ROS-I Americas

2022 Annual Meeting

The NIST Robotics Program: Agility Performance of Robotic Systems

Presenter:

William Harrison

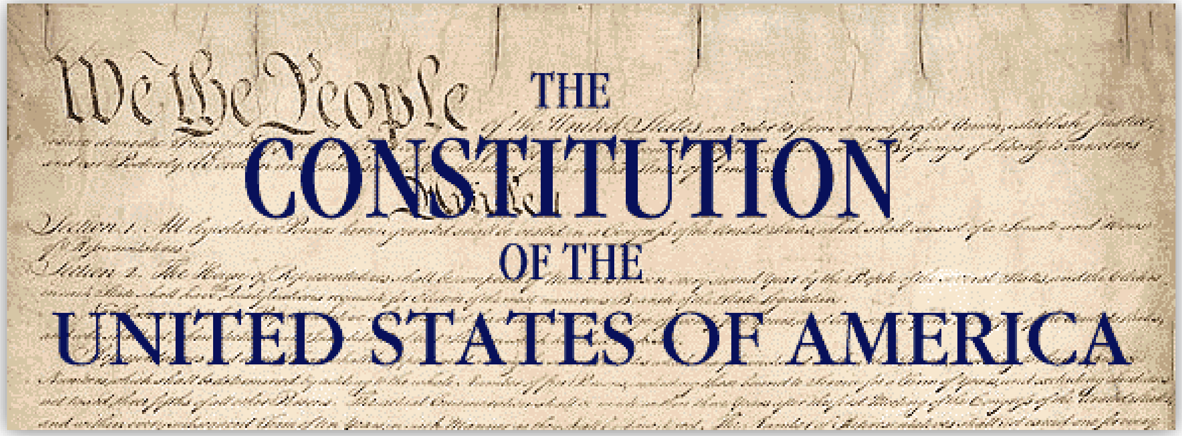
Outline

1. Overview of the NIST Robotics Program
2. The Agility Performance of Robotics Systems Project
3. IEEE Standards Work
4. The Agile Robotics for Industrial Applications Competition
5. AI Webpage
6. Intelligent Environments

The History of Standards

"Uniformity in the currency, weights, and measures of the United States is an object of great importance, and will, I am persuaded, be duly attended to."

George Washington, State of the Union Address, 1790



Article I, Section 8: "The Congress shall have the power to…*fix the standard of weights and measures*"

NIST at a Glance

Gaithersburg, MD

Boulder, CO

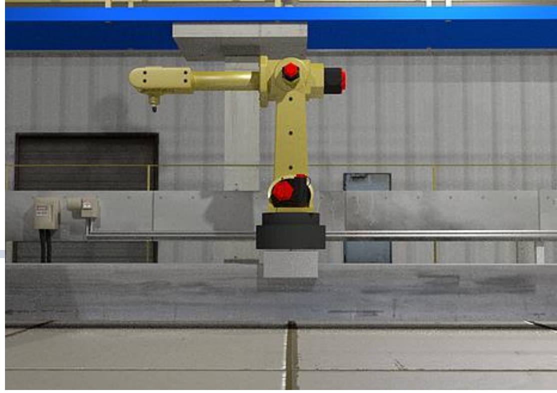
~ 2,900 employees

~ 2,600 associates and facility users

~ 1,600 field staff in partner organizations

~ 400 NIST staff serving on 1,000 national and international standards committees

What is Agility?



- Identify and recover from failures automatically
- Automated planning, minimizing robot programming, and reprogramming time
- Automated sensing within a fixtureless environment
- Swapping between robots of different manufacturers with minimal reprogramming time

IEEE Standards Work

IEEE SA
STANDARDS ASSOCIATION

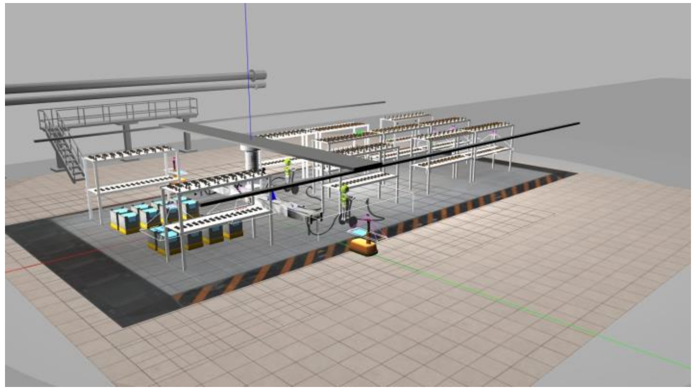
Anthony Downs

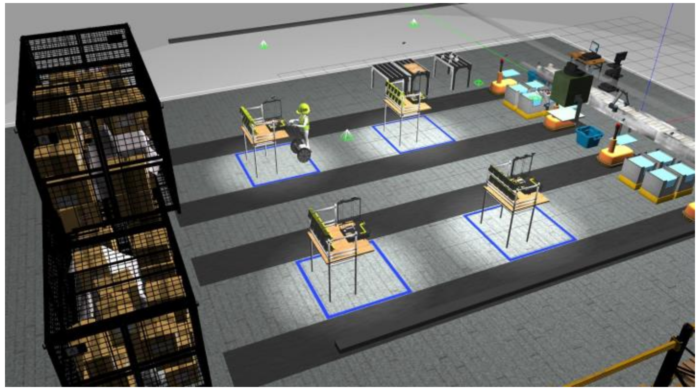
- Working as part of Working and Study Groups within the IEEE Standards Association Robotics and Automation Society

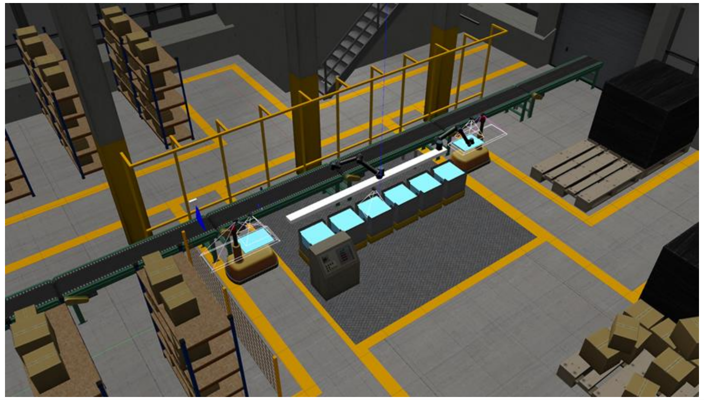
- Developed the Core Ontology for Robotics and Automation (CORA), a upper level standard ontology containing general concepts and axioms of the robotics & automation domain.
  - Designed to be extended by more specific ontologies as mid level and low level ontologies, like task representation or autonomous robots
  - IEEE 1872-2015

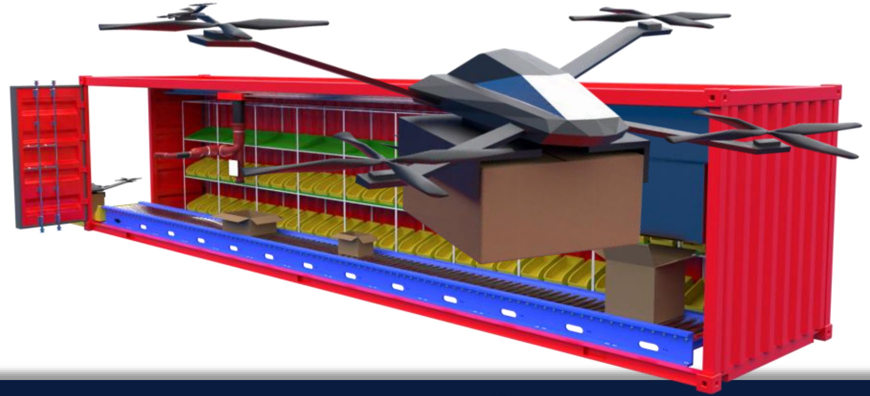
Agile Robotics for Industrial Automation Competition (ARIAC)

- 6th year running this year (5th year as a prize competition awarding $17,500 to top three eligible competitors)



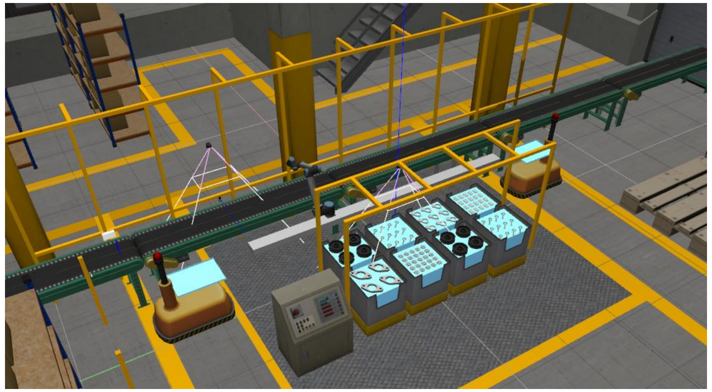


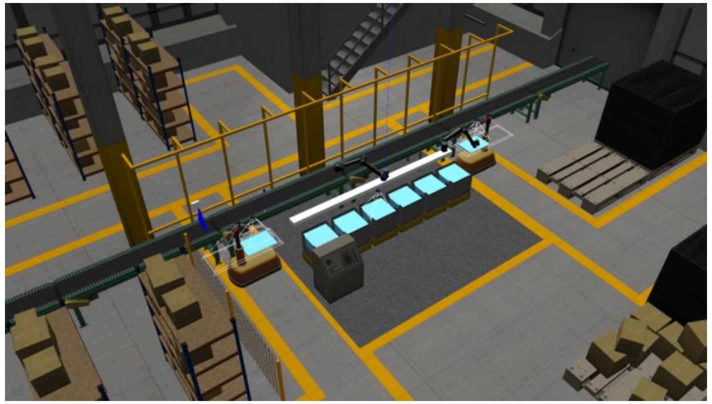




ARIAC

- Previous themes of the competition
  - Kitting for a piston / gear assembly in a factory
  - Package preparation for drone delivery
  - Multiple robot on a single rail with kitting task
  - Gantry robot and human obstacles
  - Kitting and full assembly of a ventilator with a gantry and rail-mounted robot with human obstacles





AI for Manufacturing Robotics Web Page

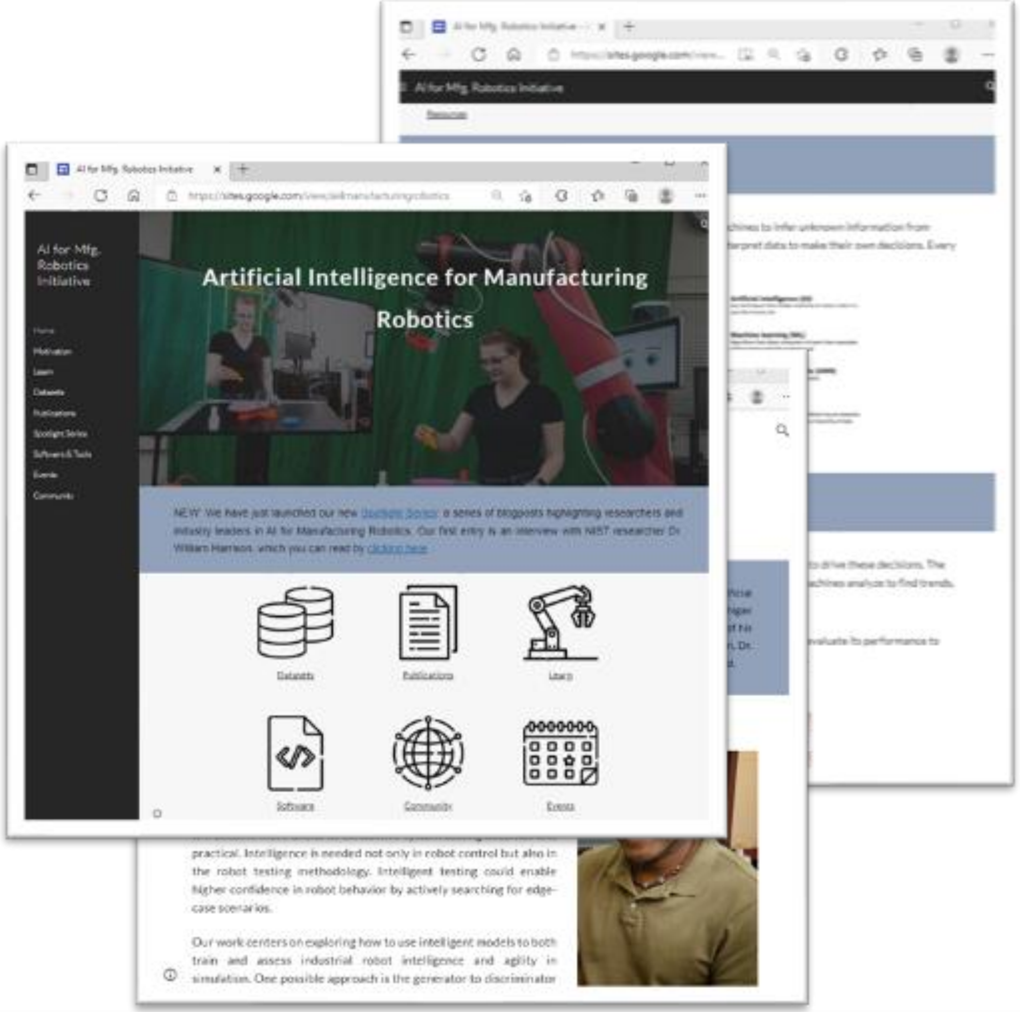
Pavel Piliptchak

Goal:

To create a central hub for the AI for Manufacturing Robotics research community

Website Content:

- A Curated selection of relevant papers and datasets
- Regular posts and updates on emerging technologies, research efforts, and workshops
- Educational resources spanning AI, Robotics and Manufacturing
- Community discussions via website Slack channel

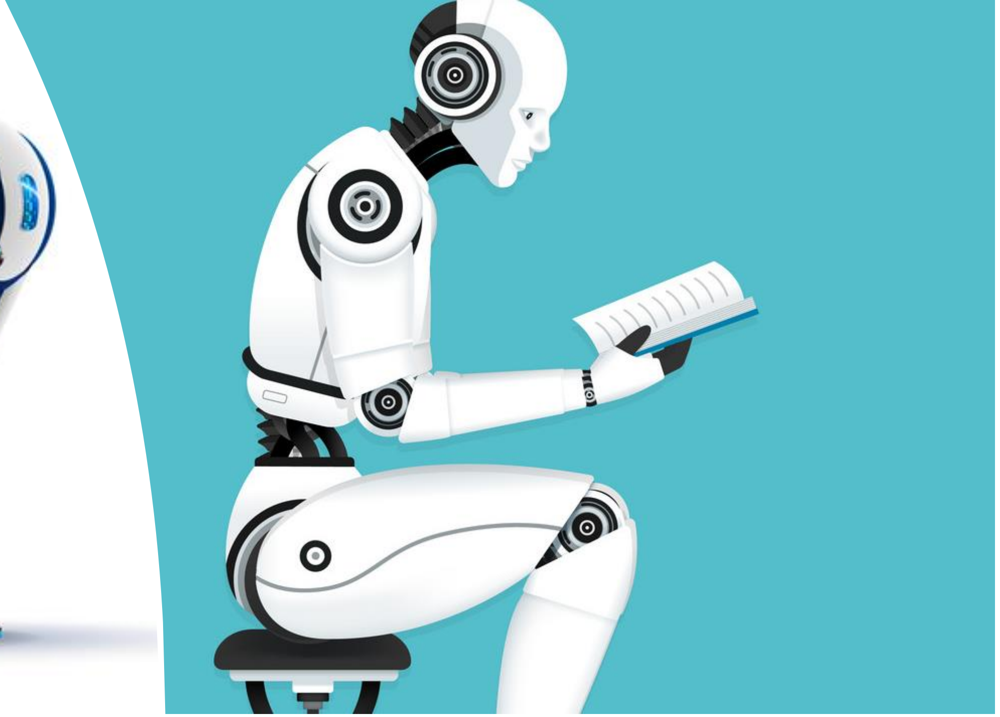


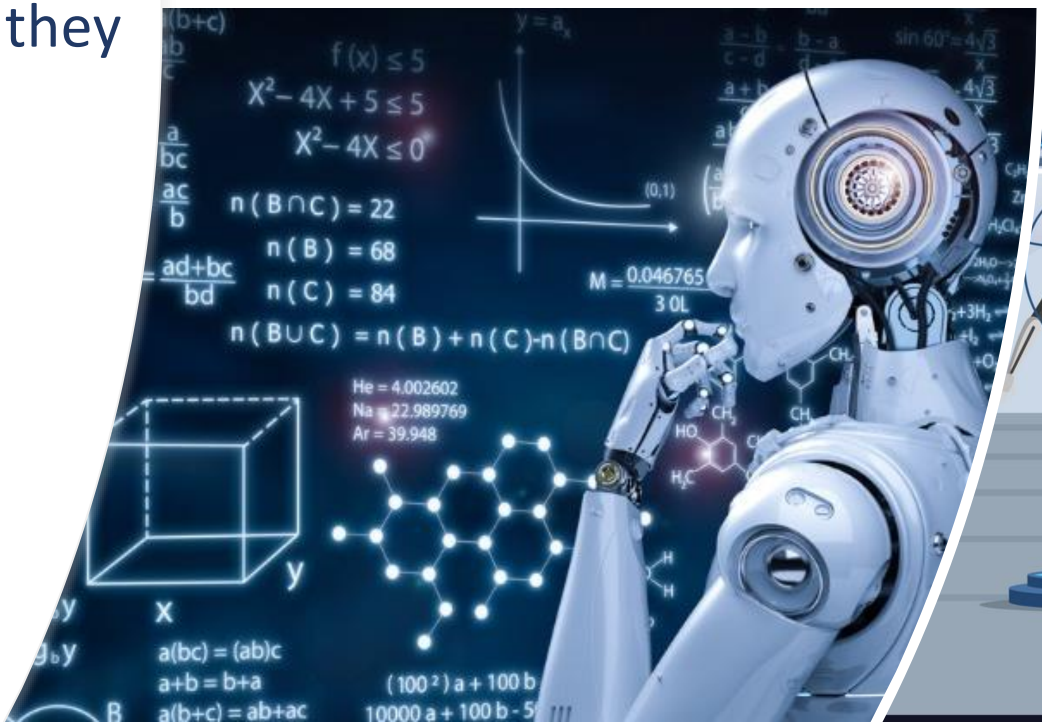
https://sites.google.com/view/ai4manufacturingrobotics/

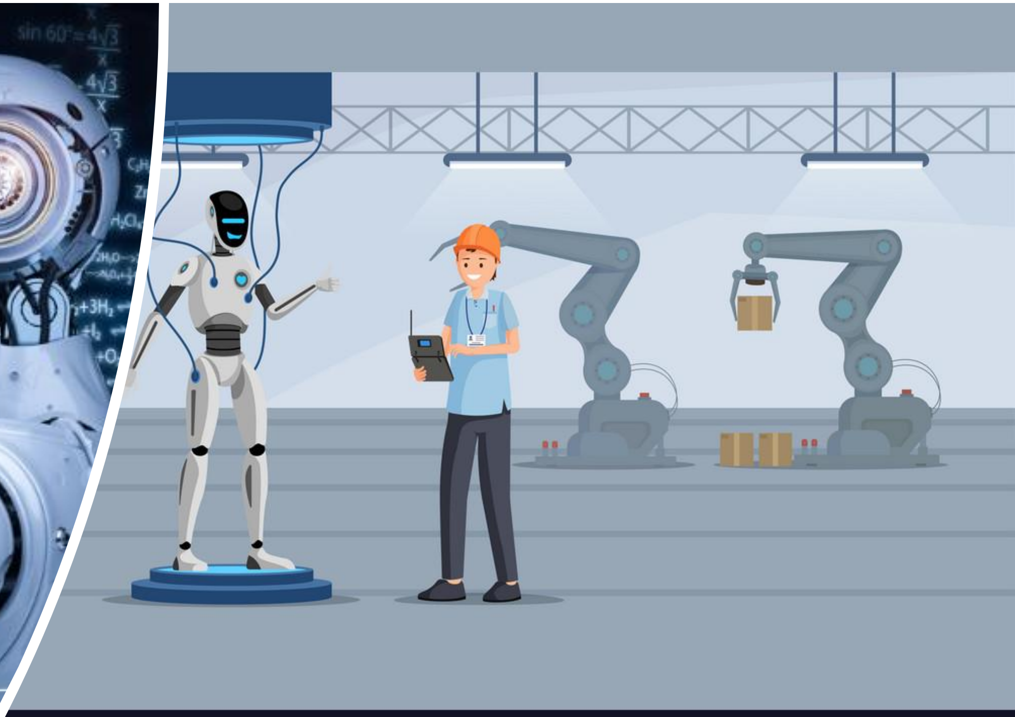
Tomorrow's Industrial Robots

How do we

- Validate them
  - Understand what they understand
- Train them
- Measure their intelligence

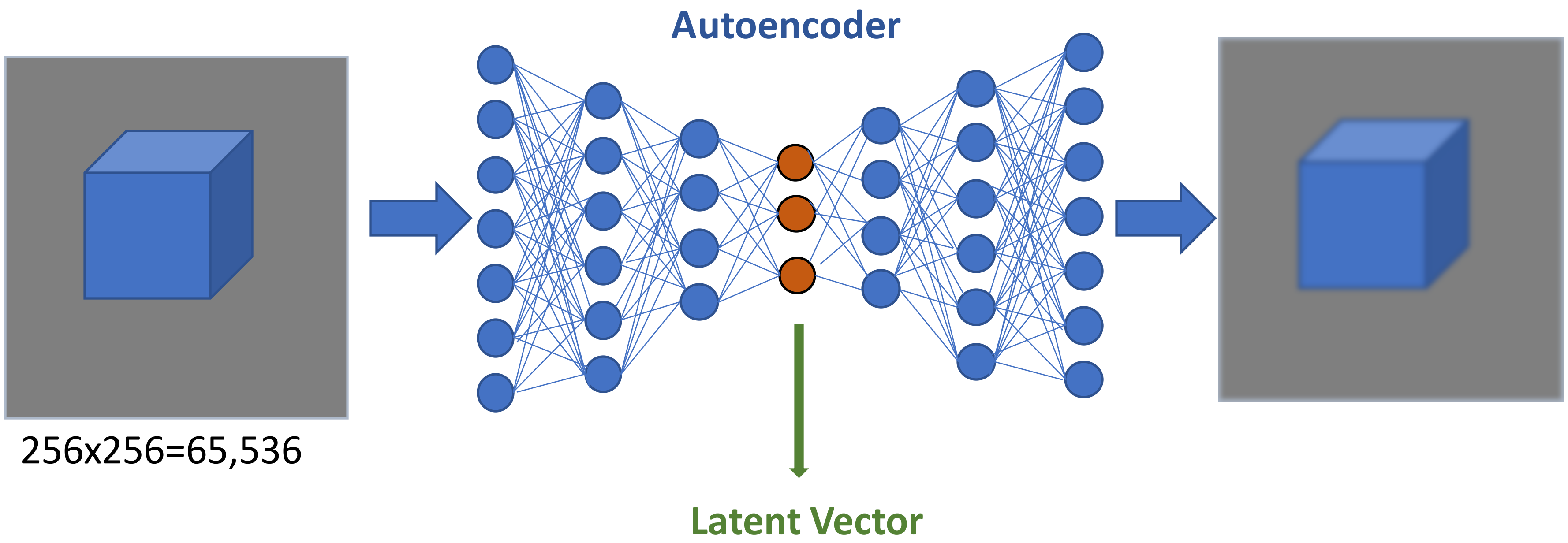






Measuring/Understanding a robot model

- Test case: Autoencoder perception system



Augmented Autoencoders: Implicit 3D Orientation Learning for 6D Object Detection 7

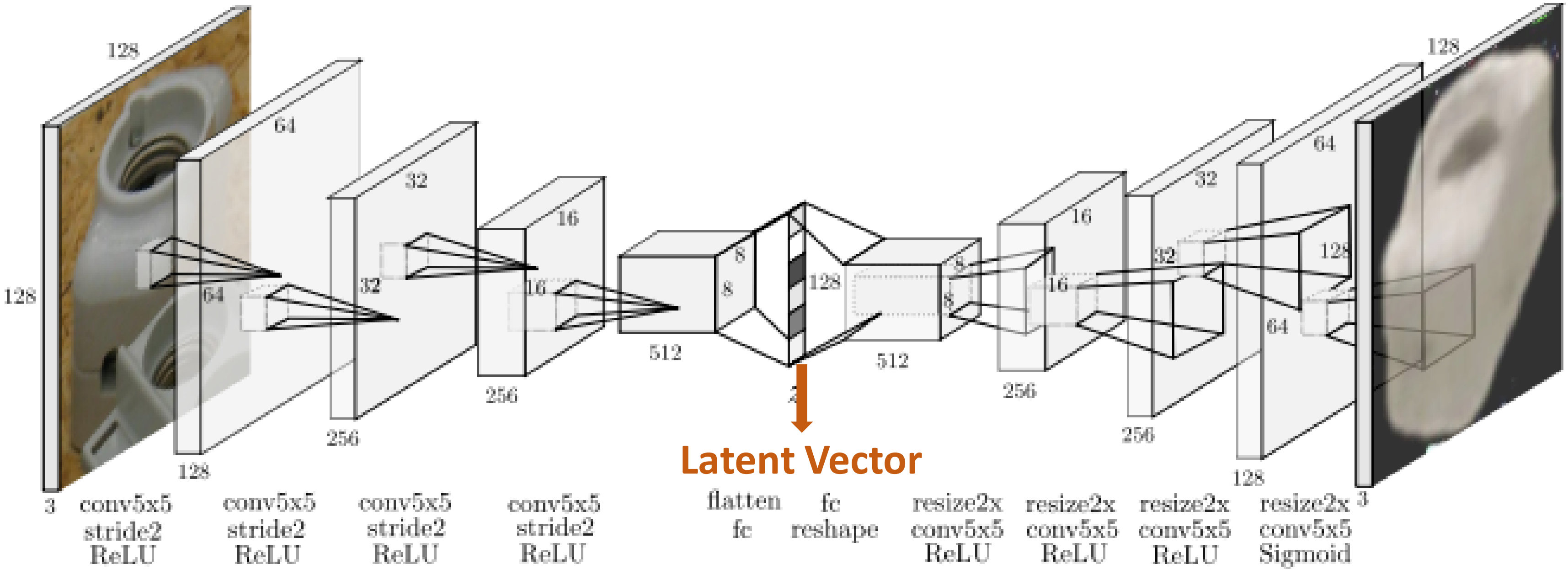


Fig. 5: Autoencoder CNN architecture with occluded test input, "resize2x" depicts nearest-neighbor upsampling

Sundermeyer, Martin, et al. "Augmented autoencoders: Implicit 3d orientation learning for 6d object detection. " *International Journal of Computer Vision* 128.3 (2020): 714-729.

Latent Space Geneation

6 Martin Sundermeyer[1] et al.

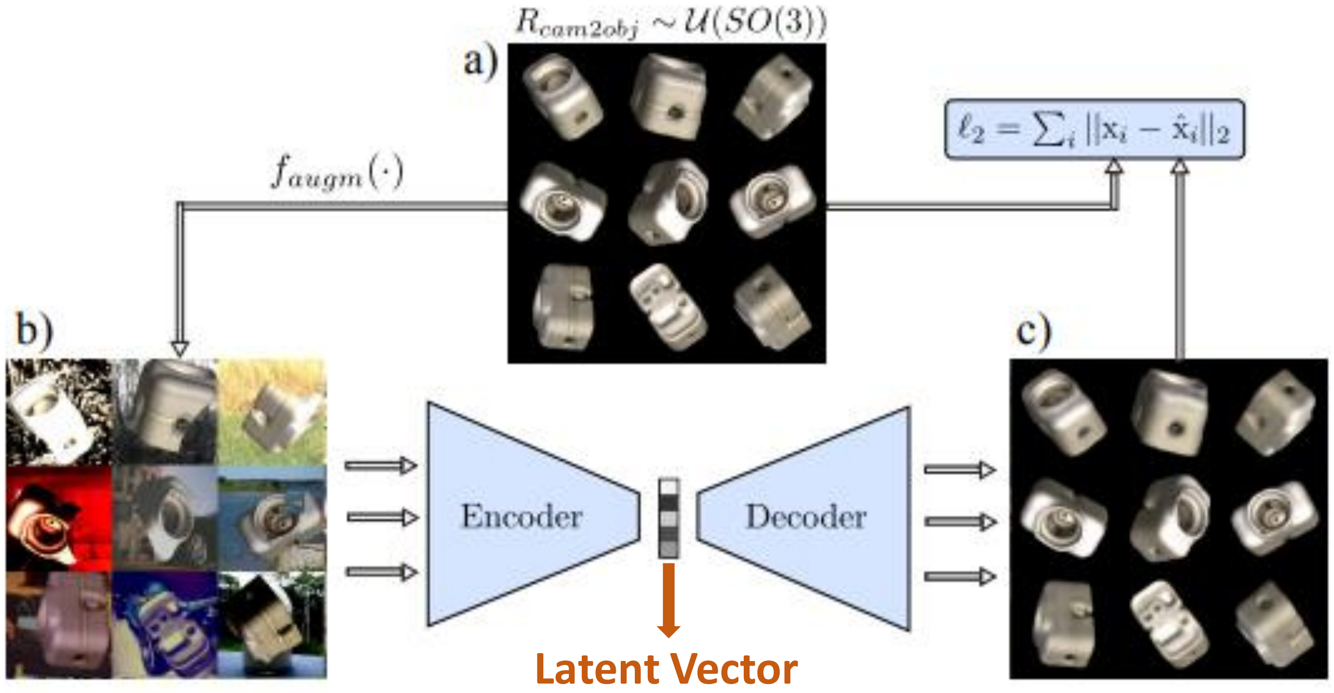
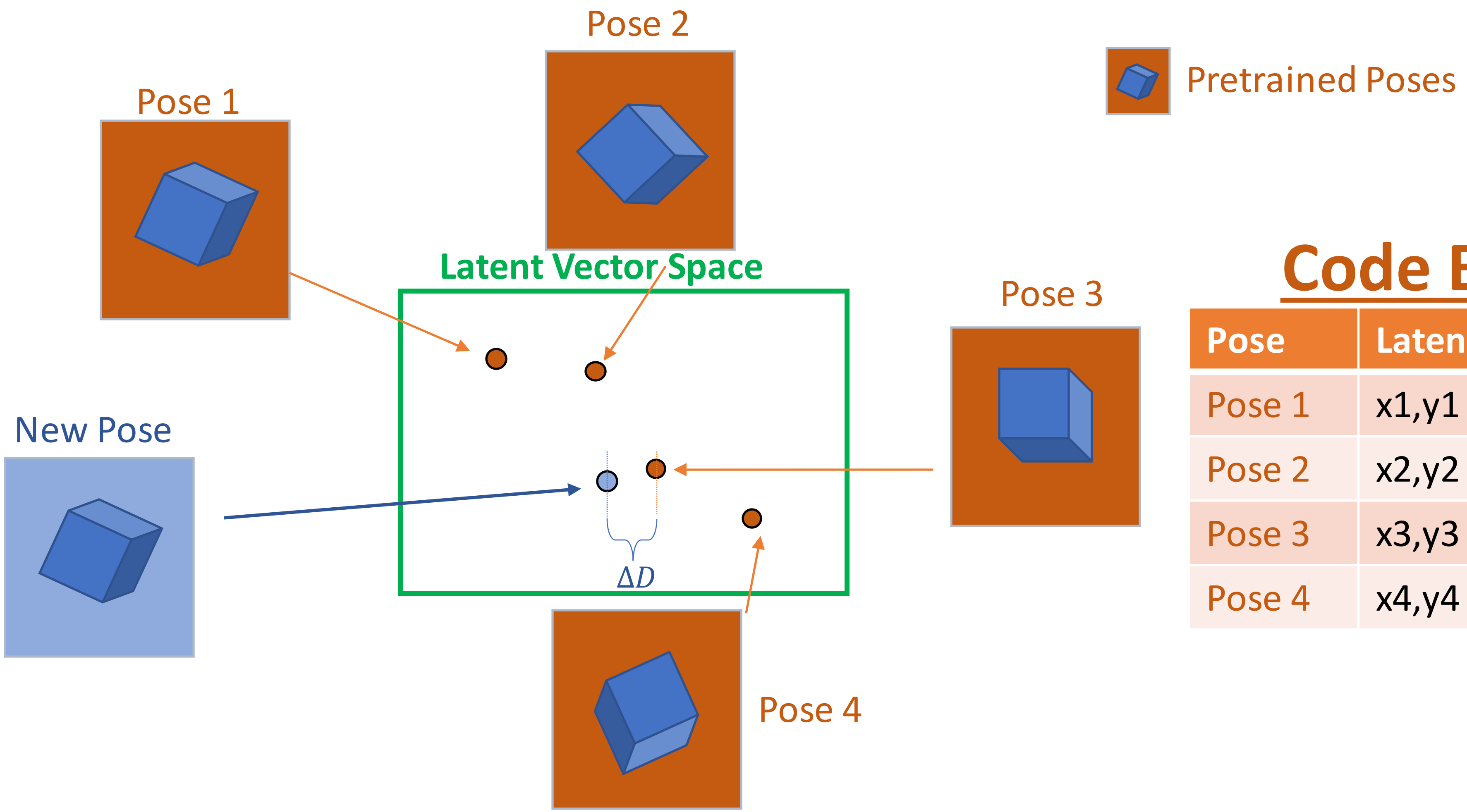


Fig. 4: Training process for the AAE; a) reconstruction target batch $\boldsymbol{x}$ of uniformly sampled SO(3) object views; b) geometric and color augmented input; c) reconstruction $\hat{\boldsymbol{x}}$ after 40000 iterations

Sundermeyer, Martin, et al. "Augmented autoencoders: Implicit 3d orientation learning for 6d object detection. " *International Journal of Computer Vision* 128.3 (2020): 714-729.

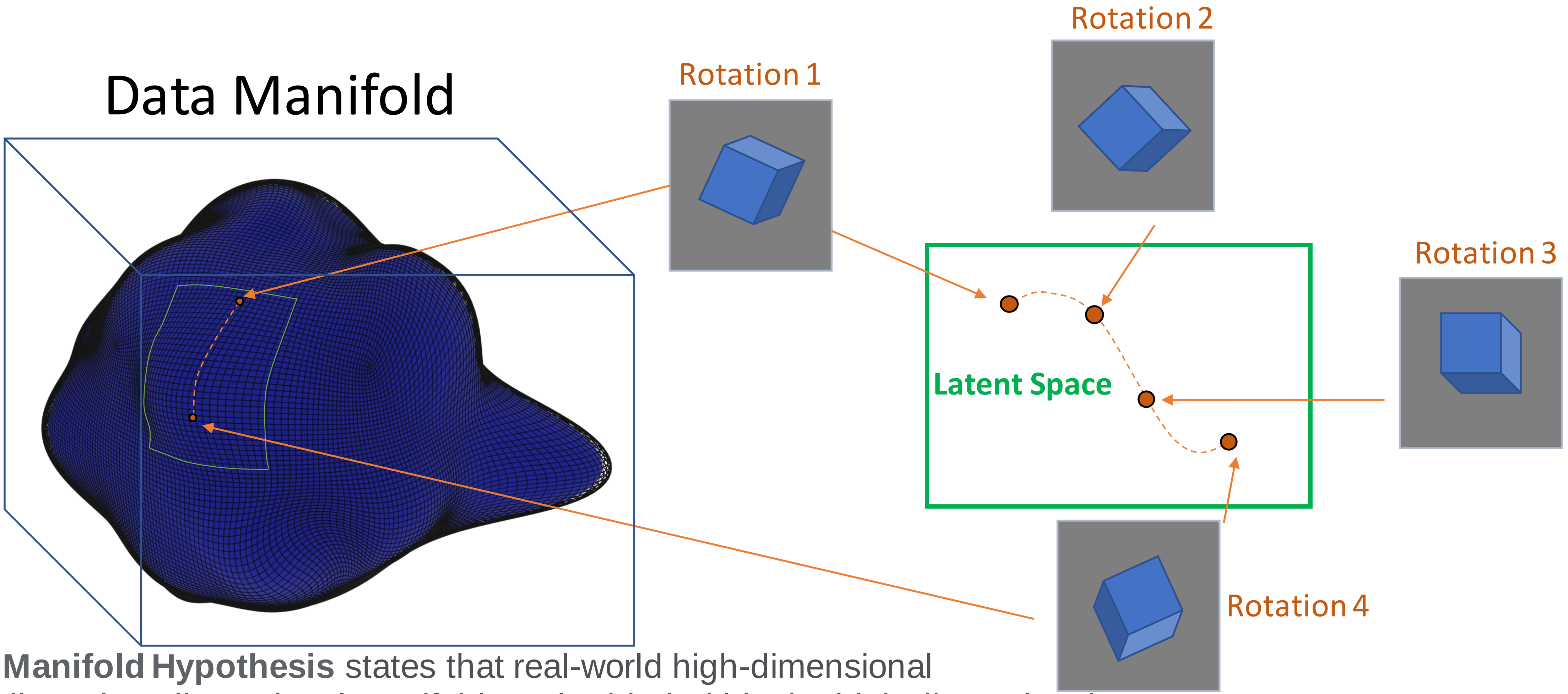
Codebook Pose Estimation



Code Book

Pose	Latent Vector
Pose 1	x1,y1
Pose 2	x2,y2
Pose 3	x3,y3
Pose 4	x4,y4

Abstract Validation: Latent Space Analysis



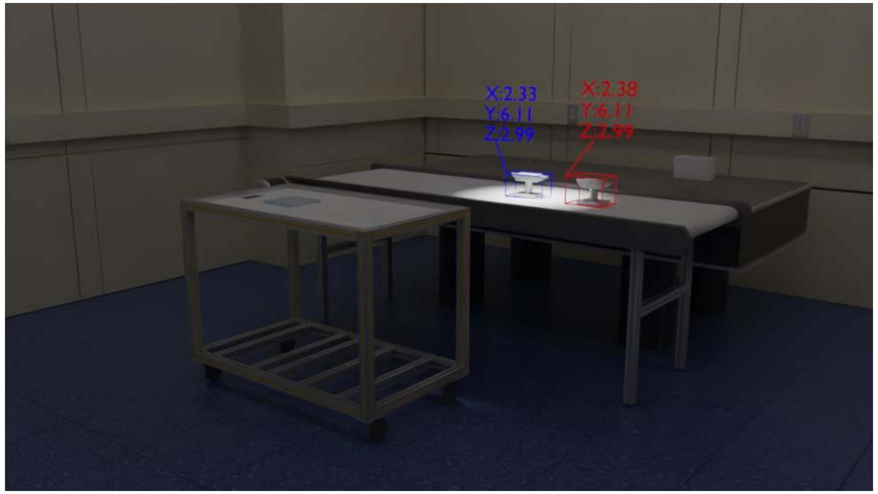
The **Manifold Hypothesis** states that real-world high-dimensional data lie on low-dimensional manifolds embedded within the high-dimensional space.

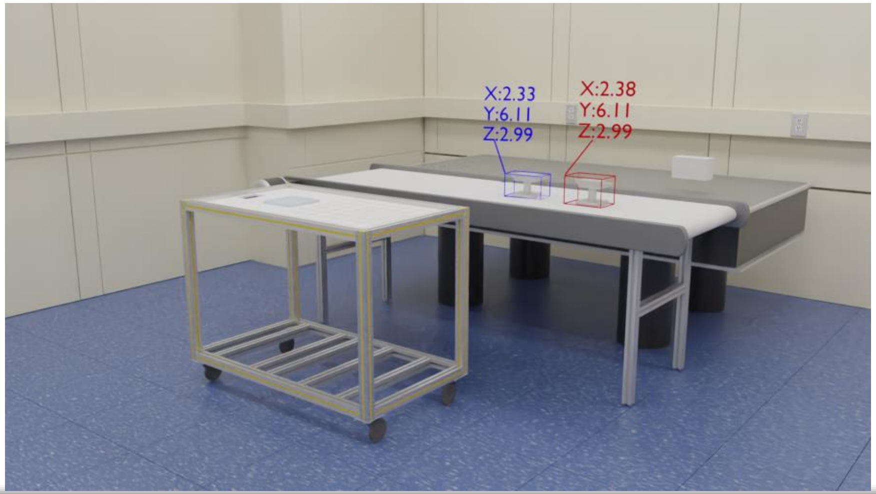
Intelligent Environment

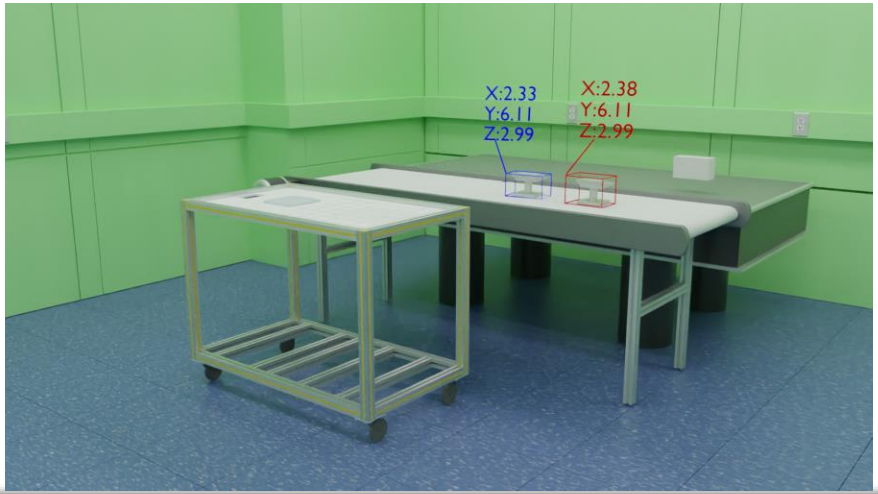
- Using the environment to train and measure robot intelligence and agility
  - Procedural Generation
  - Reinforcement learning
  - Generative Adversarial Networks

Procedural Simulation Environments

- Typical control solutions are sensitive to environmental conditions
- Procedural Environments allow for systematic creation of infinite environments

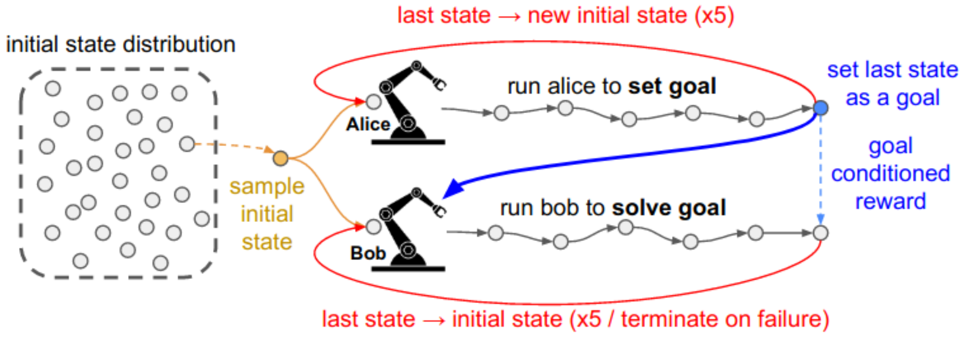




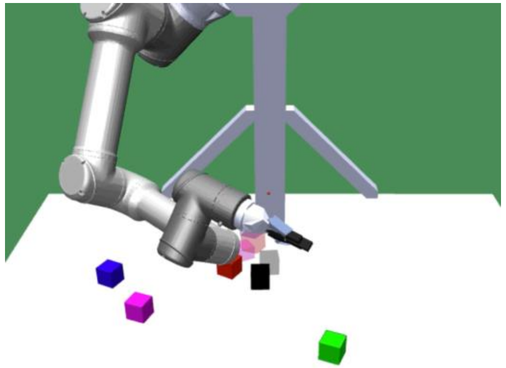


ASYMMETRIC SELF-PLAY

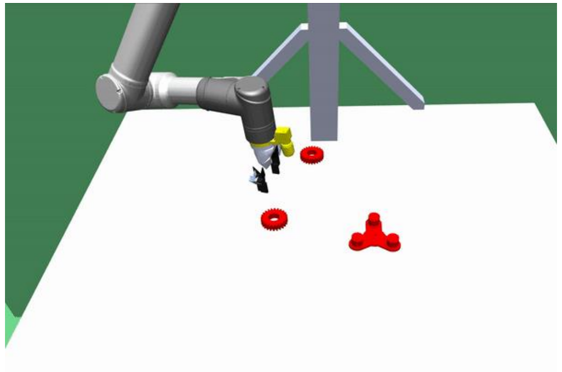
- **Asymmetric Self-Play:**
  - Adversarial multi-agent environment. Two URe16 arms competing, Alice and Bob.
    - **Alice:** learns to generate complex goal distributions for Bob to solve.
    - **Bob:** learns to solve the goals defined by Alice.
  - There is always a solution for the trajectory of Bob to solve the goal set by Alice.
  - Both agents have independent policy neural networks trained with Proximal Policy Optimization (PPO) and Alice Behavioral Cloning



Asymmetric self-play training steps [1]



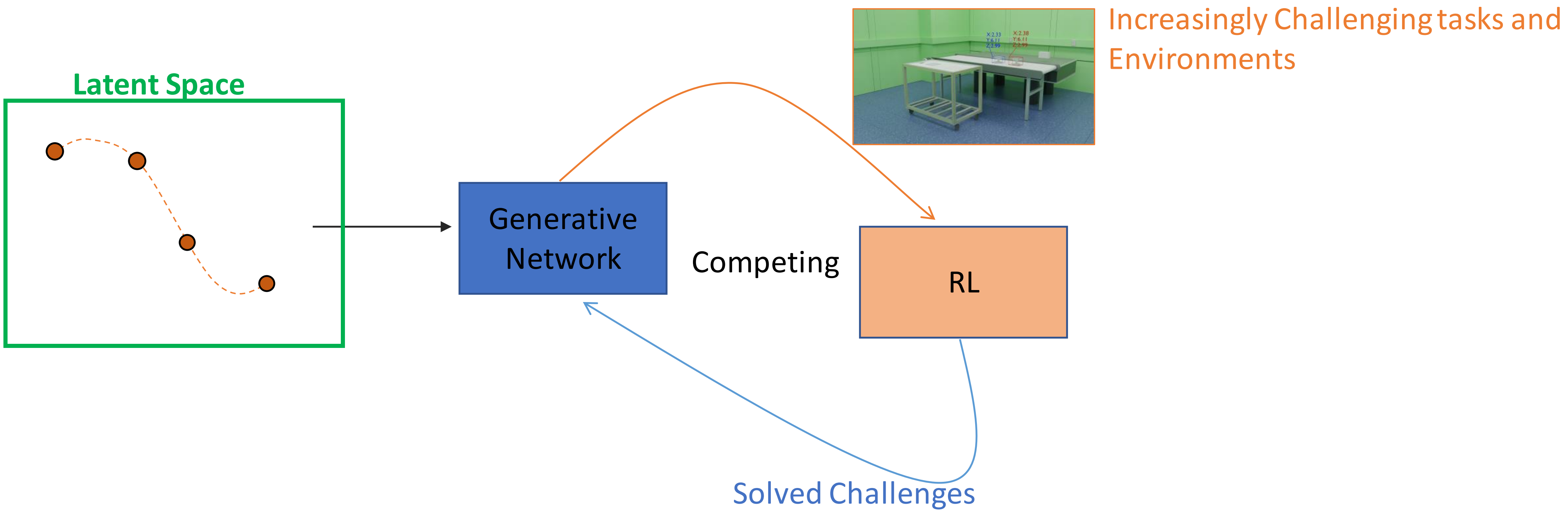
Solving goal in block environment



Manufacturing environment

[1] O. OpenAI κ.ά., 'Asymmetric self-play for automatic goal discovery in robotic manipulation'. arXiv, 2021

Hybrid Adversarial and Reinforcement Learning (RL)



Workshop

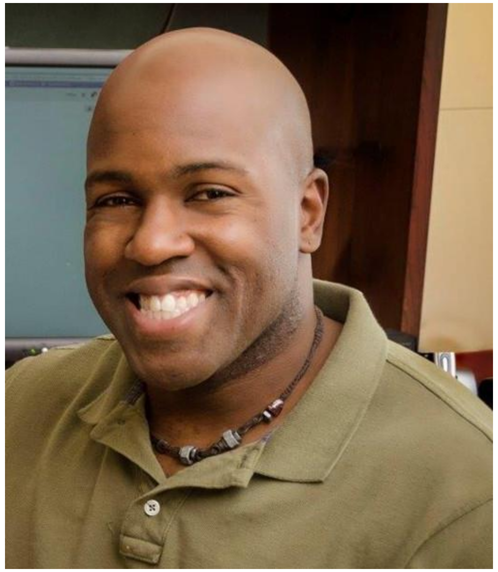
Getting started with Reinforcement Learning for Industrial Robotics

Rodrigo Perez-Vicente

August 29-30, 2022

Thank You

- My email: william.harrison@nist.gov
- AI Webpage: https://sites.google.com/view/ai4manufacturingrobotics/

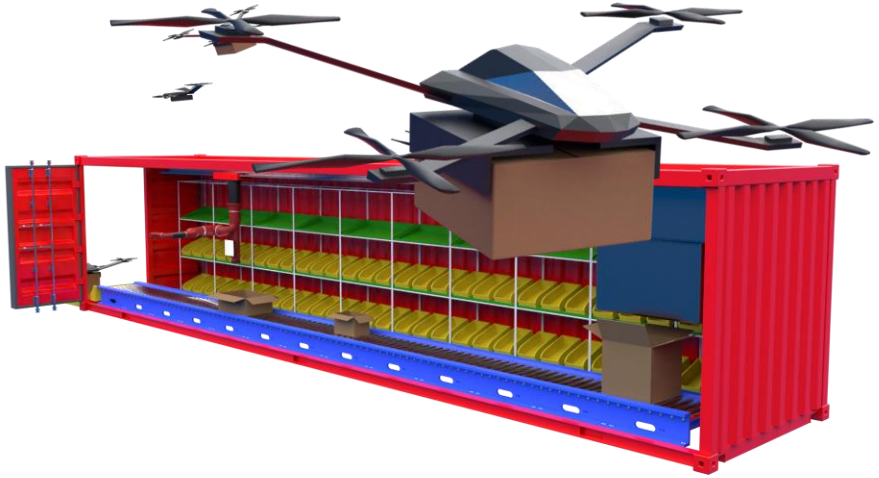


- ARIAC:
  - https://www.nist.gov/ariac
  - https://www.github.com/usnistgov/ariac
- ARIAC Contacts:
  - Project Co-Leader & ARIAC and Standards Lead: anthony.downs@nist.gov
  - ARIAC Lead Developer: zeid.kootbally@nist.gov

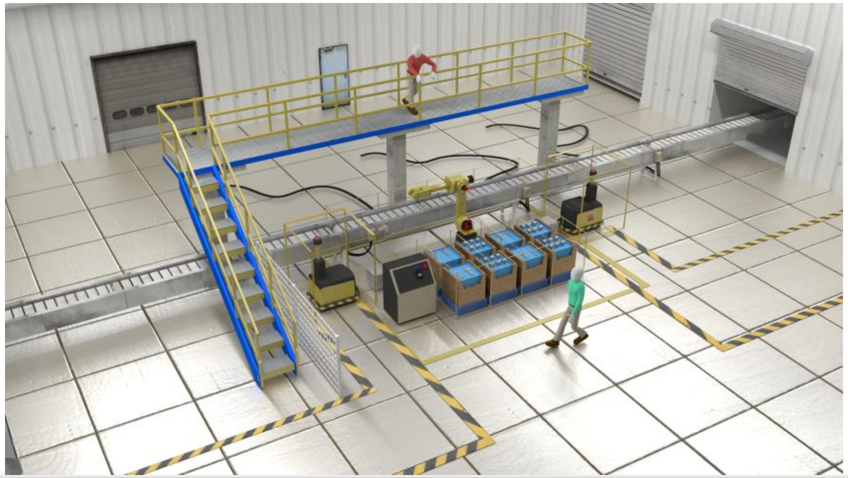
The Far Future of ARIAC: Open World

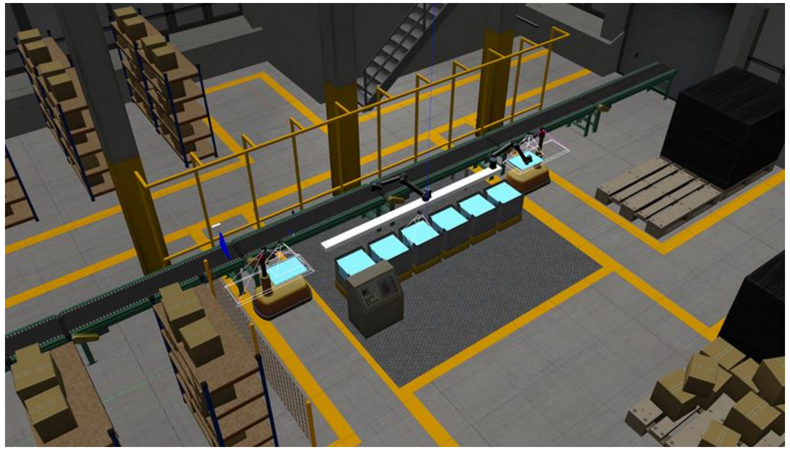
- Free open world environment with system goals and metrics
- Builders create both virtual hardware and virtual software for their robotic systems.
    - This welcomes robot designers and system creators to push the boundaries of their imaginations.

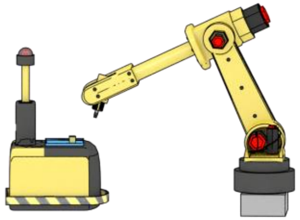
ARIAC: Past to Present



- Single arm single rail
  - Kitting for assembly 2017
  - Kitting for order fulfillment 2018
- Dual arm single rail 2019
- Dual arm dual rail 2020







The Future of ARIAC: Assembly &Agile Disaster Response

- Assembly
  - Provides a real-world robotic function common in industry

- System Changeover: Agile Disaster response manufacturing
  - Process can change over to a related task to support global and national needs for public health and safety

NOVEL TEST GENERATION USING ASYMMETRIC SELF-PLAY

•**Problem statement**: generate novel complex goals in manufacturing tasks (pick and place, assembly, …), for testing agility of industrial robots.

•**Proposal:** leverage reinforcement learning research on asymmetric self-play for robot manipulation. This research was originally done by OpenAI [1]. Manufacturing environments will be added to create the new goal distributions for industrial testing applications.

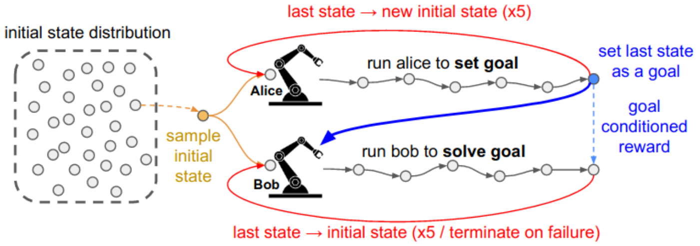
•**Asymmetric Self-Play:**

- •Adversarial multi-agent environment. Two URe16 arms competing, Alice and Bob.
  - •**Alice:** learns to generate complex goal distributions for Bob to solve.
  - •**Bob:** learns to solve the goals defined by Alice.
- •There is always a solution for the trajectory of Bob to solve the goal set by Alice.
- • Both agents have independent policy neural networks trained with Proximal Policy Optimization (PPO) and Alice Behavioral Cloning (Bob will copy some of Alice's trajectories to its experience replay buffer).
- •OpenAI proved to zero-shot generalize to other holdout tasks such as pushing, pick and place or stacking.

•**Tools used for distributed RL training:**

- •**Rllib framework from the Ray library (Anyscale)**
- •**AWS EC2 instances**

[1] O. OpenAI κ.ά., 'Asymmetric self-play for automatic goal discovery in robotic manipulation'. arXiv, 2021



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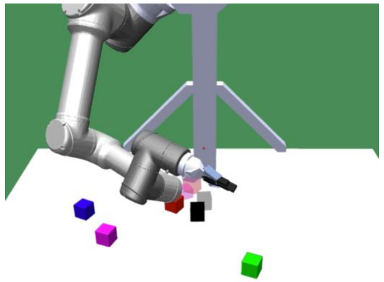

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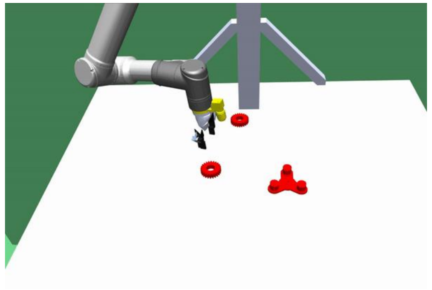

Manufacturing environment