

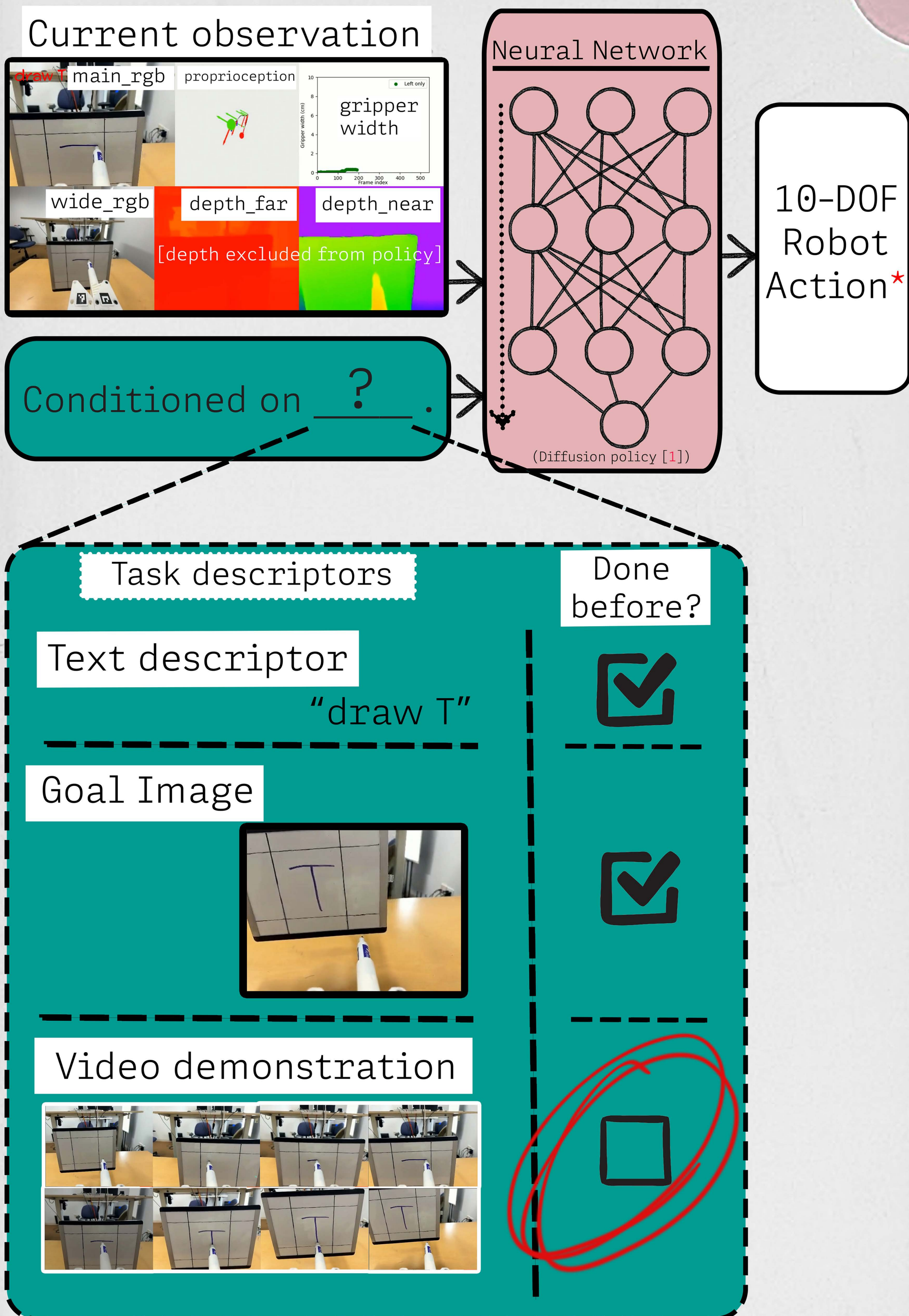
SURF Version

# Teaching Robots to Write

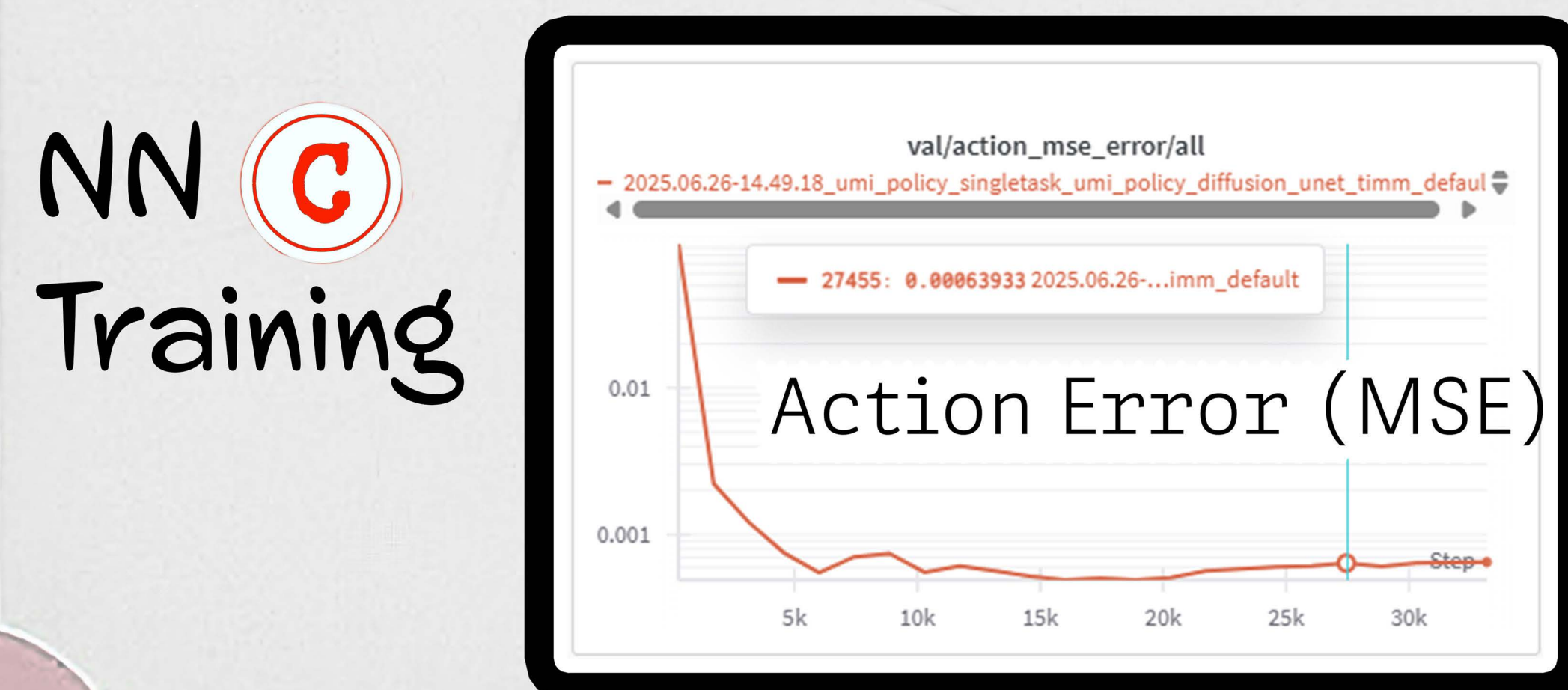
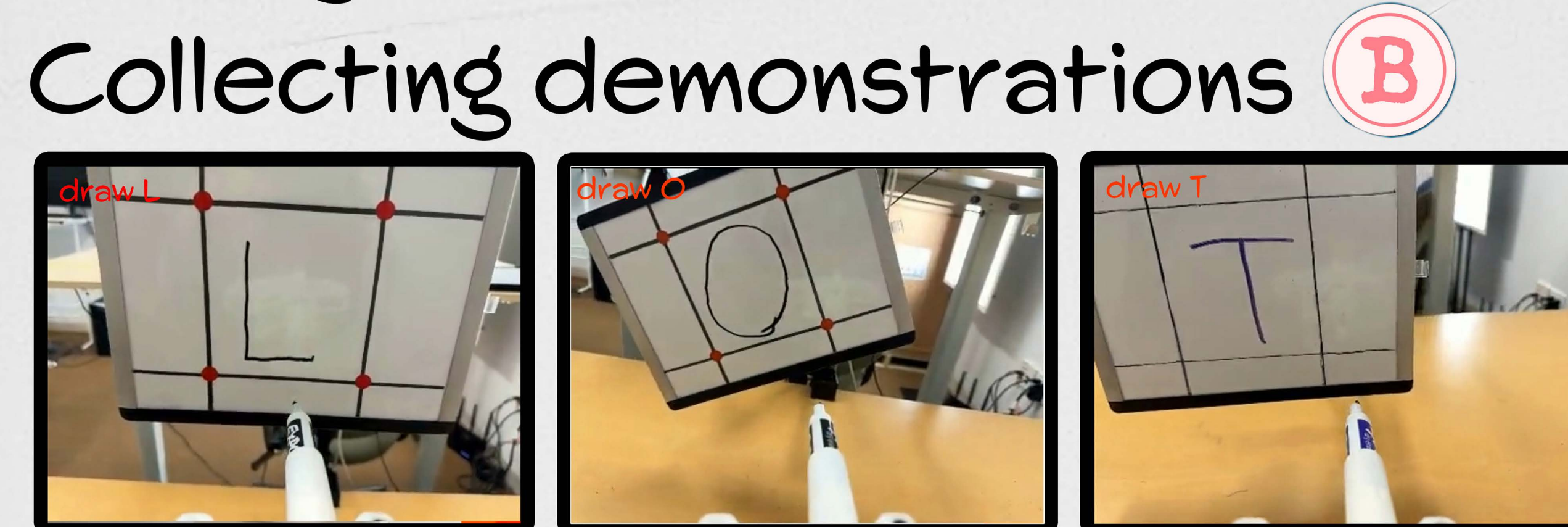
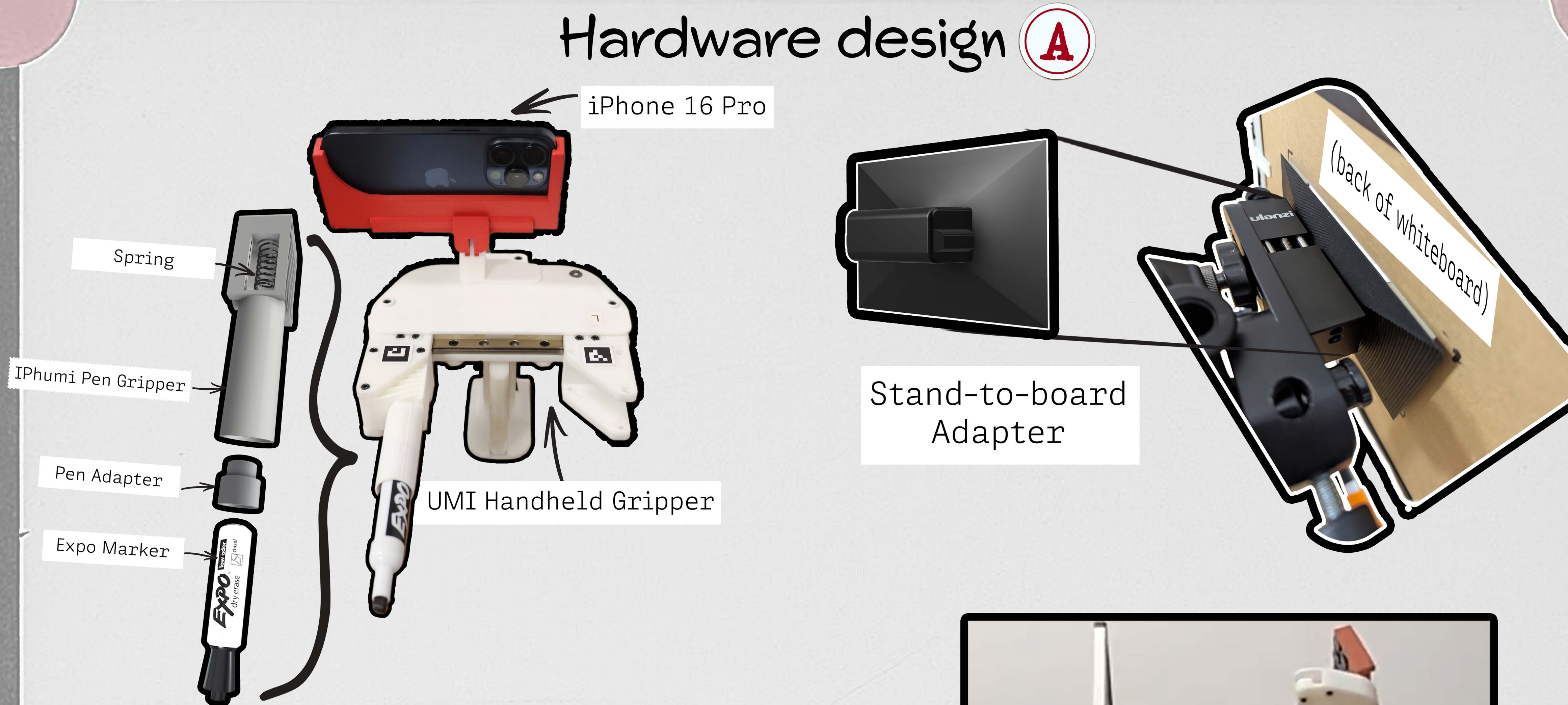
Joel Castro, Austin Patel, Shuran Song



## Background & Motivation

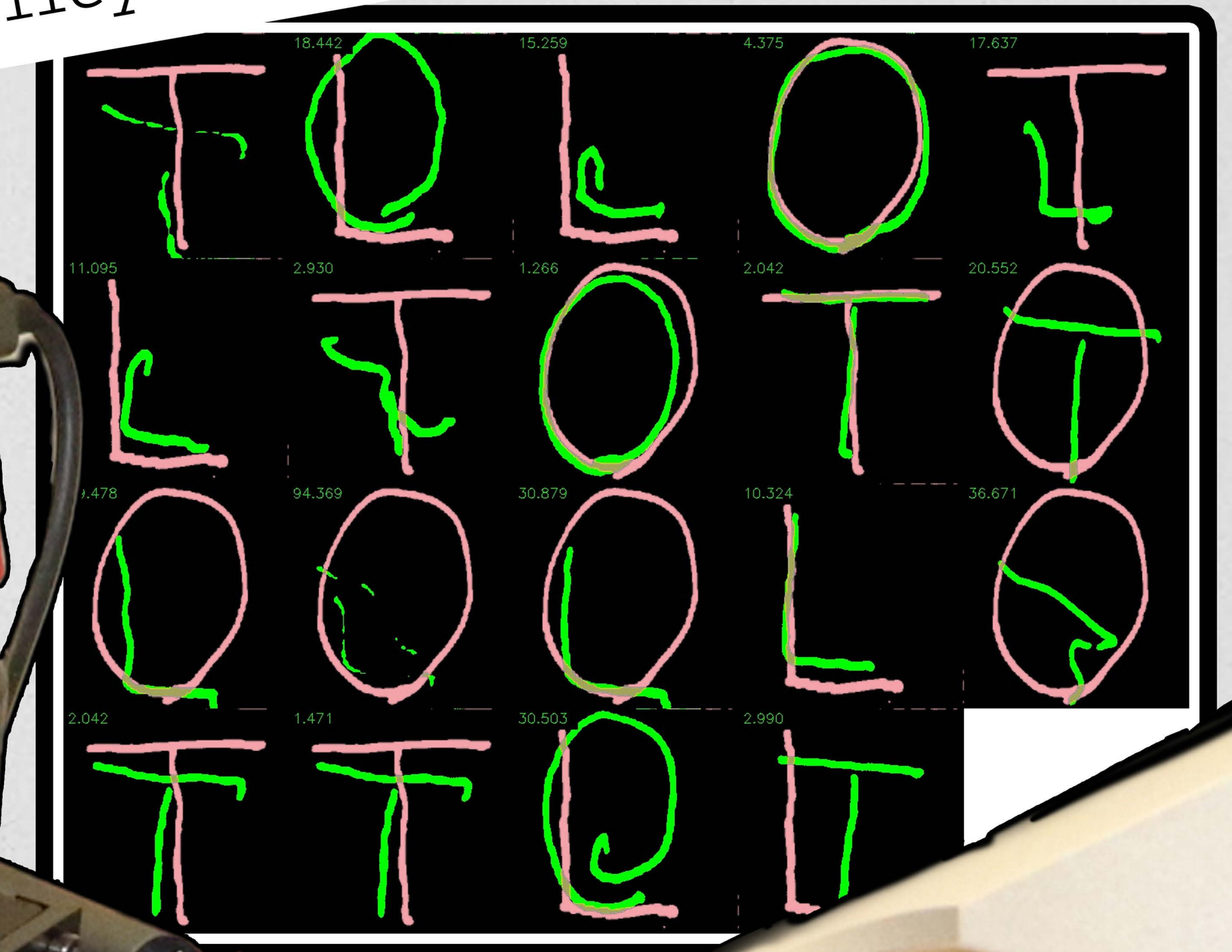
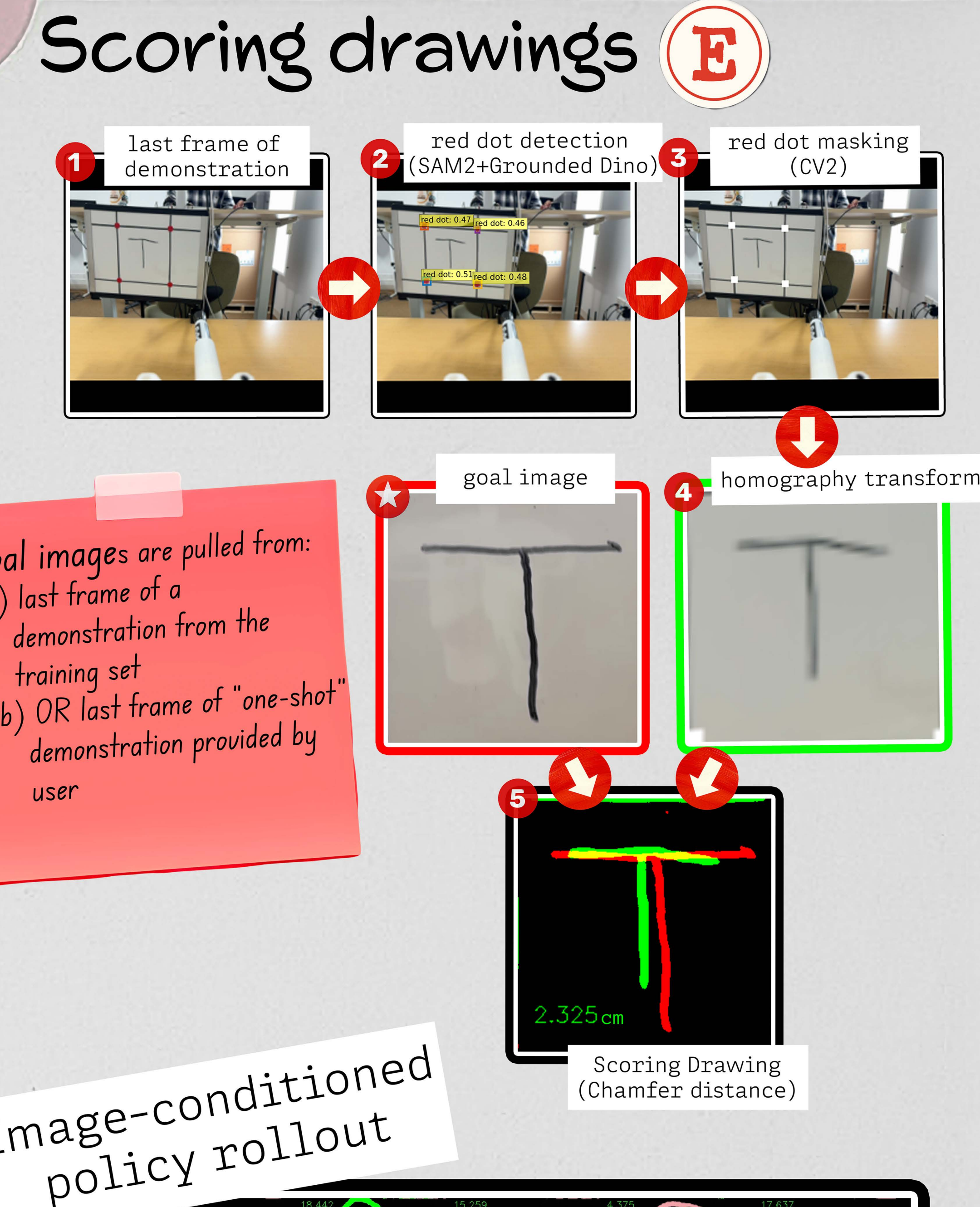


## Whiteboard Task



Rollout: hand policy control of robot (D)

## Evaluation Metric

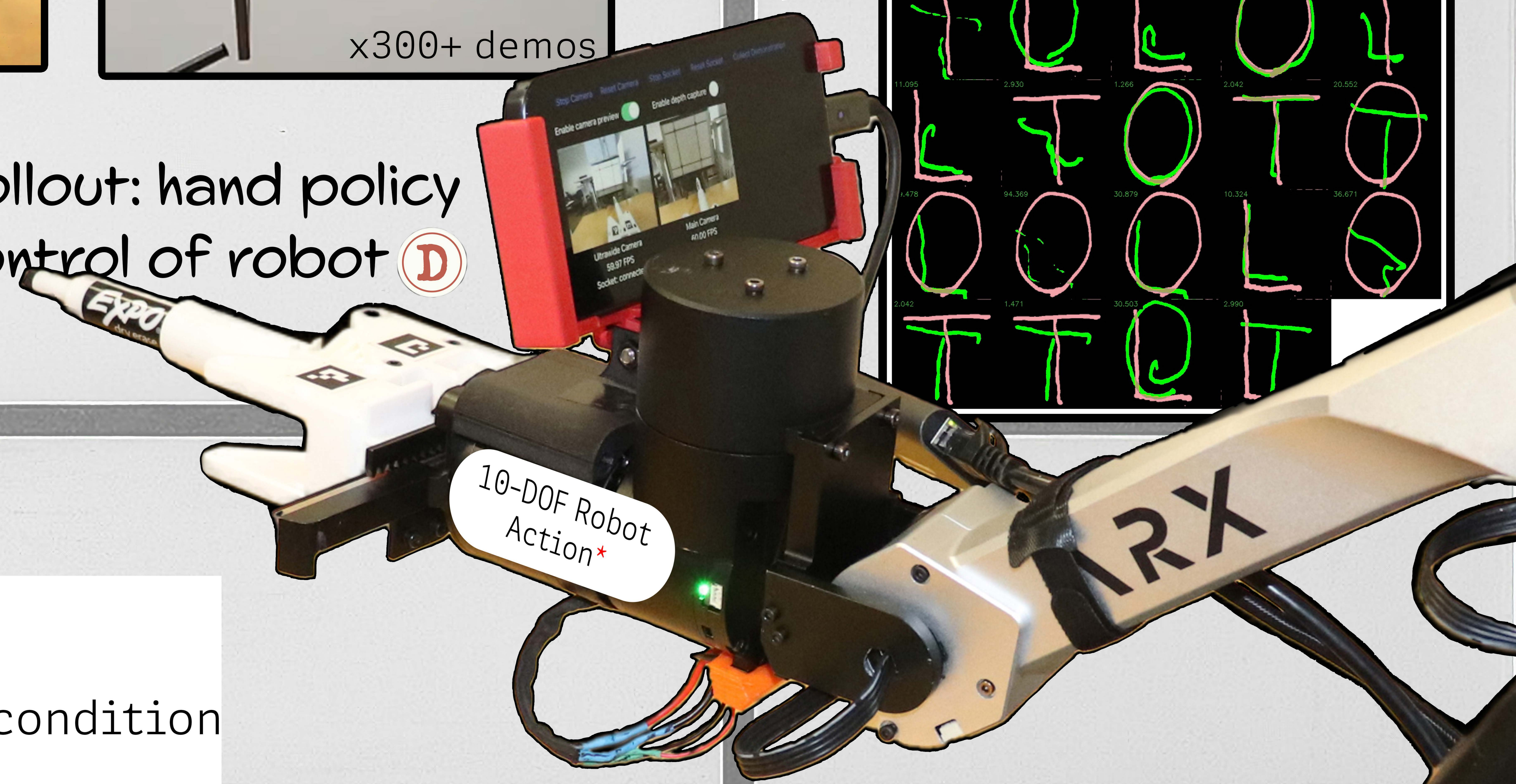


## Future Work

- Train and evaluate video-conditioned policy

## Results

- Infrastructure in place for training and evaluation
- Evaluation revealed image-condition is often ignored



Thank You!







# Teaching Robots to Write, Toward Improved Diffusion Policy

Joel Castro,<sup>1</sup> Austin Patel,<sup>2</sup> Shuran Song,<sup>2</sup>

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## Motivation

Task descriptors are used to prompt machine learning models to perform a desired task. For example, one uses a *text* task descriptor to ask an LLM to write things. In robotics, task descriptors include text (e.g. “put the cup on the plate”), but can come in many forms. For example, one can use a *goal image* to describe to an ML how you want it to manipulate the world around it (e.g. a picture of a cup on a plate). However, what if I wanted a robot to perform a task that required knowledge of intermediate steps (not just a descriptor of the end goal)? A state of the art Diffusion Policy<sup>[1]</sup>, fails to perform such tasks given text or image task descriptors.

## Approach

Our group, REAL Labs, is working to solutions to these limitations. Specifically, a Diffusion Policy architecture that is capable of taking an entire *video demonstration* as a task descriptor. To test this novel architecture, we needed a robot task that indeed requires knowledge of intermediate steps. We came up with a robot writing task. Components were CADed and 3D printed. An iPhone mounted to a hand-held gripper was used for task demonstrations data collection. Next, 3 independent baseline single-task Diffusion Policies were trained on demonstrations of drawing “T”, “L”, & “O” to verify task/hardware robustness and feasibility. Then, 1 goal-image-conditioned policy was trained on demonstrations of all 3 letters. An evaluation metric was developed to score trained policies.

## Results

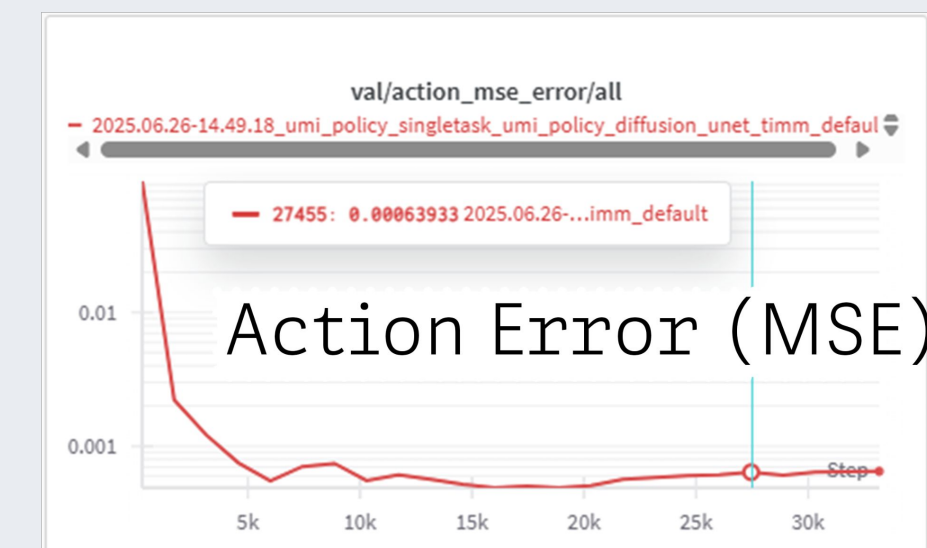
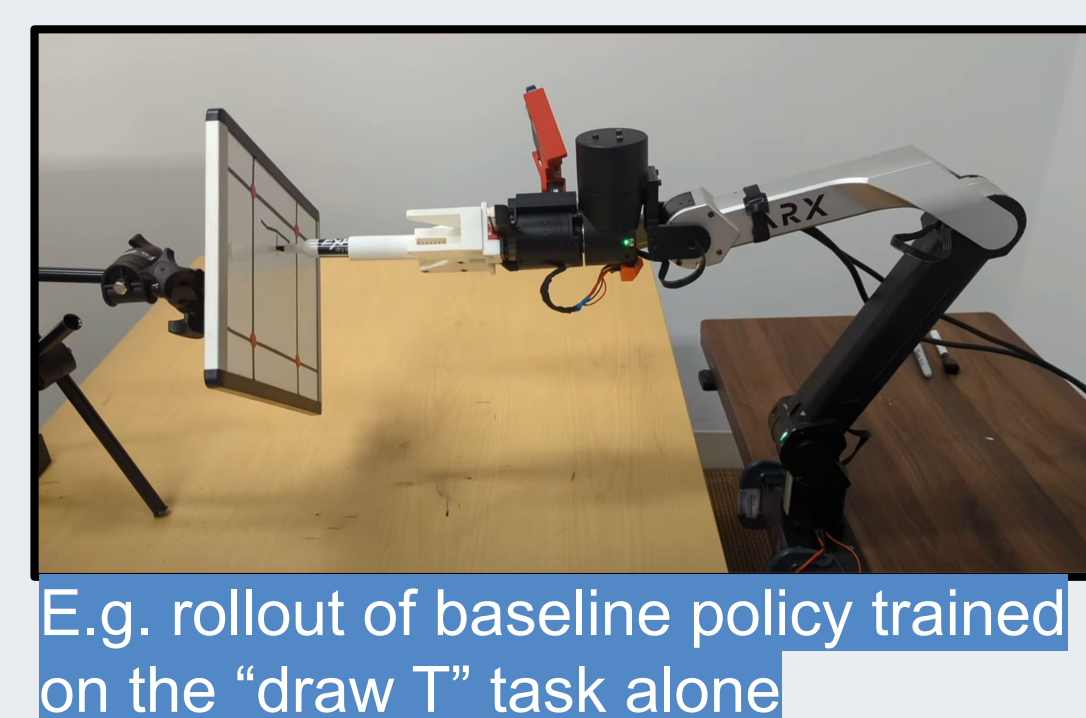
### Designed Novel Robot Writing Task & Hardware



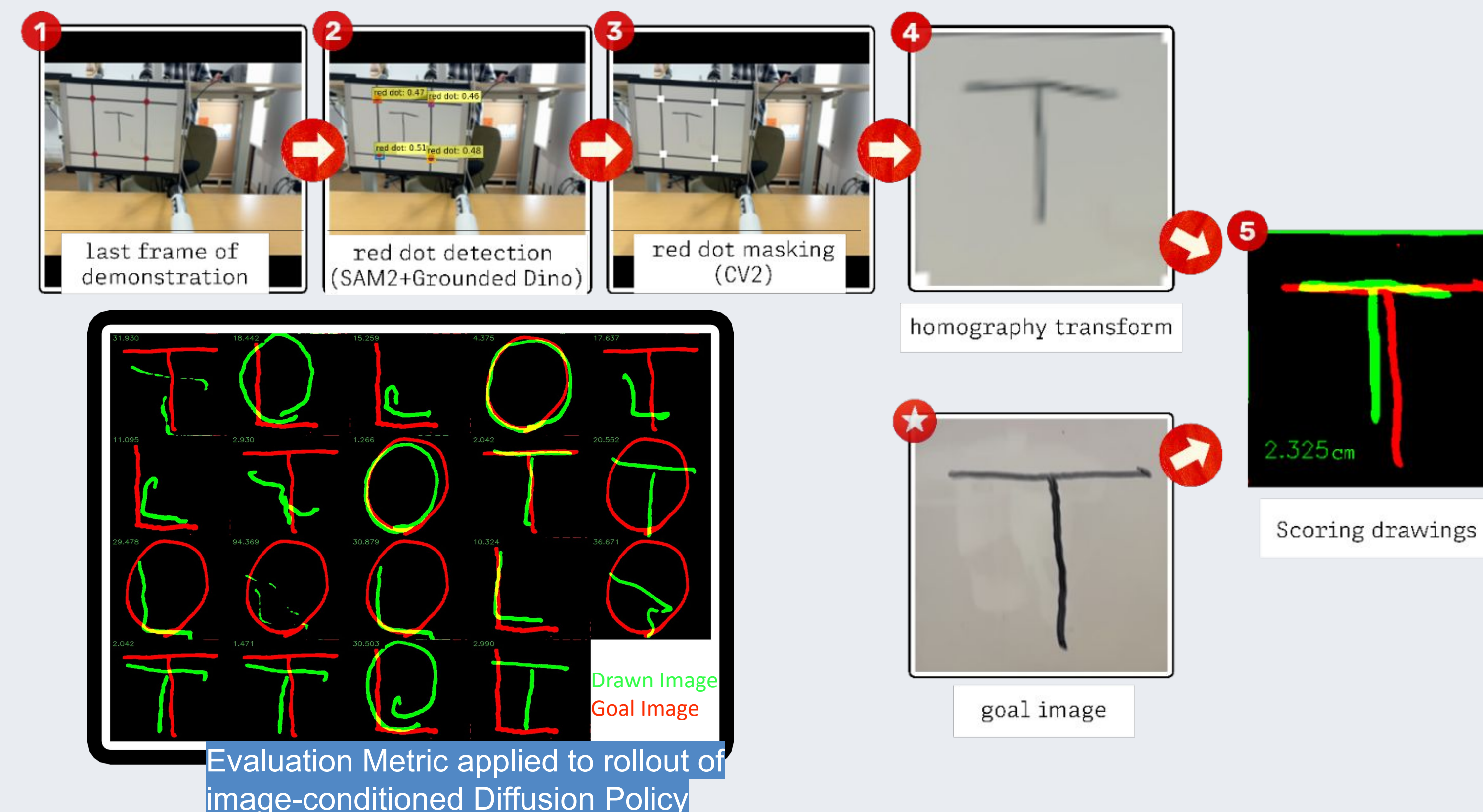
### Collected Data Set



### Trained baseline Diffusion Policies



### Developed Task Evaluation Metric



## Conclusion

Running the goal-image-conditioned Diffusion Policy trained on demonstrations “T”, “L”, and “O” revealed that the policy largely ignored the goal-image and drew letters from its dataset at seemingly random. This was the expected result for goal-image-conditioning on a task like drawing letters because of the need for knowledge of intermediate steps.

## Next Steps

With the resulting task design, manufactured hardware, compiled dataset, and a complete task evaluation metric, the infrastructure is in place to compare our group’s novel video-conditioning architecture with existing approaches (such as the goal-image-conditioned Diffusion Policies we have evaluated here). Once our video-conditioning policy is complete, we will run it through a parallel analysis and compare, anticipating significant performance improvements. This will allow us to clearly showcase the benefits of our novel policy architecture, establishing its dominance for complex robot tasks, and opening the door to more generalizable vision-to-action models that can perform even unseen tasks from single demonstrations.

## Acknowledgements

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Shuran Song et al. “Diffusion Policy.”, Robotics: Science and Systems, 2023 [1].