

# GenAug: Retargeting behaviors to unseen situations via Generative Augmentation

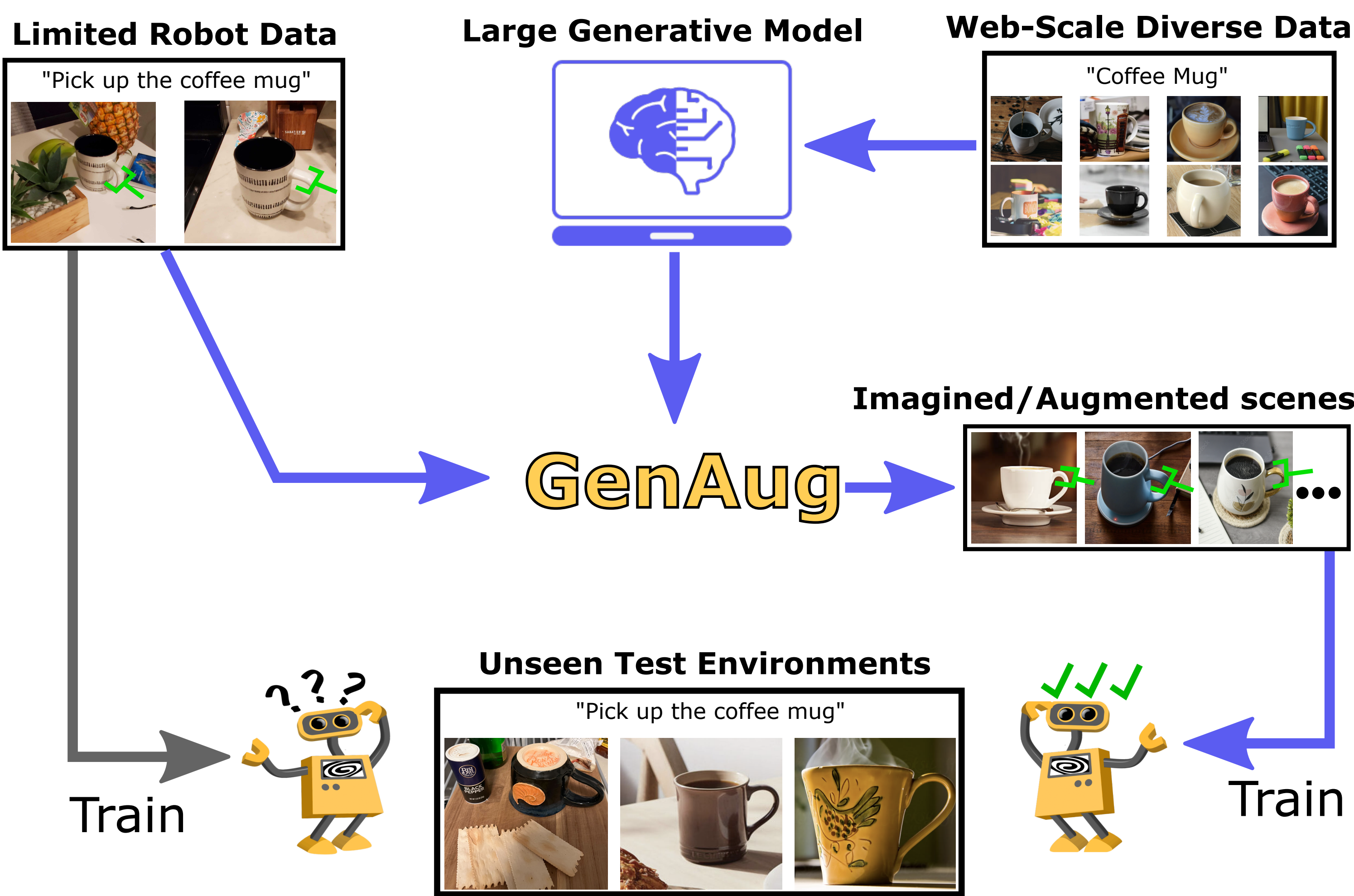


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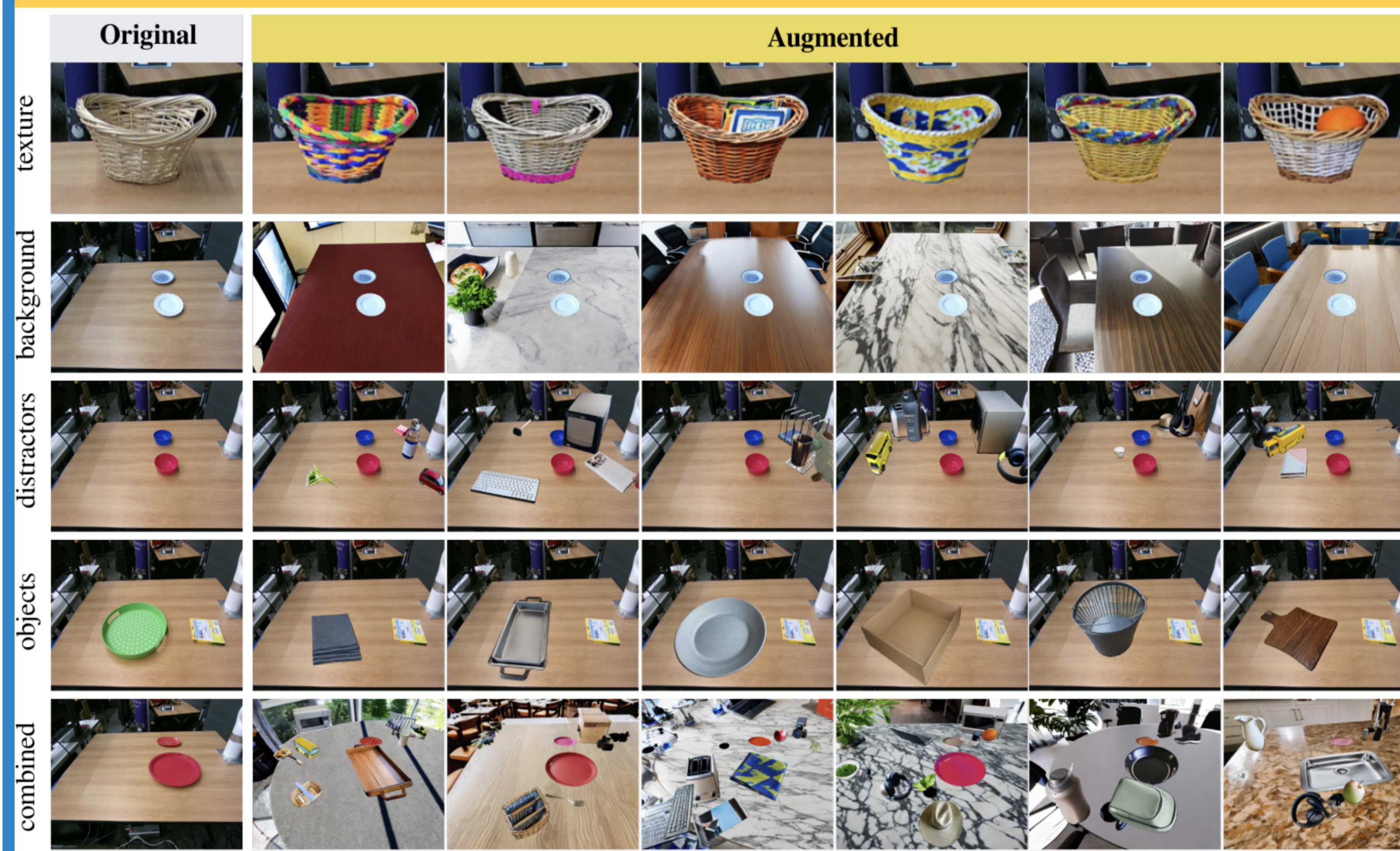


## Training Robots With Limited Data

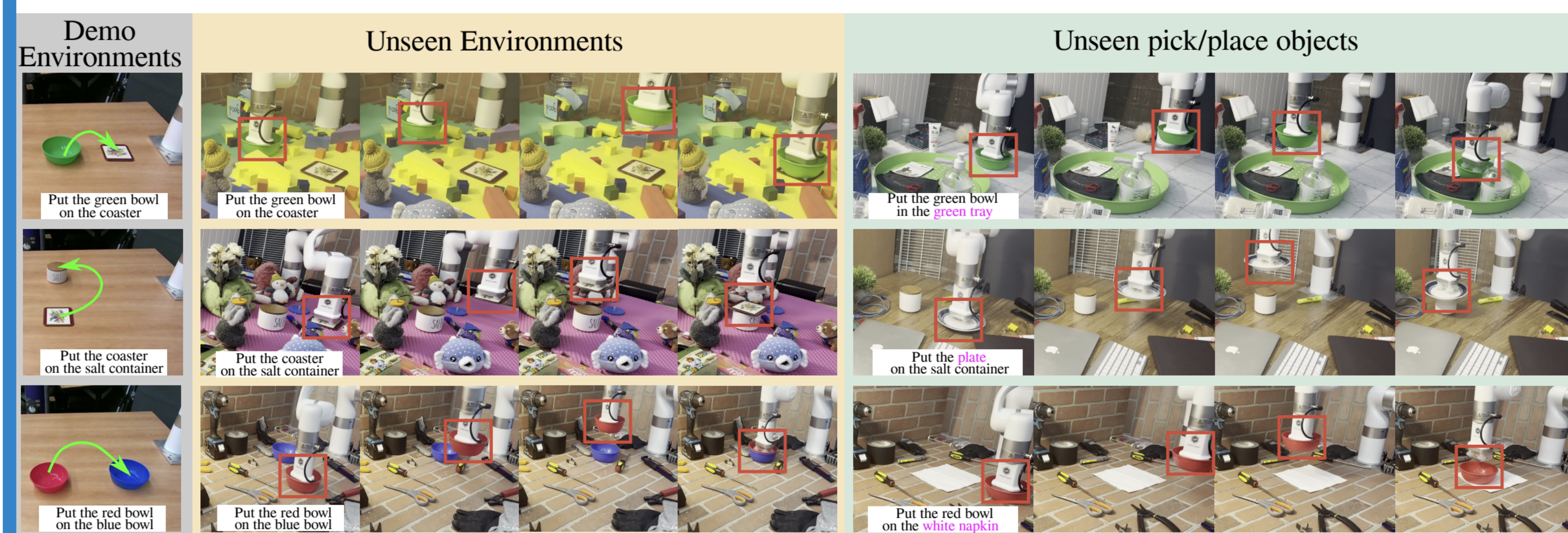
Can robots get **huge, free and diverse** data via large generative models?



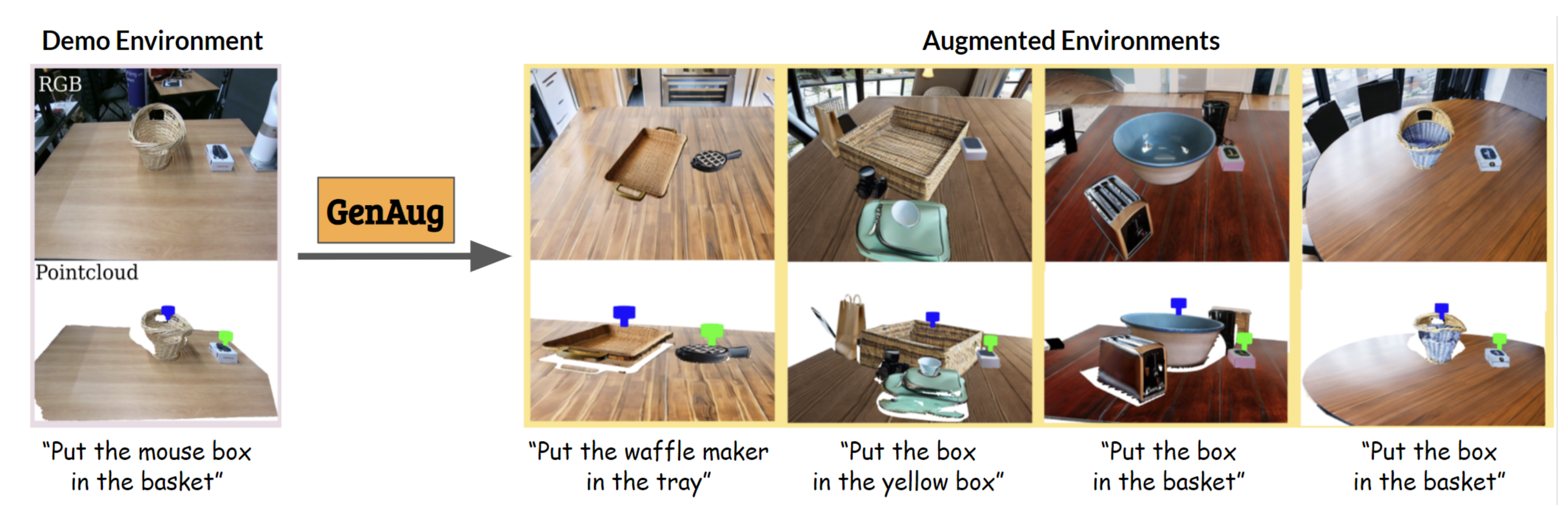
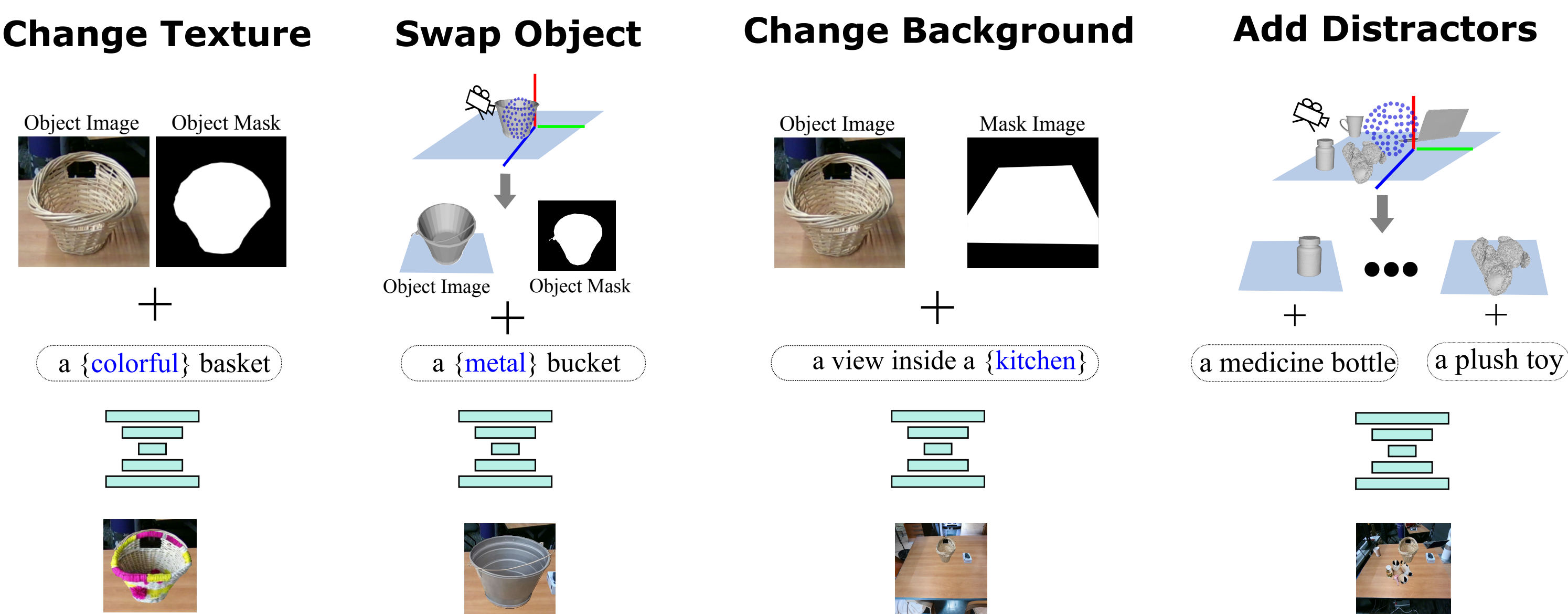
## GenAug Results



## Robot Results



## GenAug: A Controllable RGBD Data Augmentation Method



## Real World: Language-guided policy trained with and w/o GenAug on 10 pick and place tasks

	box to tray			box to basket			coaster to dust pan			plate to tray			bowl to coaster		
	env	pick	place	env	pick	place	env	pick	place	env	pick	place	env	pick	place
No GenAug	0.8	0	0	0.2	0.2	0	0.8	0.4	0.4	0	0	0	0	0	0
GenAug	1	0.6	1	0.6	0.6	0.8	1	0.4	0.4	1	0.4	0.2	0.6	0.6	0.6

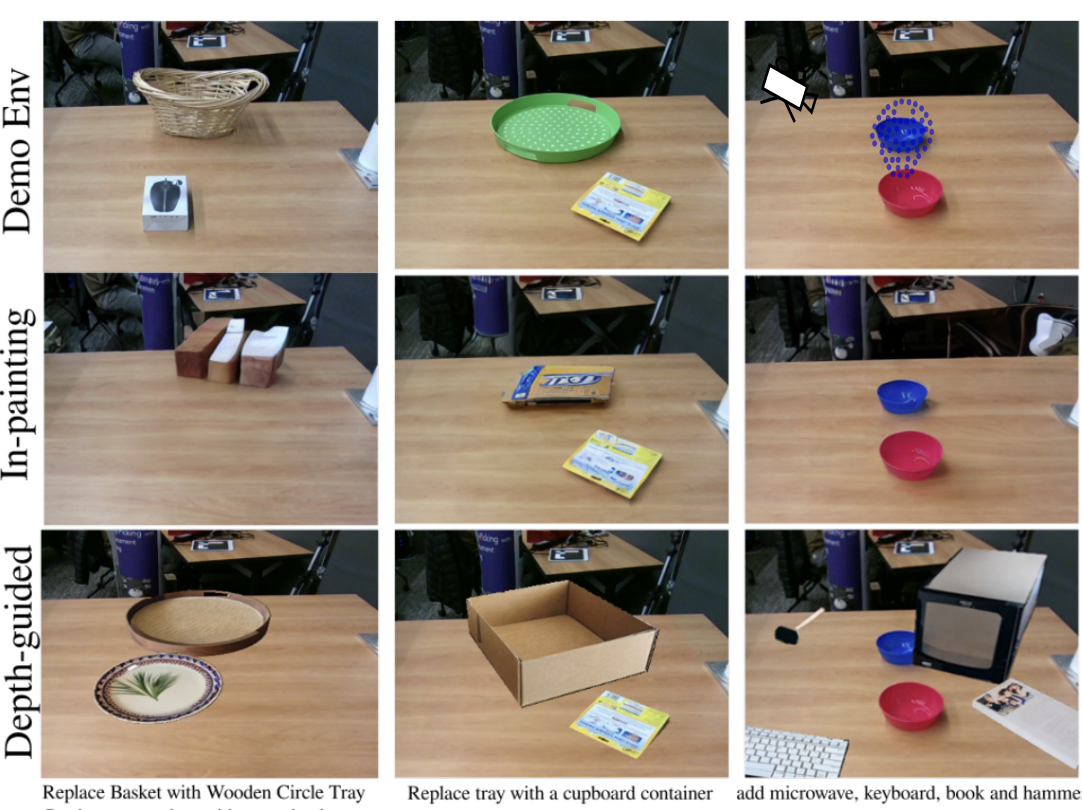
	plate to plate			box to box			plate to box			coaster to salt			bowl to bowl		
	env	pick	place	env	pick	place	env	pick	place	env	pick	place	env	pick	place
No GenAug	0	0	0.2	0.2	0	0	0.6	0.2	0	0.2	0	0.2	1	0.2	0
GenAug	1	0	0.6	0.8	0.4	0.4	1	0.8	0	1	0.4	0.4	1	0.4	1

## Simulation: GenAug shows notable improvement on unseen test environment baselines

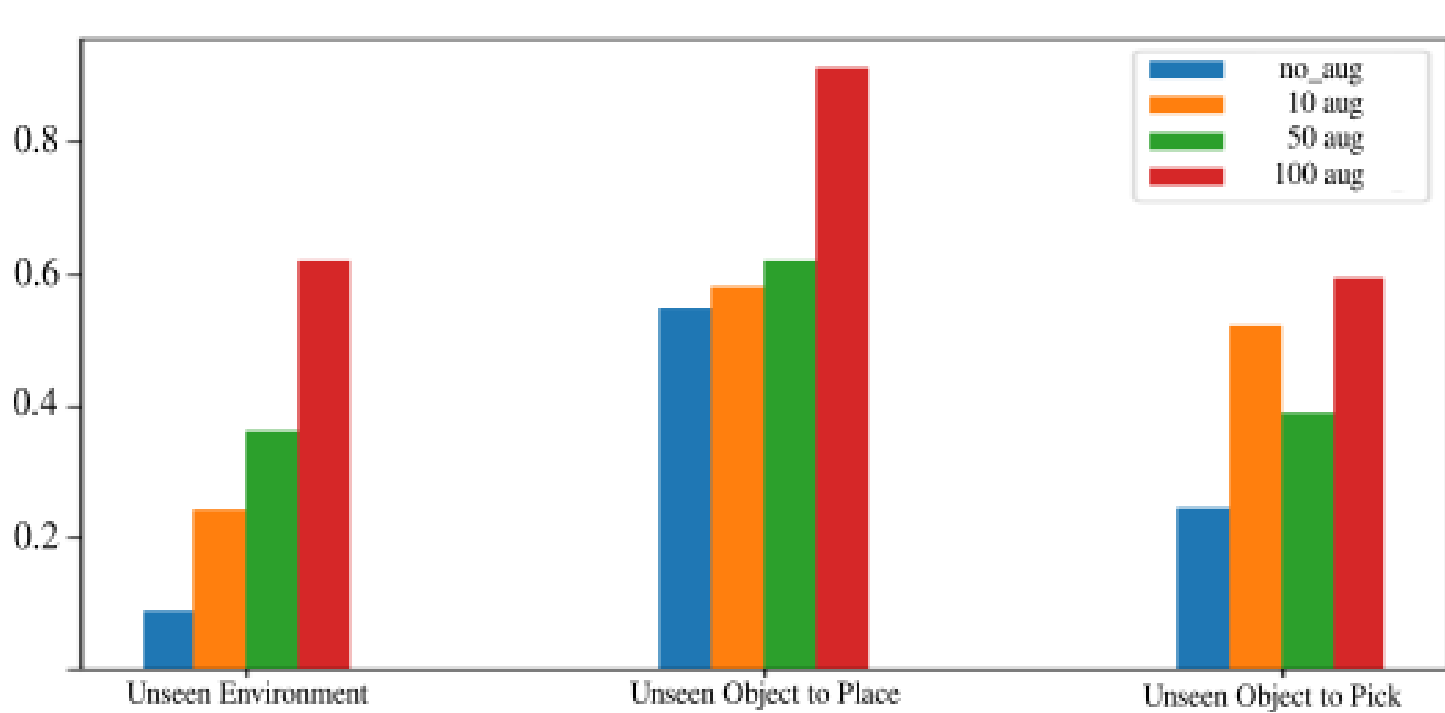
Method	Unseen Environment						Unseen to place						Unseen to pick					
	TransporterNet		CLIPort		CLIPort		TransporterNet		CLIPort		TransporterNet		CLIPort		CLIPort			
No Augmentation	4.8	8.1	9.8	11.7	14.3	14.4	15.1	30.4	52.6	39.4	40.8	44.6	8.5	34.6	54.9	46.0	67.0	64.1
Spatial Augmentation	53.1	67.0	73.5	38.2	39.8	64.3	55.1	65.4	84.9	39.7	55.9	73.9	48.3	67.0	76.1	52.5	65.0	81.0
Random Copy Paste	53.0	75.3	79.1	33.6	62.2	55.4	24.5	22.1	35.5	7.6	9.9	17.9	44.4	40.7	35.9	19.2	52.7	72.3
Random Distractors	10.1	9.7	13.7	15.4	36.2	35.8	28.2	60.7	66.0	27.5	51.8	54.3	42.5	47.4	62.3	31.0	64.0	69.1
R3M Finetune	4.1	6.0	4.8	22.2	16.8	20.9	43.5	40.6	41.9	30.9	43.5	57.5	45.6	45.7	41.1	46.7	50.7	72.7
GenAug	43.9	58.5	77.6	46.6	57.0	71.9	69.1	76.5	83.6	62.6	83.9	86.3	75.3	75.6	87.2	61.5	77.7	83.1
GenAug (w Depth)	47.8	83.8	91.2	47.2	60.9	73.4	39.9	67.2	74.2	64.8	73.8	84.6	71.2	83.4	87.1	56.2	67.3	81.5

## Analysis

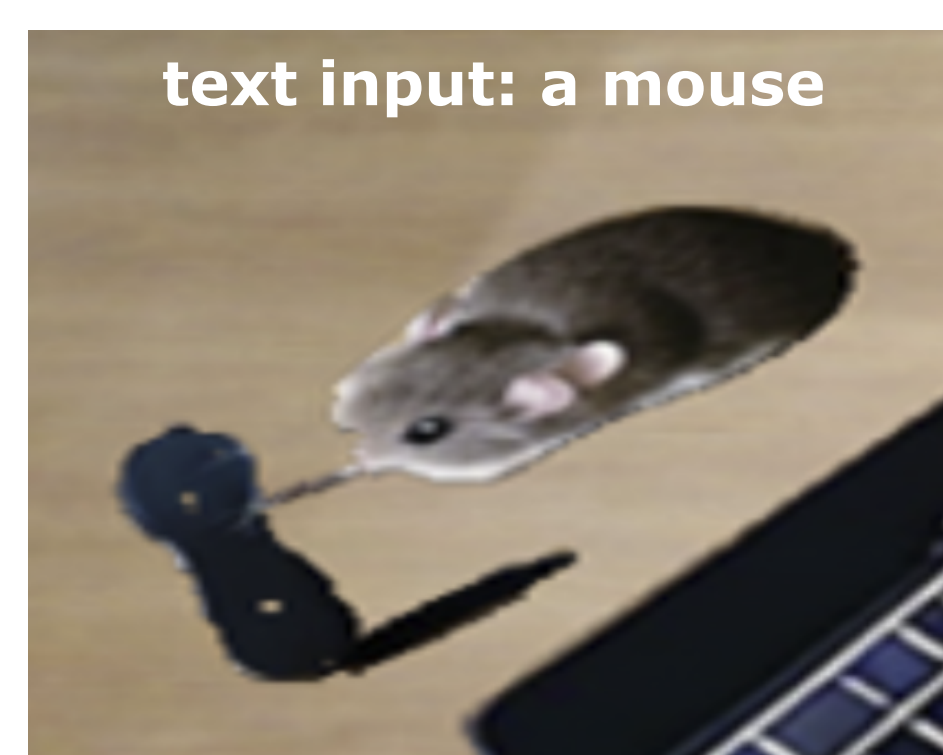
### Depth-aware vs In-painting



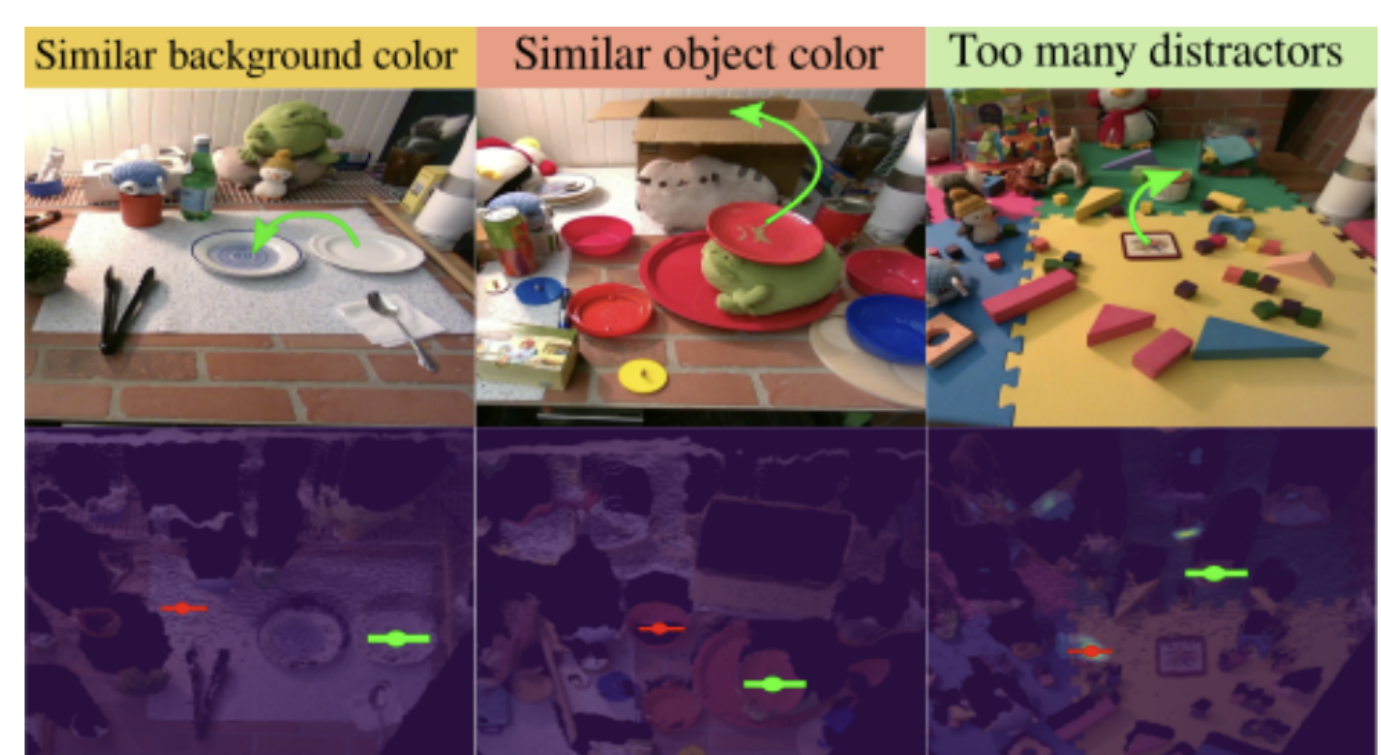
### Performance vs Augmentation



## Failure Cases



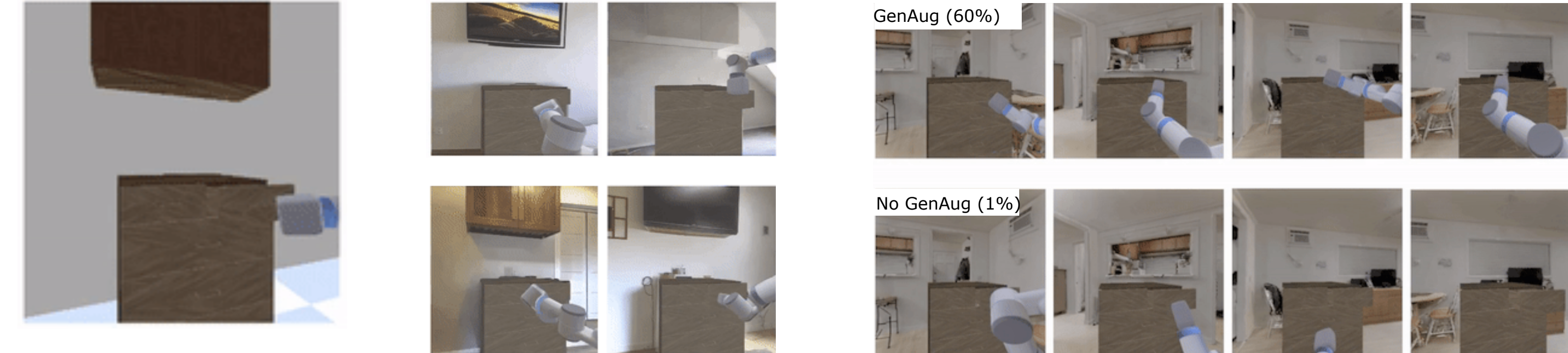
GenAug is based on text-to-image diffusion models, it cannot guarantee the generated images are perfect.



Typical Failure cases occur when the background color is similar to the pick or place object. Or one of a few distractors has a very bright color or similar colors.

## Beyond Pick-and-place Tasks

### Demo Env Augmented Envs Unseen Test Envs (iGibson)



In addition, we test GenAug on a new task "close the top drawer" with a fetch robot. In particular, we tested on 100 unseen backgrounds using iGibson rooms and observed GenAug is able to achieve 60% success rate while policy without GenAug is only 1%.

## Limitations

### 1. Assume the Same Action:

GenAug does not augment action labels and reason about physics parameters. It assumes the same action still works on the augmented scenes.

### 2. Augmentation & Speed:

GenAug cannot guarantee visual consistency for frame augmentation in a video. GenAug usually takes about 30 seconds to complete all the augmentations for one scene, which might not be practical for some approaches such as on-policy RL.

## Acknowledgment

We thank Aaron Walsman for helping with transporting materials from Home Depot for creating robot environments. We thank Mohit Shridhar for the discussions about CLIPort training. We thank all members from the WEIRD lab, the RSE lab at the University of Washington, as well as Kay Ke, Yunchu Zhang, and Abhay Deshpande for many discussions. We are thankful to Boling Yang and Henri Fung for their patience in letting us book all the slots of the machine before the deadline. We are grateful to Selest Nashef for his help to keep our robot experiments safe and organized. Part of this work was done while Zoey Chen was an Intern at Meta AI. This work was also funded in part by Amazon Science Hub.