Third-Person Visual Imitation Learning via Decoupled Hierarchical Control

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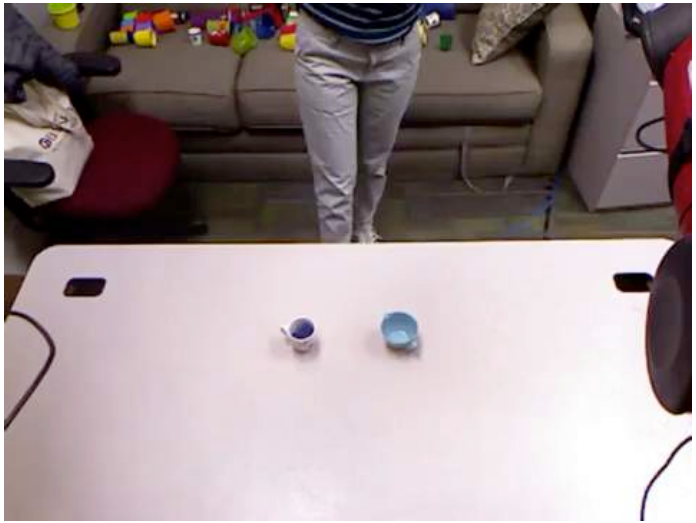
Problem / Goal



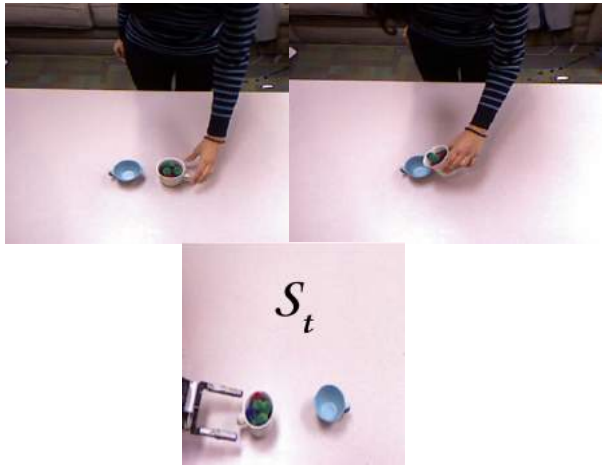
Can our robot manipulate a new object given a single human video alone?

Why is it hard?

- Inferring useful information in the video
- Handling domain shift
- Every *major* part of the sequence needs to be executed correctly - Ex: For pouring, it needs to reach the cup before twisting its hand
- The manipulation is challenging. (6D, novel objects and positioning, no force feedback)

Issue

Scenario 1:



Input: Human demonstration + first image of object

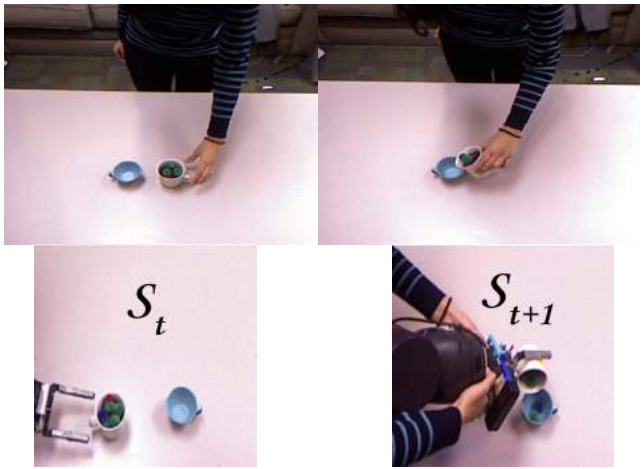
Sequentially predict the states of the robot arm

Output

Issue: Not closed loop. No understanding of how the positions of the objects placed in front of the robot change with time!

Issue

Scenario 2:



Input: Human Demo + Robot visual state

Sequentially predict the states of the robot arm

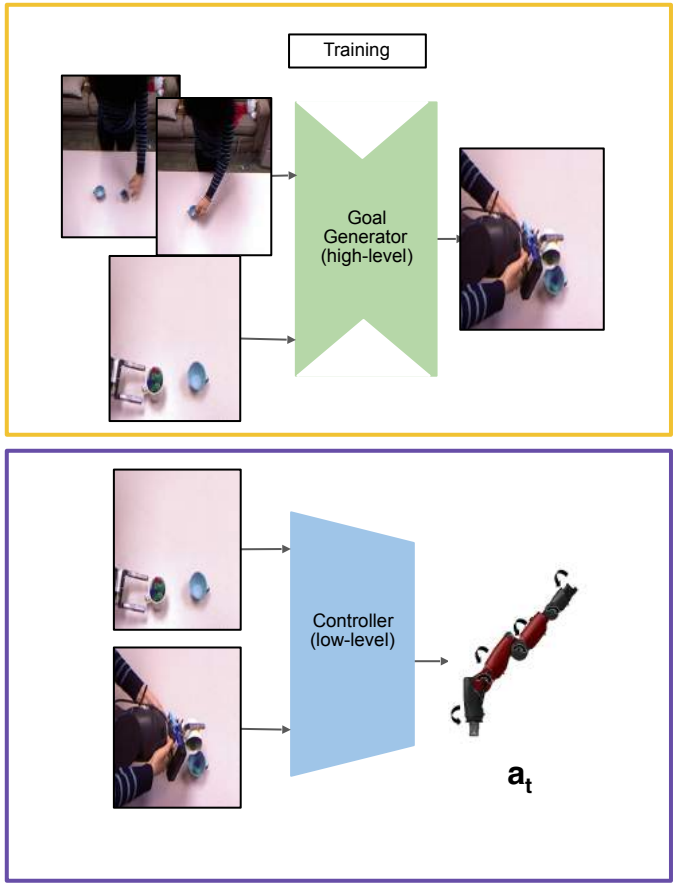
Output

How do we force it to use task information from Human demonstration ***alone*** *but condition its action on current observable state?*

*We want to build a model that can **infer the intent from the Human Demonstration** of a task and **act in the Robot's current environment** to then accomplish the task.*

Approach

We decouple the task of ***Goal Inference*** *from* ***Local Control***



Training and Test Scenarios - Data Availability

Training

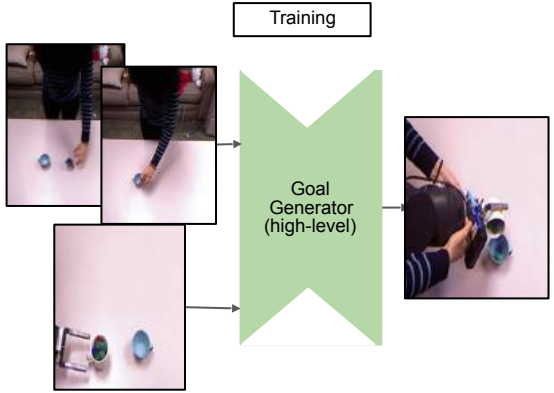
- Human demo video
- Robot demo video
- Robot joint angles

Test (deployment)

- Human demo video
- Current visible image of the table

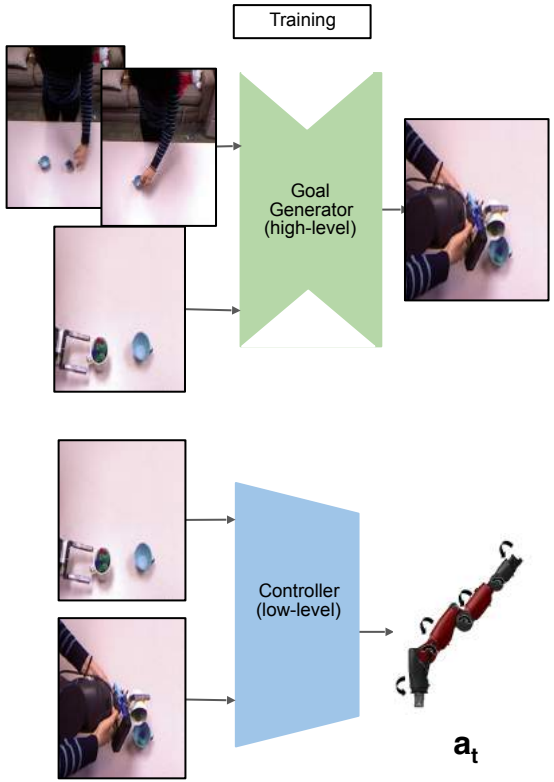
Approach - Training

Goal Generator: Given human demo and present visual state of the robot we hallucinate the next step



Approach - Training

Goal Generator: Given human demo and present visual state of the robot we hallucinate the next step

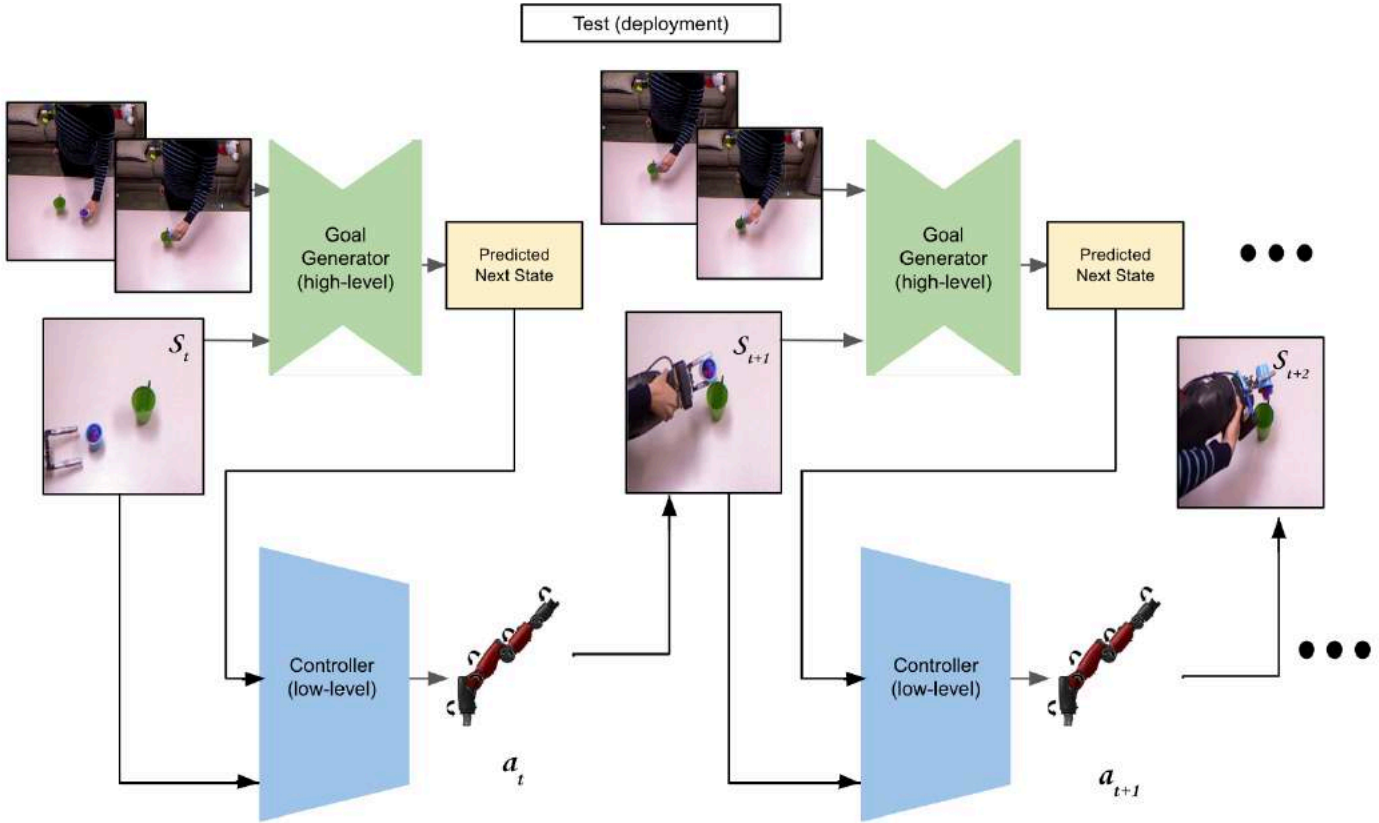


Inverse Model : Use the hallucinated prediction with the current visual state to predict the action!

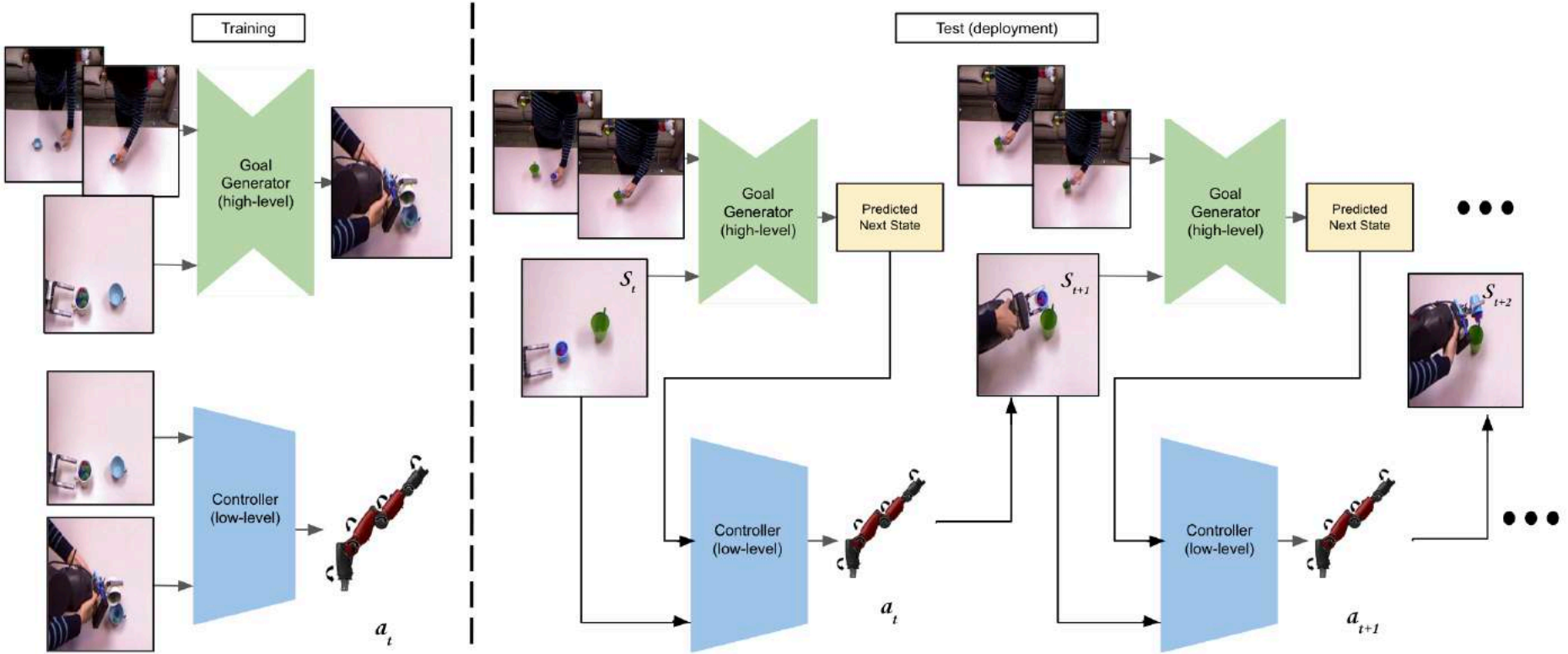
Train Time:The Goal Generator and Inverse Model are trained separately

Test Time: The Goal Generator and Inverse Model are executed alternatingly

Approach - Test



Approach - Train Vs Test

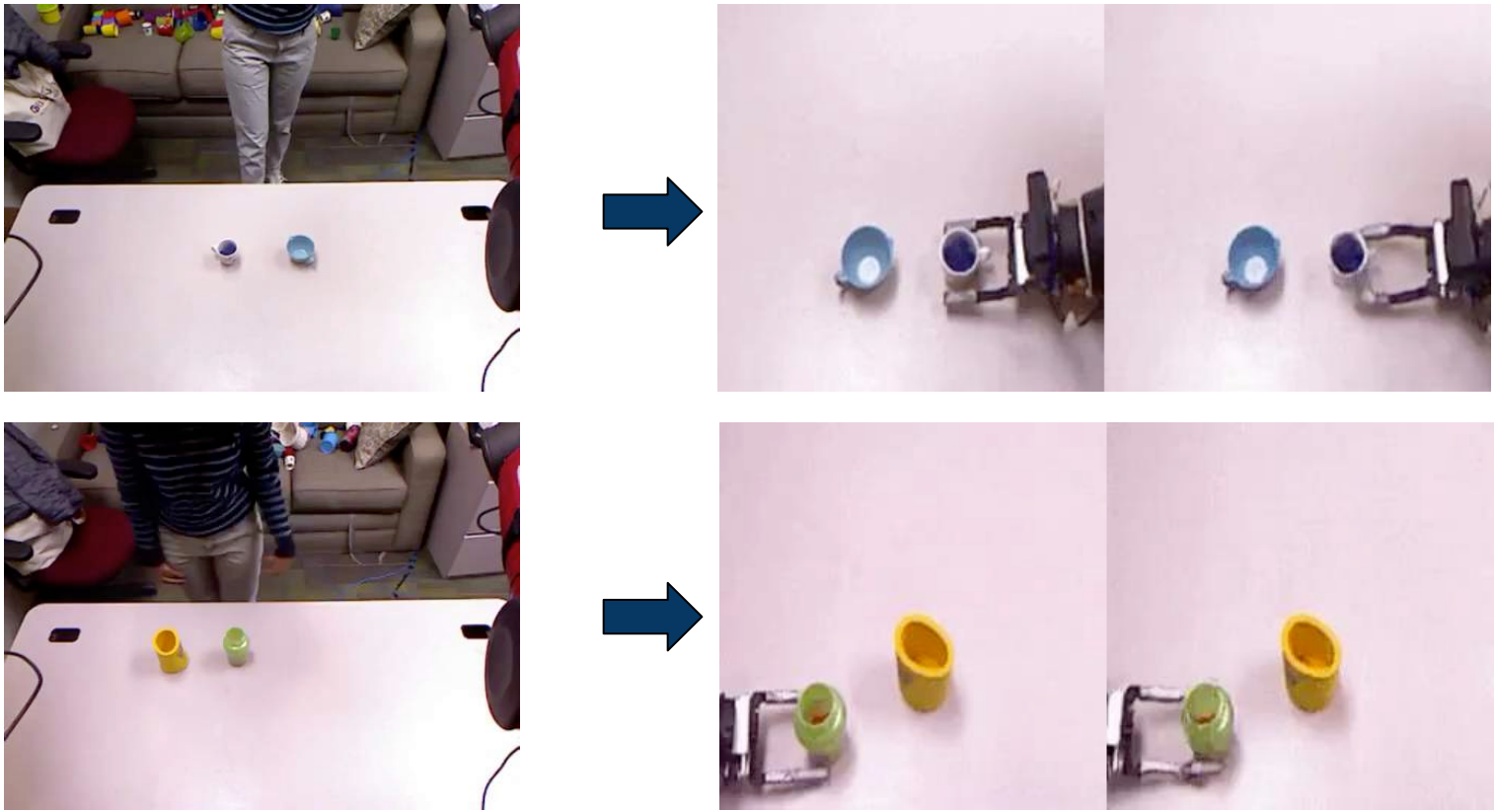


Experiments and Results

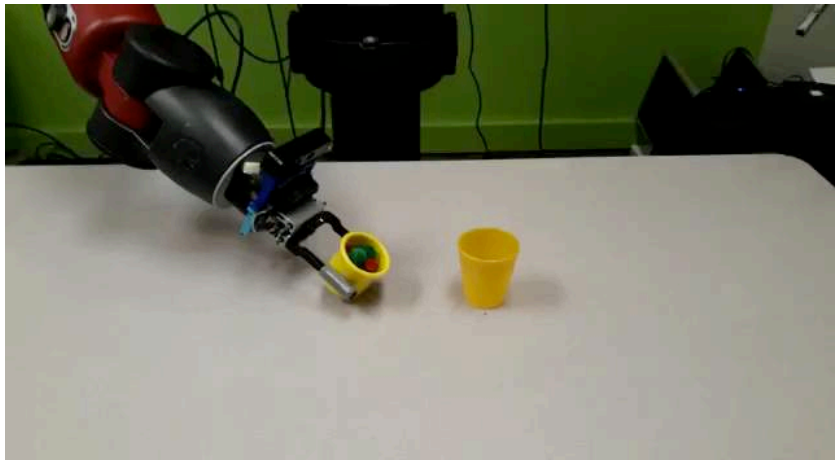
We evaluate the models trained as follows:

- Goal generation model with a perfect inverse model
- Inverse model with a perfect goal generation model
- Goal generation model and inverse model in tandem

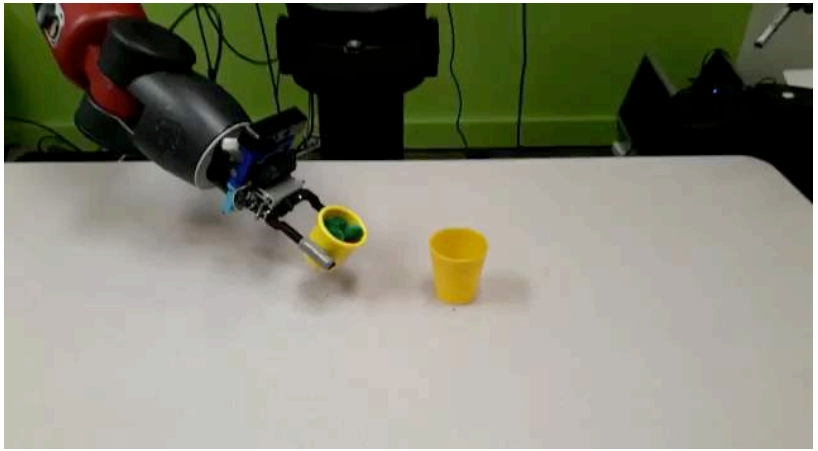
Results: Goal generation model with perfect inverse model



Results: Inverse model with perfect goal generator

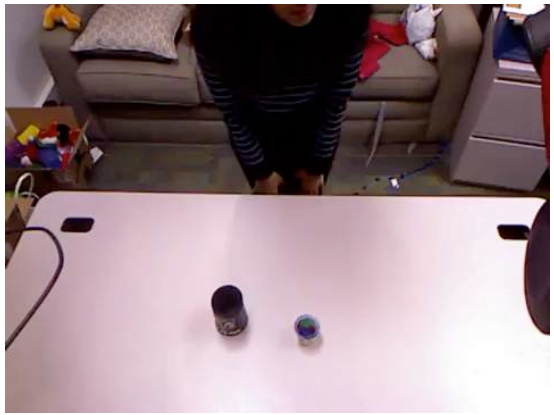


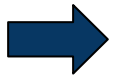
GT trajectory

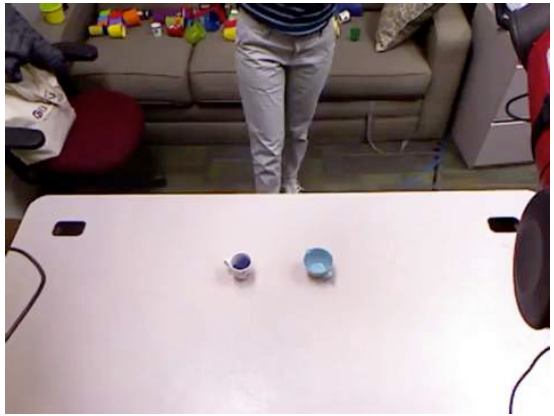


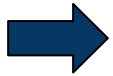
Predicted trajectory from GT-images

Results: Final experiment runs

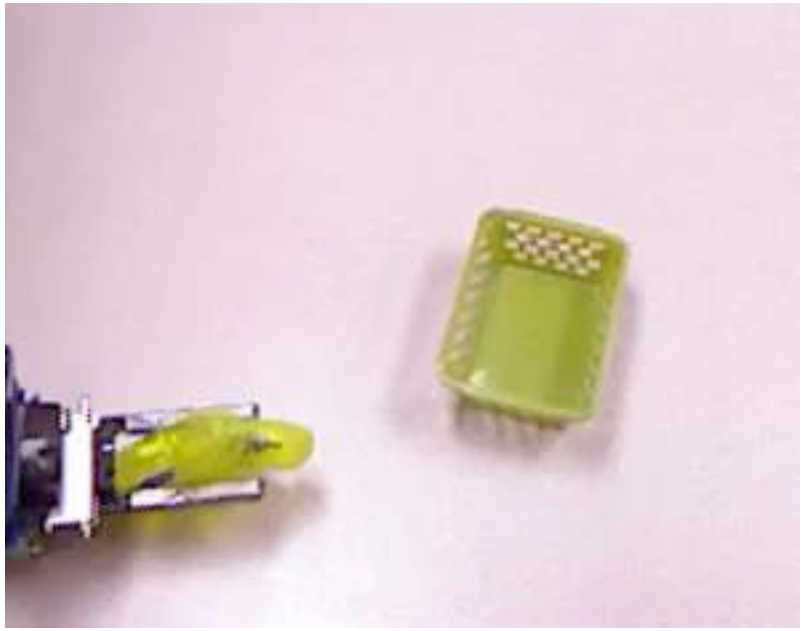








Results: Final Experimental Runs : Placing in a box



Shortcomings:

1. Robot trajectory is shaky: The robot trajectory looks shaky because of the absence of any temporal knowledge. Though trajectories predicted by inverse models with memory units(LSTM) look far less shaky but the models then over fit to the task

Thank you!