

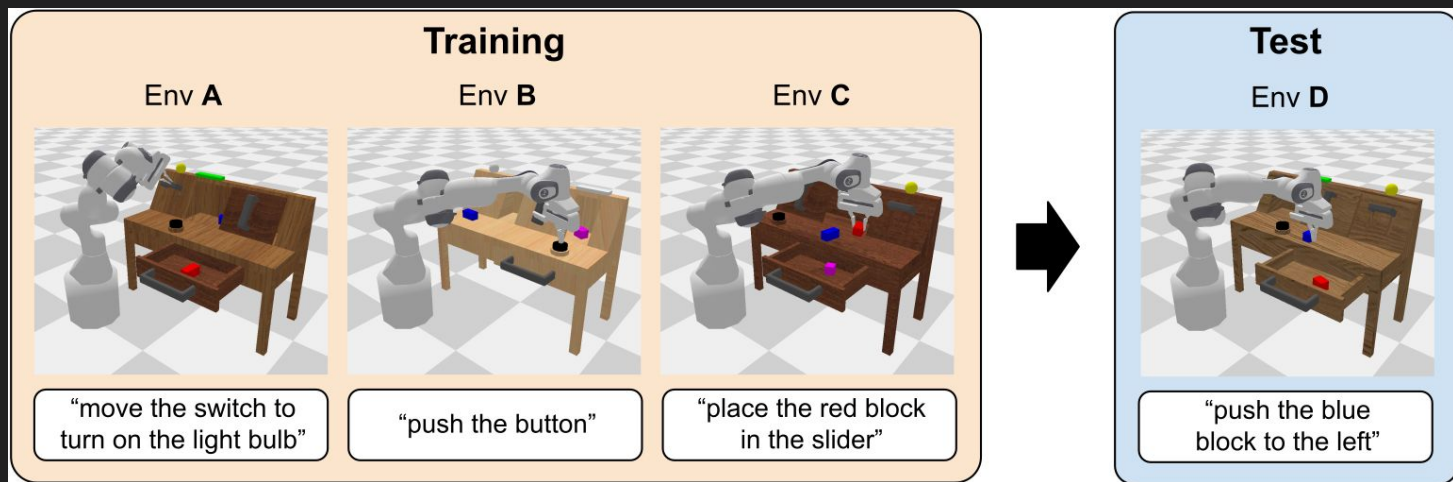
# CALVIN benchmark

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# TL;DR

CALVIN consists of a novel manipulation benchmark for learning Goal Conditioned policies using either goal images or language as free-form text. It includes a simulated manipulation environment, an annotated dataset taken from Play, and a baseline algorithm (MCIL) introduced by Lynch & Sermanet (2).



# Background

The key takeaways from previous work are listed below:

- **Learning Latent Plans from Play**
  - Goal Conditioned Behavior Cloning
  - Dataset generation via Goal Relabelling
- **Language Conditioned Imitation Learning over Unstructured Data**
  - MultiContext Imitation Learning

# Dataset Generation via Goal Relabelling

The data collected from Play is later separated into small 1-2 second sequences, from which the last step of this trajectory is labeled as a goal state which is used to condition the policy.



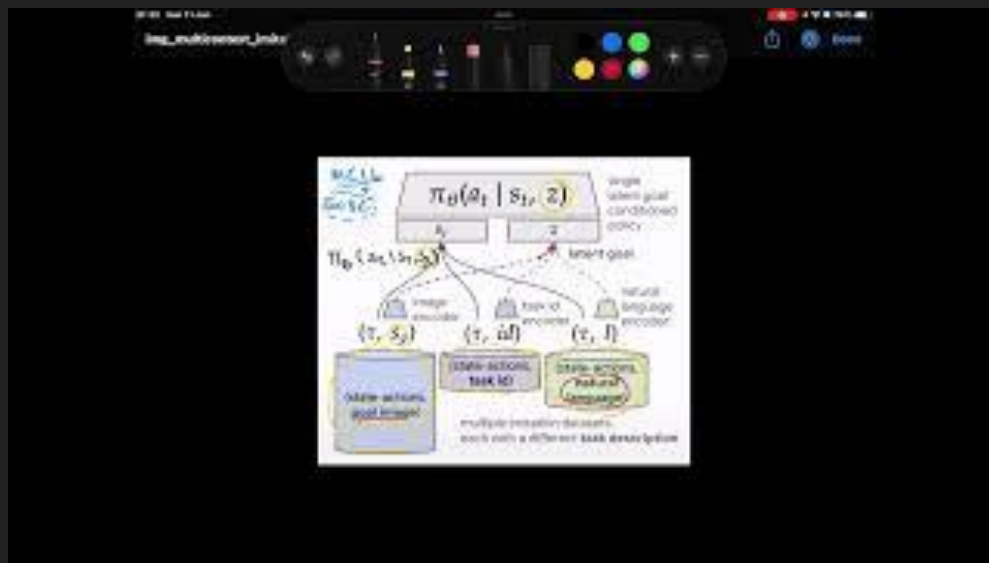
# Goal Conditioned Behavior Cloning (GCBC)

The key idea of GCBC is to use a conditioning goal state to make the policy follow a specific task given by the goal image.



# Multi Context Imitation Learning (MCIL)

MCIL key idea is to allow the user to condition using various sources, like goal images, or goals given by natural language. The idea is to have separate encoders that map the various contexts into a single latent goal vector.



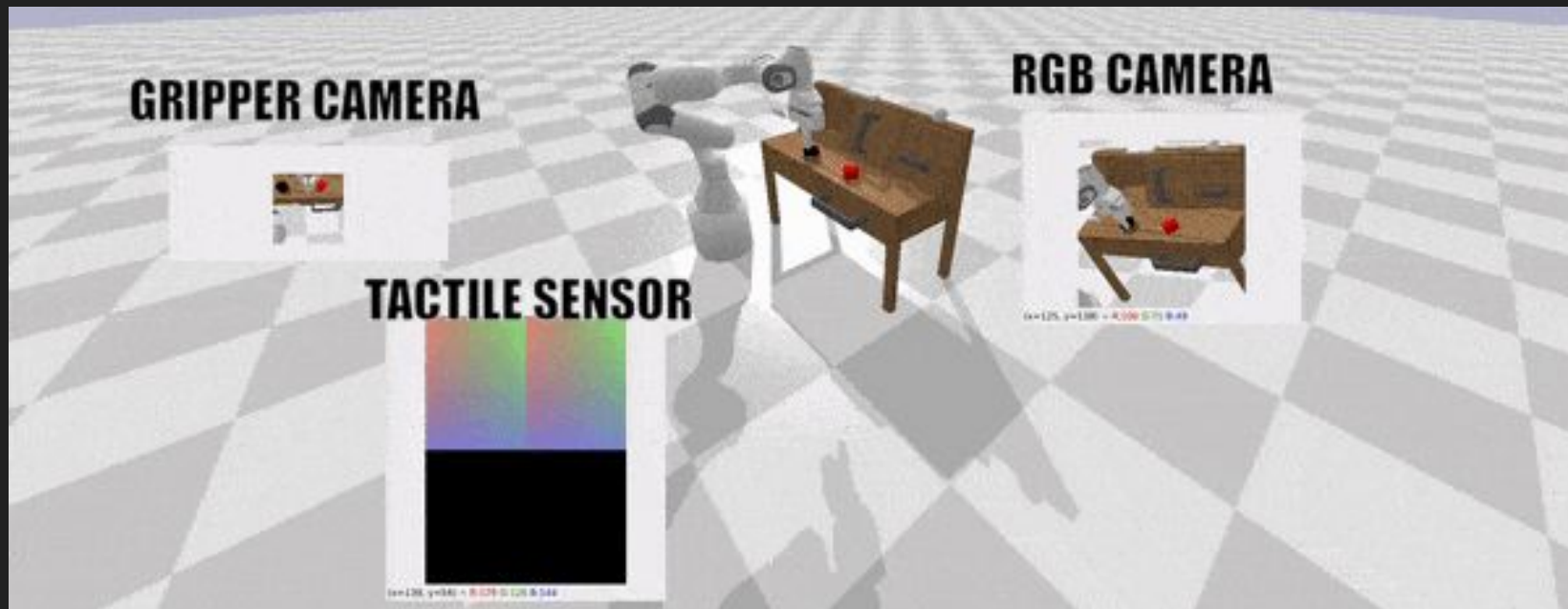
# CALVIN Environment

CALVIN reproduces the original environment introduced by Lynch & Sermanent (2) using the open-source [PyBullet](#) alternative, as [MuJoCo](#) back in the day was still closed source and most likely the authors of (2) (3) weren't allowed to share their simulated environment.

CALVIN's simulated environment also allows for a wider range of sensors, as shown below. These include:

- Proprioceptive information (including robot's joint positions, velocities, etc).
- RGB and Depth information from cameras mounted statically in the scene.
- RGB and Depth information from cameras mounted on the gripper frame.
- Vision based tactile sensors.

# CALVIN Environment





# CALVIN Environment

```
# Go back to where the repository was cloned
cd $CALVIN_ROOT
# Go go the location of the script (some absolute paths must be hard coded :c)
cd calvin_env/calvin_env/envs
# Run the test-env script (spawns the D variant of the environment)
python play_table_env.py
```

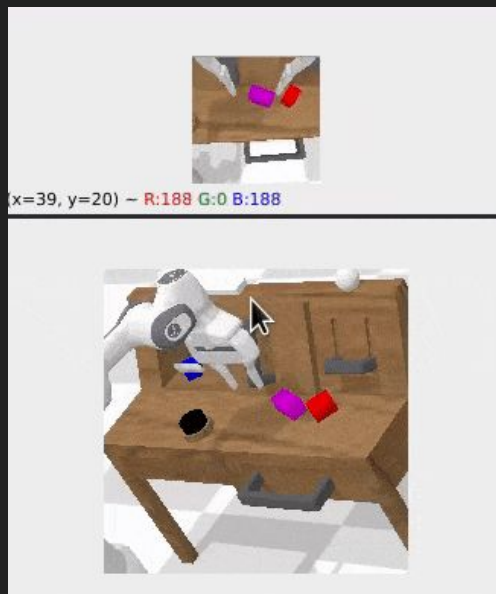


# CALVIN Dataset

CALVIN provides a rich dataset collected in a similar fashion to the dataset used in Lynch & Sermanet [2]. The authors use also data collection through teleoperation to reach 24 hours of teleoperated **Play** data, which covers most of the state space in a similar way to the dataset mentioned before. The only difference in this stage is that the teleoperated data collected in VR corresponds to the simulated environment that uses [PyBullet](#), instead of [MuJoCo](#) Haptix, which is the one used by Lynch & Sermanet [2].

# CALVIN Dataset

```
# Go back to where the repository was cloned
cd $CALVIN_ROOT
# Run the visualizer pointing to the debug dataset (location of scene_info.npy)
python scripts/visualize_dataset.py dataset/calvin_debug_dataset/training
```



# Some Results

Below we show some results obtained from training the *MCIL* baseline on the *Debug* dataset. We have selected just a few successes and failures of some a few of the 21 tasks. You can click [here](#) to see some more results logged in *Weights & Biases*.

Lift blue block drawer (**Fails**)



## Move slider left (Successes)



## Move slider left (Fails)



## Close drawer (Successes)



## Close drawer (Fails)



# References

1. Mess, Oier et. al. *CALVIN: A Benchmark for Language-conditioned Policy Learning for Long-horizon Robot Manipulation Tasks.*
2. Lynch, Corey & Sermanet, Pierre. *Language Conditioned Imitation Learning over Unstructured Data.*
3. Lynch, Corey et. al. *Learning Latent Plans from Play*

Thank you for  
your consideration!