

# Scaling Up and Distilling Down Language-Guided Robot Skill Acquisition

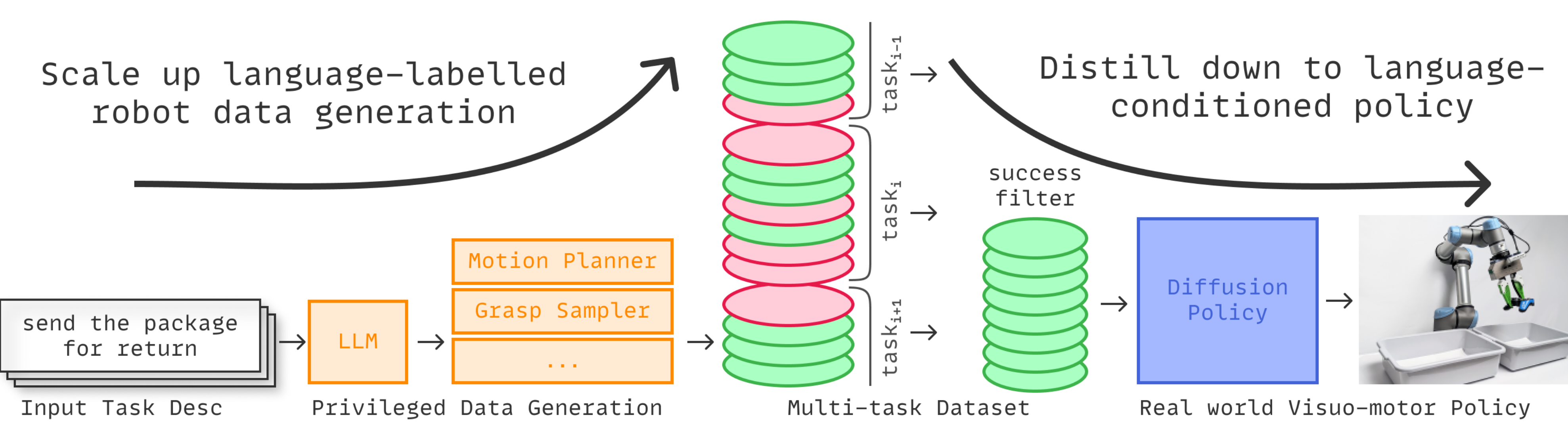
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## Language-guided Robot Skill Learning

For SCALING UP data generation, a language model guides sampling-based robot planners to generate **rich and diverse** manipulation trajectories.



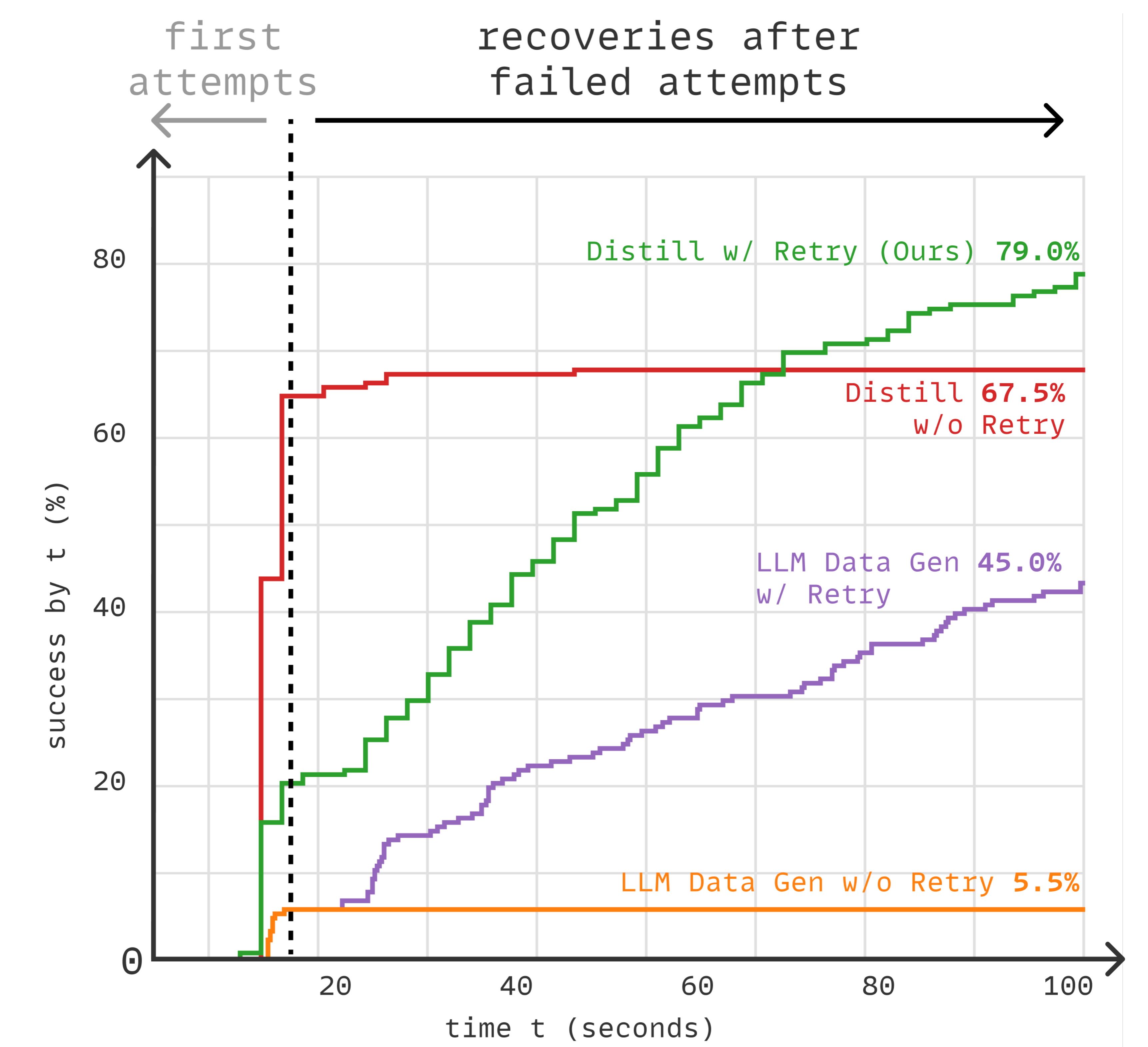
For DISTILLING DOWN for real world deployment, we extend Diffusion Policy to multi-task settings with language conditioning.

**Scaling Up and Distilling Down** is a framework for language-guided skill learning. Give it a task description, and it will automatically generate rich, diverse robot trajectories, complete with success label and dense language labels.

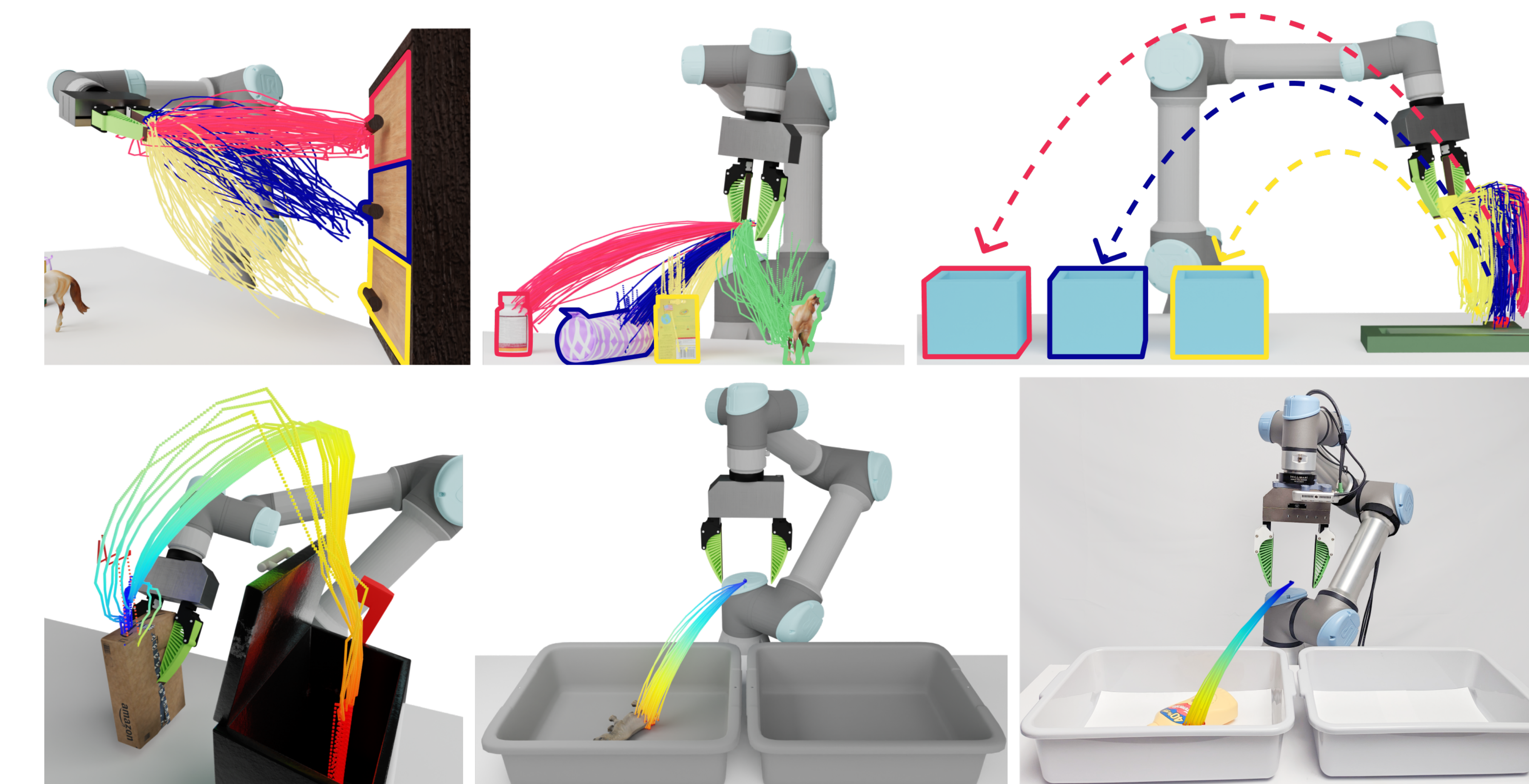
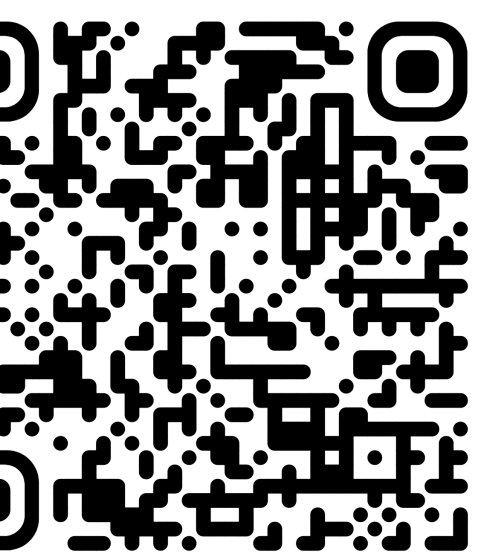
**The best part?** It uses no expert demonstrations, manual reward supervision, and no manual language annotation.

## Robust Retries After Failures

Using a language model to predict each task's success condition code snippet allows the robot to retry failed tasks. The result are demonstrations of robust behavior, which teach the policy to **recover after failed attempts**.



See how well your policy scales with infinite language-labeled and diverse robot trajectories.



## A New Multi-Task Benchmark

DOMAINS	TASKS	ASSETS	LANGUAGE LABELS
5	18	30	∞
Intuitive Physics & Tool-use			
balance the bus on the block	catapult the yellow block into the furthest bin	put the horse toy into the bottom drawer	
put the toy into the left bin	send the package for return	put the vitamin bottle into the top drawer	
Novel Geometry up to 400 control cycles			

## Language-guided not Language-constrained

Our framework is a step towards putting robotics on the same scaling trend as large language models while *not compromising* on rich low-level manipulation.

Approach	6 DoF Manipulation	Common-sense	No Sim State
Sampling-based Planners	✓	✗	✗
LLM Planners	✗	✓	✗
Our Data Generation	✓	✓	✗
<b>Our Policy</b>	✓	✓	✓

## Run it in Real with Zero Finetuning

Using domain randomization, we deployed our diffusion policy on a real robot with no fine-tuning.



## Language-conditioned Diffusion Policies

