# **SAFE**: Multitask Failure Detection for Vision-Language-Action Models

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vla-safe.github.io









## VLAs still have limited success rates and diverse failure modes.





"Take toast out of toaster"

"Replace the paper towel"

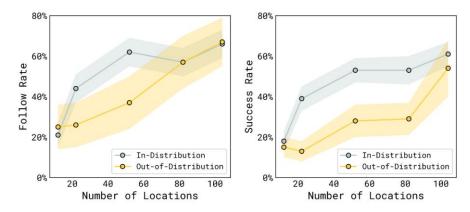


Fig. 9: Evaluating language following with different numbers of training locations. We evaluate language following rate and success rate for picking up user-indicated items and placing them into drawers or sinks, averaged over seen object categories ("in-distribution") or unseen categories ("out-of-distribution"). Performance increases steadily as we increase the number of training locations.

SOTA VLAs achieve <80% average task progress.

We need a failure detector for safe and reliable deployment of VLA models.

#### Generalist VLAs need multitask failure detectors

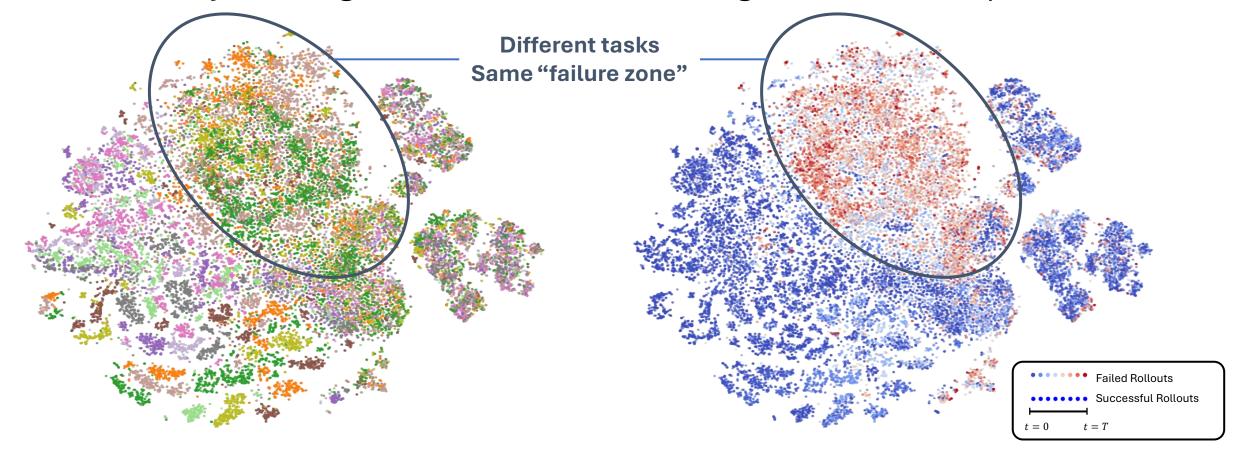
#### Existing Task-specific Failure Detection Train a failure Task 1 Collect rollouts Detect failure for task 1 detector Train a failure Detect failure for Task 2 Collect rollouts detector task 2 Task 3 Collect rollouts Train a failure Detect failure for detector task 3 Detect failure for Task 4 Collect rollouts Train a failure task 4 detector × No cross-task generalization × Labor-intensive × Only for task-specific policies

#### **Multitask Failure Detection** Detect failure for Seen Task 1 Collect rollouts task 1 Seen Task 2 Detect failure for Collect rollouts task 2 SAFE: A Multi-task **Failure** Unseen Task 3 Detect failure for **Detector** task 3 for VLA Models Detect failure for Unseen Task 4 task 4 √ Work for unseen task zero-shot ✓ Avoid data collection and re-training

√ For generalist policies like VLAs

## Key insight: VLA captures high-level knowledge about task failure in its feature space

• VLAs may have high-level semantic knowledge in its feature space.



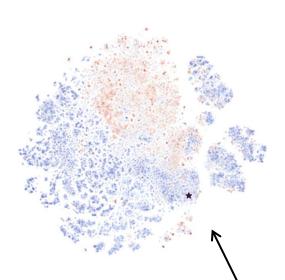
t-SNE of policy latent features, colored by task failures

### How Features Evolve in the Feature Space?

turn on the stove and put the moka pot on it Ep 10, Succ 1

RGB obs frame 0



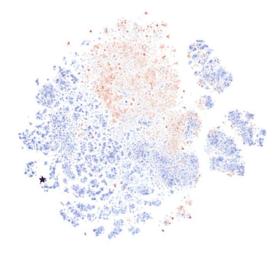


Successful rollouts: Embeddings always stay out of the red "failure zone".

turn on the stove and put the moka pot on it Ep 30, Succ 0

RGB obs frame 0



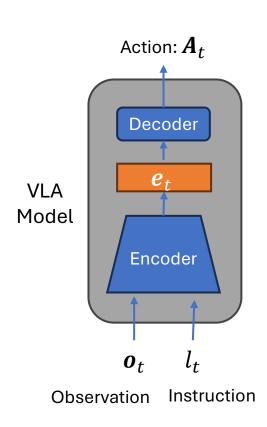


Failed rollouts: Robot drops the pot by accident. Embeddings go into the "failure zone".

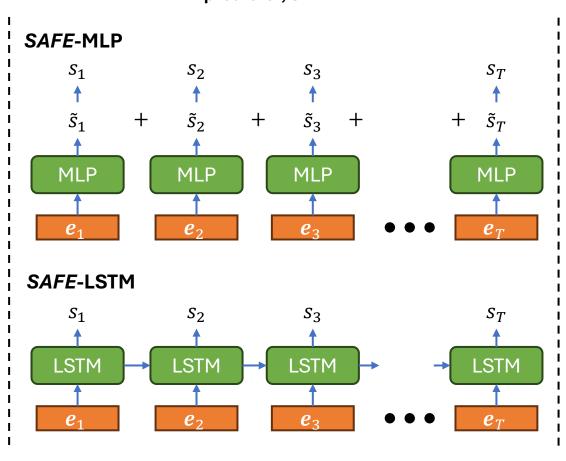
VLA Embeddings in this rollout are visualized as popping stars.

# Multi-task Failure Detector based on VLA Internal Features

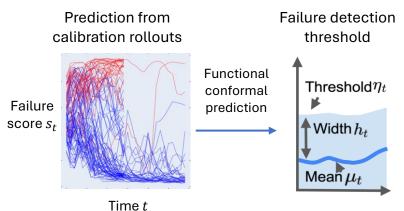
#### 1. Extract latent features from VLA models



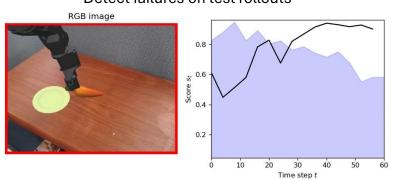
### 2. Learning the failure score predictor, *SAFE*



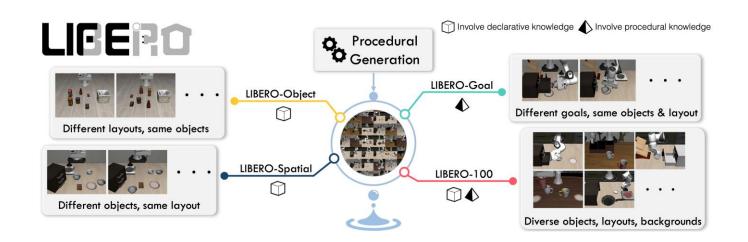
### 3. Calibrate failure detection threshold and deploy



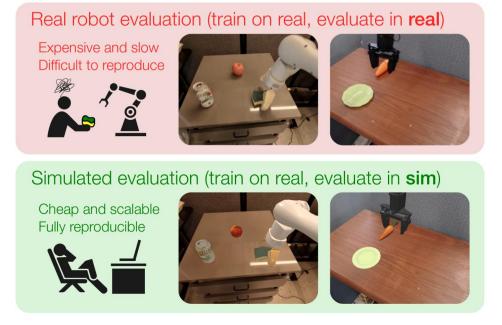
Detect failures on test rollouts



## Simulation Experiment Setup



LIBERO-10

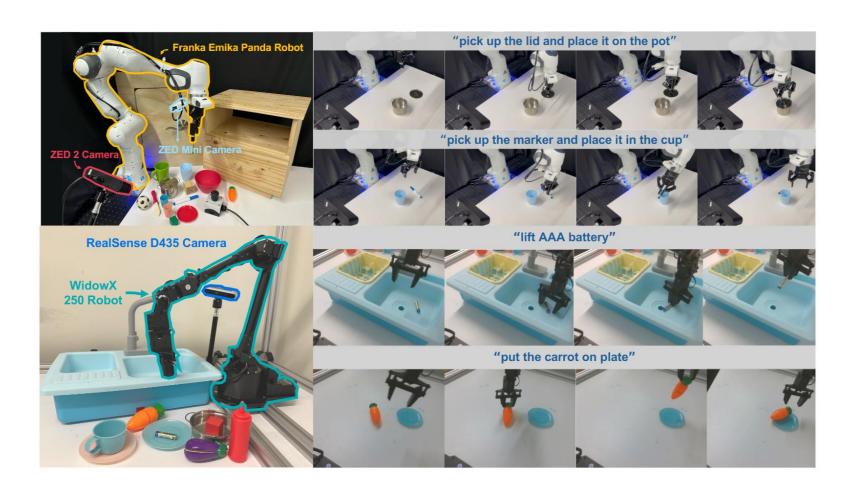


SimplerEnv

### Real-world Experiment Setup

 $\pi_0$ -FAST on Franka

**OpenVLA on WidowX** 



## SAFE outperforms diverse baselines in both simulation and real world

	VLA Model OpenVLA Benchmark LIBERO		$\pi_0$ -FAST LIBERO		$\pi_0$ LIBERO		$\pi_0^*$ SimplerEnv		Average		
	Eval Task Split	Seen	Unseen	Seen	Unseen	Seen	Unseen	Seen	Unseen	Seen	Unseen
Token Unc.	Max prob.	50.25	53.83	61.32	69.44	-	-	-	-	55.79	61.64
	Avg prob.	44.05	51.58	52.46	58.04	-	-	-	-	48.26	54.81
	Max entropy	52.94	53.09	46.69	62.96	-	-	-	-	49.81	58.03
	Avg entropy	45.27	50.03	50.93	58.63	-	-	-	-	48.10	54.33
Embed. Distr.	Mahalanobis dist.	62.03	58.85	93.56	83.79	77.12	74.31	88.42	52.84	80.28	67.45
	Euclidean dist. k-NN	66.00	55.23	92.04	84.12	75.64	70.73	89.73	68.41	80.85	69.62
	Cosine dist. k-NN	67.09	69.45	92.09	84.64	75.76	70.31	90.19	71.32	81.28	73.93
	PCA-KMeans [9]	57.18	55.10	68.46	57.12	64.92	60.35	66.88	61.19	64.36	58.44
	RND [39]	52.57	46.88	88.67	81.57	71.92	69.44	85.07	65.89	74.56	65.95
	LogpZO [8]	61.57	52.91	91.52	83.07	76.80	73.23	88.79	74.66	79.67	70.97
Sample Consist.	Action total var.	62.76	65.43	76.95	74.50	77.20	75.18	68.41	67.94	71.33	70.76
	Trans. total var.	55.33	58.99	78.21	80.03	49.38	54.71	63.27	55.90	61.55	62.41
	Rot. total var.	47.85	55.30	80.87	77.29	52.94	61.06	58.07	62.10	59.93	63.94
	Gripper total var.	61.84	64.48	76.82	74.42	77.19	75.19	69.16	69.29	71.25	70.84
	Cluster entropy	50.16	51.44	80.22	80.53	76.19	72.12	68.25	73.66	68.71	69.44
Action Consist.	STAC [18]	-	-	83.07	85.31	46.55	47.91	60.74	62.21	63.45	65.14
	STAC-Single	-	-	85.46	81.16	68.46	69.39	68.71	70.40	74.21	73.65
SAFE (Ours)	SAFE-LSTM	70.24	72.47	92.98	84.48	76.98	71.09	88.85	80.11	82.26	77.04
	SAFE-MLP	72.68	73.47	90.06	80.44	73.50	73.27	89.50	84.82	81.43	<b>78.00</b>

	$\pi_0$ -FAS	T Franka	OpenVLA WidowX			
Method	Seen	Unseen	Seen	Unseen		
Max prob.	53.74	48.59	50.77	54.25		
Avg prob.	51.60	47.30	48.94	44.36		
Max entropy	59.23	53.50	51.88	49.19		
Avg entropy	50.67	46.08	47.72	53.84		
Mahala. dist.	75.54	53.93	82.37	70.00		
Euclid. k-NN	80.35	60.27	72.01	53.64		
Cosine $k$ -NN	80.23	59.51	74.76	65.88		
PCA-KMeans	49.98	51.03	75.62	47.22		
RND	62.00	45.83	66.68	47.67		
LogpZO	64.43	52.24	62.94	51.32		
STAC-Single	45.24	38.01	_	_		
SAFE-LSTM	77.27	58.70	84.29	<b>71.80</b>		
SAFE-MLP	86.76	64.16	89.11	88.42		

Failure detection ROC-AUC on simulation benchmarks

Failure detection ROC-AUC on real-world benchmarks

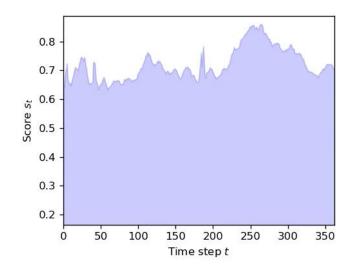
### SAFE Detecting Failure in Simulation

• SAFE-LSTM on OpenVLA + LIBERO

put both the alphabet soup and the tomato sauce in the basket Ep 6, Succ 1, Frame 0

RGB image

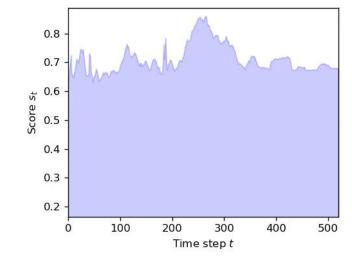




put both the alphabet soup and the tomato sauce in the basket Ep 28, Succ 0, Frame 0

**RGB** image





Successful rollout

Failed rollout: When the robot gets stuck while picking up alphabet soup, it raises a failure signal

## Thank you!

Paper & code: vla-safe.github.io