



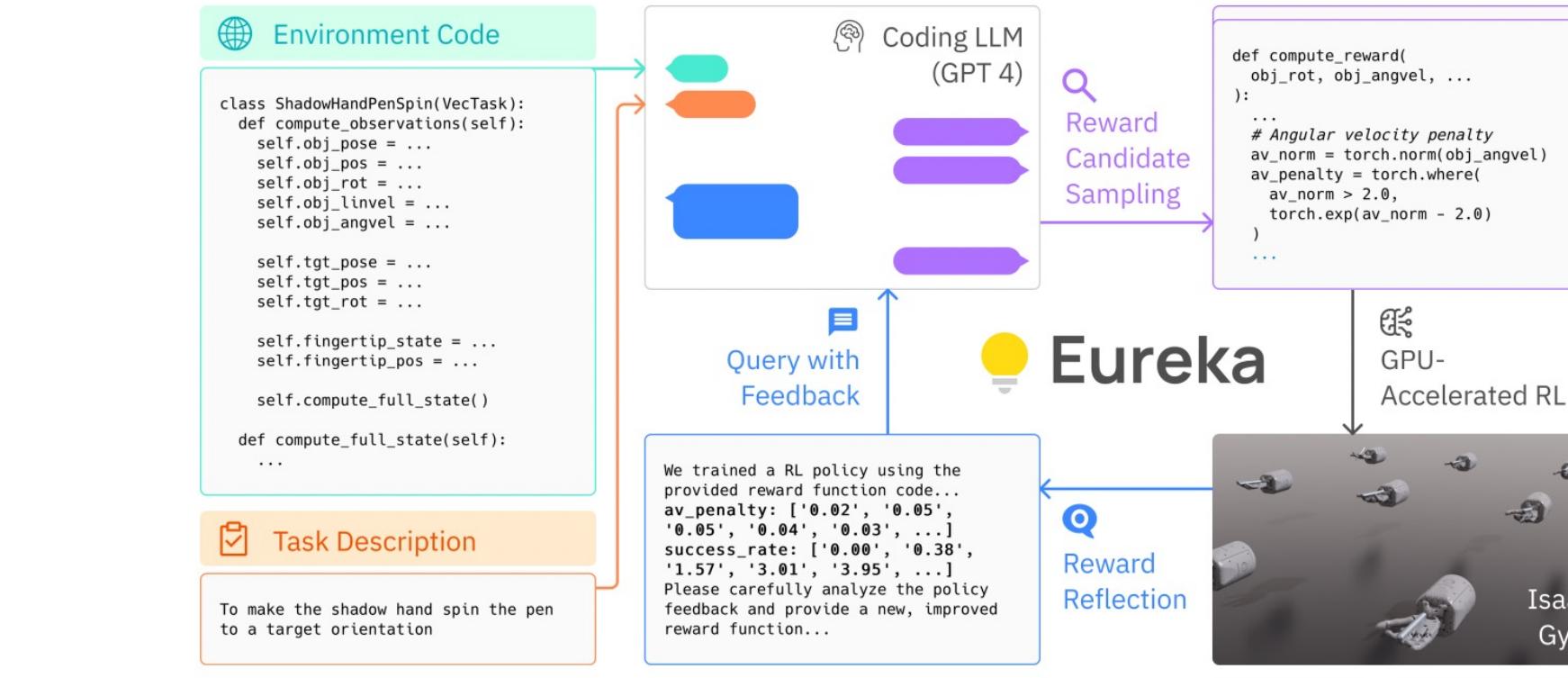
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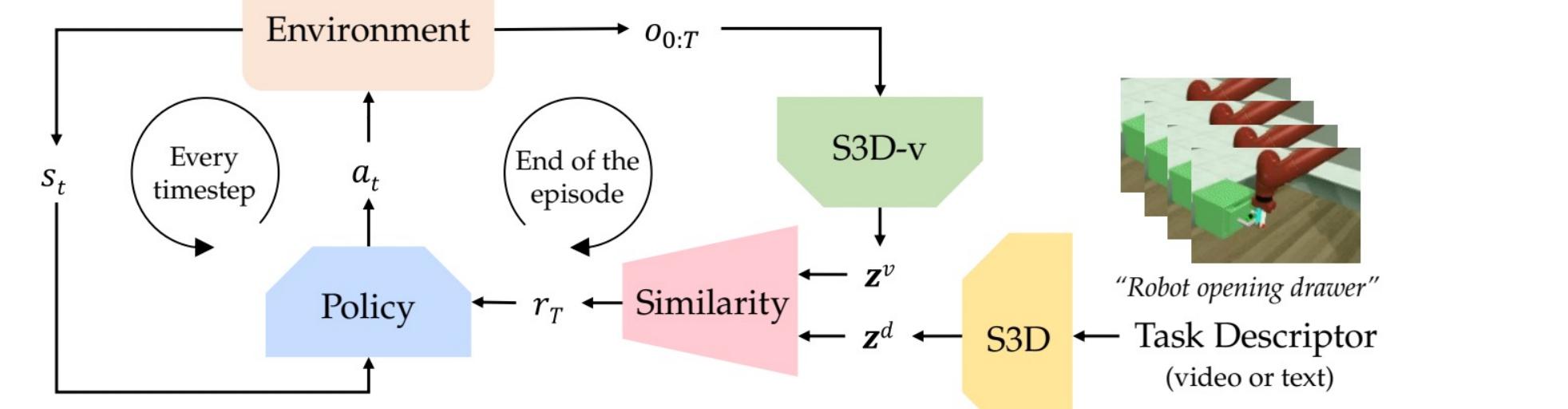
rlvlmf2024.github.io/

Prior Work: Automatic Reward Generation from Foundation Models



1. LLMs that write reward functions (Ma et al., 2018)

Requires access to *environment code* and *low-level state info*.



2. Alignment score from CLIP-style models (Sontakke et al., 2018)

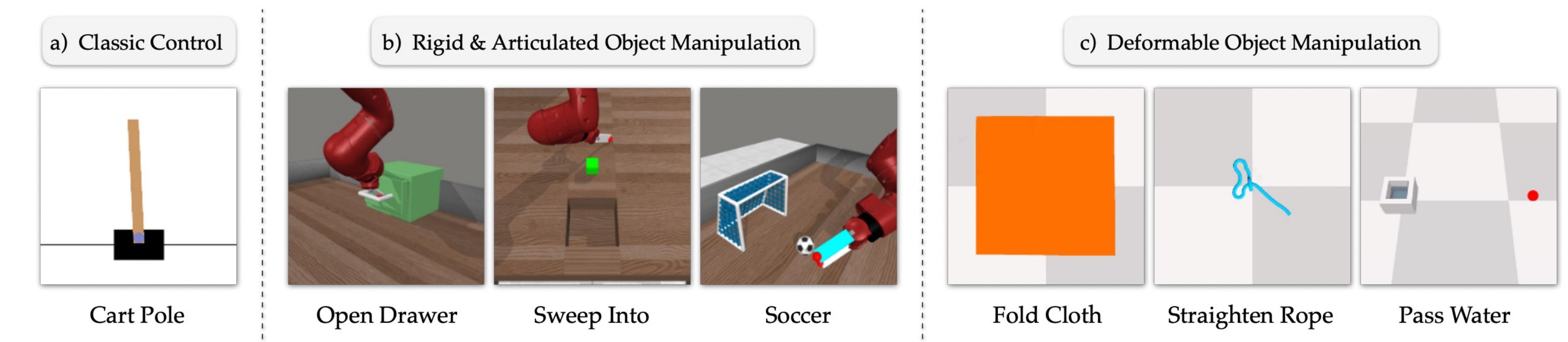
Generated rewards are often of *high variance and noisy*

RL-VLM-F: Rewards from VLM Preferences Over Agent Observations

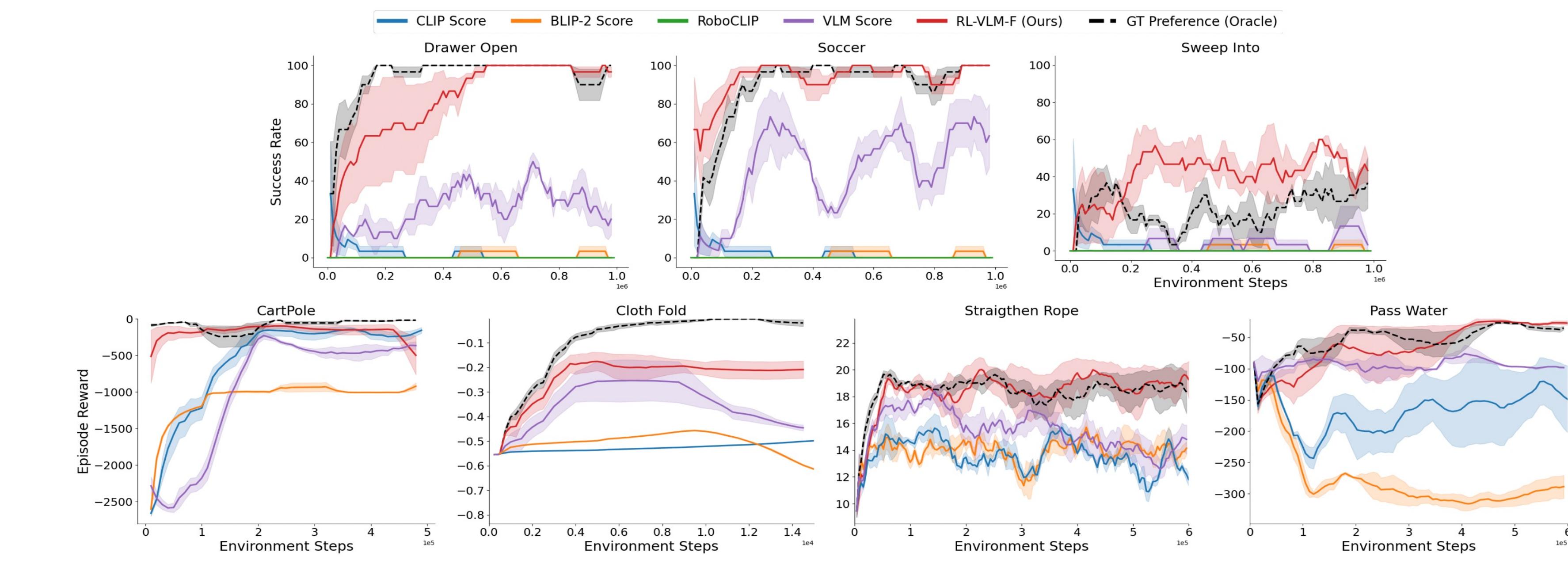
TL;DR: Train RL policies by learning reward models from VLM *preferences* over *image obsvertion* pairs given just the *task description*.

- No need for:**
 - Ground truth state info
 - Environment code
- Assumes** only a text description of the task goal and the agent's image observations.
- Works on tasks with:**
 - Image observations
 - States difficult to describe with language (e.g., complex deformable objects)

Experiments and Analysis

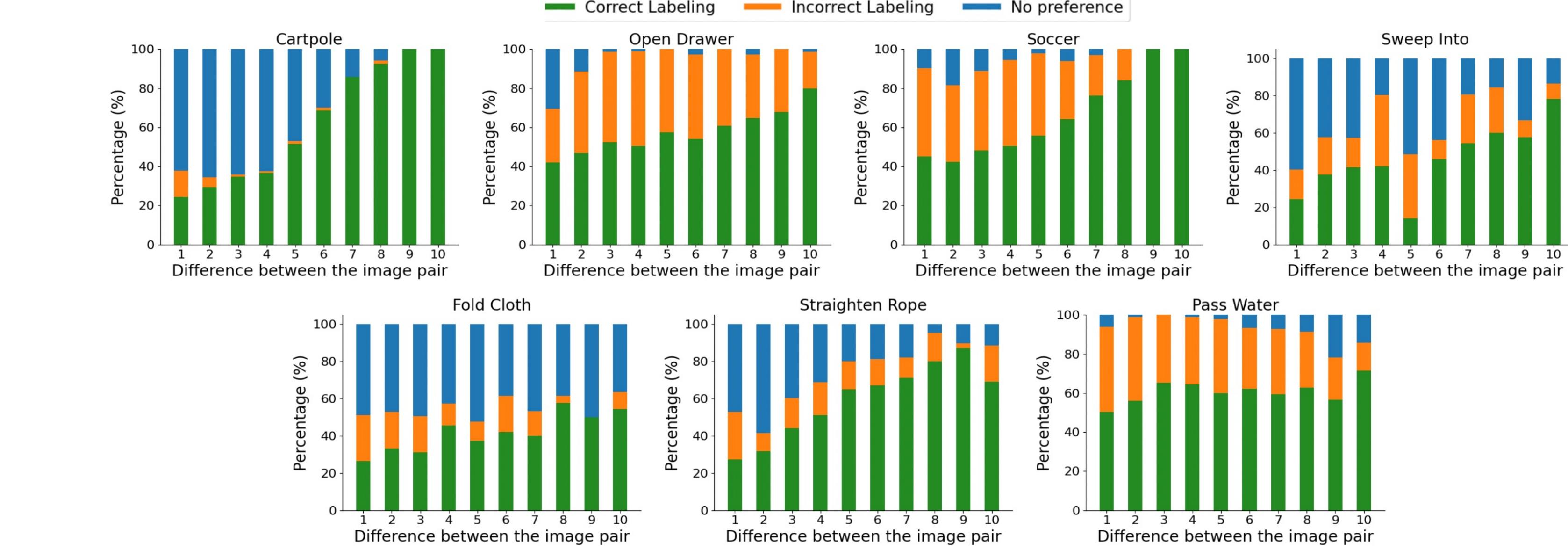


➤ How does RL-VLM-F compare to baselines?



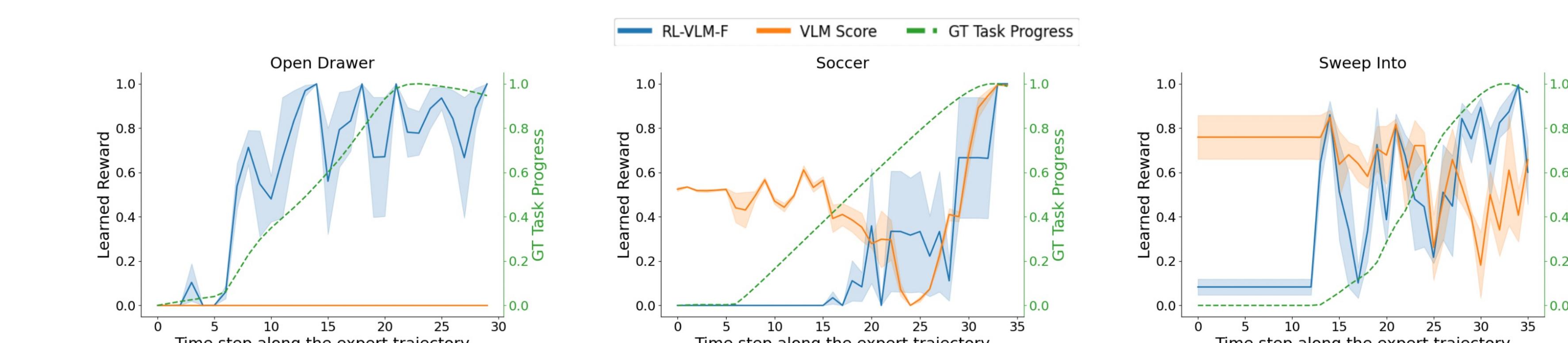
- RL-VLM-F outperforms all baselines** in all tasks
- RL-VLM-F** matches/surpasses the ground-truth preference oracle on 6 of 7 tasks.

➤ What is the Accuracy of VLM Preference Labeling?



- VLMs closely match ground truth preferences on many tasks!
- VLMs perform like humans when images are similar

➤ How Does the Learned Reward Align With the Task Progress?



RL-VLM-F rewards align better with ground-truth task progress compared to baselines

