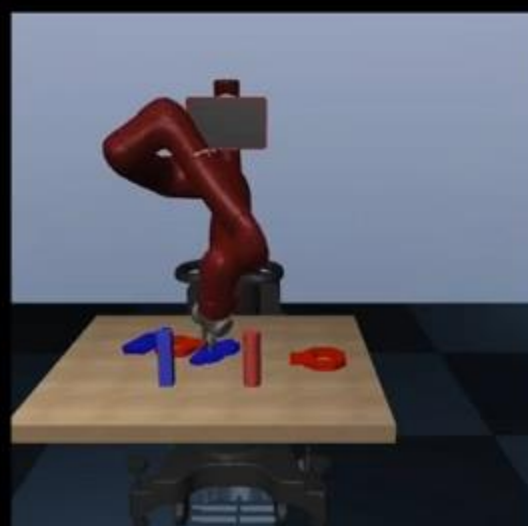
Bimanual Peg-in-Hole



Bimanual Lifting



Block Stacking



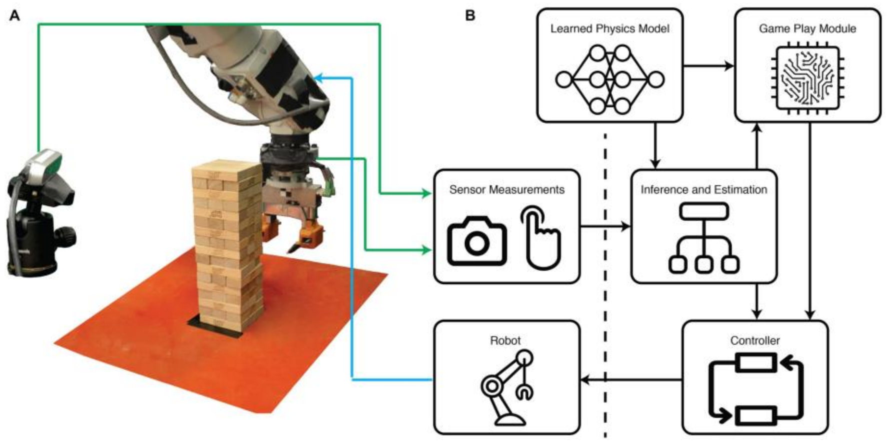
Nut-and-Peg Assembly

Bin Picking

https://surreal.stanford.edu

See, feel, act: Hierarchical learning for complex manipulation skills with multisensory fusion

By N. Fazeli, M. Oller, J. Wu, Z. Wu, J. B. Tenenbaum, A. Rodriguez



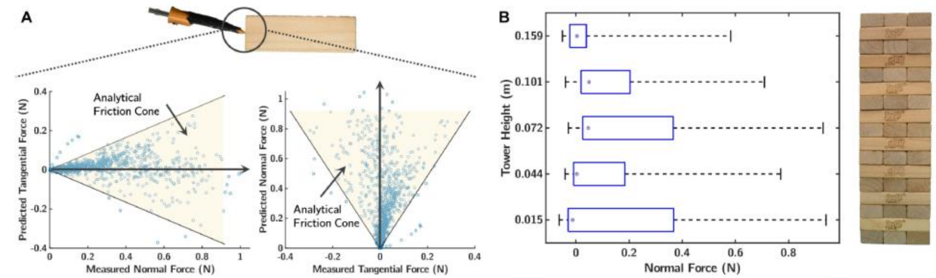


Fig. 4. **Learned intuitive physics.** (A) Overlay of the analytical friction cone and predicted forces given the current measurements. The friction coefficient between the finger material (PLA) and wood is between 0.35 and 0.5; here, we use 0.42 as an approximation. (B) Normal force applied to the tower as a function of the height of the tower. Each box plot depicts the minimum, maximum, median, and standard deviation of the force measures.

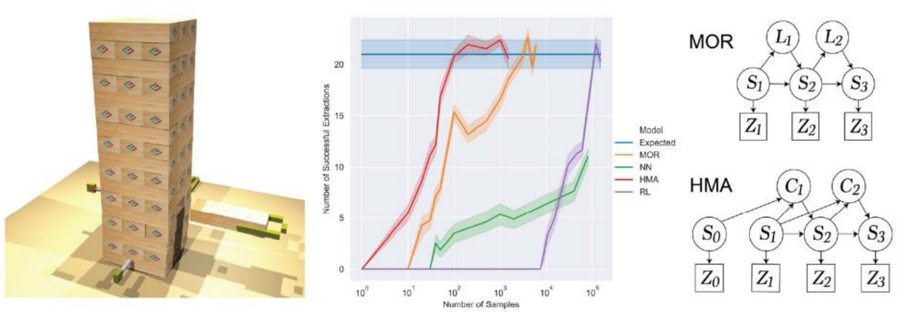
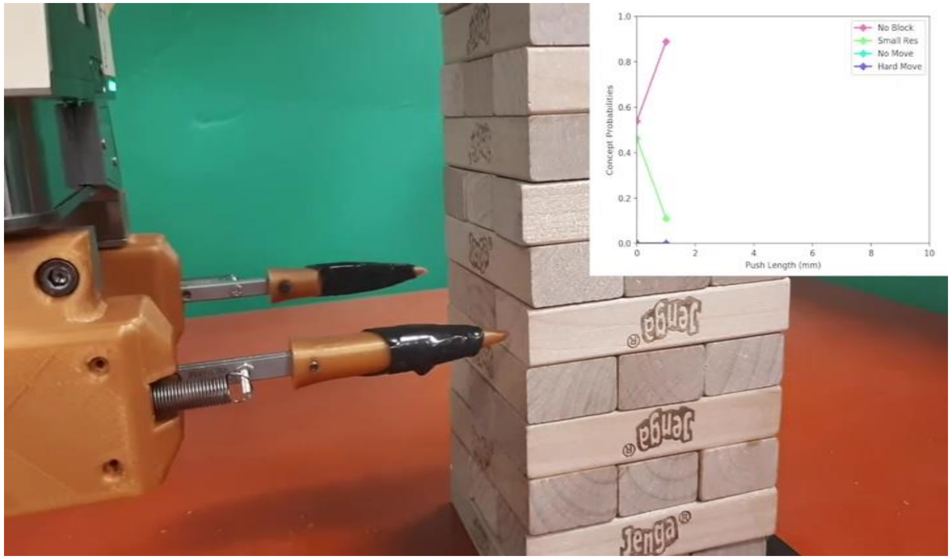


Fig. 2. **Jenga setup in simulation and the baseline comparisons.** (A) The simulation setup is designed to emulate the real-world implementation. (B) Learning curve of the different approaches with confidence intervals evaluated over 10 attempts. Solid lines denote the median performances; shadings denote one standard deviation. (C) Visual depiction of the structure of the MOR and the proposed approach (HMA).



http://robotics.sciencemag.org/content/4/26/eaav3123

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Learning-based Robot Picking

Future Directions

- End-to-End pick learning
- Picker-level sensory integration
- Depth-wise image processing
- On-board real-time computation
- Reproducible and Shareable
- Physical Benchmarking
- Picker-oriented system integration
- …

Scene Segmentation
- What we are going to interact with …

Object Recognition
- Representation & Classification

Pose Estimation
- Object & Picker

Pick Planning
- Picker & Arm

Pick Execution
- MoveIt & PickIt

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Thank you!

Prof. Song Chaoyang

- Dr. Wan Fang (sophie.fwan@hotmail.com)

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