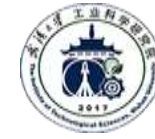




OCTOBER 1 - 5, 2023

IEEE/RSJ International Conference on
Intelligent Robots and Systems



武汉大学 工业科学研究院
The Institute of Technological Sciences, Wuhan University

Robust Robotic Grasping - From Hundreds to Millions

Miao Li

Wuhan University

2023.10.1

Grasping is very useful for many industry applications



Automotive

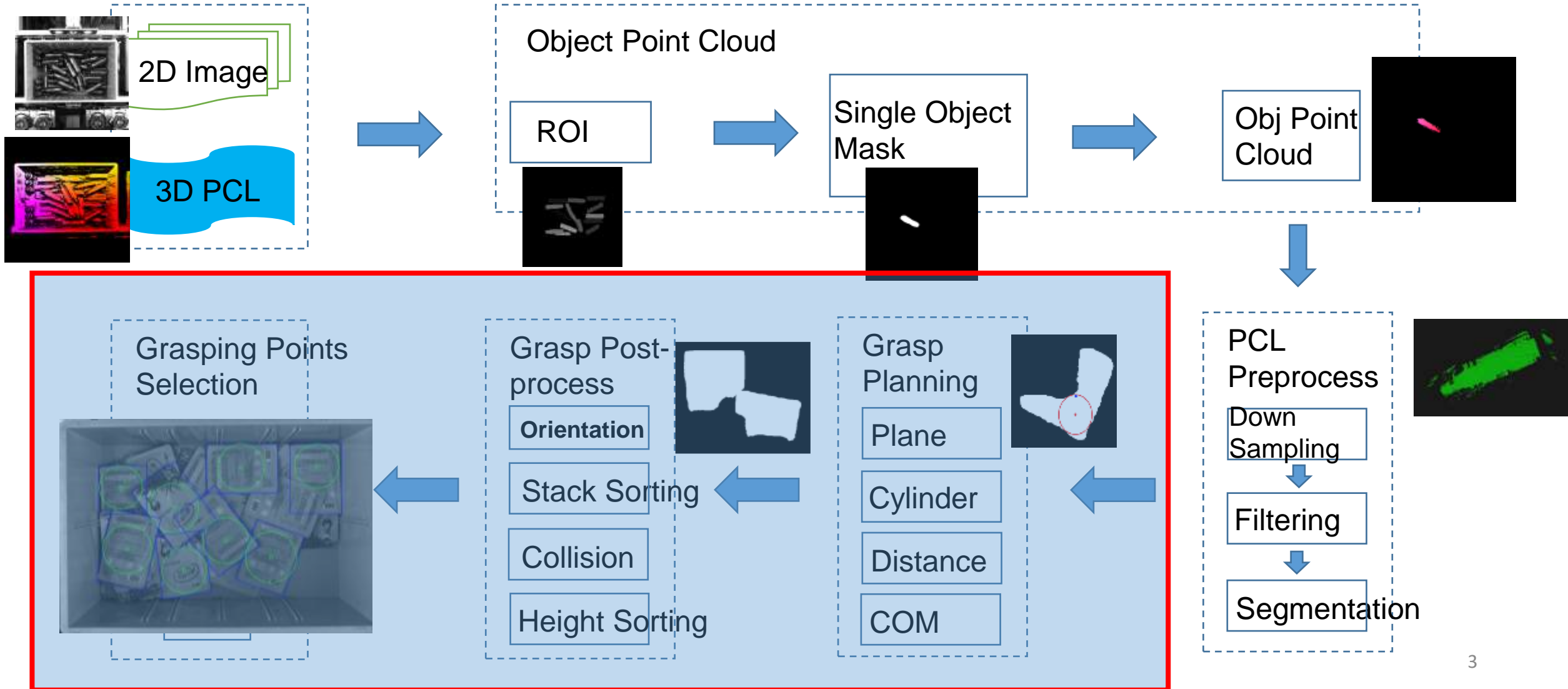


Warehouse

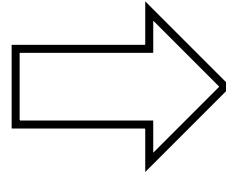


Machining

A general pipeline of robotic grasping

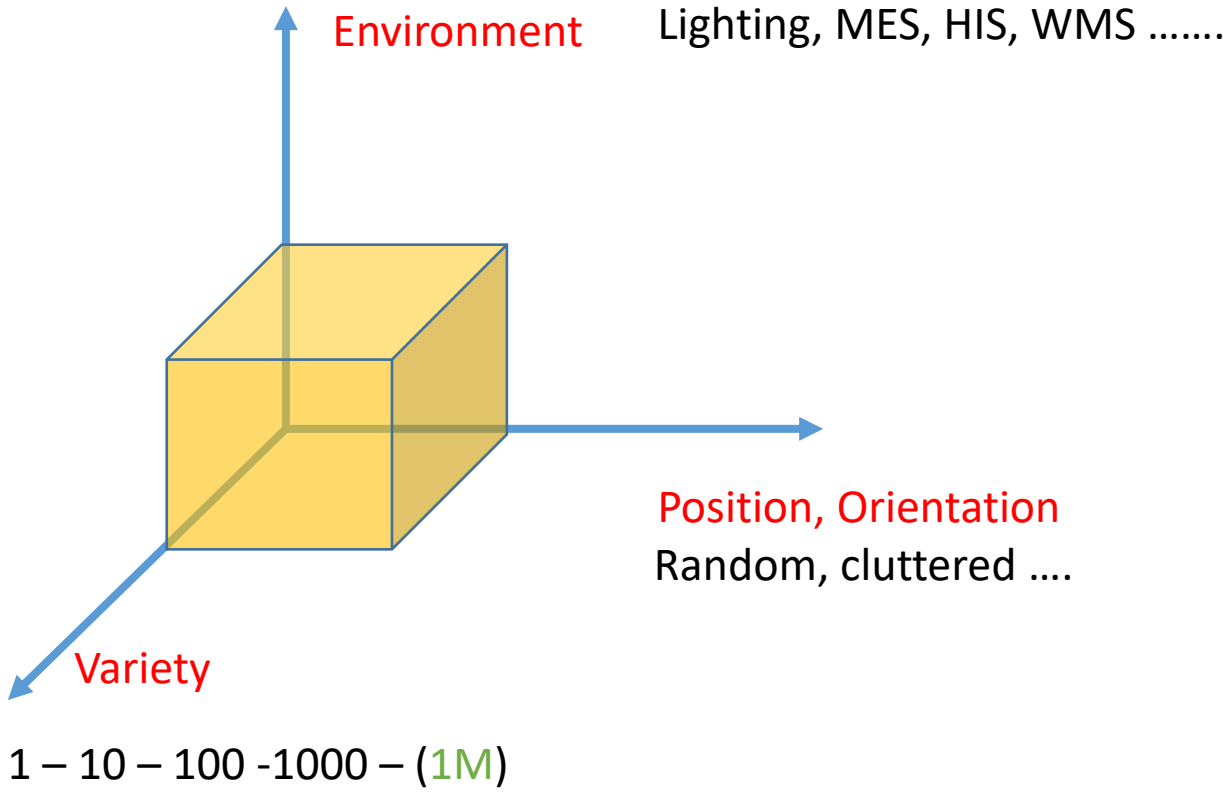


What is missing for grasping?

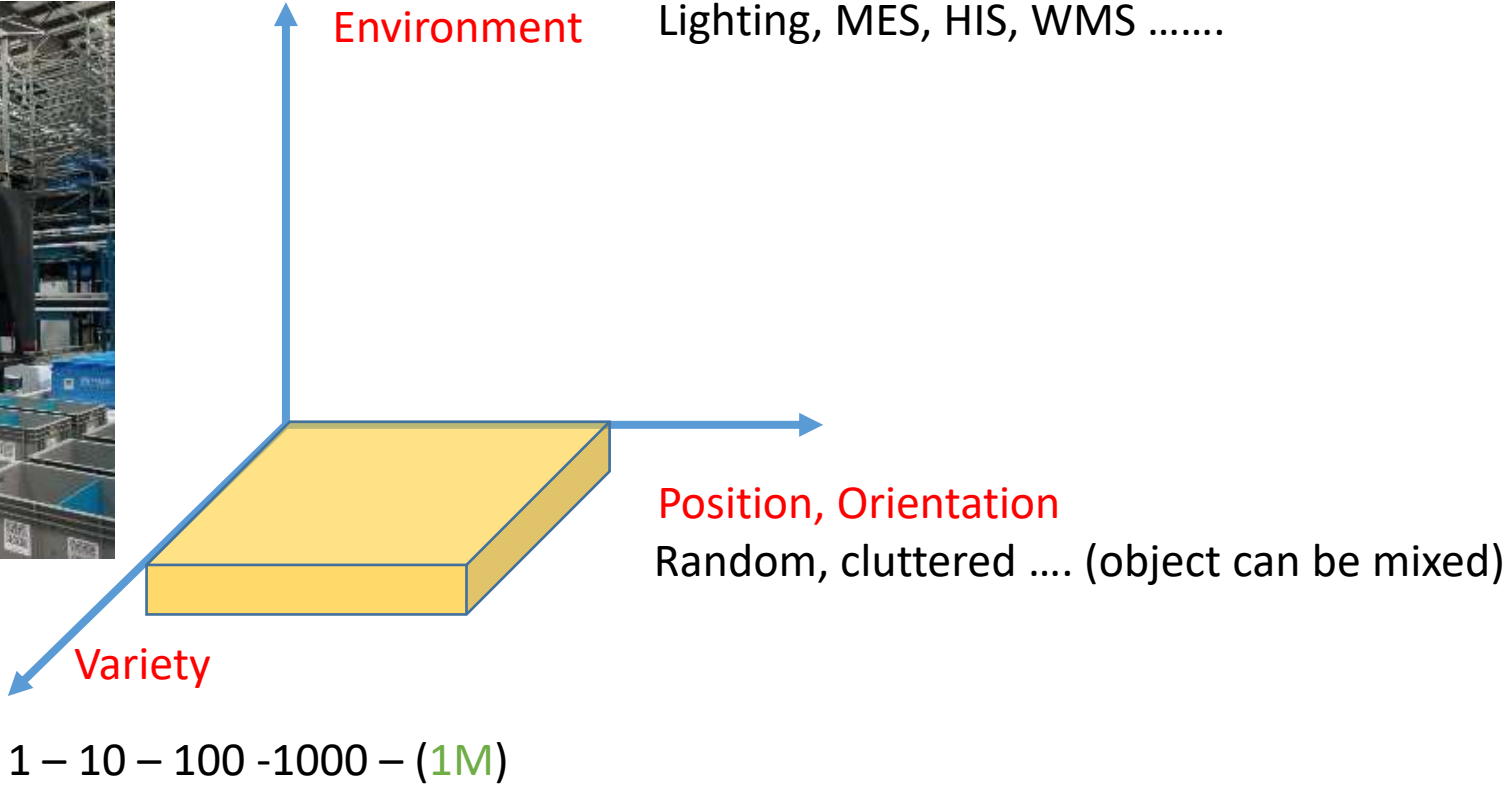


- How about **Millions of Objects**?

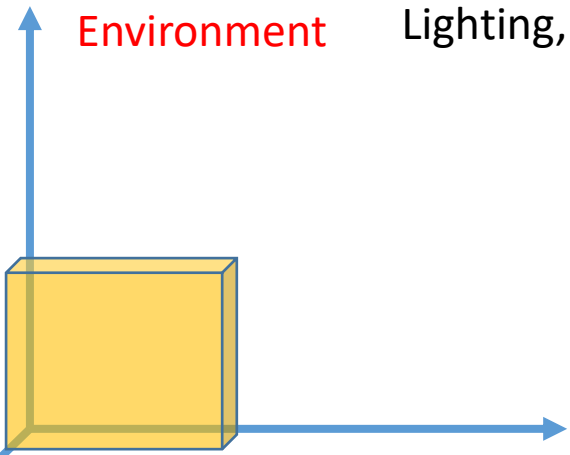
What is the new challenge?



What is the new challenge?



What is the new challenge?



Environment Lighting, MES, HIS, WMS

Position, Orientation
Random, cluttered

Variety

1 - 10 - 100 - 1000 - (1M)



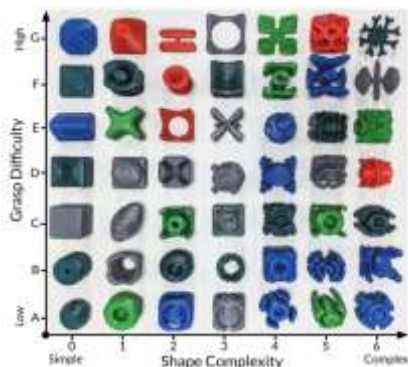
Pipeline for the new challenge

Dataset

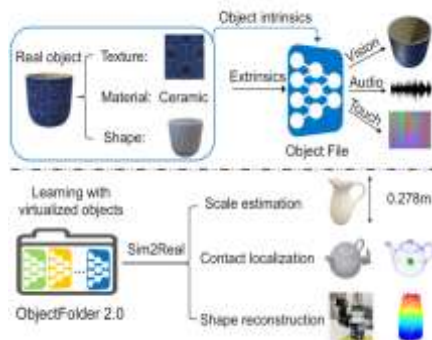
Grasping Datasets



Cornell



EGAD



ObjectFolder

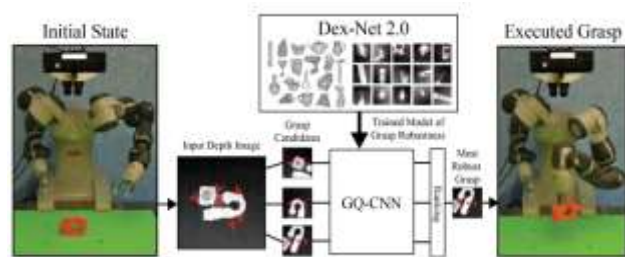


YCB

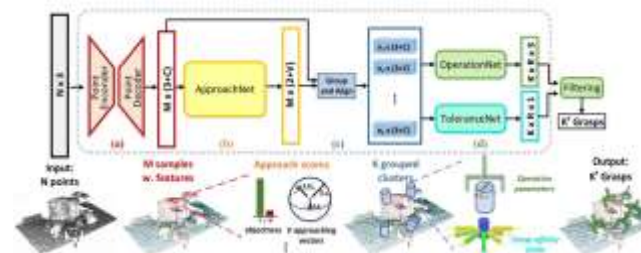


Data-Driven Grasp Planning

Neural Network



DexNet



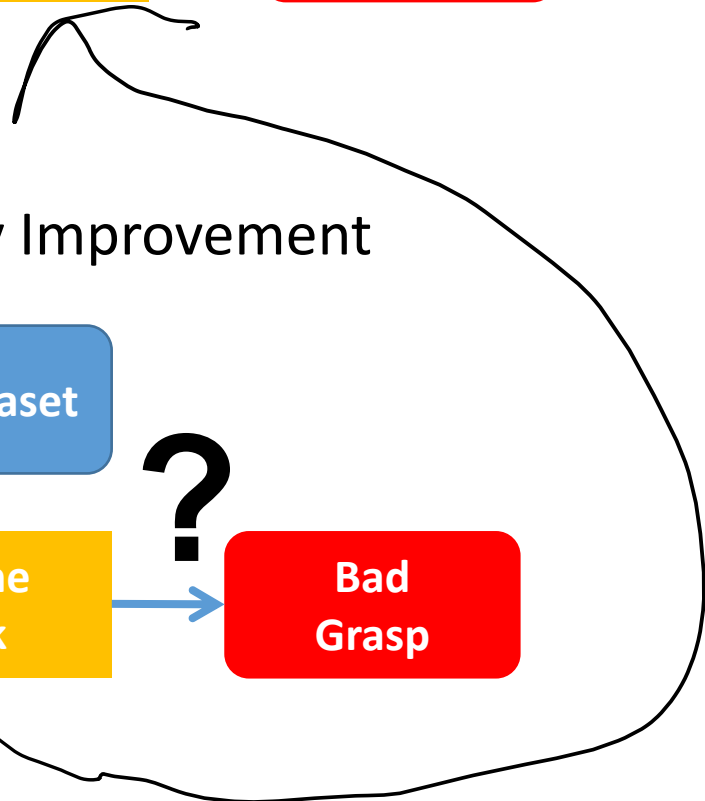
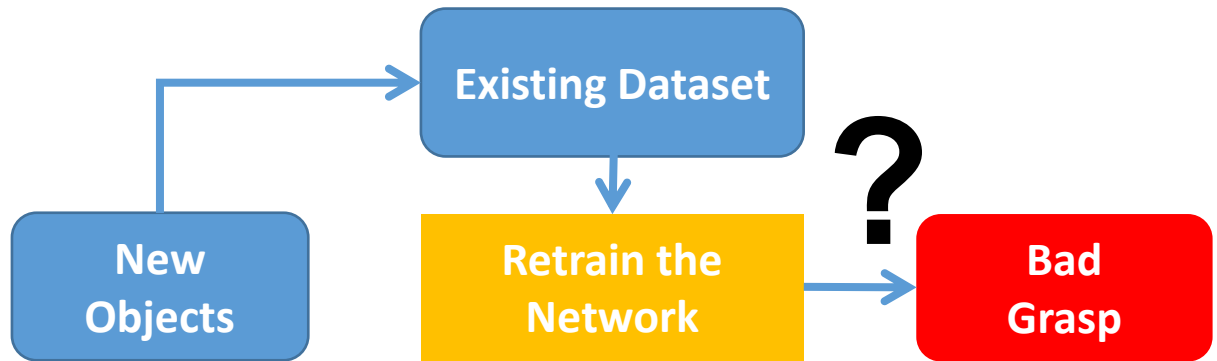
GraspNet-1Billion

What will happen if a grasp fails?



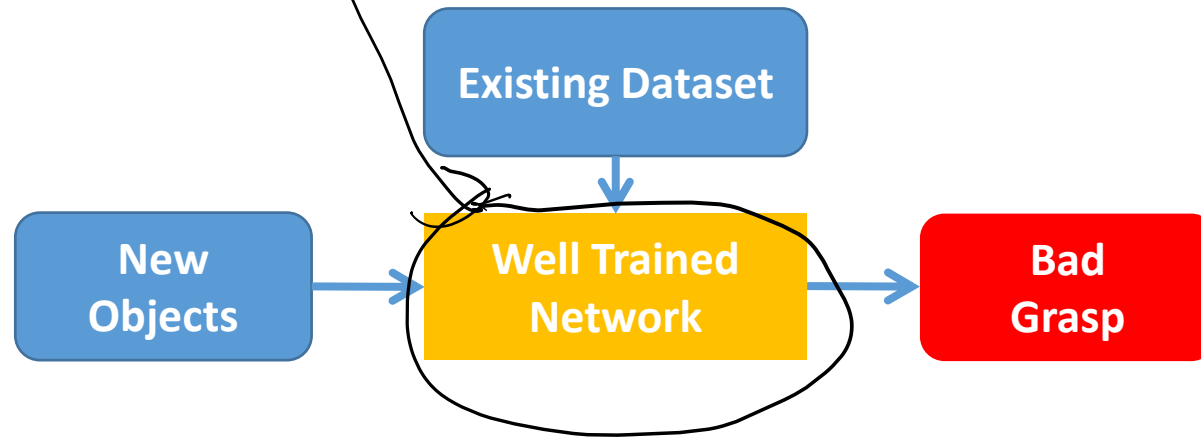
Retrain the model

Grasping Dataset Quality Improvement



What will happen if a grasp fails?

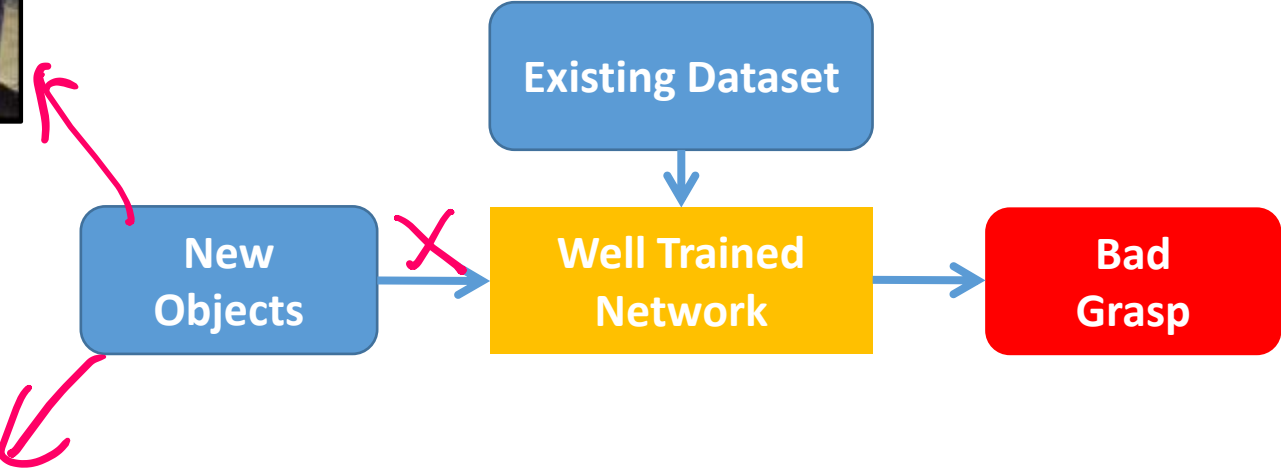
Design new algorithm



What will happen if a grasp fails?

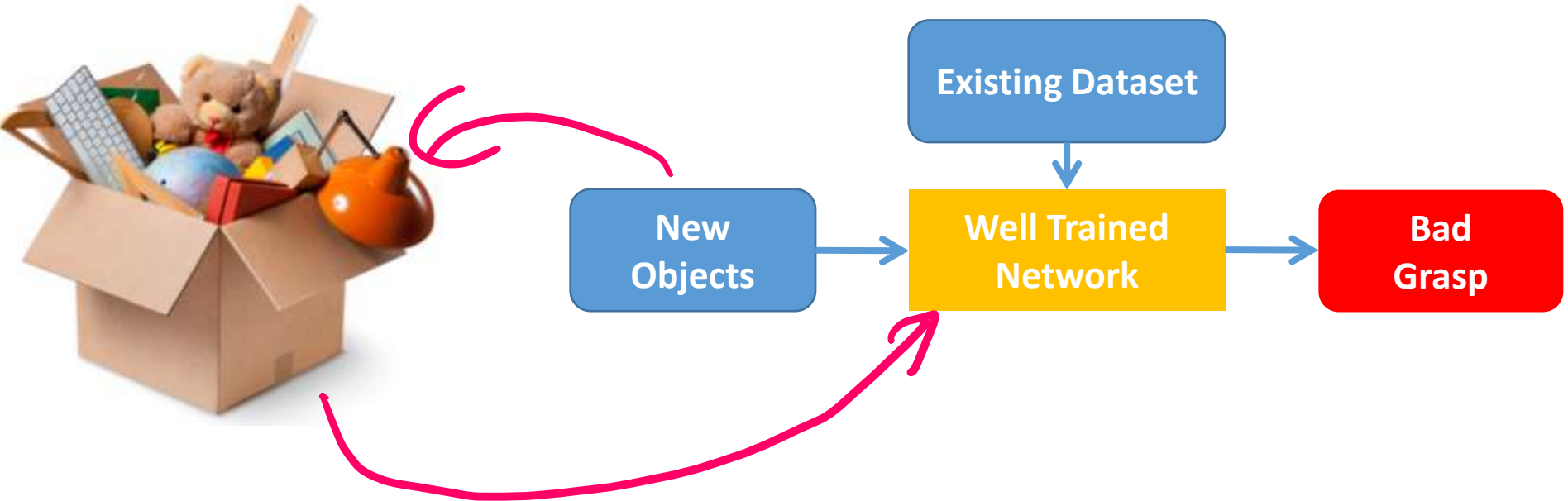


Human in the loop

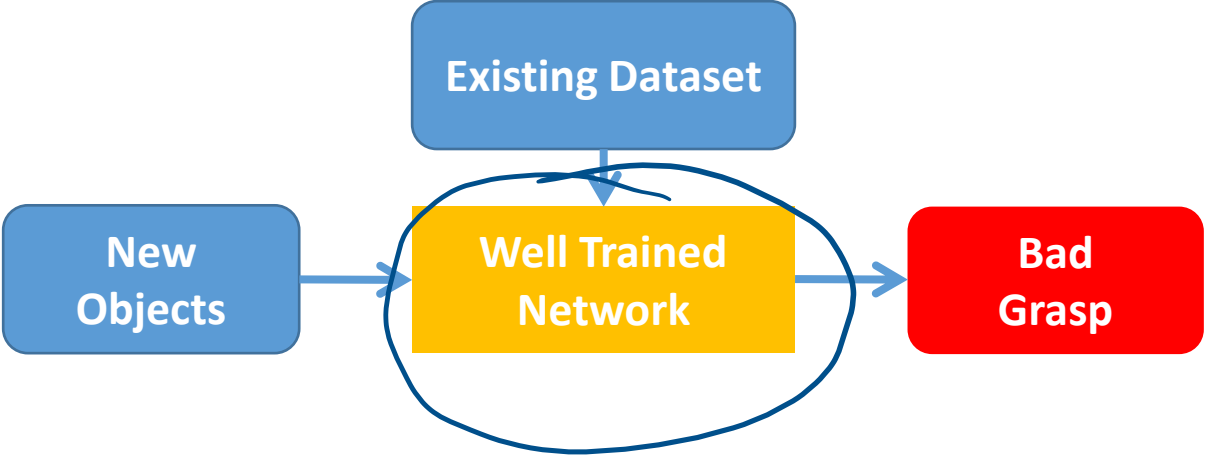


What will happen if a grasp fails?

Re-design the objects

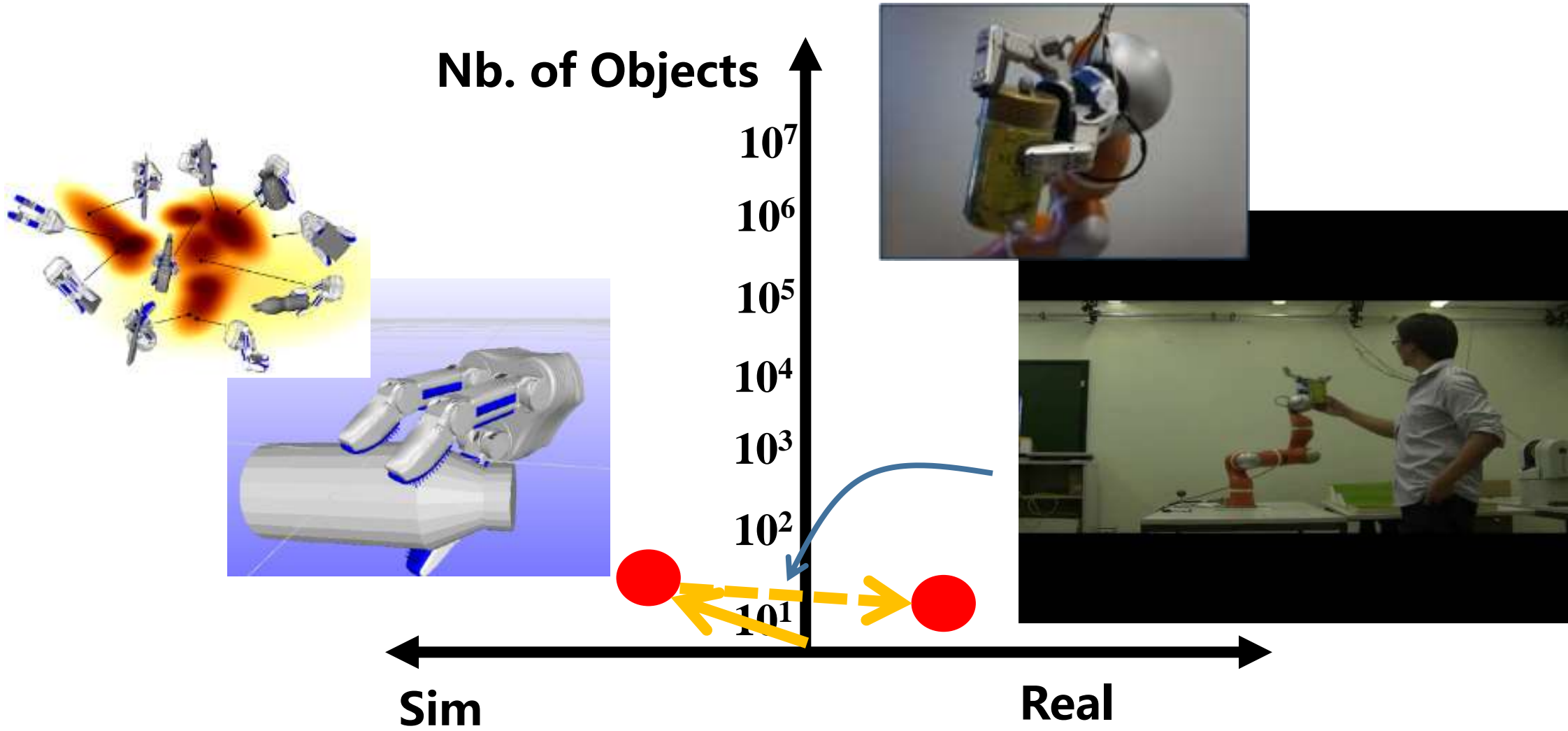


What will happen if a grasp fails?



Can we get a robust (and better) **pre-trained** planning algorithm **before failures**?

Recap of the grasp planning (1)



Model-based+ small data learning

Recap of the grasp planning (2)

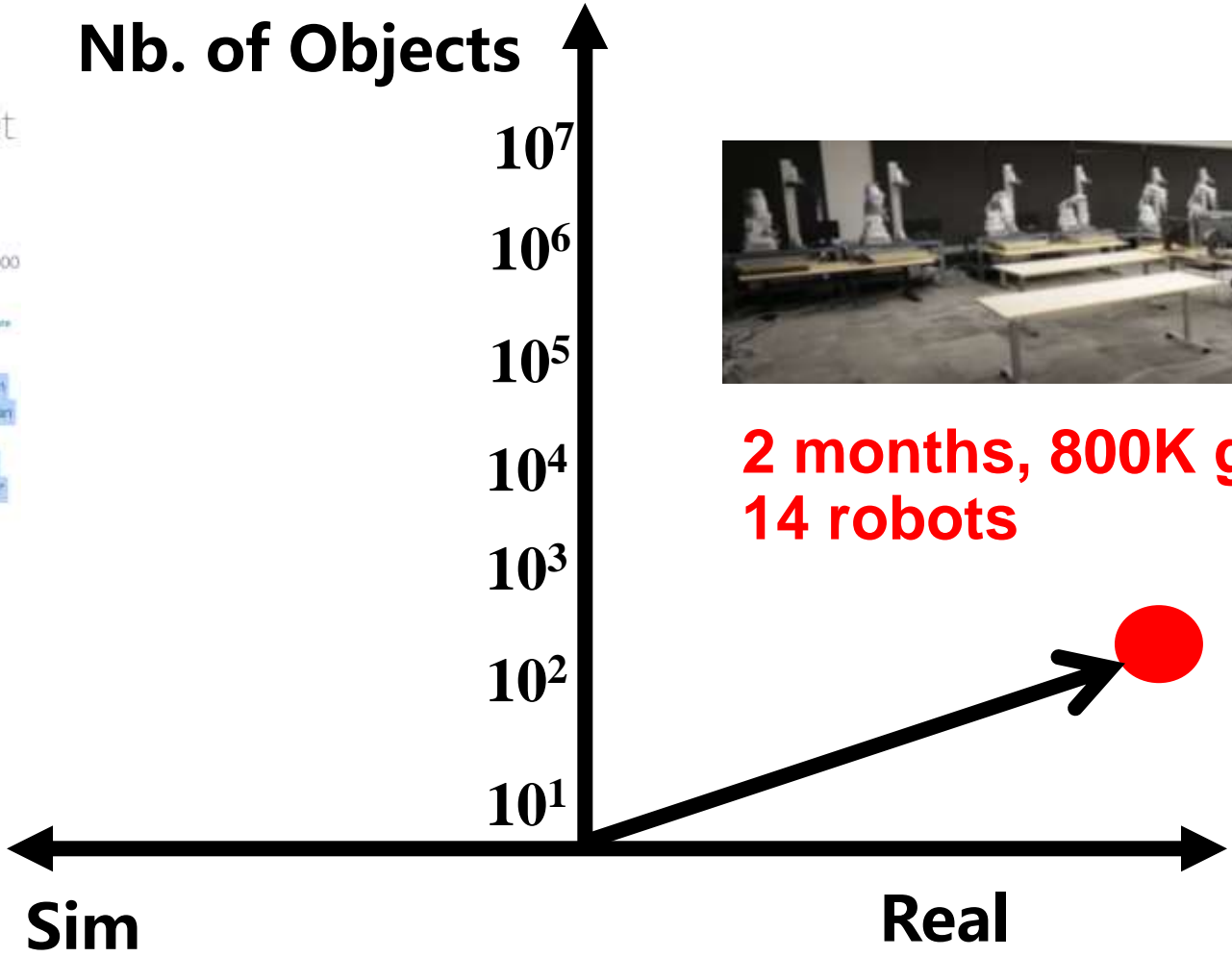
ROBOTICS
 Amazon releases largest dataset for training "pick and place" robots
 Dataset of images collected in an industrial setting features more than 190,000 objects, orders of magnitude more than previous datasets.
 By Mankaran Norouzi, Chaitanya Mitash, Fan Wang
 April 10, 2023

In an effort to improve the performance of robots that pick, sort, and pack products in warehouses, Amazon has publicly released the largest dataset of images captured in an industrial product-sorting setting. Where the largest previous dataset of industrial images featured on the order of 100 objects, the Amazon dataset, called ARM-Bench, features more than 190,000 objects. As such, it could be used to train "pick and place" robots that are better able to generalize to new products and contexts.



190000 objects

Nb. of Objects

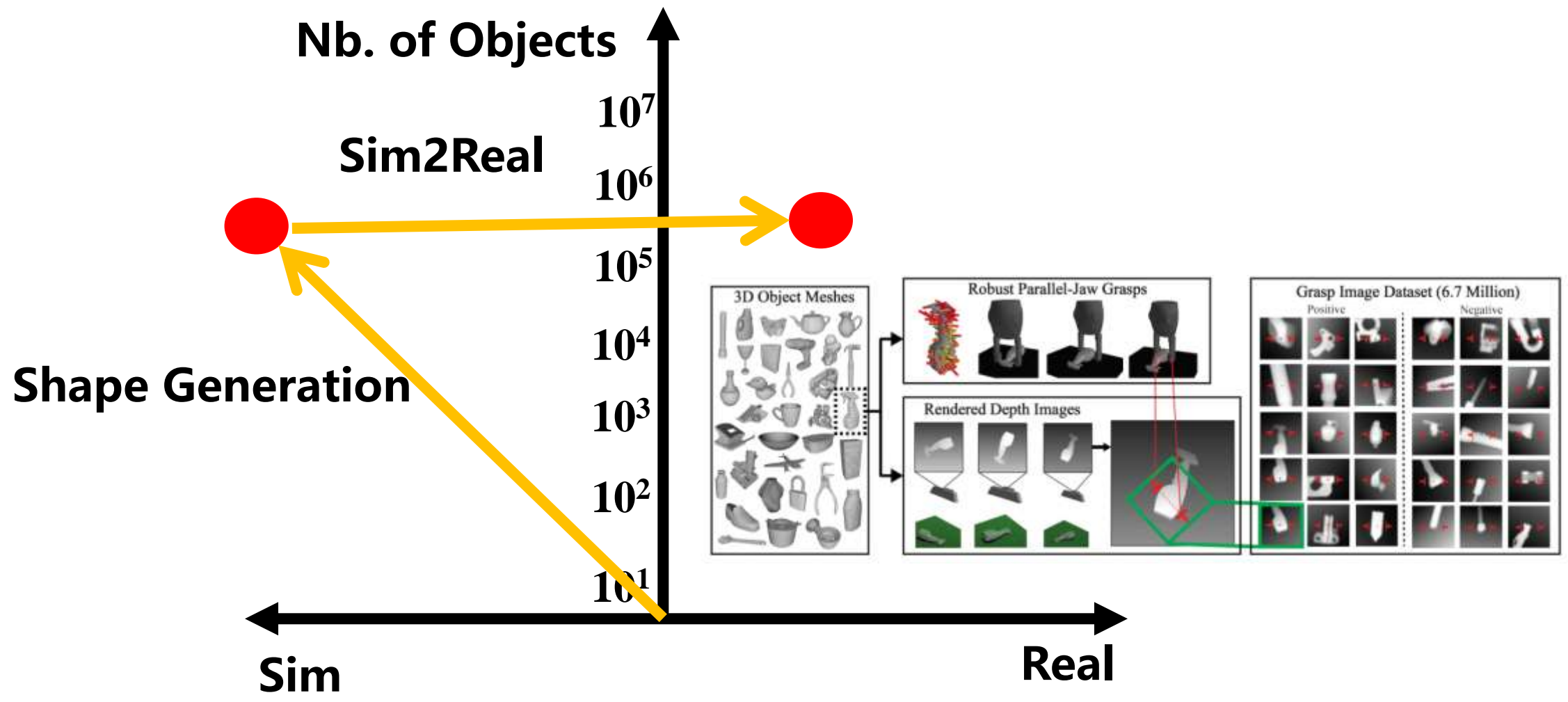


**2 months, 800K grasps
 14 robots**



Big data in real world

Recap of the grasp planning (3)

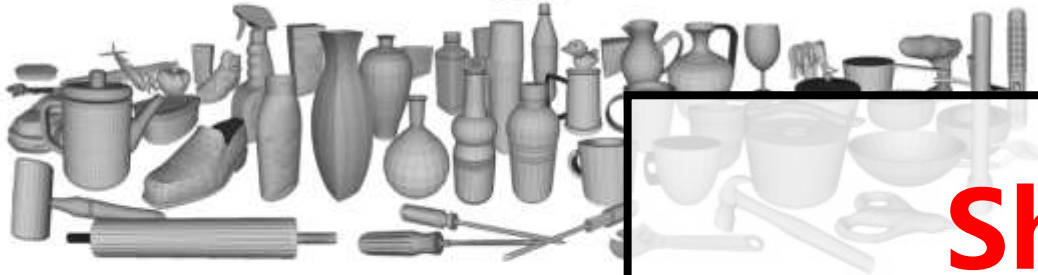


Big data in simulation + Sim2Real

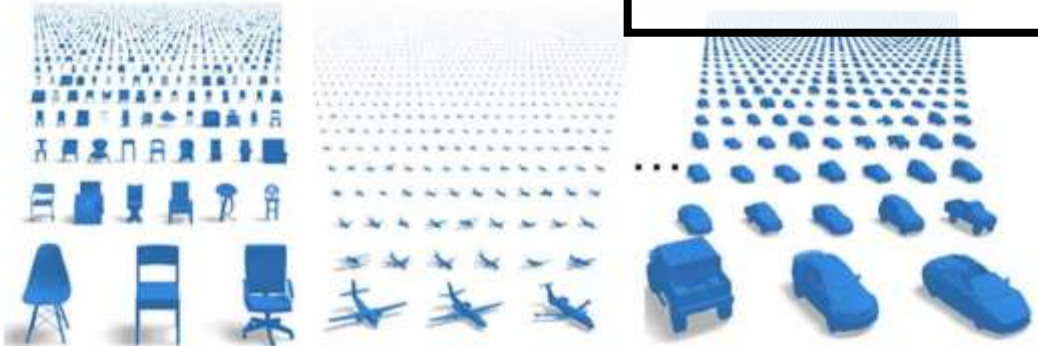
Shape generation



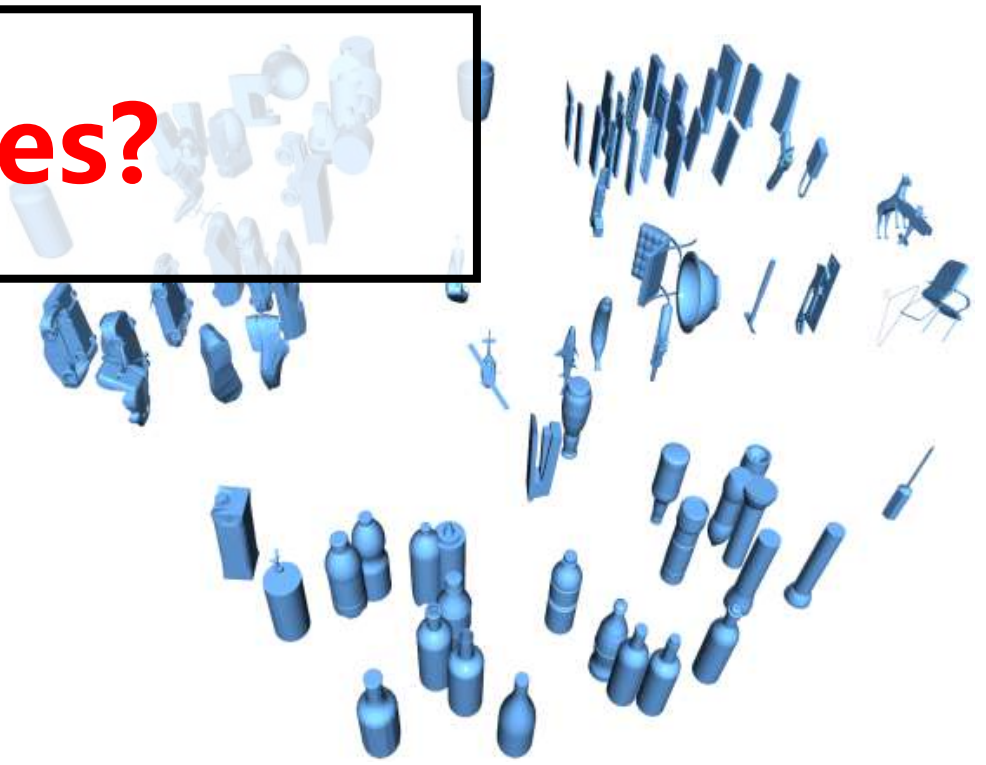
YCB



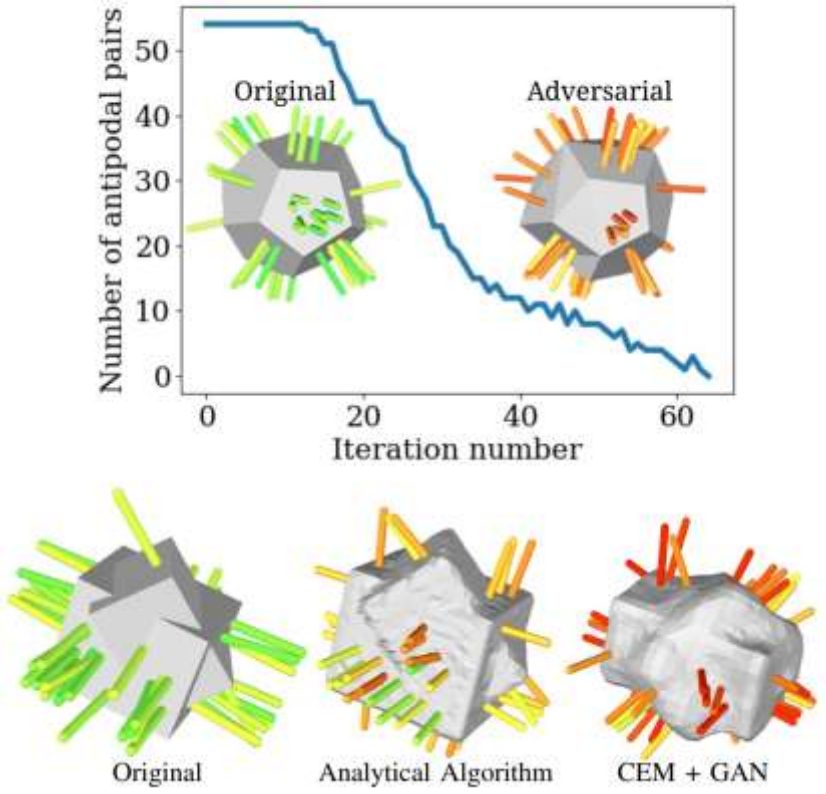
3DNet



ShapeNet

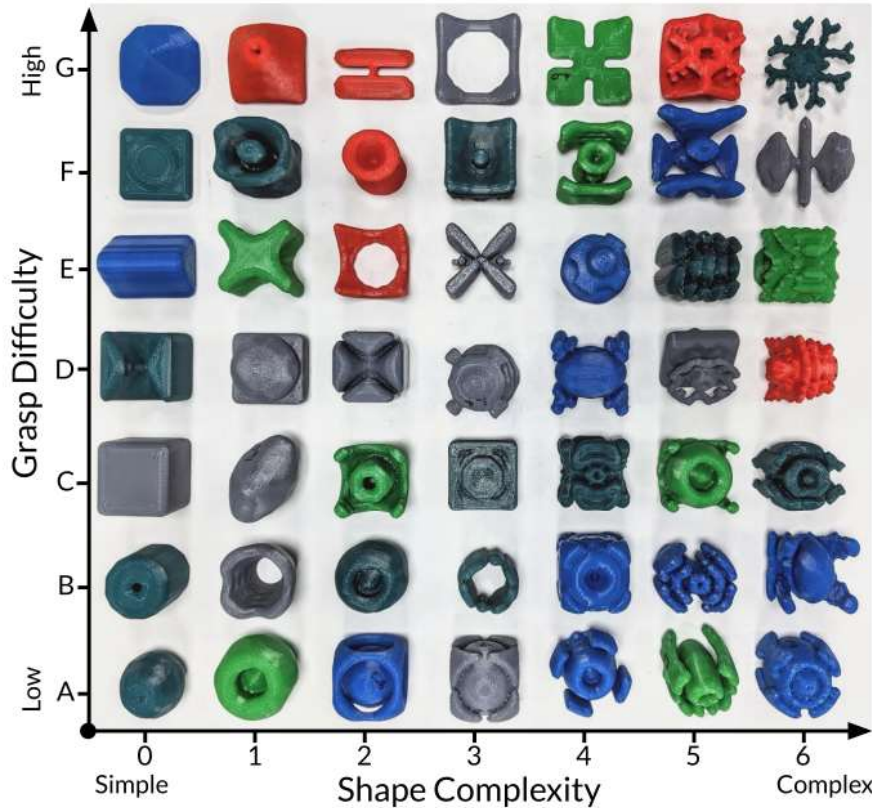


Shape generation- Previous works



Adversarial Grasp Object
 (Wang et. Al 2019)

A class of “adversarial grasp objects that are physically similar to a given object but significantly less “graspable” in terms of a specified robot grasping policy.

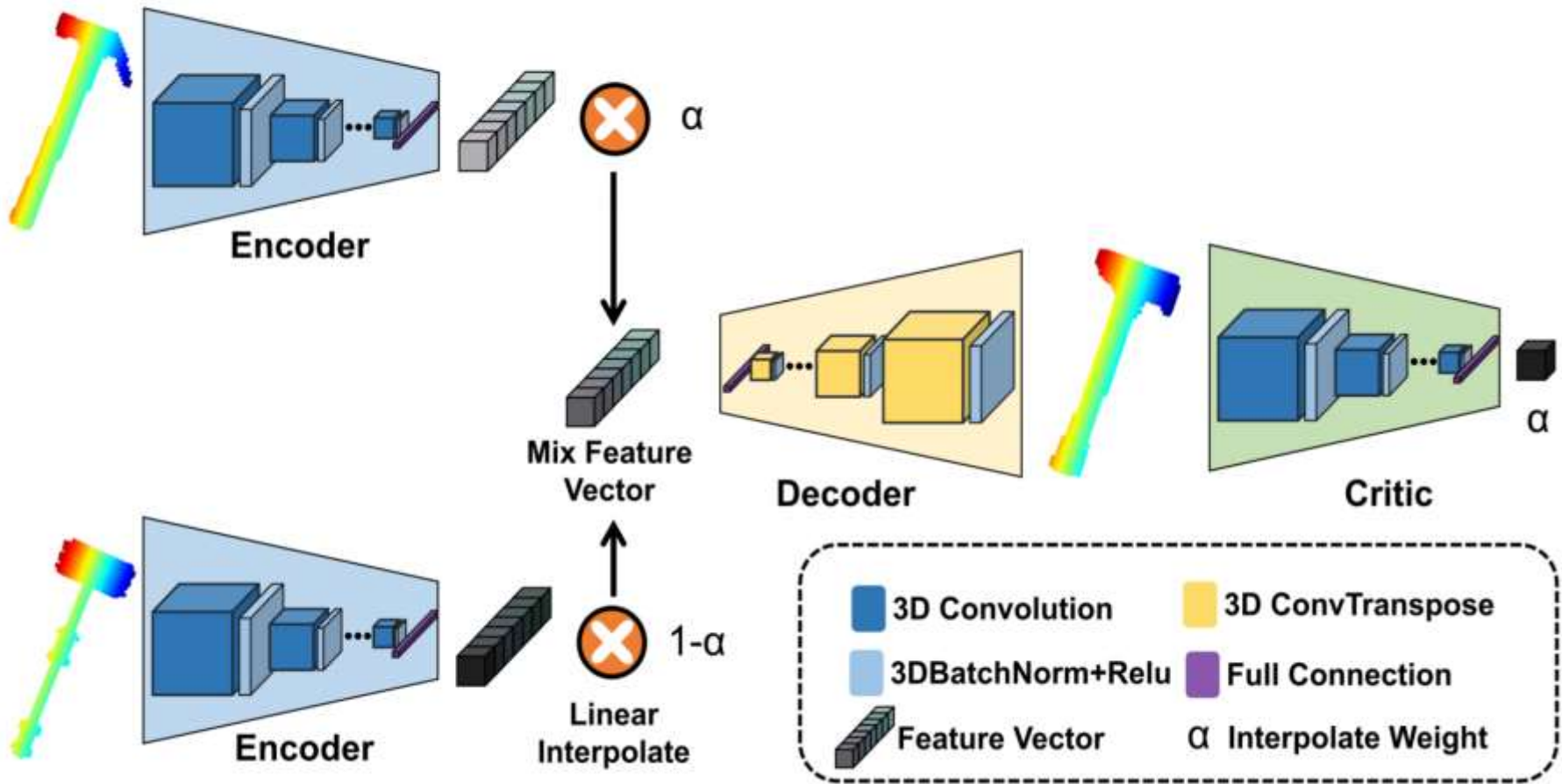


EGAD (Morrison et. Al 2020)

The objects in EGAD are geometrically diverse, filling a space ranging from simple to complex shapes and from easy to difficult to grasp

Shape generation

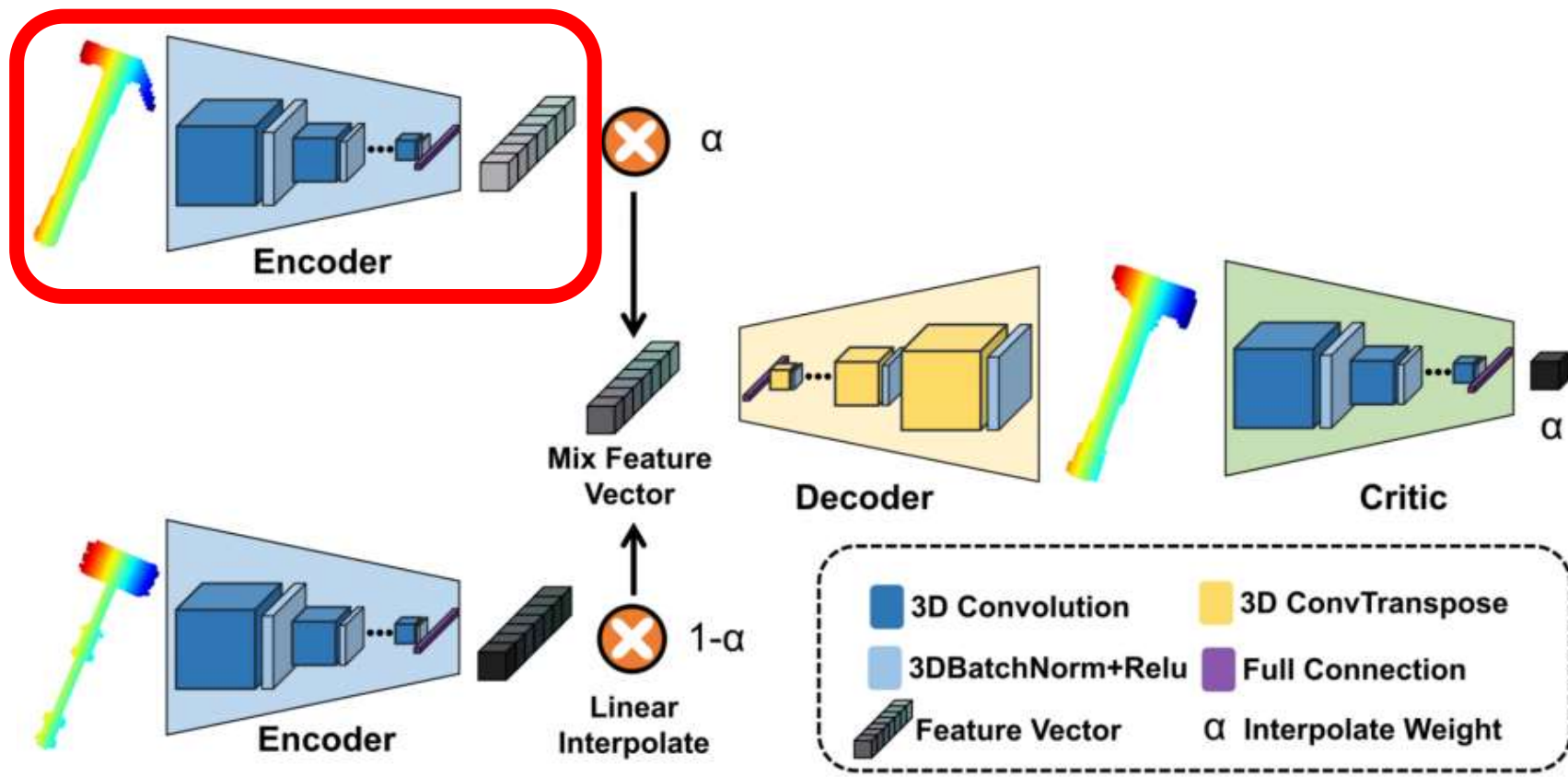
AE-Critic Network



- Deep shape generation for robust grasping, Sci-China, 2023 (under review)
- Improving robotic grasping ability through deep shape generation, 2022

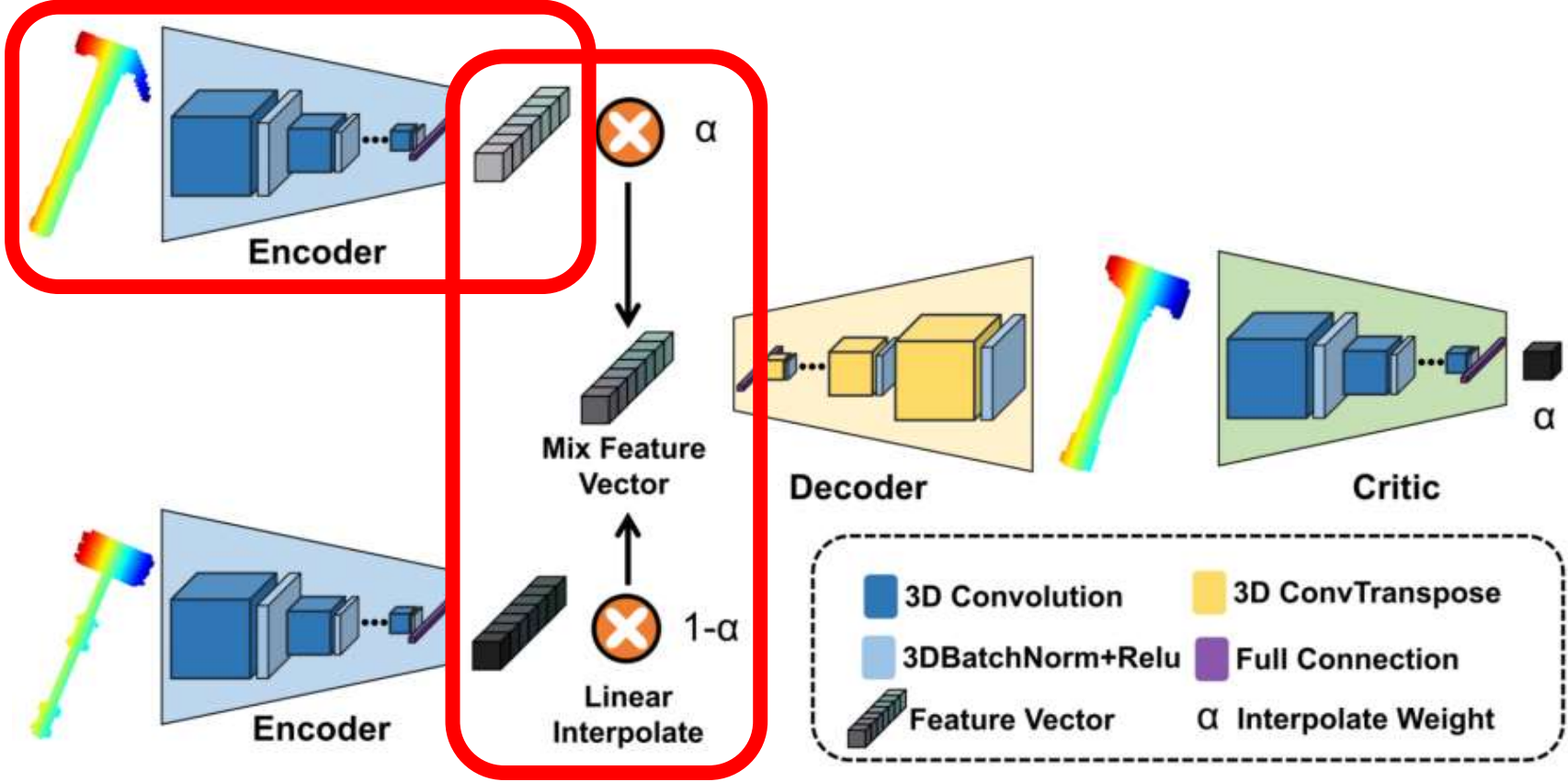
Object shape encoding

- Encode shapes into feature vectors



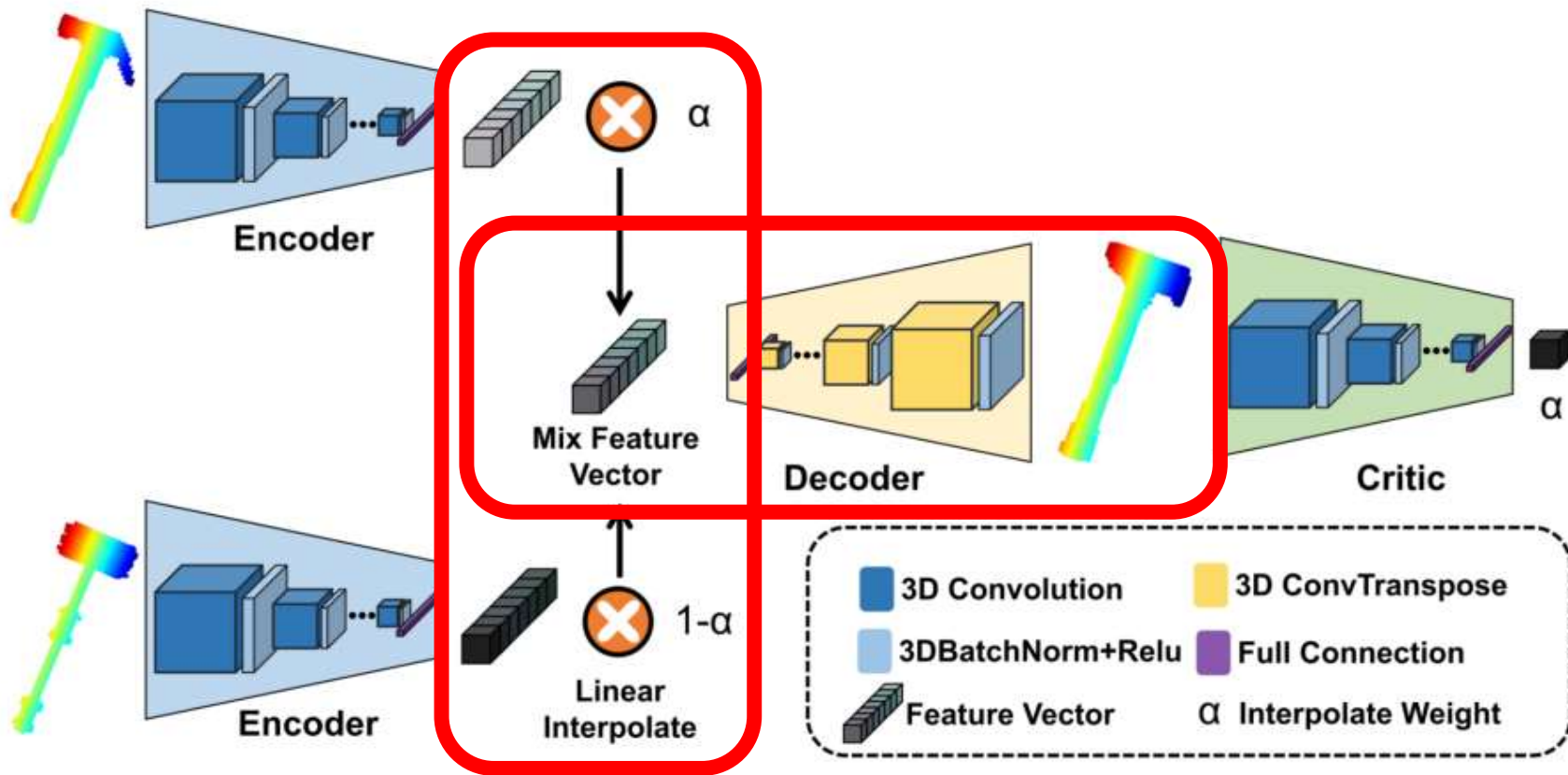
Object shape encoding

- Encode shapes into feature vectors
- Interpolate feature vectors

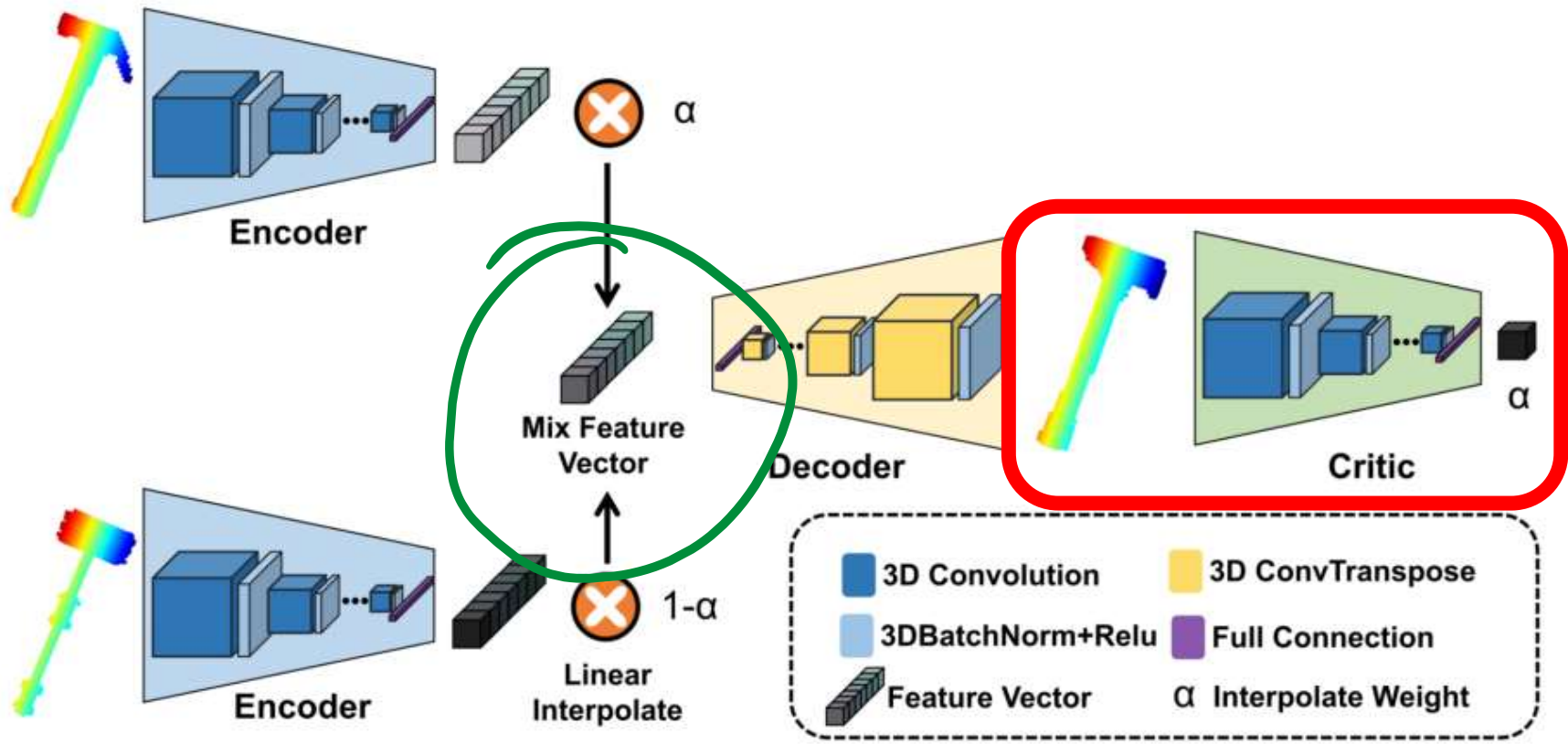


Object shape encoding

- Encode shapes into feature vectors
- Interpolate feature vectors
- Decode mix feature vector and generate new shapes



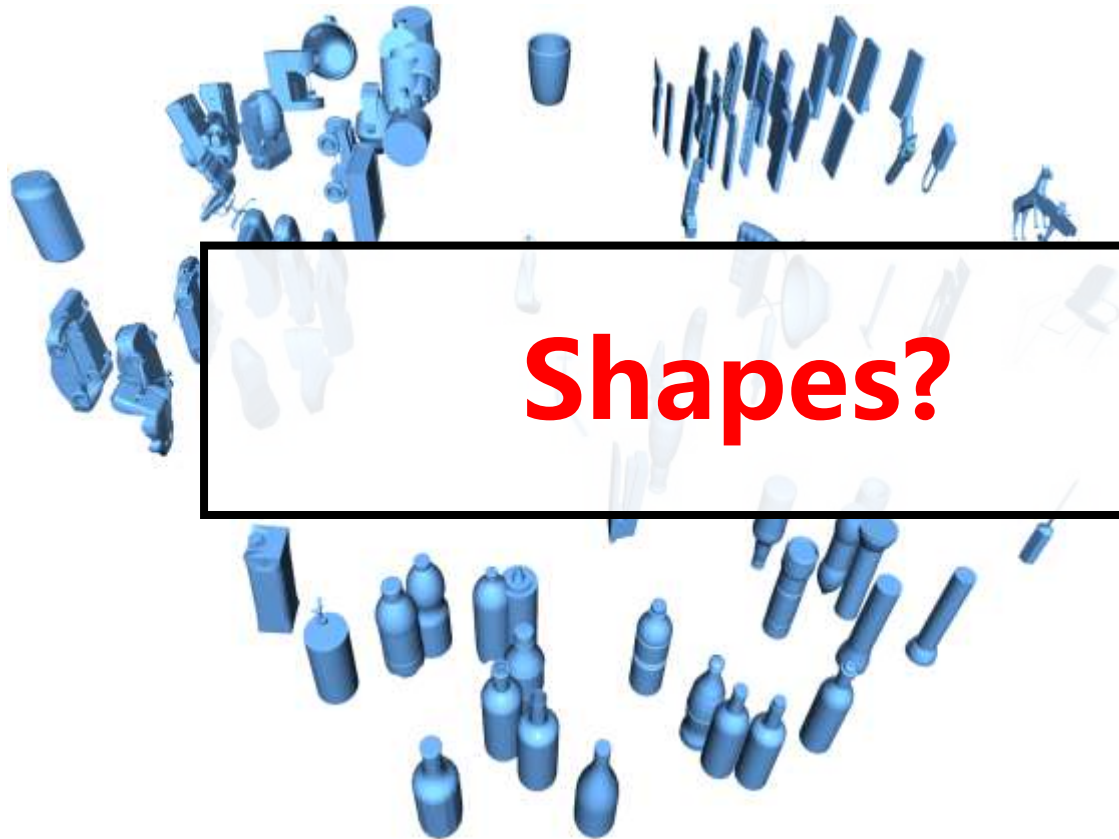
Object shape encoding



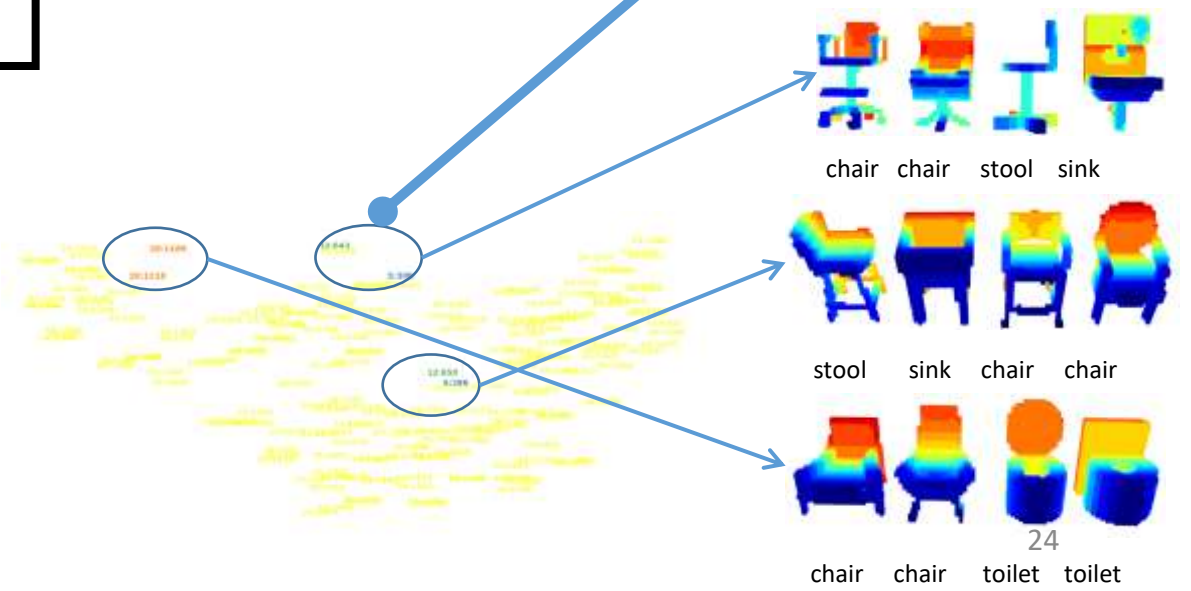
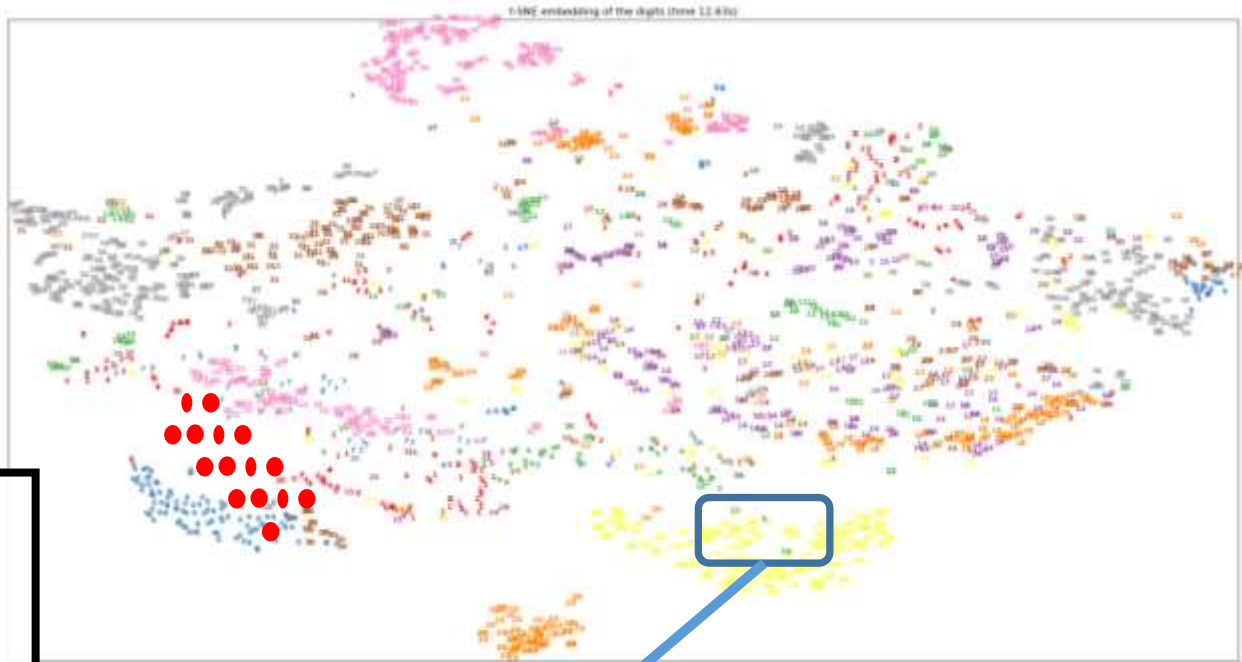
Critic is used to predict the **interpolate weights** and regularize the generated shapes to be more realistic

Object shape distribution

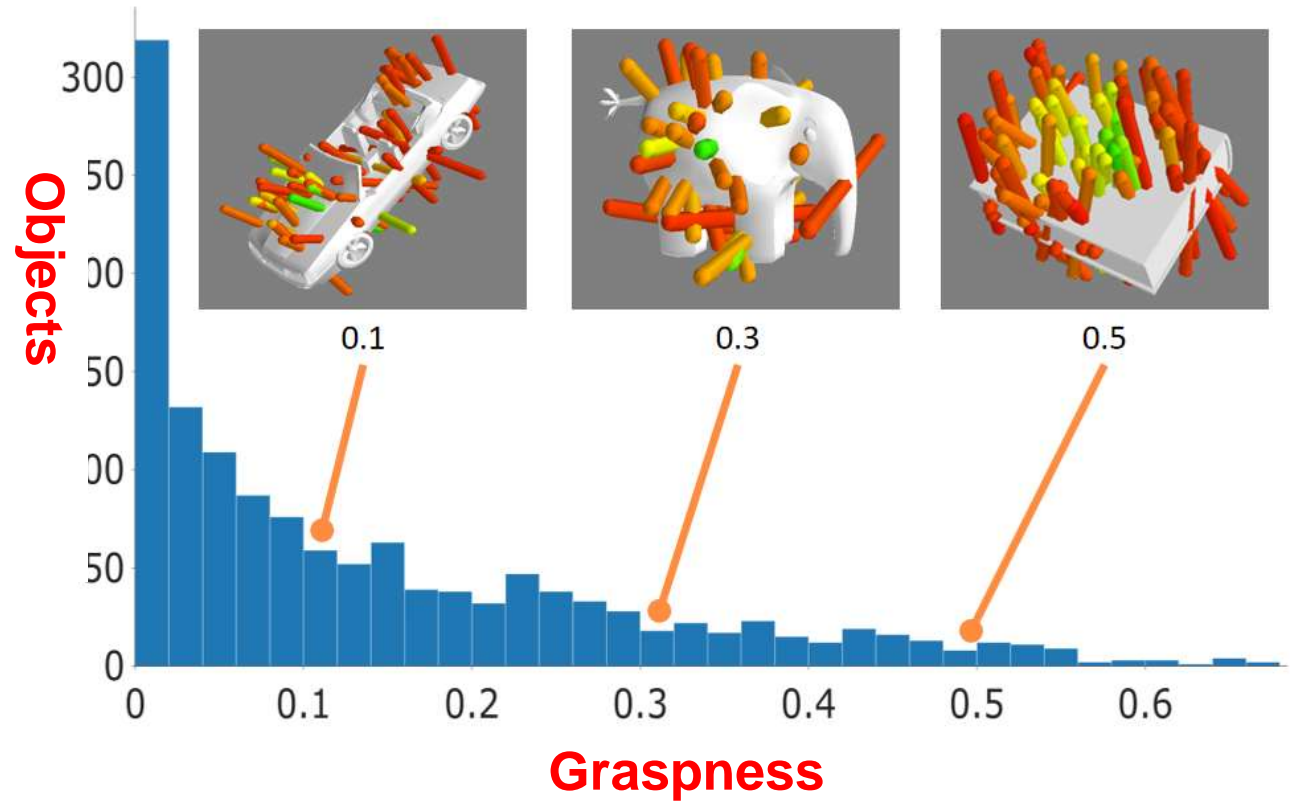
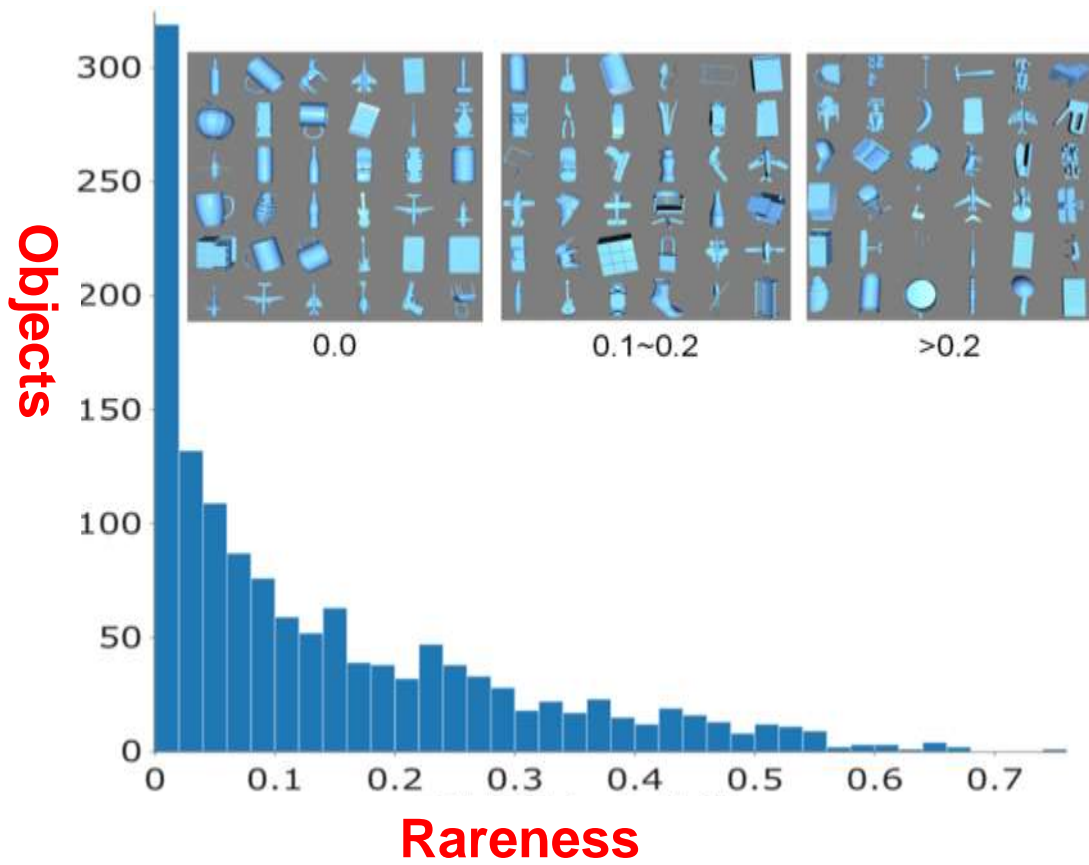
Shape Distribution



Shapes?



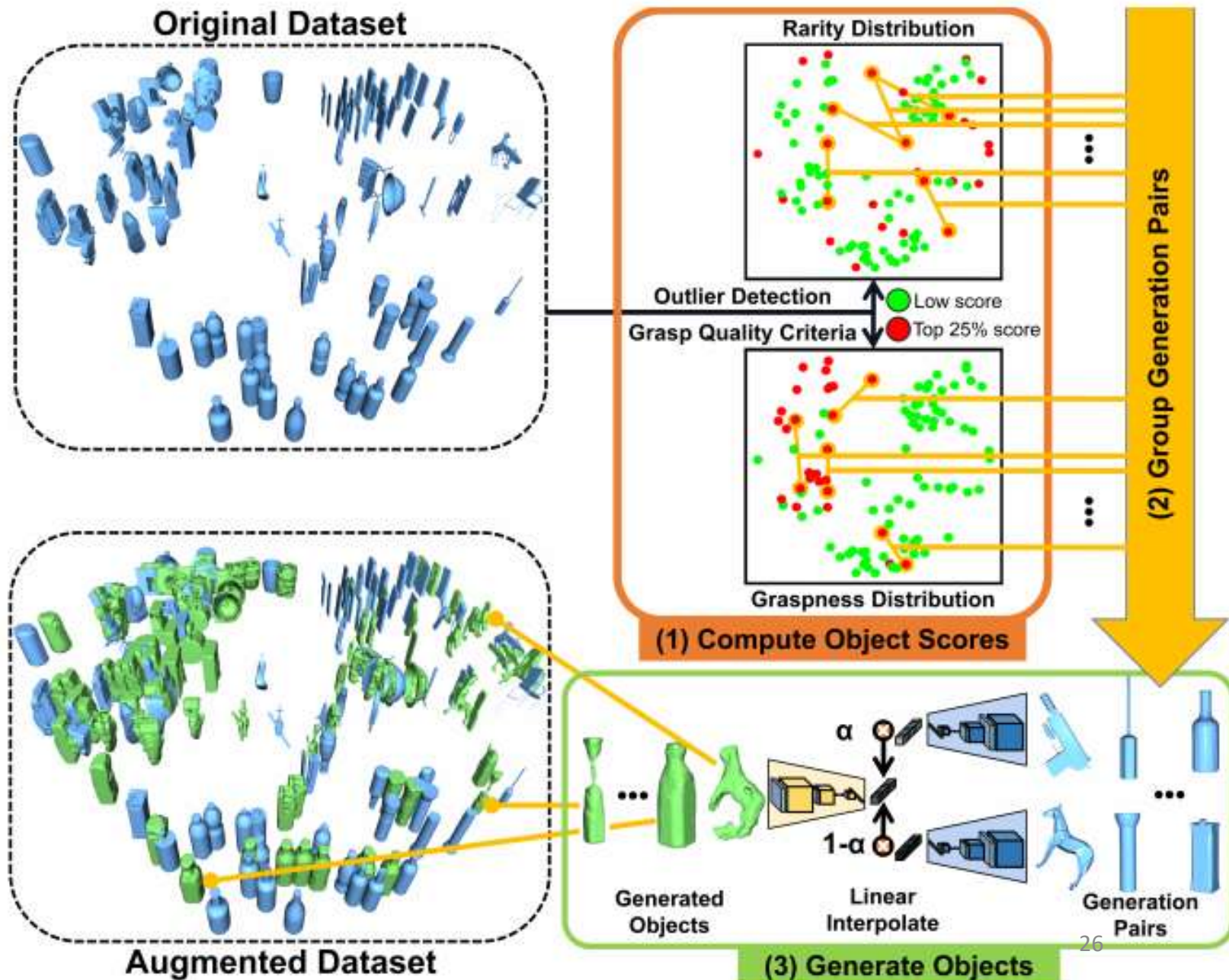
Shape generation



Rare + Difficult to grasp

Shape generation

- Compute object scores through outlier detection and grasp-quality criteria
- Group high-scoring data as generation pair
- Generate new objects by AE-Critic network

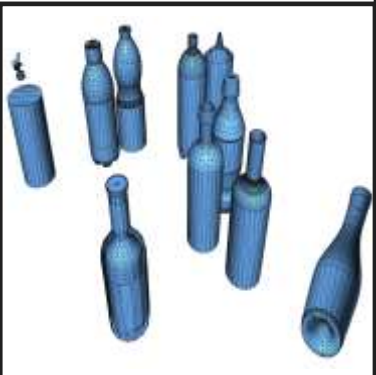
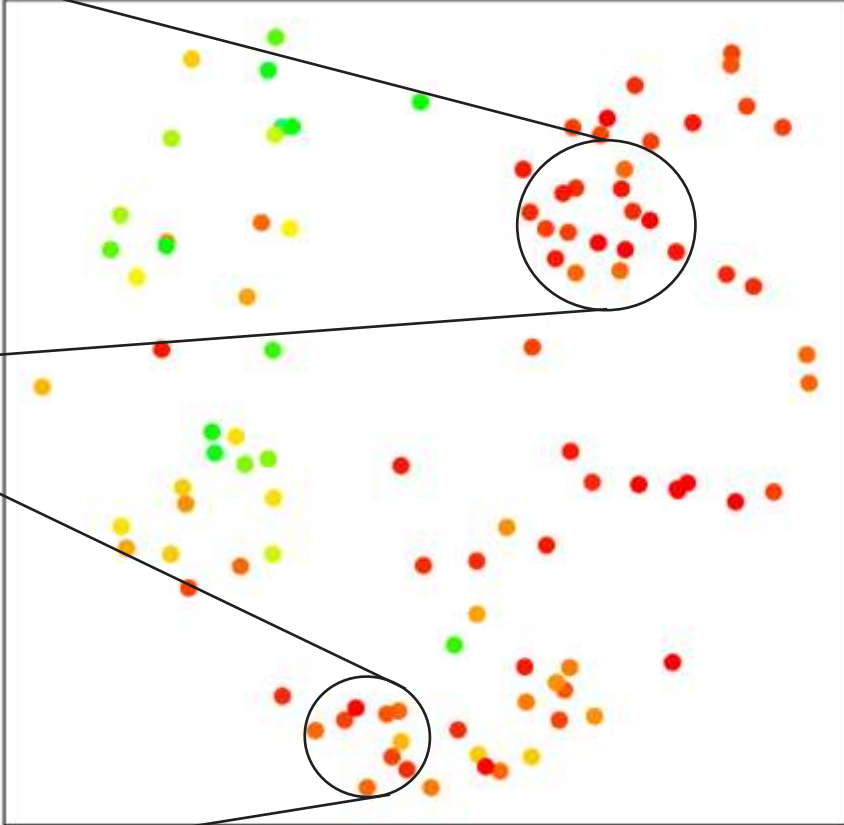


Shape generation

Original Data Distribution



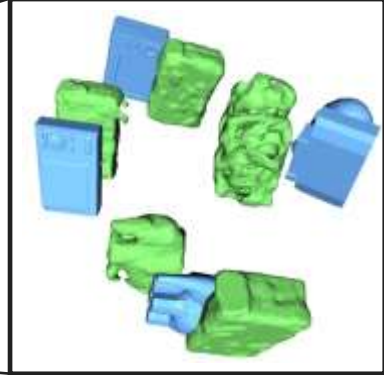
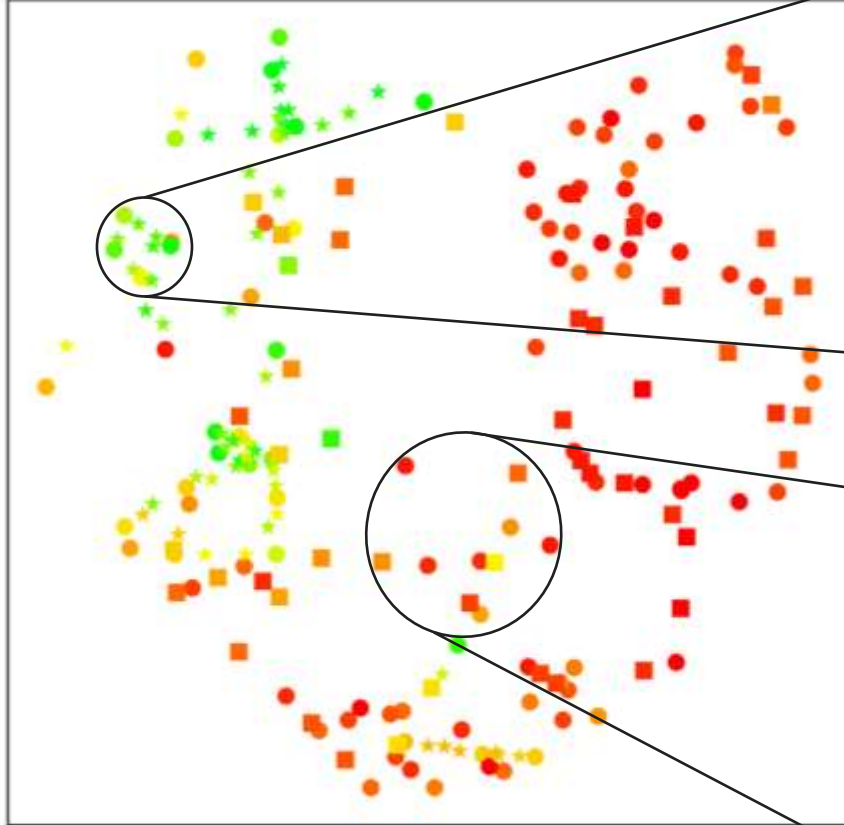
duplicate shapes



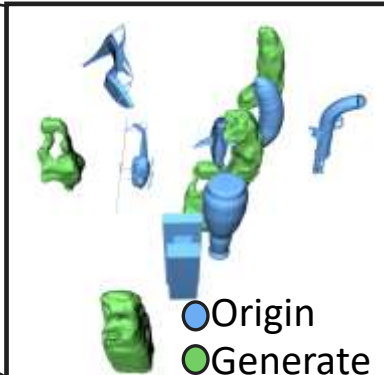
high graspness shapes



Augmented Data Distribution



low graspness shapes

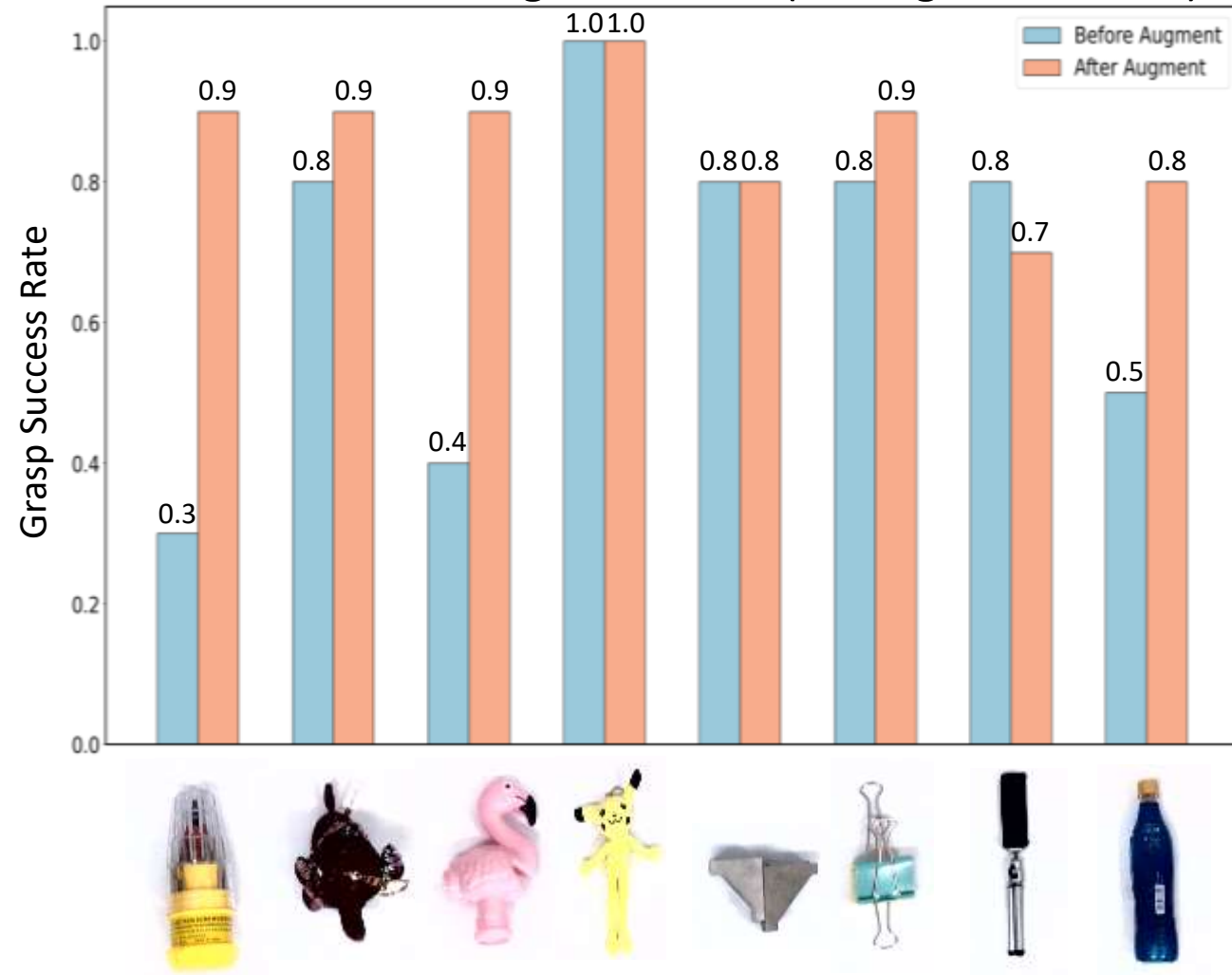


rare shapes

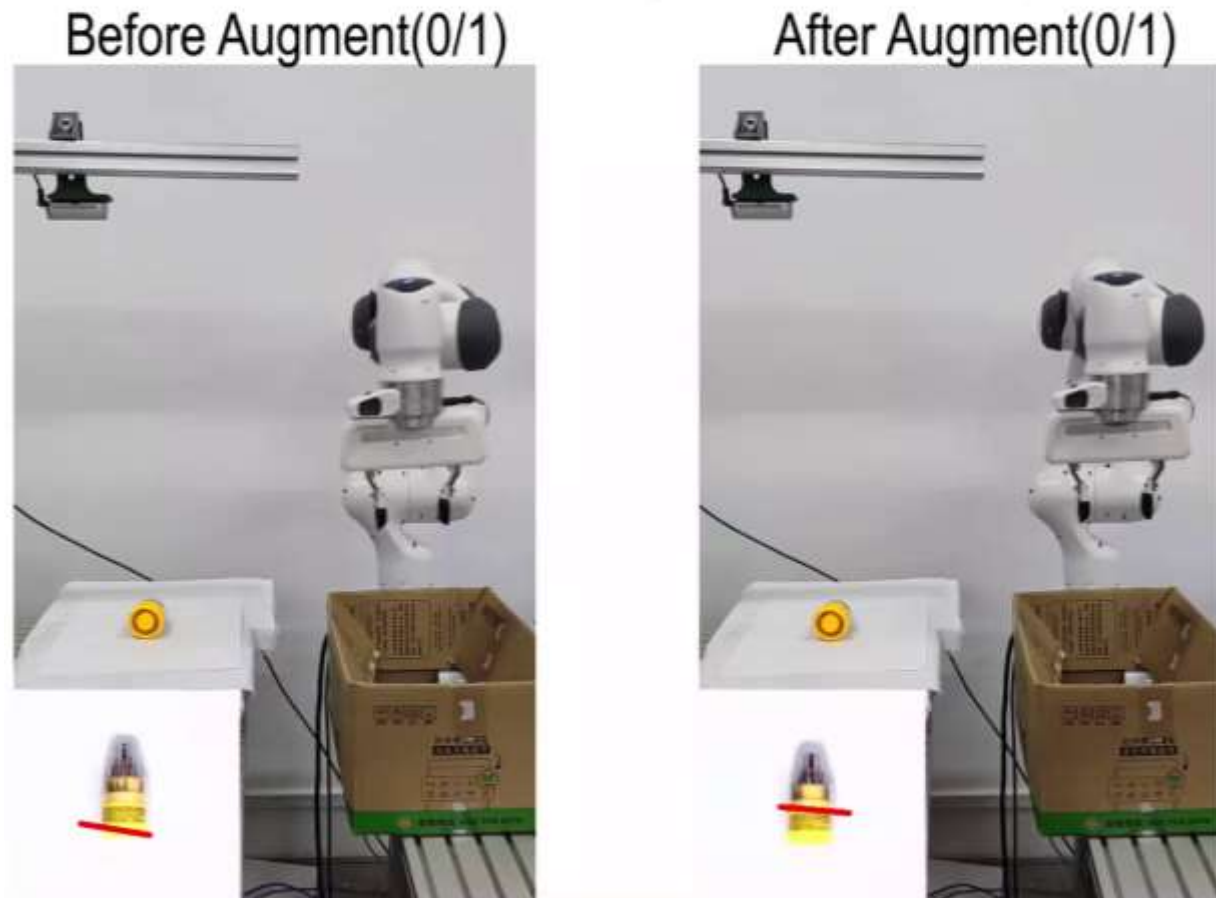
- Original Data
- Generated from rare shape
- ★ Generated from high graspness shape

Real-Robot Experiment

Grasp Success Rate Comparison between
 Before and After Augmentation (Average 68% : 86%)



Grasp Trials(Success/All)



Experiments Results

Before

After



Before

After

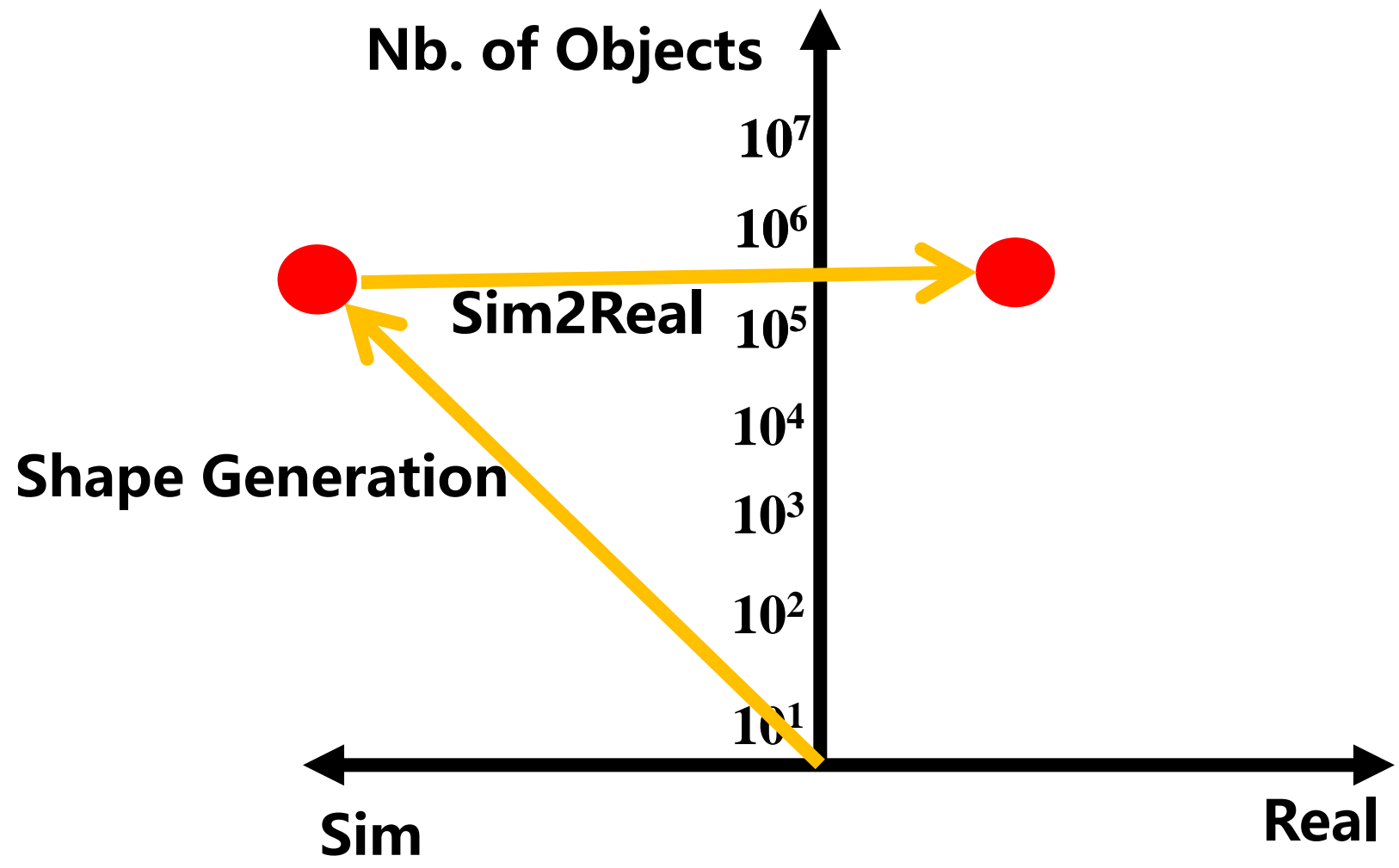


Before

After

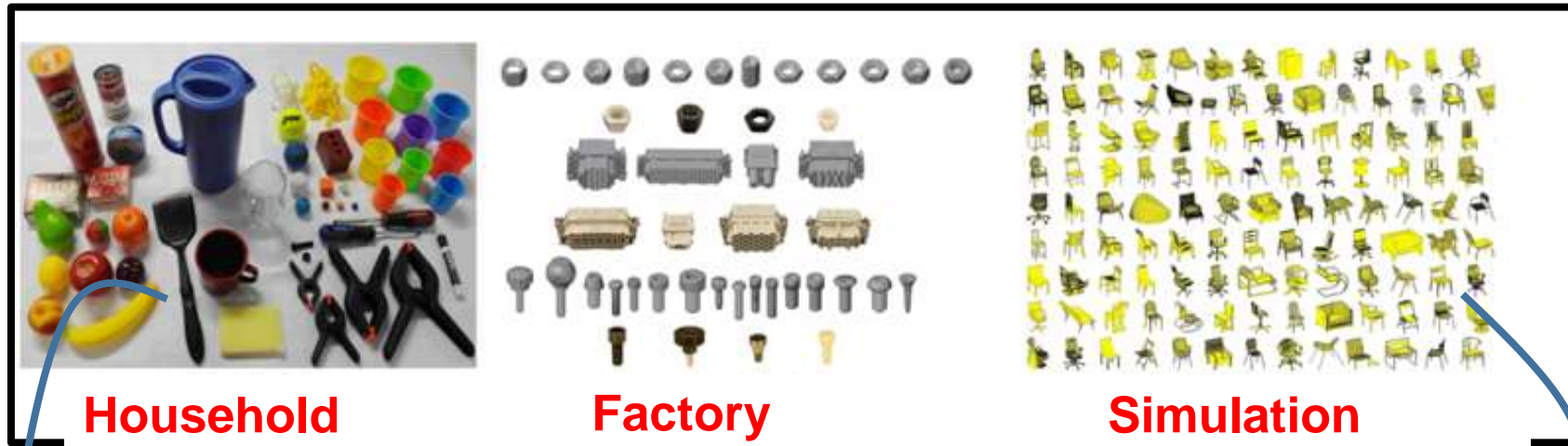


Recap of the grasp planning (3)



Big data in simulation + Sim2Real

Grasp transfer



Household

Factory

Simulation

Real-world Dataset:

Labeled training data from real-world scenarios

Synthetic Dataset:

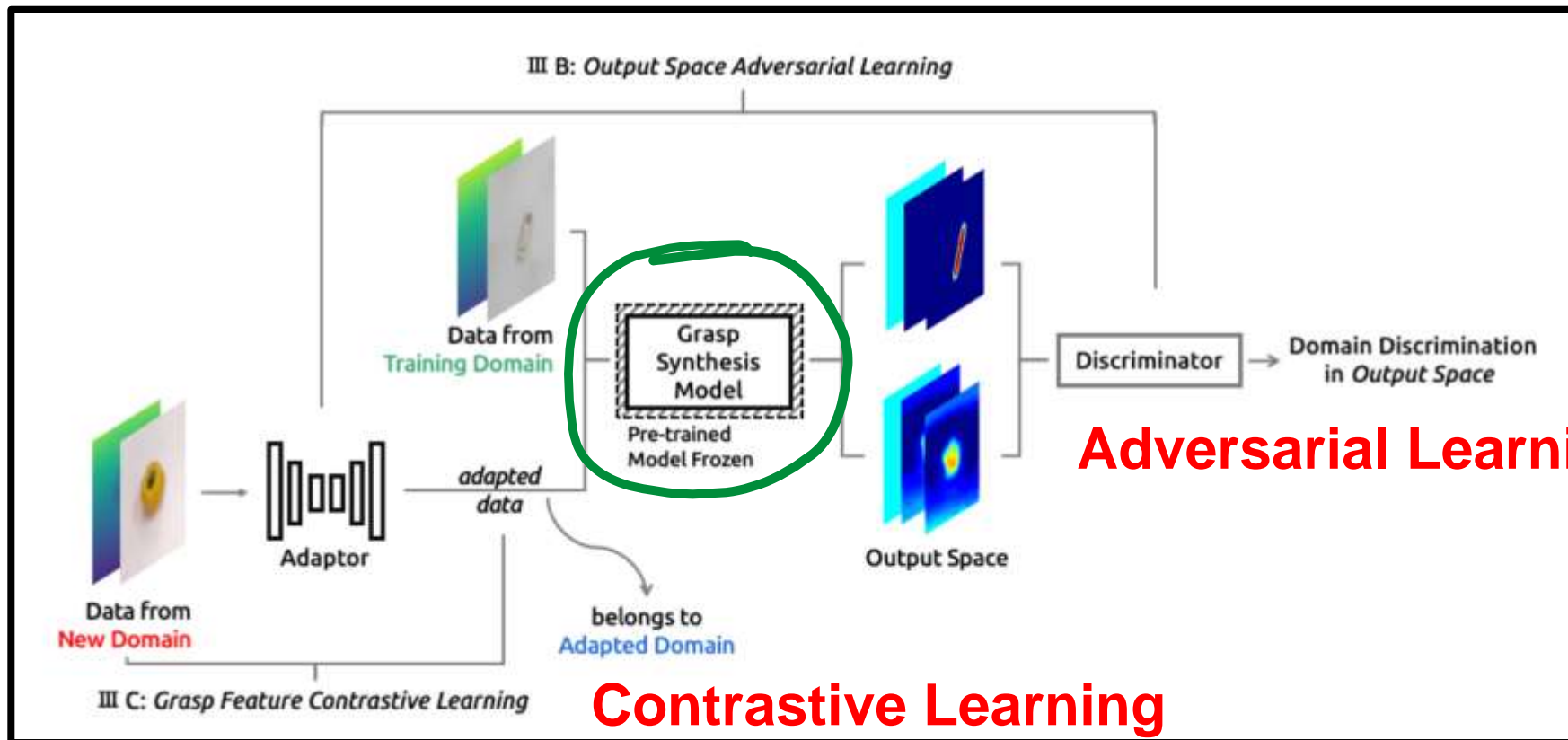
Generating Labeled Data from Simulation

Drawbacks: *expensive, gap between different scenarios*

Drawbacks: *simulation-to-reality gap*

How to **transfer** the learned grasping ability to new domains?

Sim2Real (Joint Work with Fei Chen, Yasemin Bekiroglu)

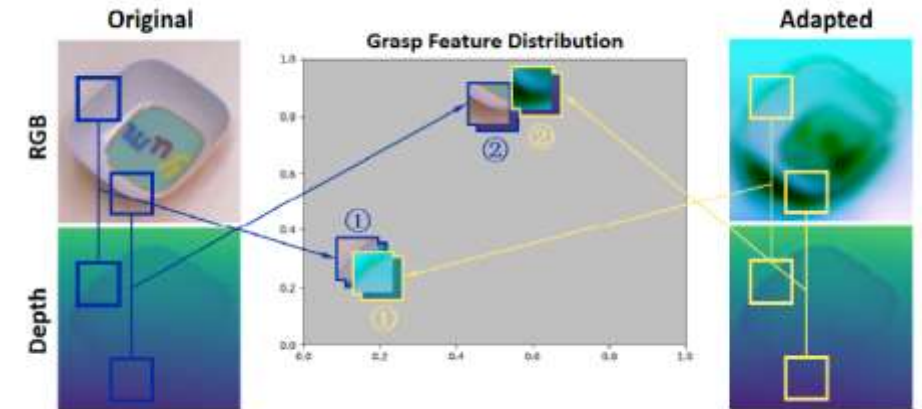
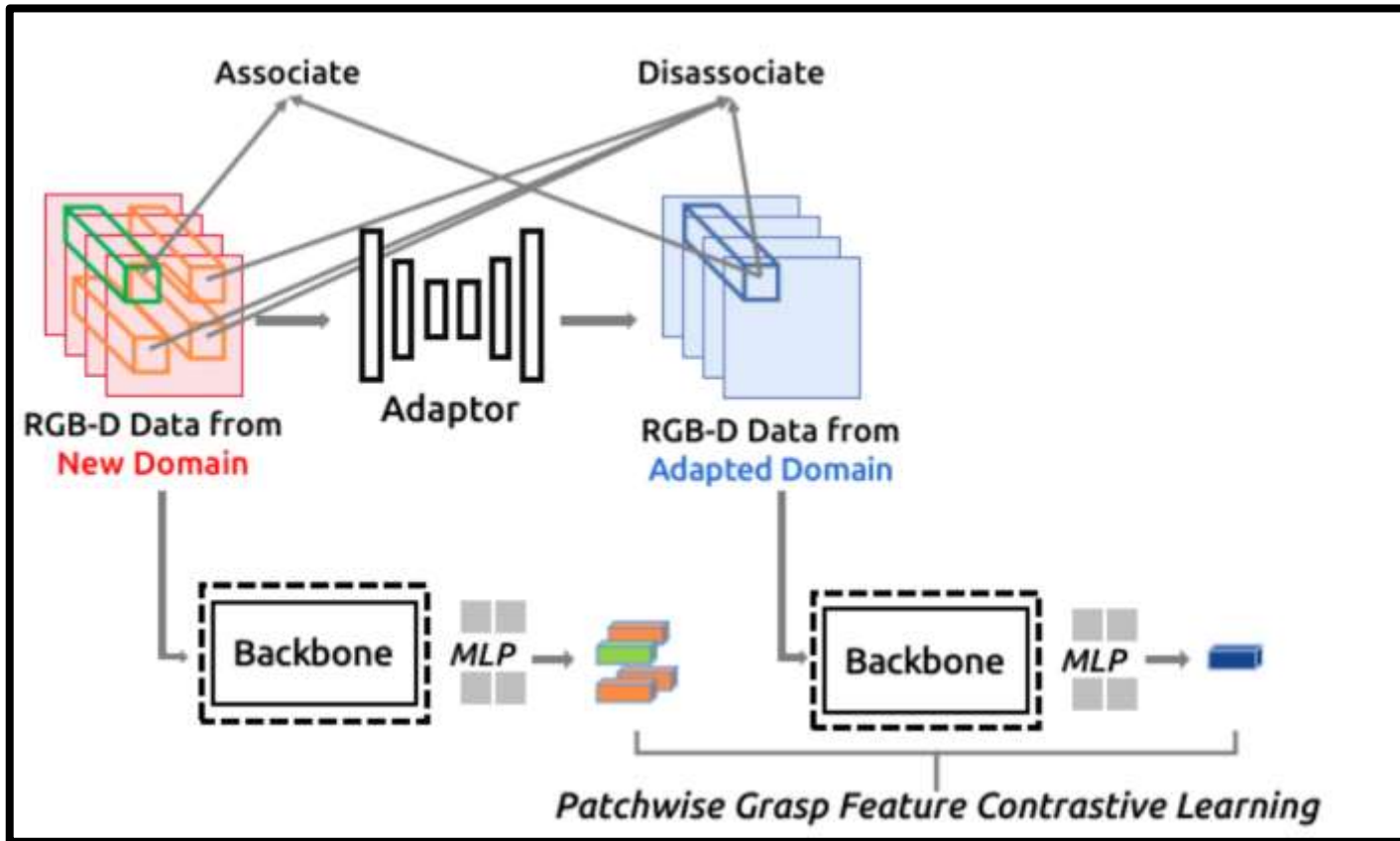


Grasp Adaptation

Output Space Adversarial Learning **What to transfer?**

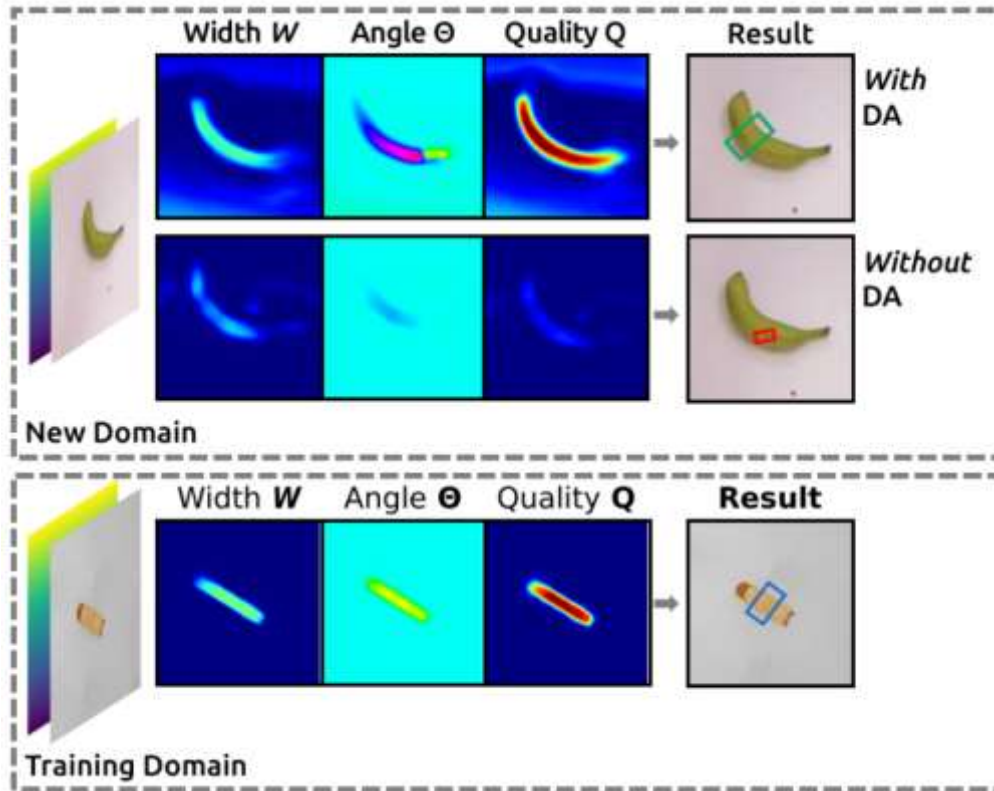
and

Grasp Feature Contrastive Learning **How to transfer?**



A **feature-level contrastive learning scheme** is developed to enforce the grasp relative feature **consistency** during adaptation.

GraspAda

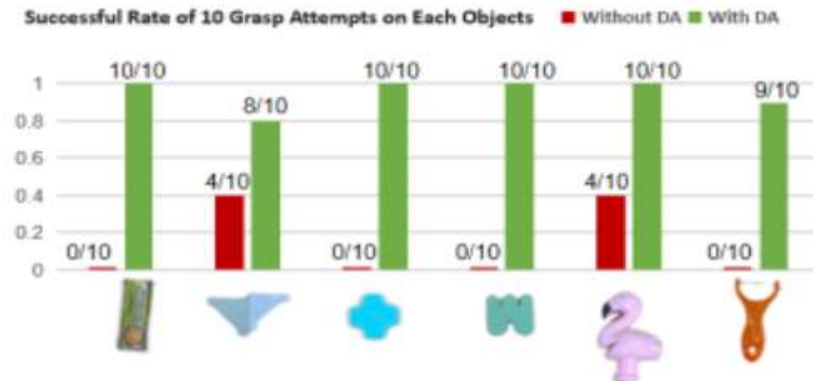
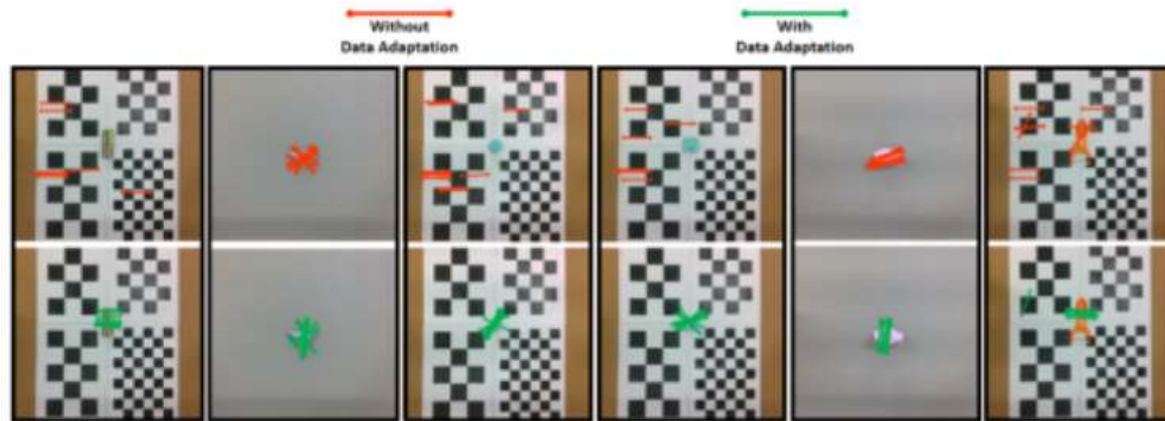


GraspAda

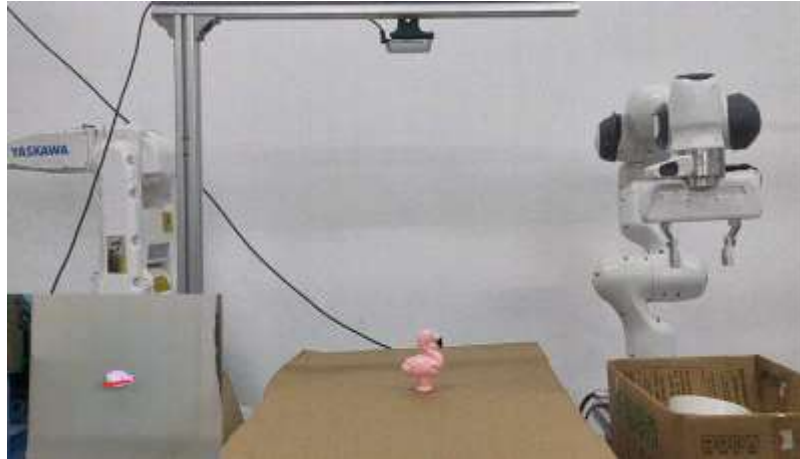
Overall grasping success rate: **40%**



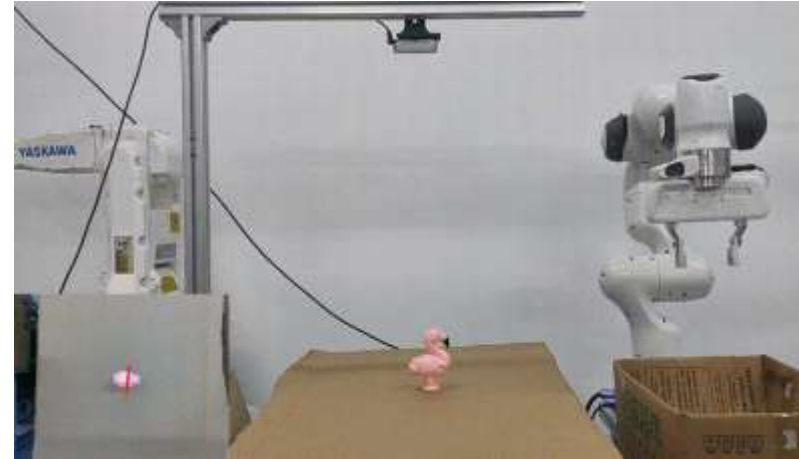
Overall grasping success rate: **80%**



GraspAda



Without Data Adaptation
Successful Rate: 4/10



With Data Adaptation
Successful Rate: 10/10

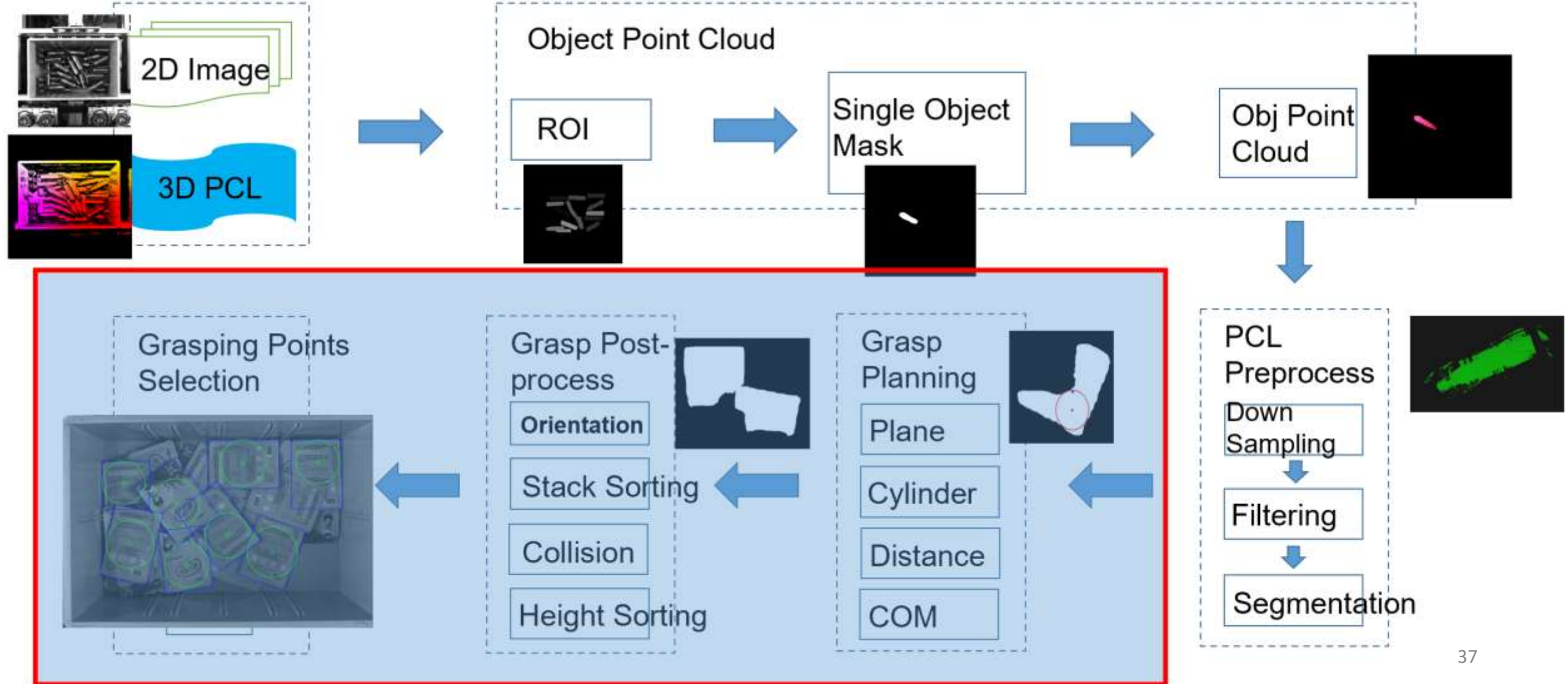


Without Data Adaptation
(strong background noise)
Successful Rate: 0/10



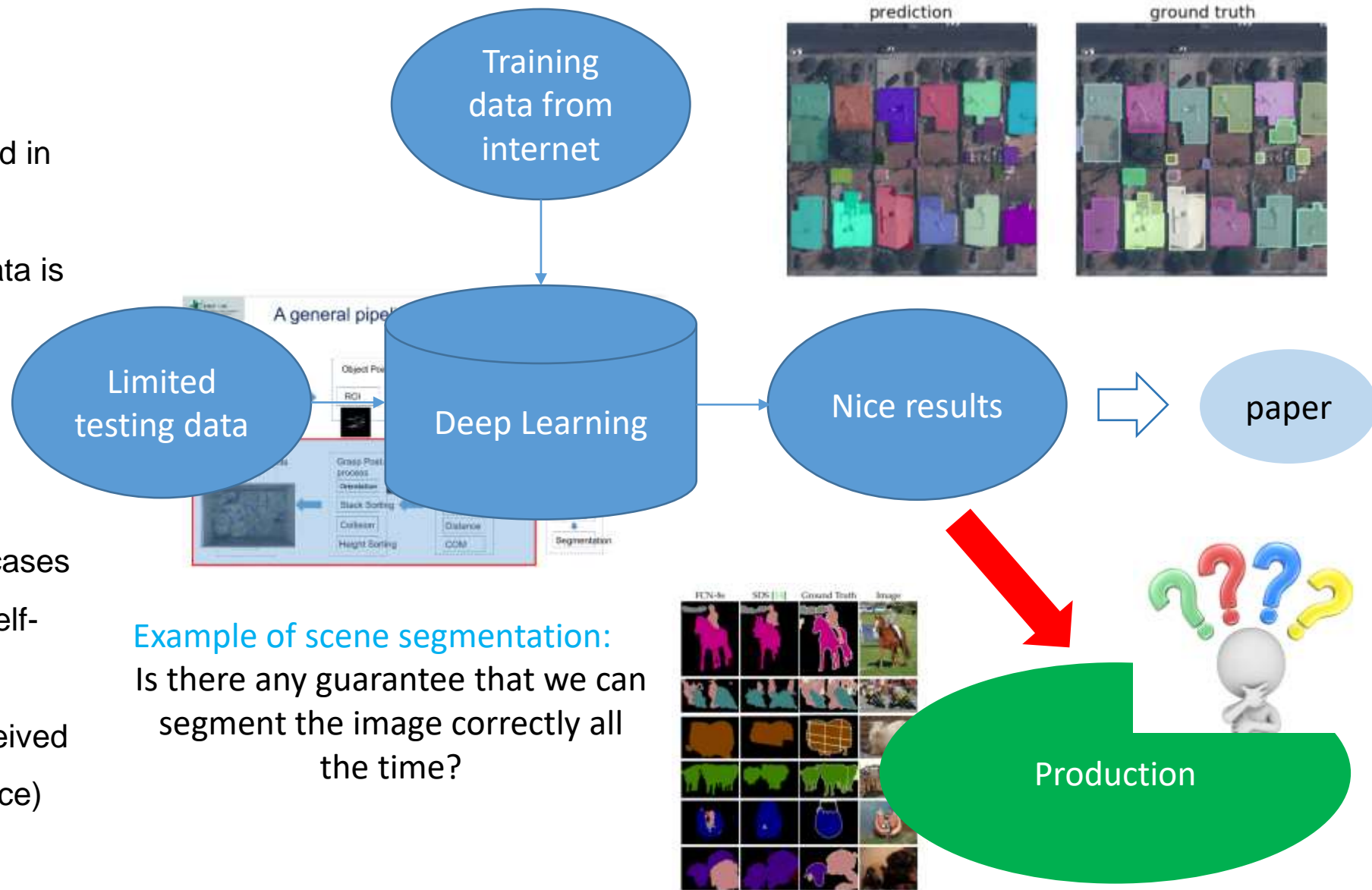
With Data Adaptation
(strong background noise)
Successful Rate: 10/10

A general pipeline of robotic grasping

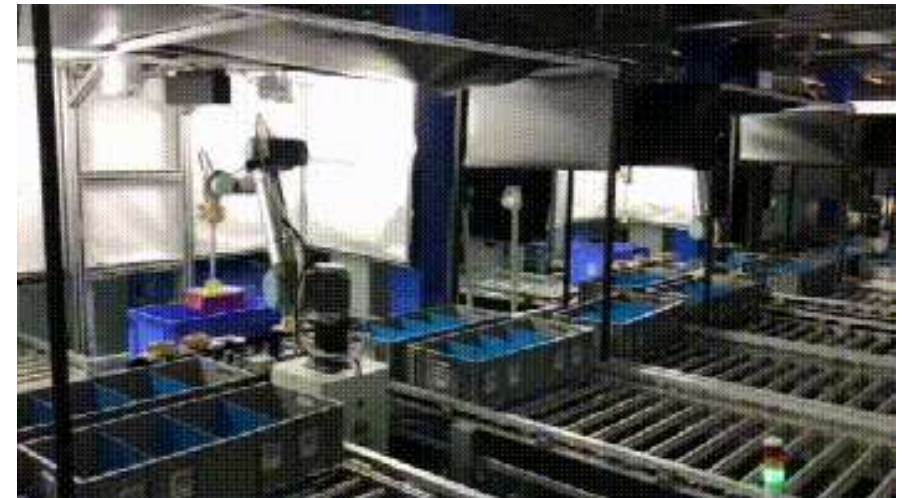
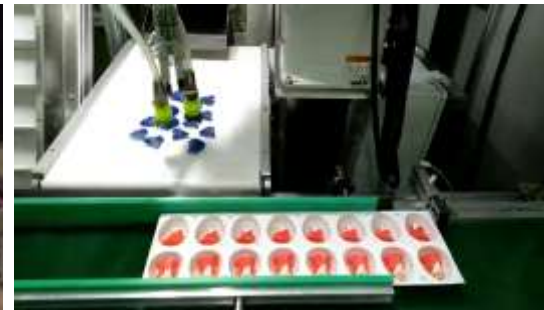


Transfer grasping to real world

- All the algorithms from DL is probabilistic (deterministic required in production)
- A large number of well-labelled data is required (data is expensive in production)
- 90% success rate could be a nice paper (99% is not enough)
- Ignore the corner cases (Corner cases must be taken into account, e.g self-driving)
- 1ms in prediction time is not perceived (1 ms could make a huge difference)
- Low (zero) stake vs high stake
-



Grasping in the real world



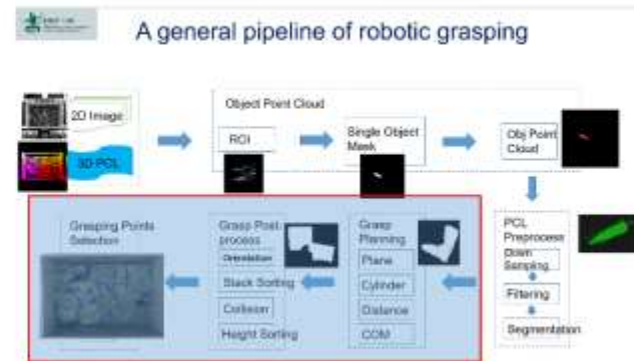
Transfer grasping to real world

✓ Data is expensive

✓ 99.99% is still far away! (4s per grasp)

✓ 1ms is important

✓ System is important



1. Robustness – Grasping is solved without this constraint

2. Speed – What makes grasping useful in real life

3. Adaptability – What makes grasping intelligent

Thanks for your attention!

Email: miao.li@whu.edu.cn