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TEXAS
The University of Texas at Austin

Online State Transition Classification for Procedural Activities

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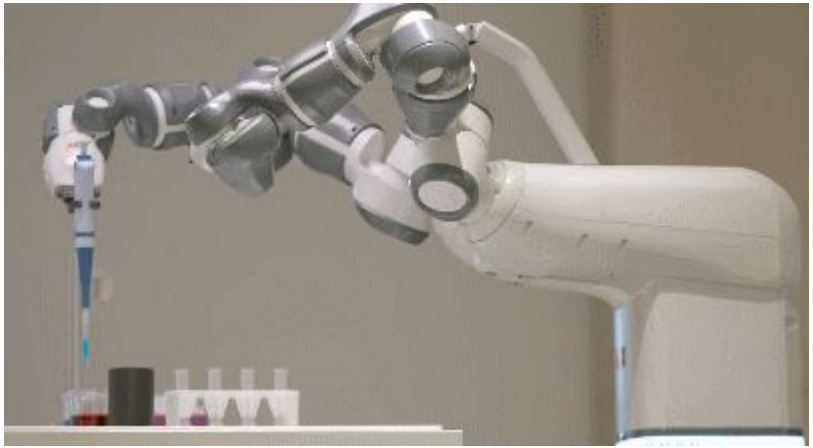
Procedures!

Pipetting and sorting test tubes



Assembly line monitoring

Actions are decided by object state changes, not just by motion!

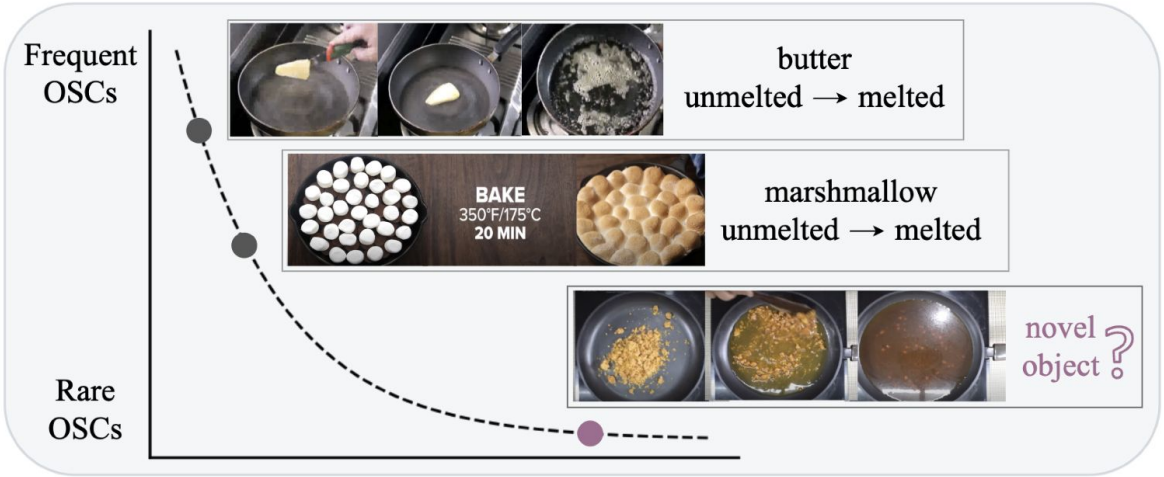
Cutting Tomato =

Uncut → Sliced

Pouring water =

Empty → Full

VidOSC: Learning 3 Stages of an OSC



Object agnostic state prediction

Requires seeing future frames to predict current state

Xue, Zihui, et. al. "Learning object state changes in videos: An open-world perspective." Proceedings of the CVPR Conference. 2024.

Detecting Object state change ***IN REAL TIME*** becomes important!

Why Online?

Why Online?

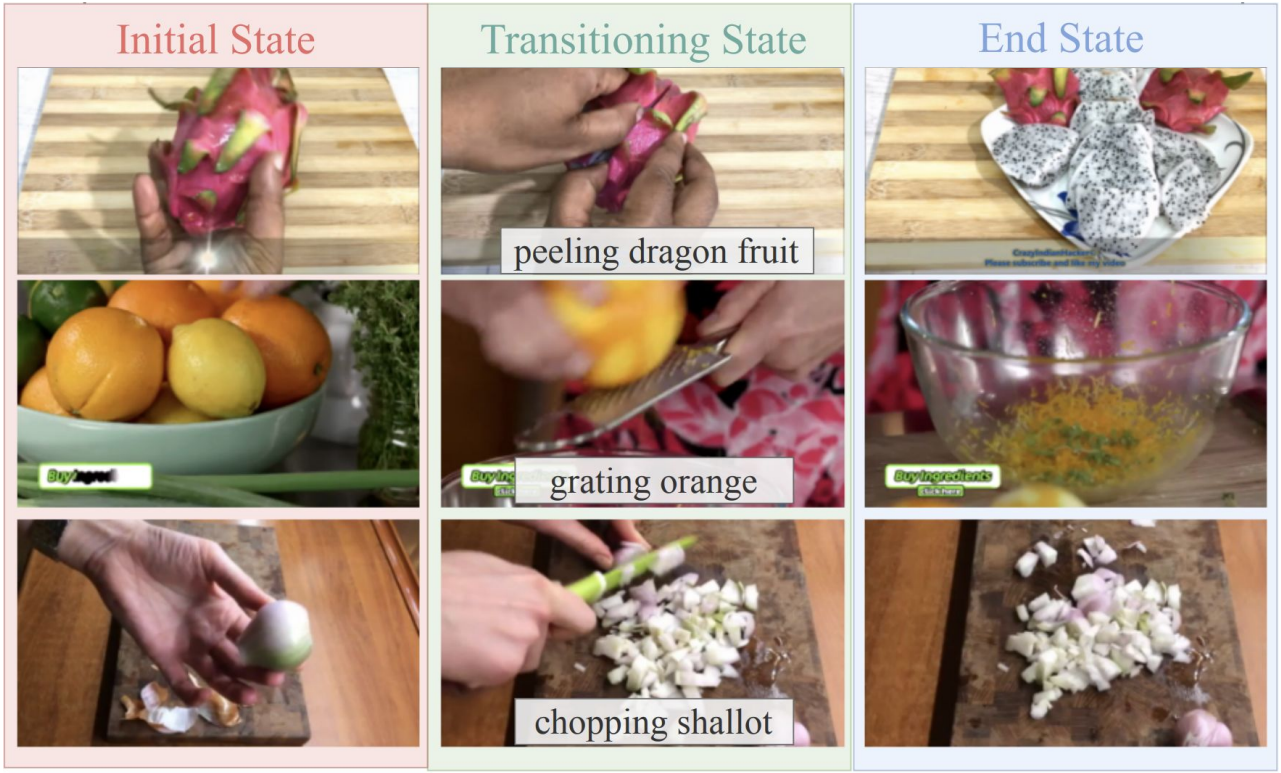
Wait until the end for feedback.

"The butter is melted. Let's proceed!"

Get feedback immediately!

GOAL: provide live feedback to move on from the current step

HowToChange Dataset



HowTo100M Food & Entertaining Category

Actions and passive transformations

5000+ eval videos
400+ unique OSCs

HowToChange Dataset

[0, 13.02] [13.82, 25.49] [29.62, 35.36]

Frame-Wise HowToChange Dataset

[0, 13.02] [13.82, 25.49] [29.62, 35.36]

1 1 1 1 1 1 1 1 1 0 1 1 1 1 1 1 1 1 0 0 2 2 2 2 2 2 2 2 2 0

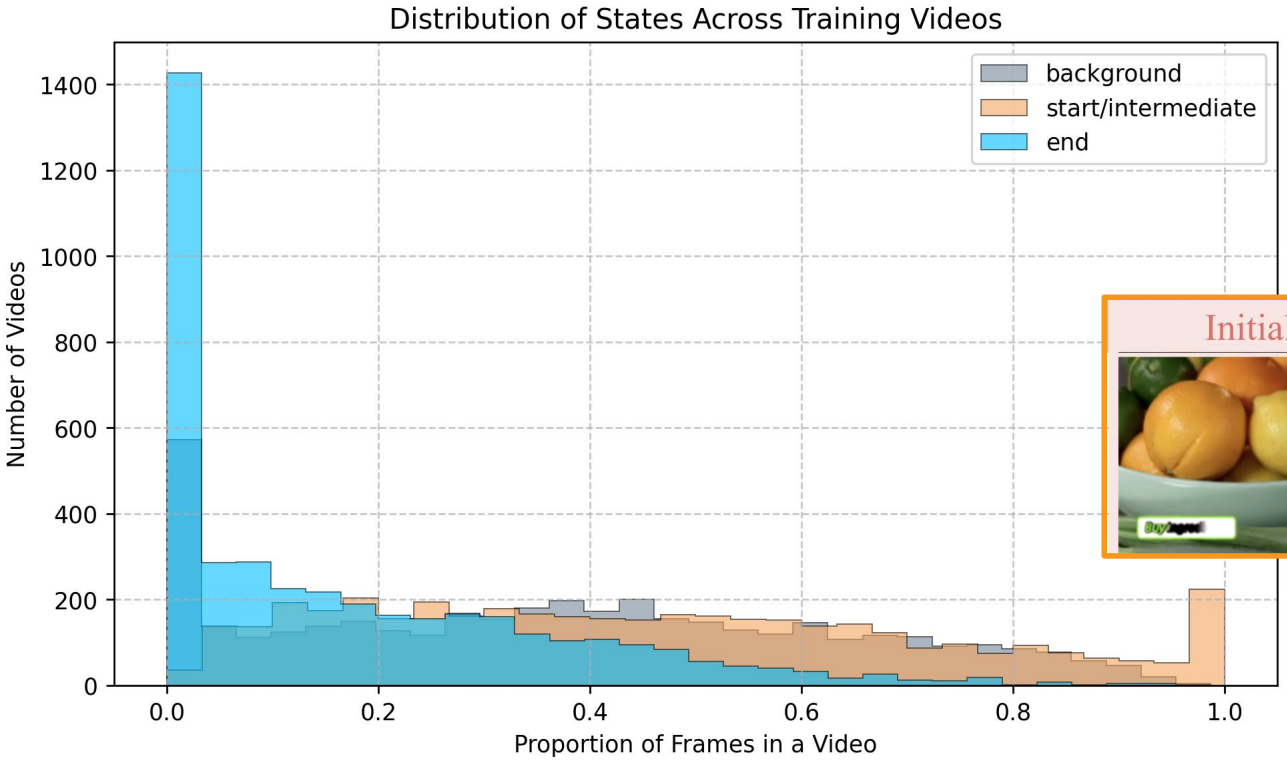
Background State

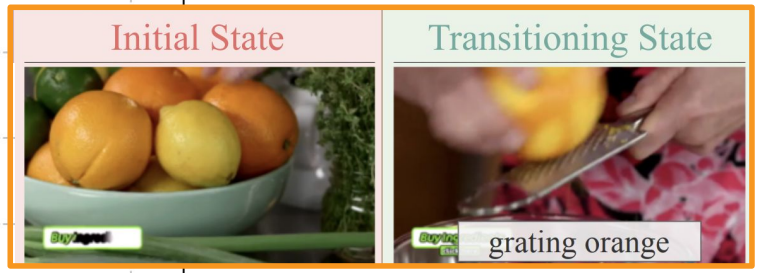
Frame-Wise HowToChange Dataset

1 1 1 1 1 1 1 1 1 0 1 1 1 1 1 1 1 1 1 0 0 2 2 2 2 2 2 2 2 2 0

Background: **14483 segments**
Initial/transition: **11514 segments**
End: **5757 segments**

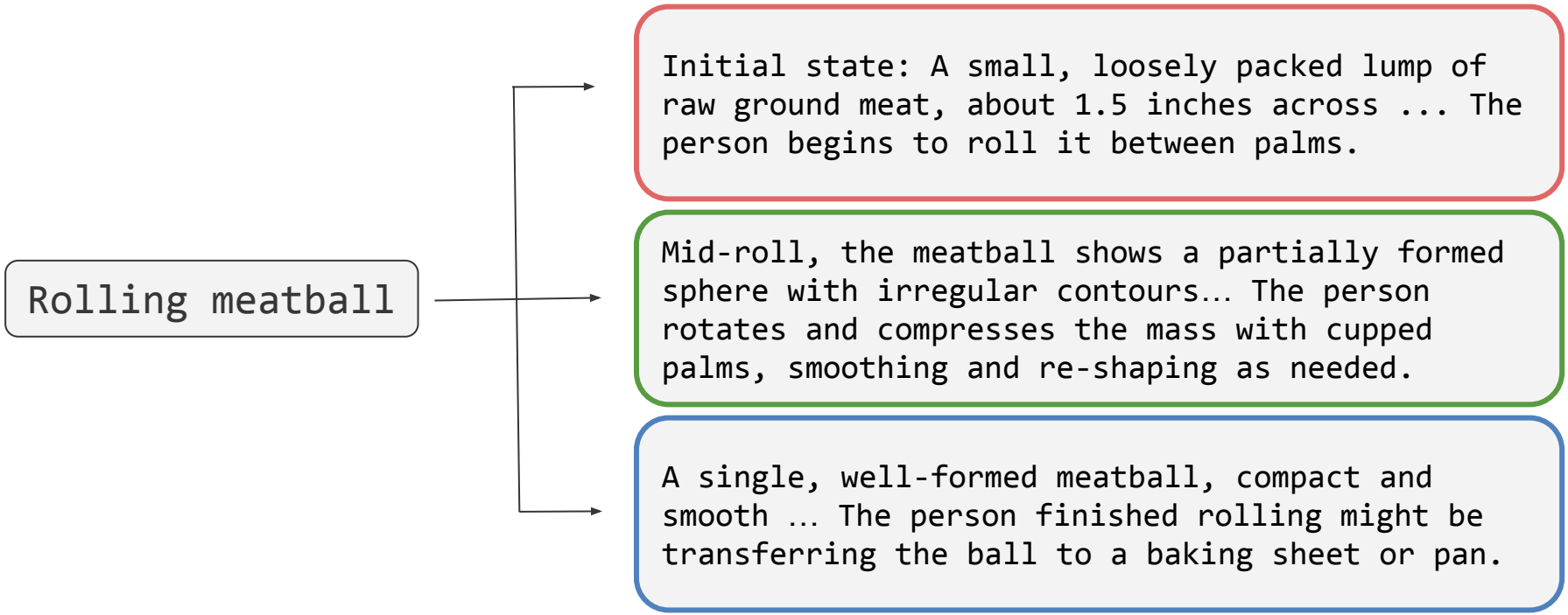
Frame-Wise HowToChange Dataset



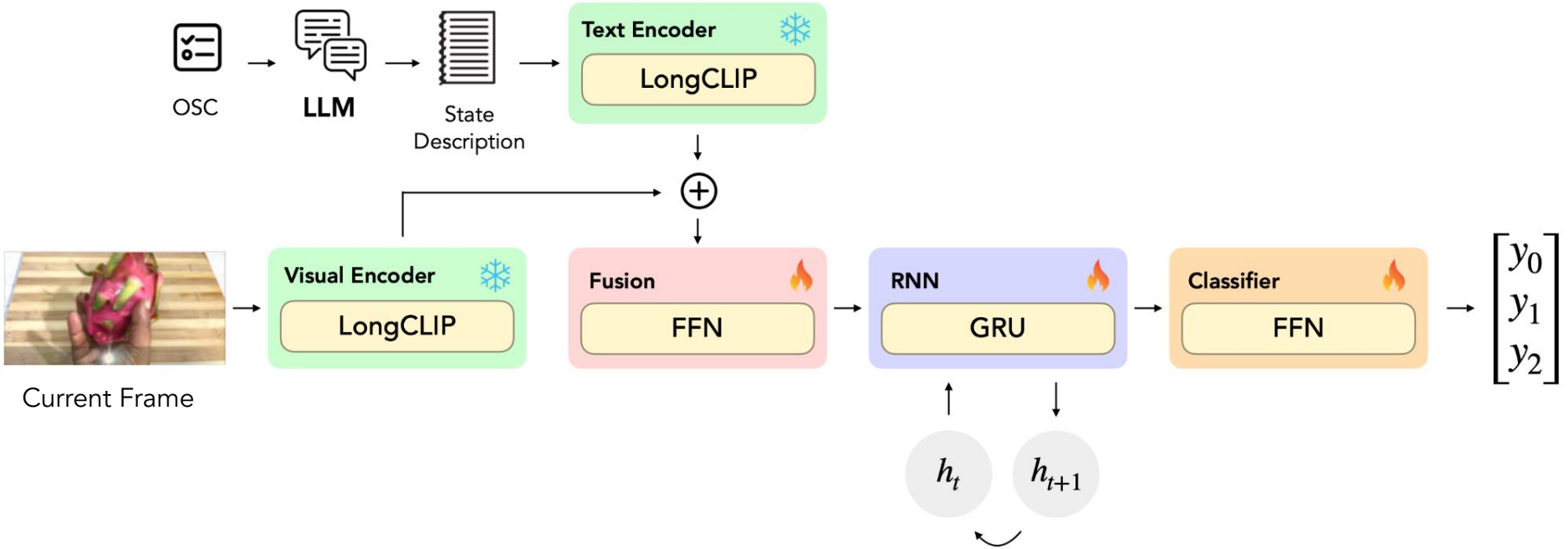


Dataset: Description Bank

Maps OSC to LLM state descriptions



Architecture



Current Frame

Training

Frame-wise prediction on train set of ~4000 videos

Sampled each video at 1 FPS

Loss = Weighted cross-entropy loss + $\lambda_E \cdot$ Entropy Loss + $\lambda_M \cdot$ Monotonicity Loss averaged over all frames

Parameter	**Value**
Learning Rate	0.001
Monotonicity λ	0.1
Entropy λ	0.1
Window size	5
Epochs	1
Batching	False

Results

Evaluated on test set of ~700 videos

	Acc (%) ↑	F1 (%) ↑	End State F1 (%) ↑	End State IoU (%) ↑
VidOSC (Multitask)	38.07	17.21	1.37	1.64
VidOSC (Single task)	53.15	34.23	31.51	36.91
Ours	49.50	31.91	31.25	36.92
Ours (+ LLM desc)	51.54	41.80	34.73	41.36

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Success Example: Slicing Lemon

Failure Example: Roasting Coconut

Future Work

- Unedited, egocentric video
- Long stream videos
- Unseen or novel state changes
- Non-cooking tasks
- Self or weak supervision

…

Conclusion

- **Motivation**: provide live feedback to move on from the current step based on state change detection
- **Method**: supervised learning + recurrent network + LLM-generated state description as knowledge bank
- **Results**: outperformed offline OSC segmentation baselines on end state detection