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Real2Gen: Imitation Learning from a Single Human Demonstration with Generative Foundational Models

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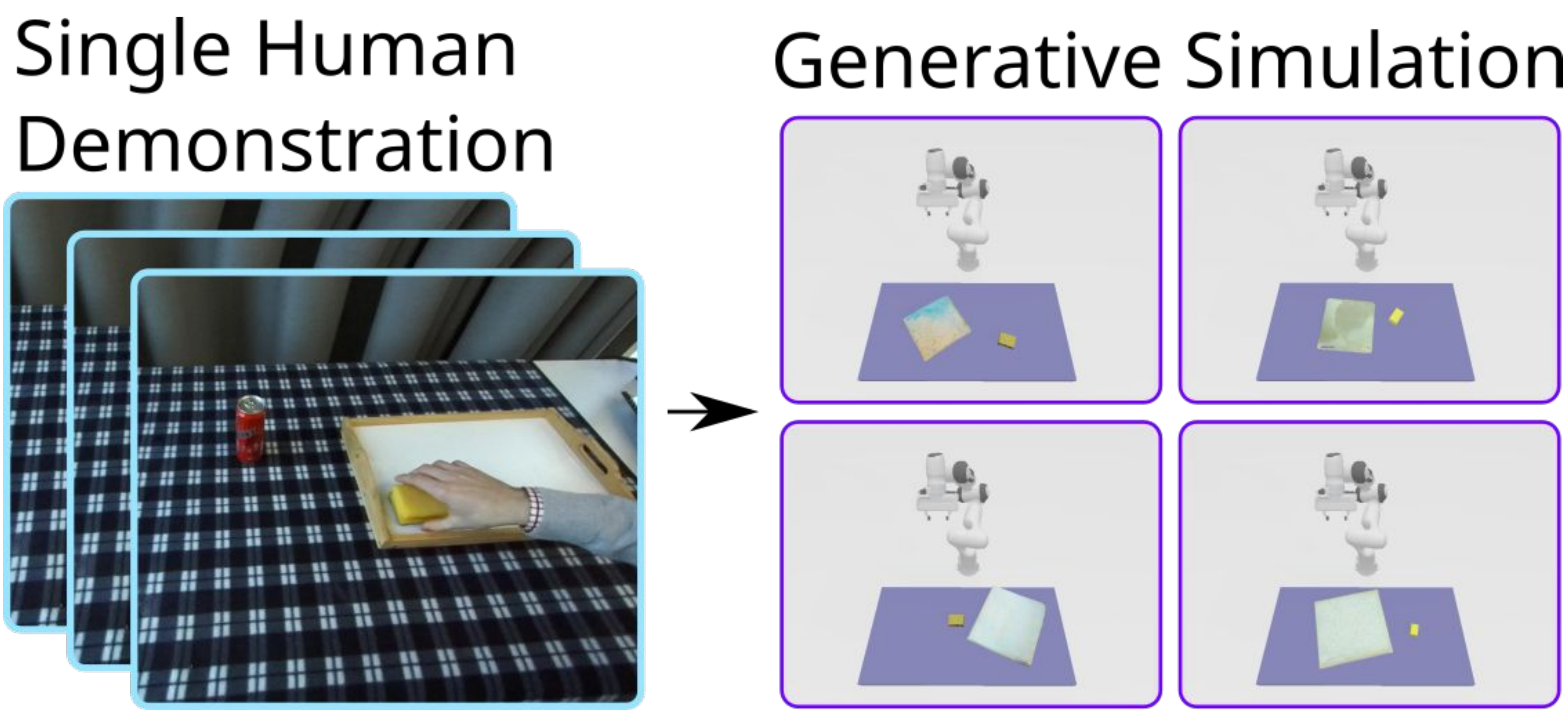
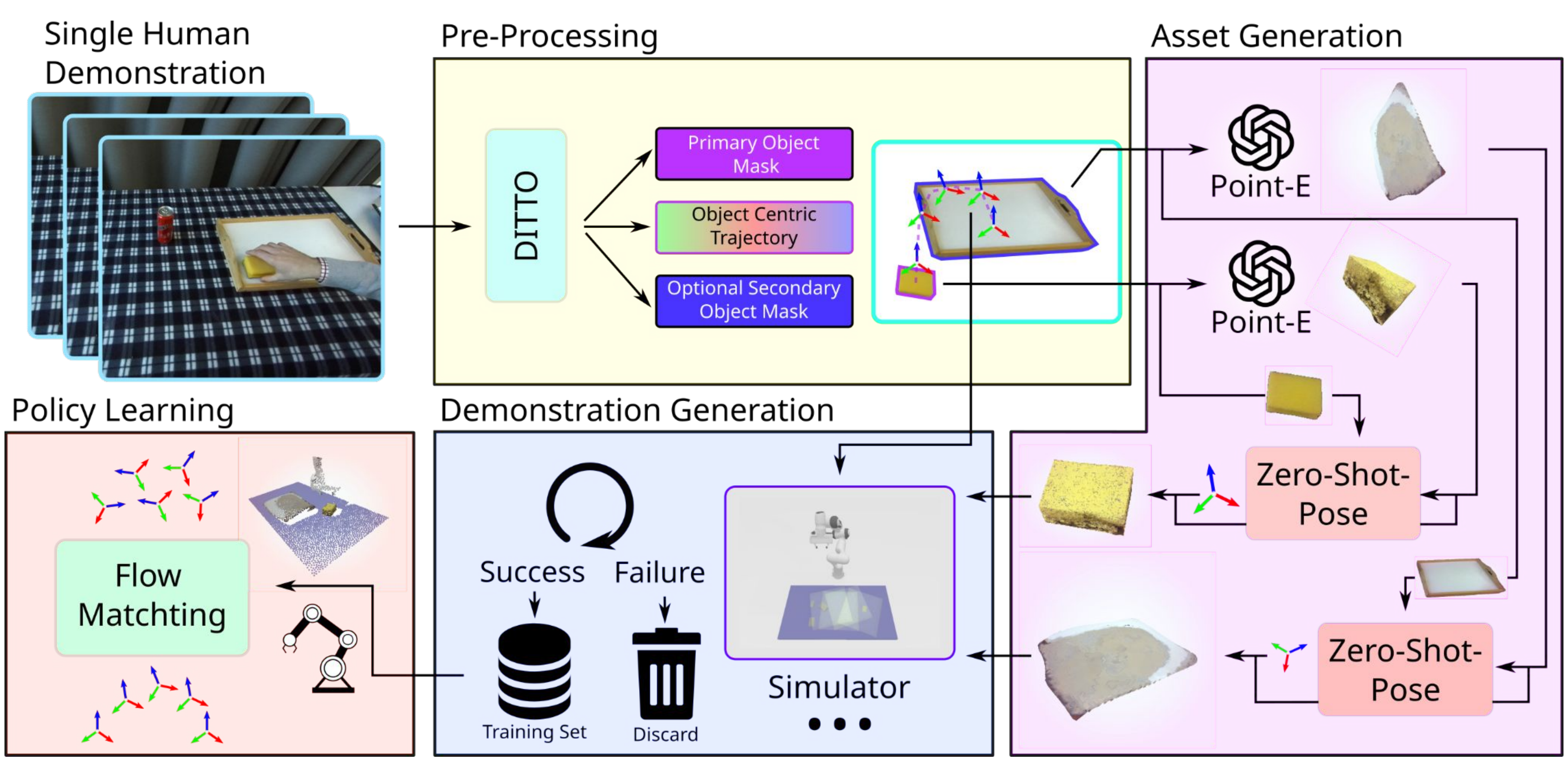
Motivation



- Imitation learning promising paradigm to learn new tasks
- Commonly trained on robot demos, but collecting with tele-operation or kinesthetic teaching is tedious

→ Real2Gen: Transform human demos to robot demos using generative simulation

Real2Gen Overview



1. Use DITTO[1] or ORION[2] to extract object masks + traj.
2. Generate 3D asset using Point-E[3] and align to demo with ZSP[4]
3. Re-generate scenarios and use privileged info to generate demonstrations
4. Train a policy, e.g. flow matching[5]

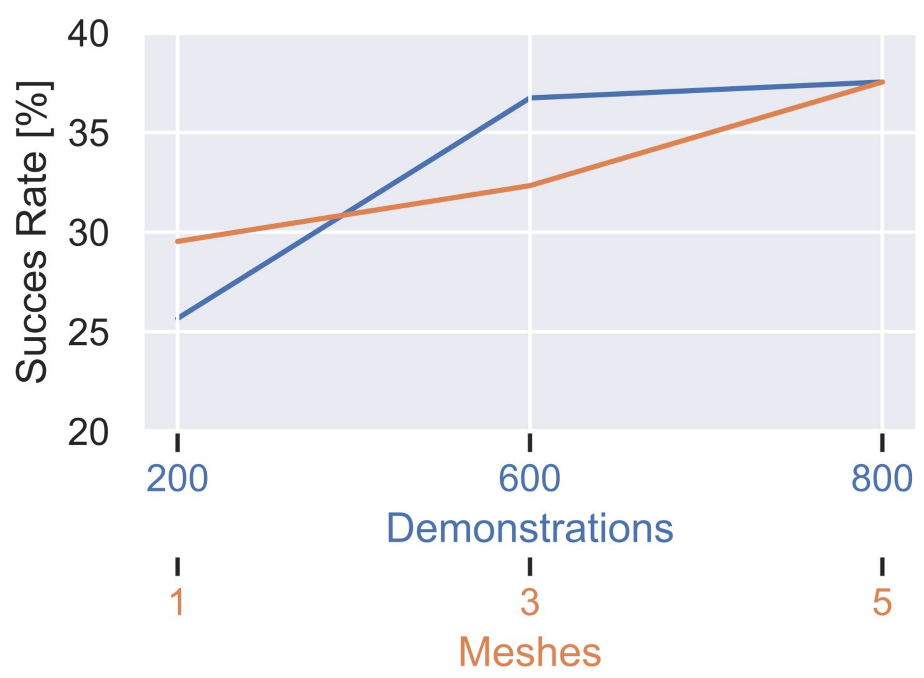
Experiment – Policy Learning

Policy Learning Results

Method	Sponge on Tray [%] (↑)	Coke on Tray [%] (↑)	Paperroll upright [%] (↑)	Mean SR [%] (↑)
DITTO[1]	$6.3^{\pm 2.1}$	$26.0^{\pm 3.6}$	$0.3^{\pm 0.5}$	$10.9^{\pm 2.1}$
DITTO[1] w/ ZSP[4]	$4.3^{\pm 1.2}$	$19.7^{\pm 3.8}$	$0.7^{\pm 0.6}$	$8.2^{\pm 1.8}$
Real2Gen (ours)	$41.3^{\pm 4.5}$	$46.3^{\pm 6.4}$	$25.0^{\pm 1.0}$	$37.5^{\pm 3.0}$

- Real2Gen shows robustness over DITTO

Ablation Study



- Performance gain diminishes with more demonstrations
- Mesh amount are more relevant

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Experiment – Mesh Generation

- Compare human effort for mesh retrieval against querying a database using tags
- Apply matching and manually verify
- Real2Gen provides almost 3x more available meshes

Mesh Source	Available Meshes	100 Mesh Pre-Selection	Matching Successful and Task Relevant
Point-E[3] (ours)	∞	Random	**54%**
Objaverse[6]	690	Most viewed*	19%
		Random*	18%

**if less than a 100 meshes are available we use all*

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