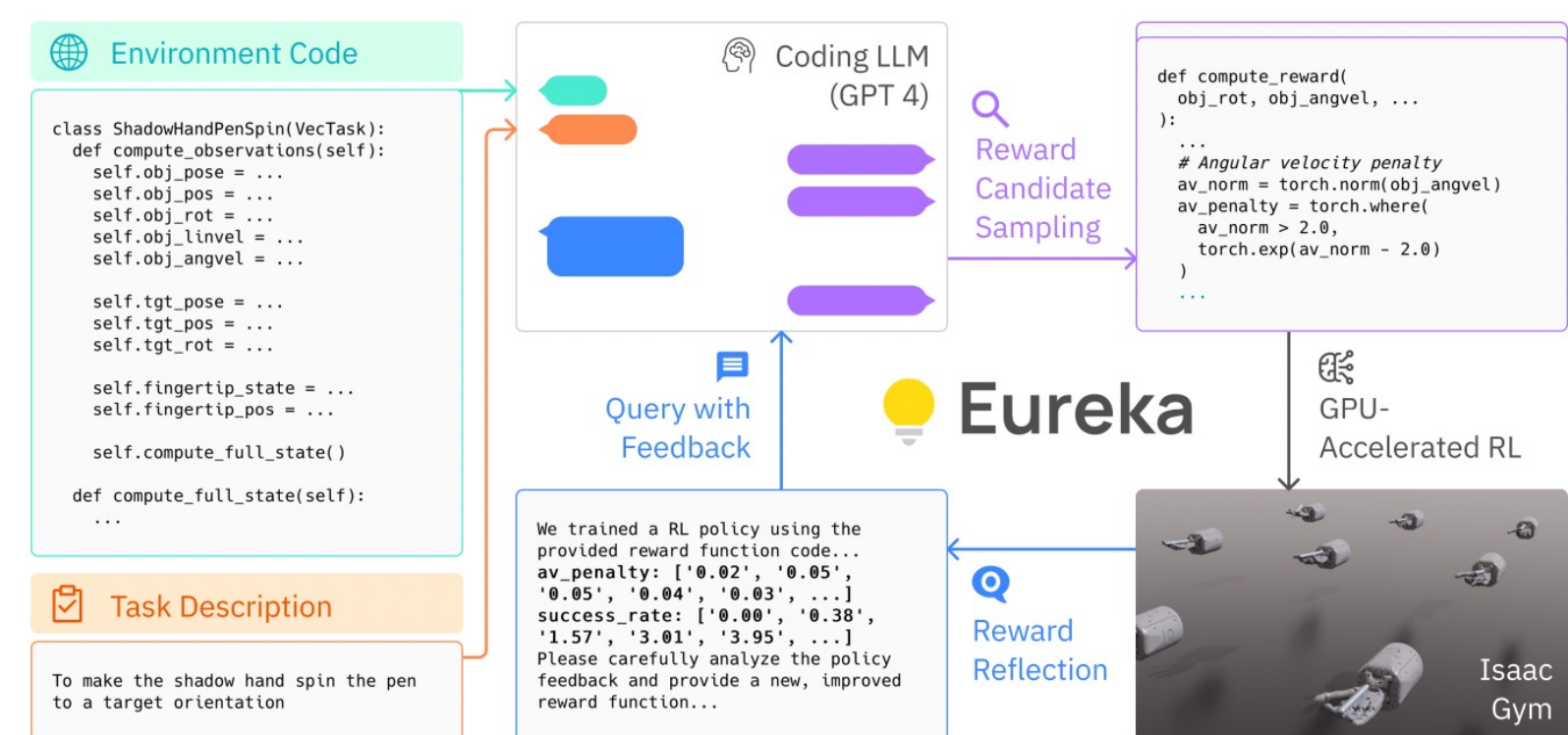
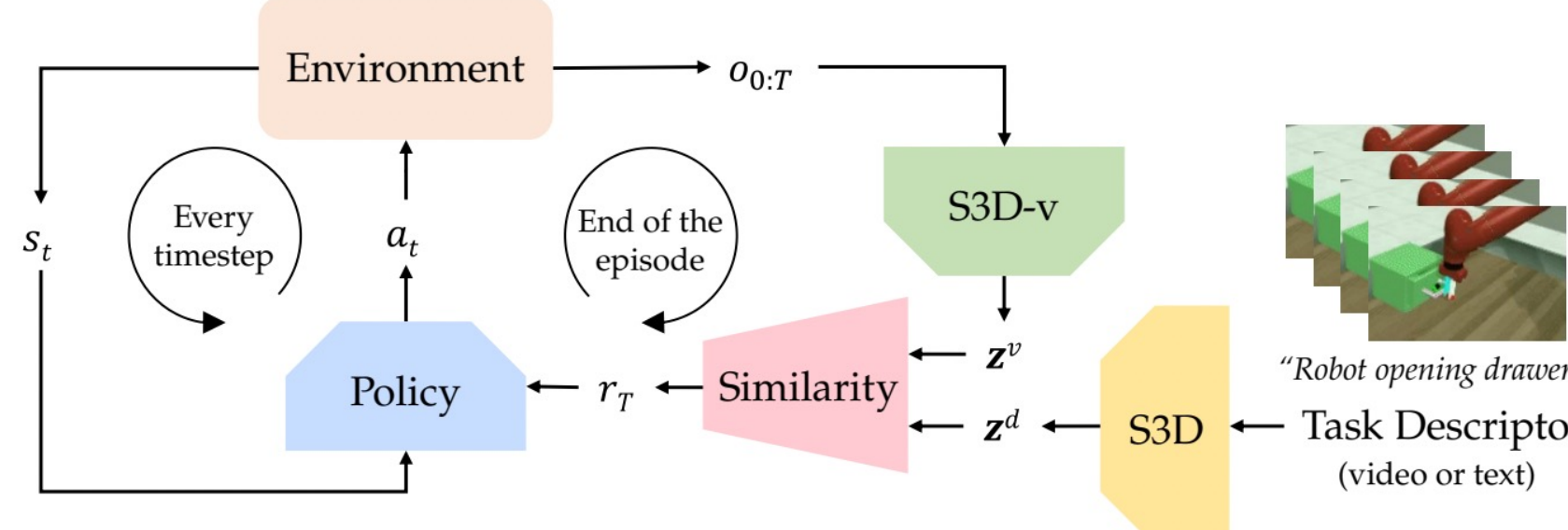




Prior Work: Automatic Reward Generation from Foundation Models



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)

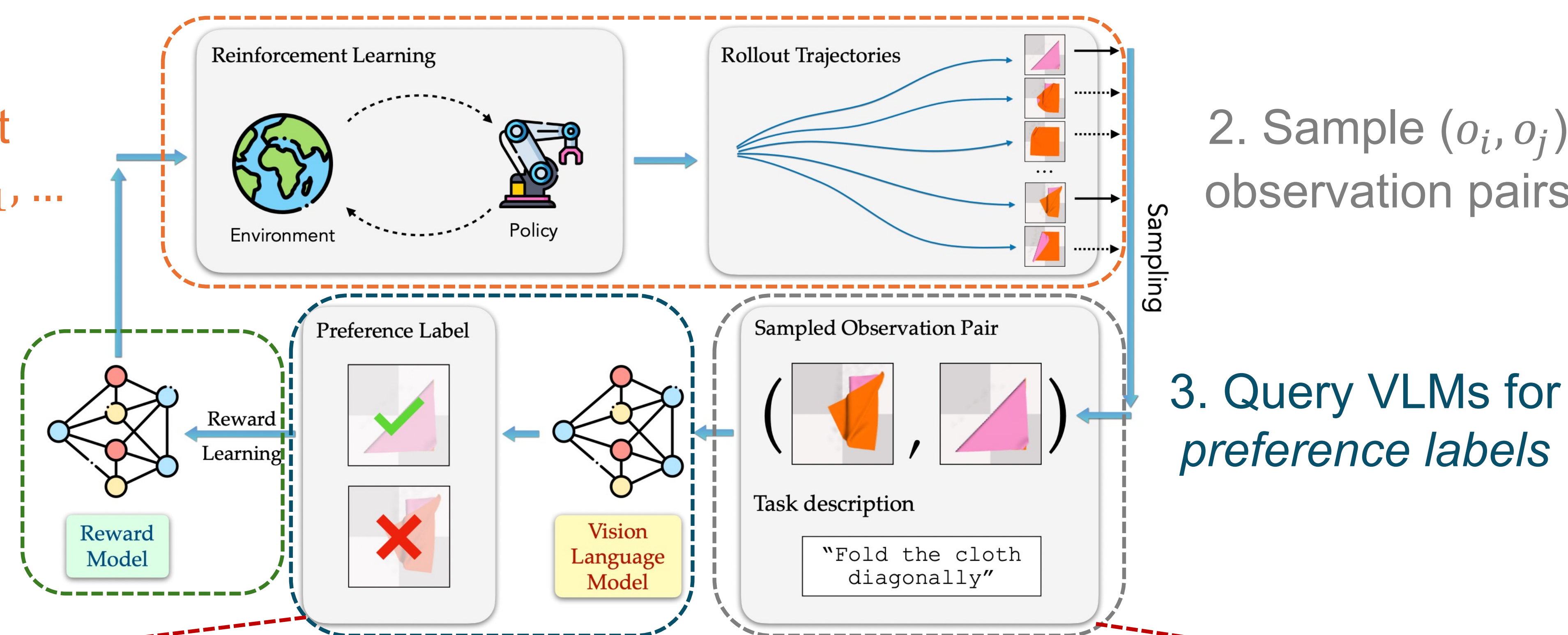
Generated rewards are often of *high variance and noisy*

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

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

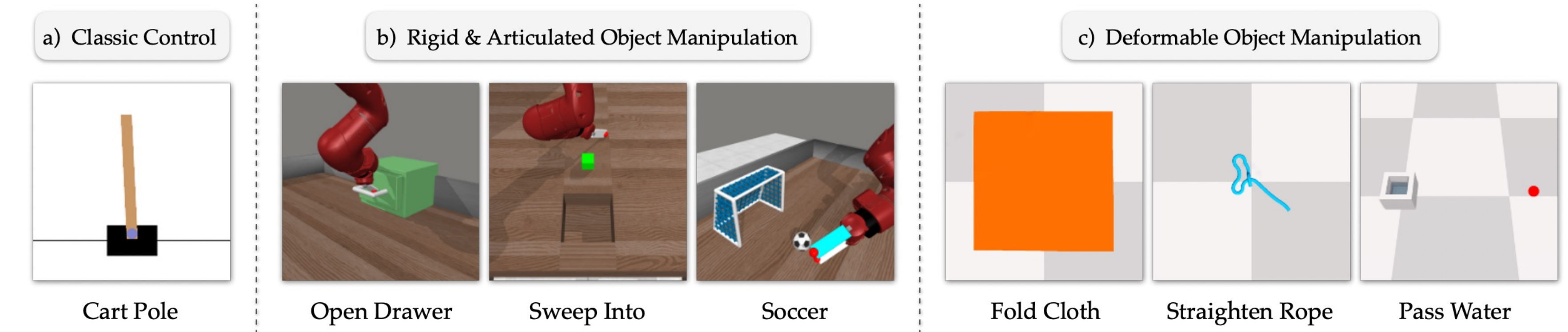
- **No need for:**
 - Ground truth state info
 - Environment code
- **Assumes** only a text description of the task goal and the agent's image observations.
- **Works on tasks with:**
 - Image observations
 - States difficult to describe with language (e.g., complex deformable objects)

Method Overview

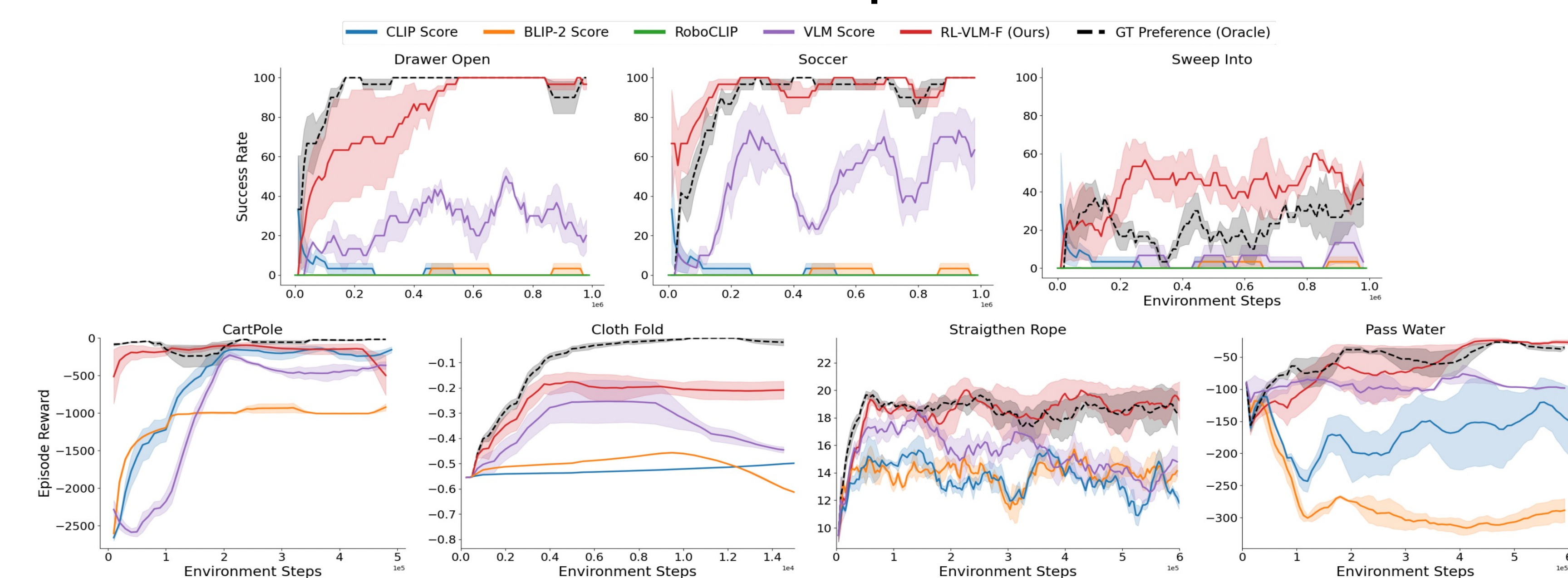
1. Rollout π to collect image-action trajs o_1, a_1, \dots 5. Train π with r_θ 4. Train reward model r_θ on VLM preferences2. Sample (o_i, o_j) observation pairs

3. Query VLMs for preference labels

Experiments and Analysis

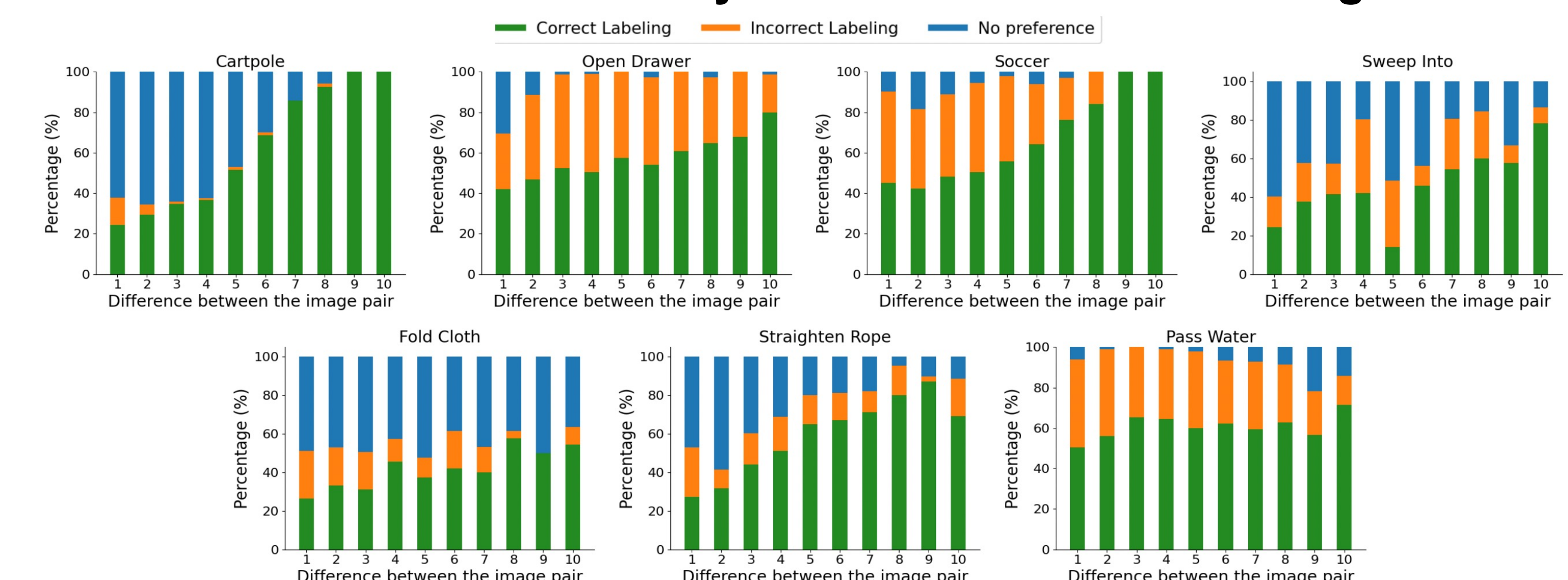


➤ How does RL-VLM-F compare to baselines?



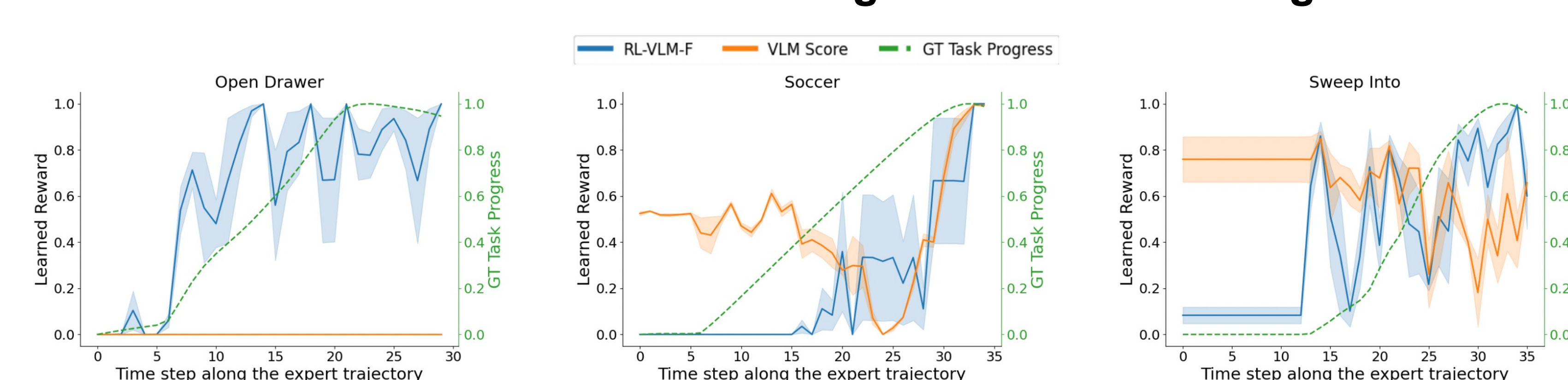
- **RL-VLM-F outperforms all baselines** in all tasks
- **RL-VLM-F matches/surpasses the ground-truth preference oracle** on 6 of 7 tasks.

➤ 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