# QDGset : A Large Scale Grasping Dataset Generated with Quality-Diversity

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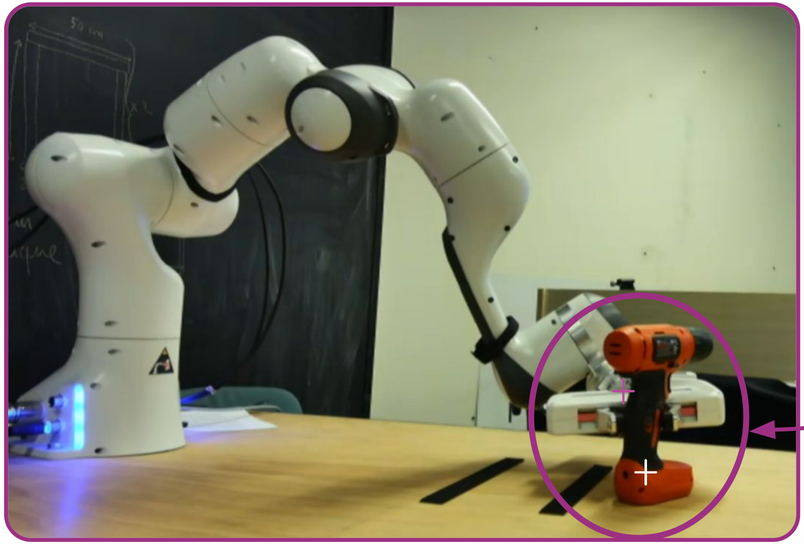
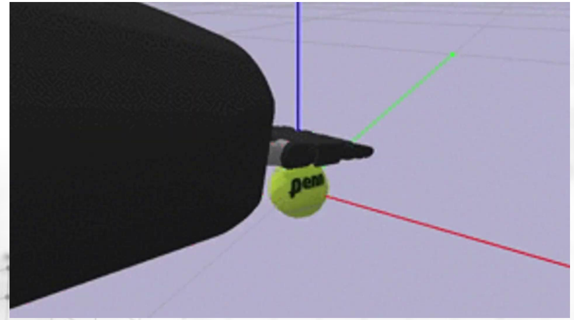
# Challenge of learning to grasp in robotics



One 6 Degree of Freedom Grasp
(6DoF grasp)

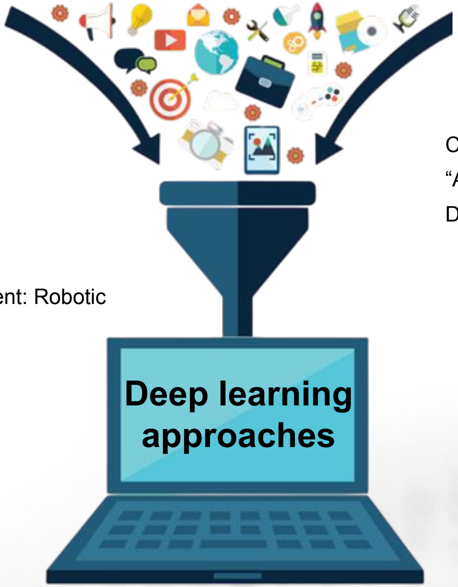
- $g \in SE(3)$
- Sparse reward task 💎
- No reward $\rightarrow$No learning



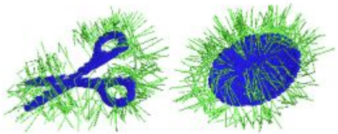
# Data-driven methods require big datasets

## Real world demonstrations (limited ❌ )


O. X.-E. Collaboration *et al.*, “Open X-Embodiment: Robotic Learning Datasets and RT-X Models” 2025



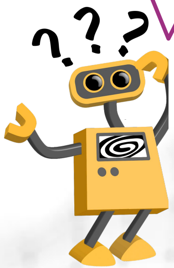

## Automatic demonstration (unlimited, but challenging ✅)



C. Eppner, A. Mousavian, and D. Fox, “ACRONYM: A Large-Scale Grasp Dataset Based on Simulation,” 2020,

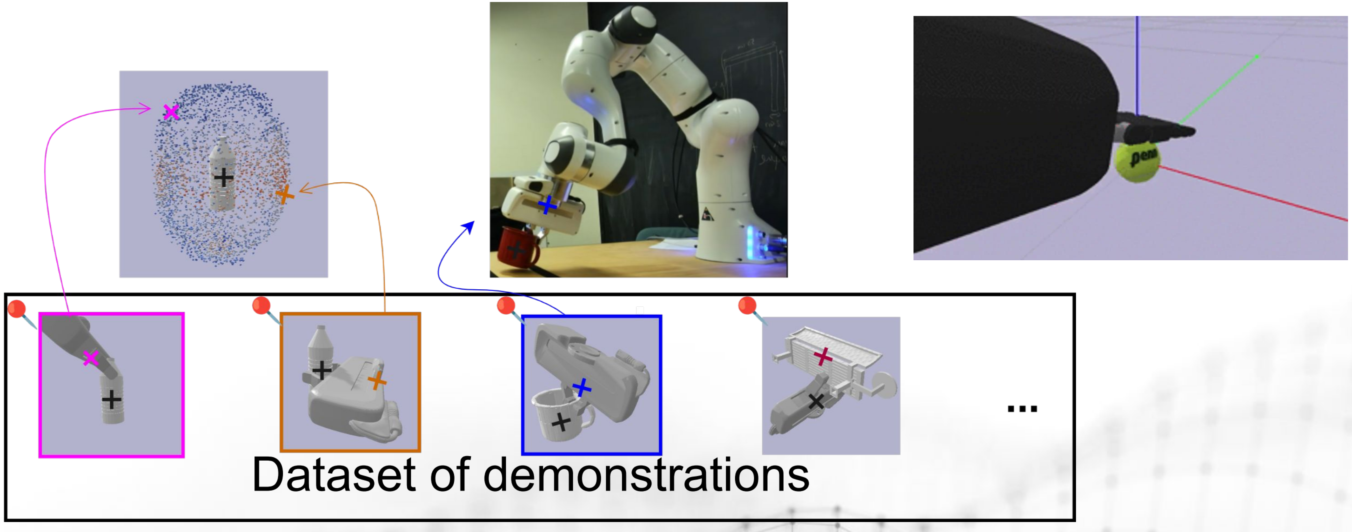
J. Huber *et al.*, “Speeding up 6-DoF Grasp Sampling with Quality-Diversity,” *2024*

How to automatically generate a grasp demonstrations dataset in a sparse reward environment ?



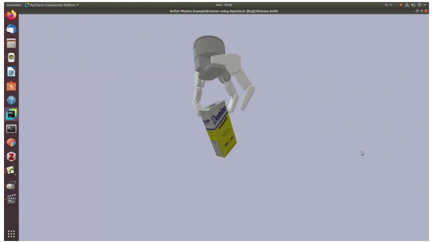
# Problem framing

- Dataset of object-centric grasp demonstrations $g \in SE(3) \times \mathbb{R}^n$
- A demonstration = a 6-DoF end effector pose relative to the object frame
- From 1K to 5K grasps per objects
- Simulated demonstrations transferable in the real world [1]

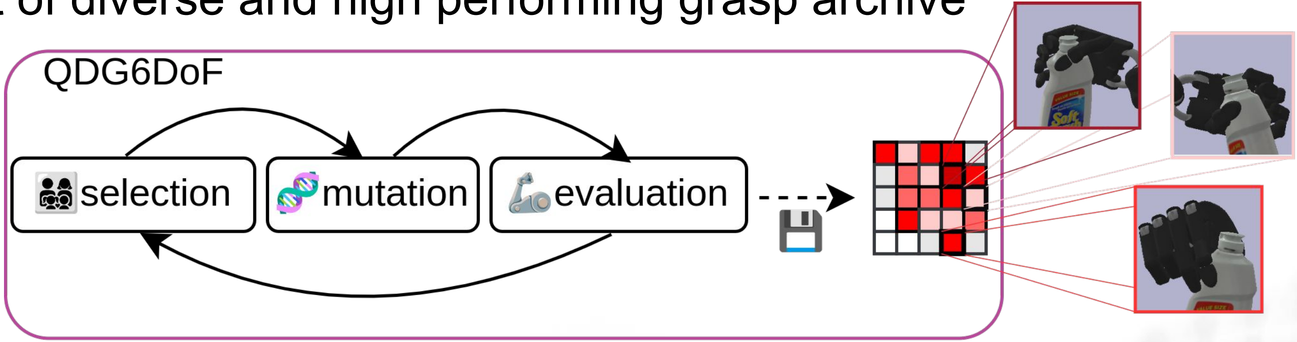



[1] : Huber, J., Hélénon, F., Watrelot, H., Amar, F. B. & Doncieux, S. (2024). Domain randomization for sim2real transfer of automatically generated grasping datasets

# Generating grasps with Quality-Diversity (QD)



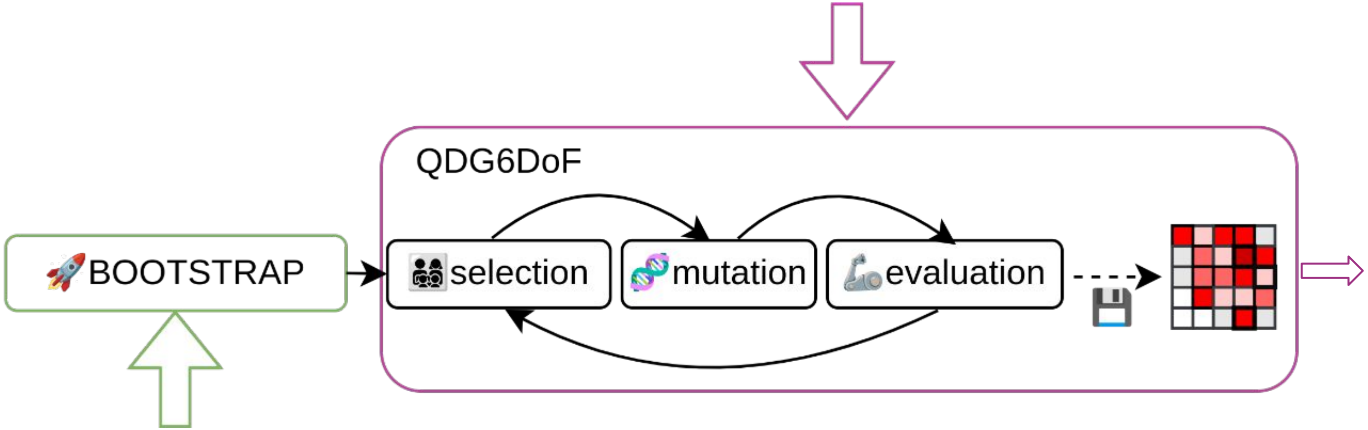
- Efficient exploration of sparse reward environments
- Evolutionary algorithms $\Longrightarrow$ selection-mutation loop
- **Input** = (gripper, object model)
- **Output** = set of diverse and high performing grasp archive

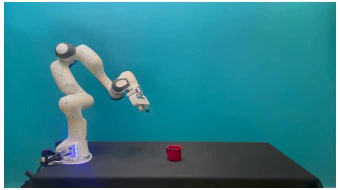



- **QD equations :** $\begin{cases} \forall b \in \mathcal{B}_{reach},\ \exists \theta \in A,\ d_{\mathcal{B}}(\phi_{\mathcal{B}}(\theta), b) < \epsilon & \text{diverse solutions} \\ \forall \theta' \in A,\ \theta' = \operatorname{argmax}_{\theta \in N(b_{\theta'})} f(\theta) & \text{best-performing solution} \end{cases}$

# Scale up the production of synthetic grasping datasets

📄 Huber, J., Hélénon, F., Kappel, M., Chelly, E., Khoramshahi, M., Ben Amar, F., & Doncieux, S. ***Speeding up 6-DoF Grasp Sampling with Quality-Diversity***. *(IROS'24)*

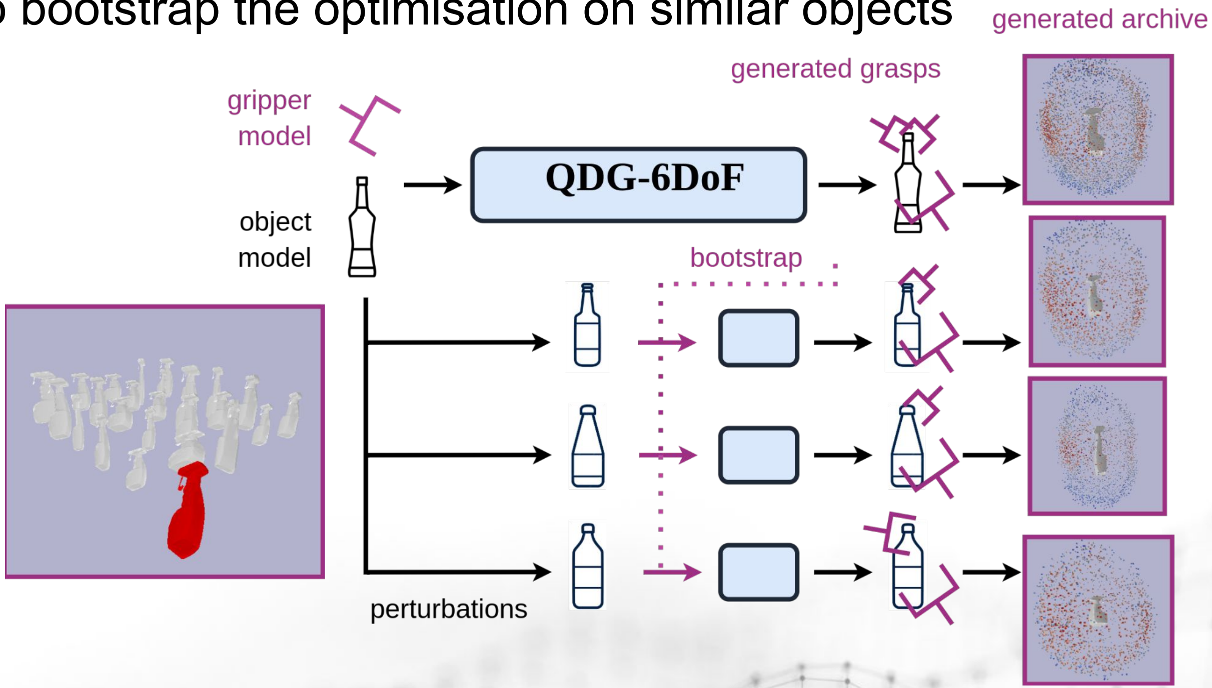


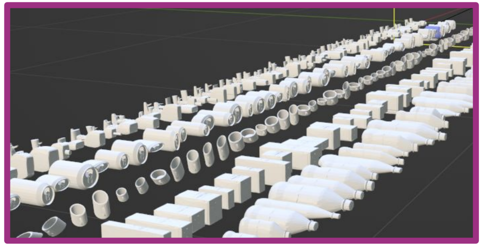
📄🆕 Huber, J., Hélénon, F., Kappel, M., Páez-Ubieta, I. de L., Puente, S. T., Gil, P., Ben Amar, F., & Doncieux, S. ***QDGset: A Large Scale Grasping Dataset Generated with Quality-Diversity***. Sorbonne Université / University of Alicante.

# Bootstrap speeds up and scales up demonstrations 🚀

- Run QD optimisation module on a given object ⇒ generate $A_s^b$
- Use $A_s^b$ to bootstrap the optimisation on similar objects



# Object data augmentation



- Core initial object datasets $P$, $n$ = **29 651 objects**

$$\mathrm{P} = (\mathcal{P}_i)_{1 \leq i \leq n} \quad \text{where } \mathcal{P}_i = \{p_j \in \mathbb{R}^3 \mid p_j = (x_j, y_j, z_j),\ j = 1, 2, \ldots, m_i\}$$

- Data augmentation = point cloud deformation $\varphi D_a$

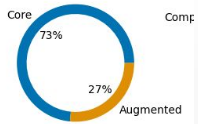
$$\mathcal{P}_i^a = \{\varphi_{D_a}(p_j) = D_a \cdot p_j \mid p_j \in \mathcal{P}_i\} \quad \text{where } D_a = \mathrm{DIAG}(\alpha_1, \alpha_2, \alpha_3)$$

- **Final dataset ⇒ size 40 353 objects**

$$\mathrm{P}' = (\mathcal{P}_i^a)_{1 \leq i \leq n, 1 \leq a \leq a_{\max}}$$

- QDGset is 4 times bigger than ACRONYM [2]

62M grasps

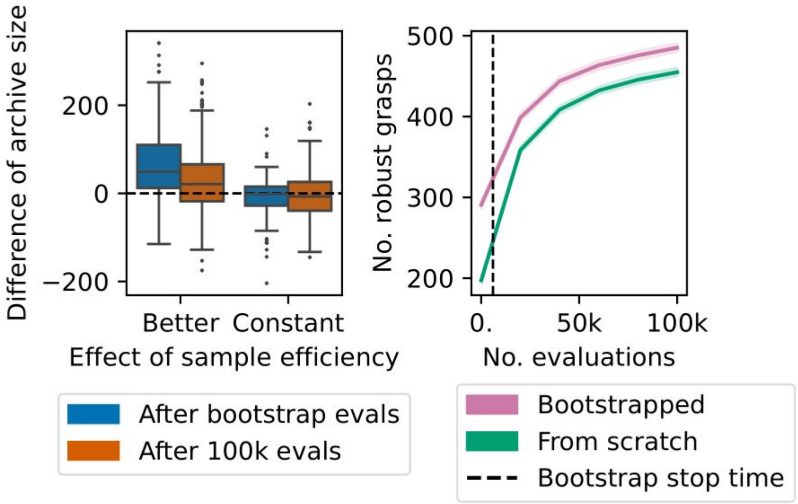



17.7M grasps

[2] : Eppner, C., Mousavian, A. & Fox, D. (2021). *Acronym: A largescale grasp dataset based on simulation*. In *2021 IEEE International Conference on Robotics and Automation (ICRA)* (pp. 6222–6227).

# Results of bootstrap on augmented data

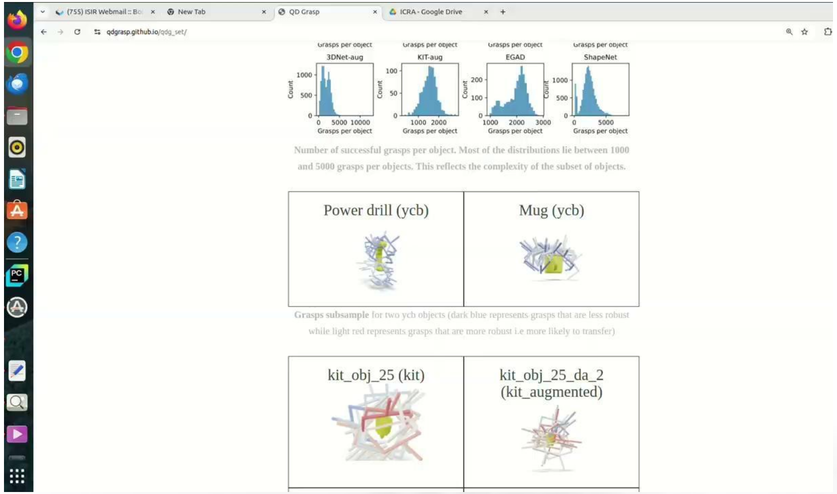
- Bootstrap reduces the required number of evaluations by up to **20%**
- Better performances when stopping the optimization right after the bootstrap




- Bootstrapping does maintain the quality of the grasps

# Conclusions on QDGset

- Framework for scaling up object-centric poses
- 62M grasps on about 40K objects
- Allow anyone to easily produce data they need




https://qdgrasp.github.io/qdg_set/