

Learning Camera Viewpoint Selection in Instructional Videos

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Instructional videos

Videos made for teaching how to do skilled activities



How to pack a suitcase?



How to apply makeup?

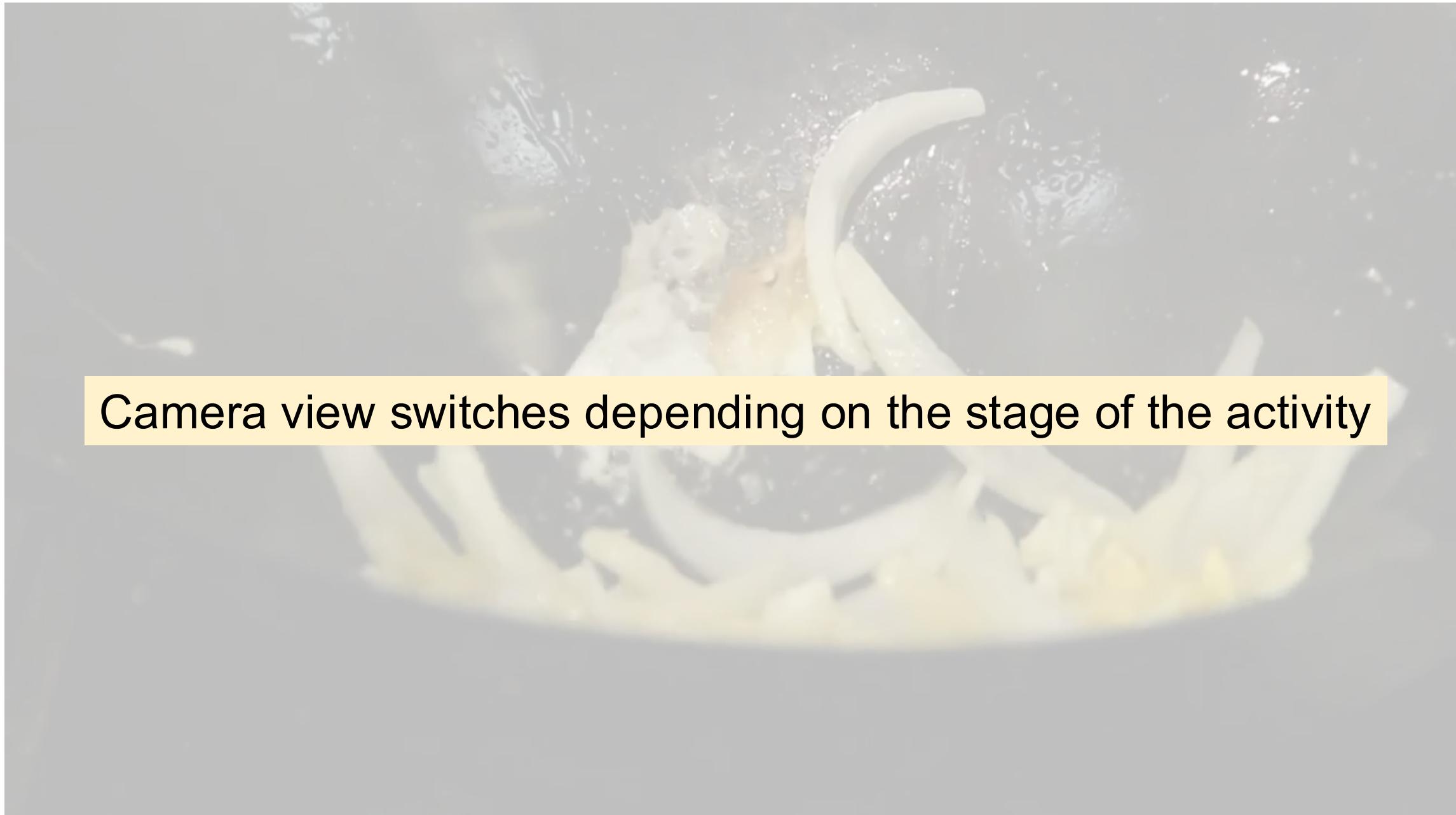


How to hand-make pasta?



How to use a bidet?

Typical in-the-wild instructional video



Creating a varying-view instructional video



Source: justinodisho.com

Post-capture editing

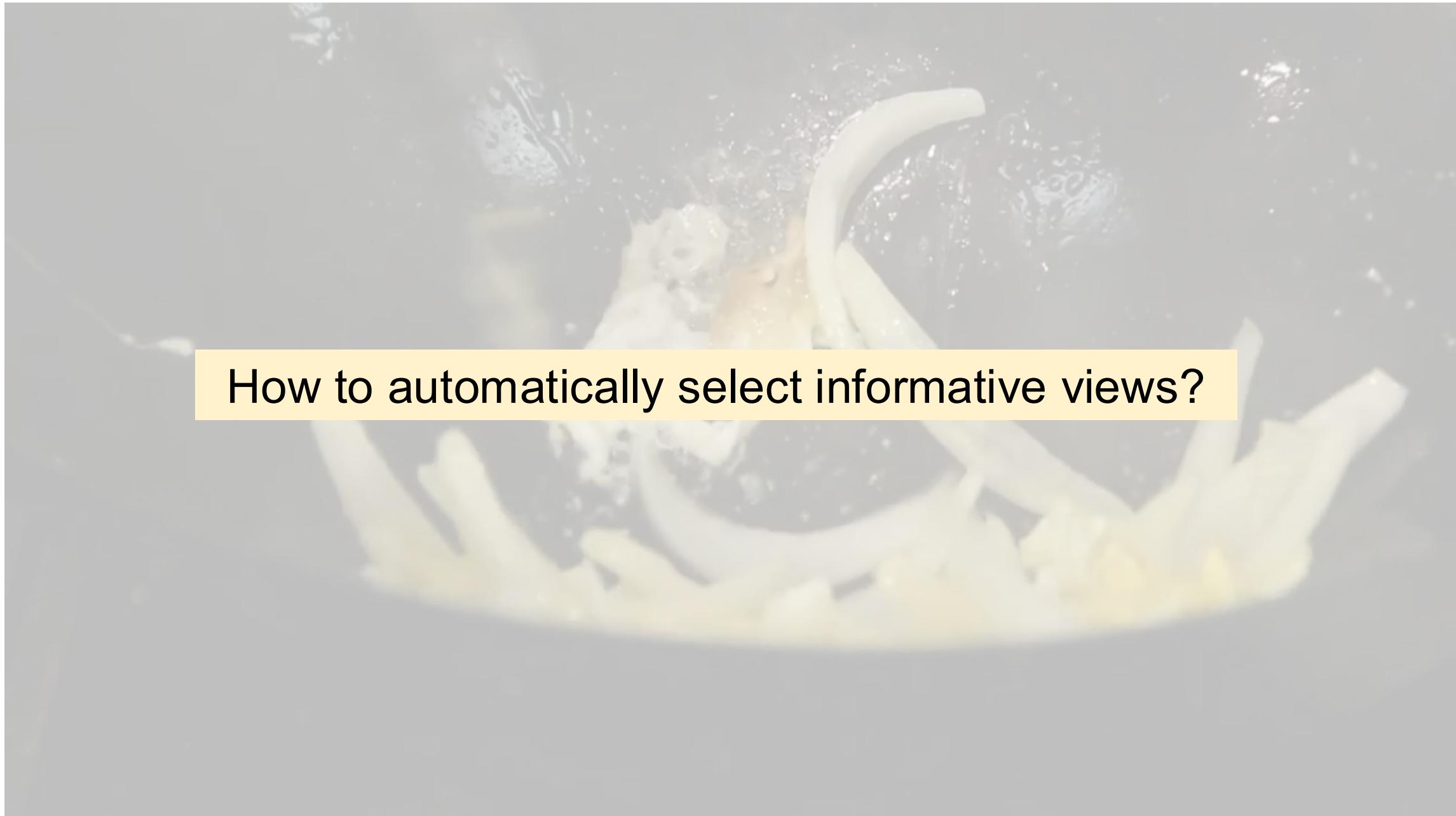


Source: premiumbeat.com

Active camerawork

Laborious and time-consuming

View selection in multi-view instructional videos



View selection in multi-view instructional videos



Given an instructional video scene captured using multiple cameras,
select the sequence of camera views that best illustrates the activity

Narrations

View-independent dense captions describing the instructional activity

Controlled capture (e.g., Ego-Exo4D[1])

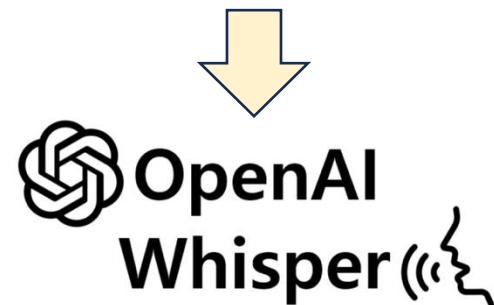


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03:45.833333 ◀ 4312 ⏪ ⏴ Speed 1x ⏵ 🔍 51% 🔍 ⏴ ⏵ ⏴ ⏵



The person pours a spoon of salt with their right hand

In-the-wild capture (e.g., HowTo100M [2])



I am adding the sausages to the rice now

We will use medium heat throughout

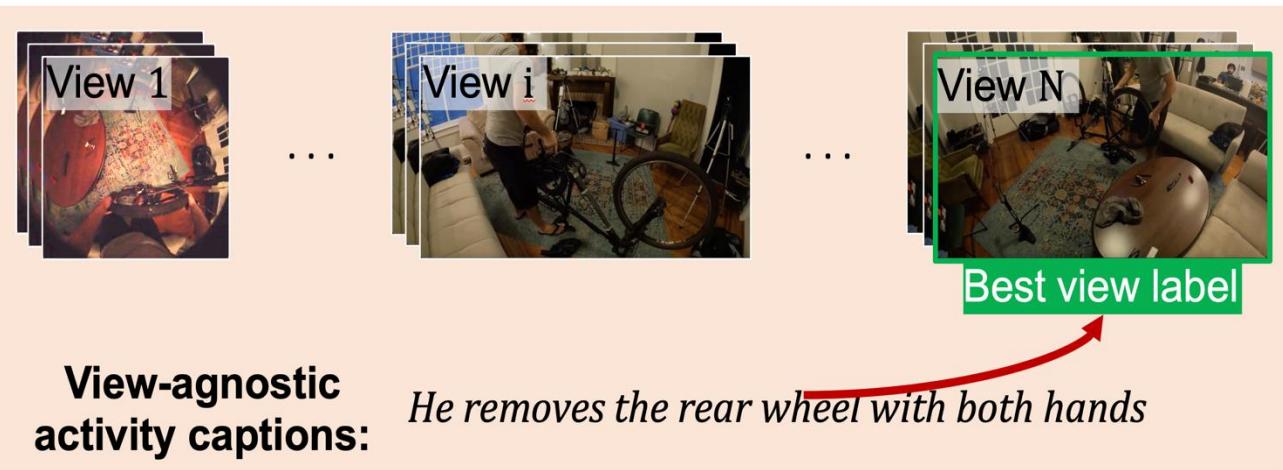
Stir the rice until you have a uniform mix



View selection in label-scarce settings

View selection in label-scarce settings

Main conference: Wed
(10/22) AM, poster #185



LangView

... by using captions for producing best-view pseudo-labels during training

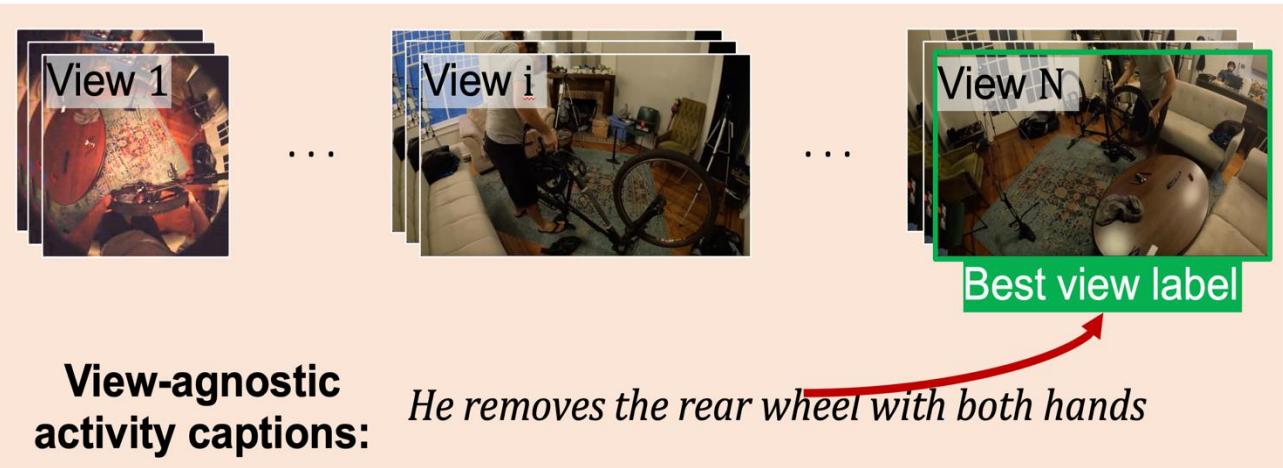


Switch-a-View

... by learning human view choices from unlabeled but edited in-the-wild how-tos

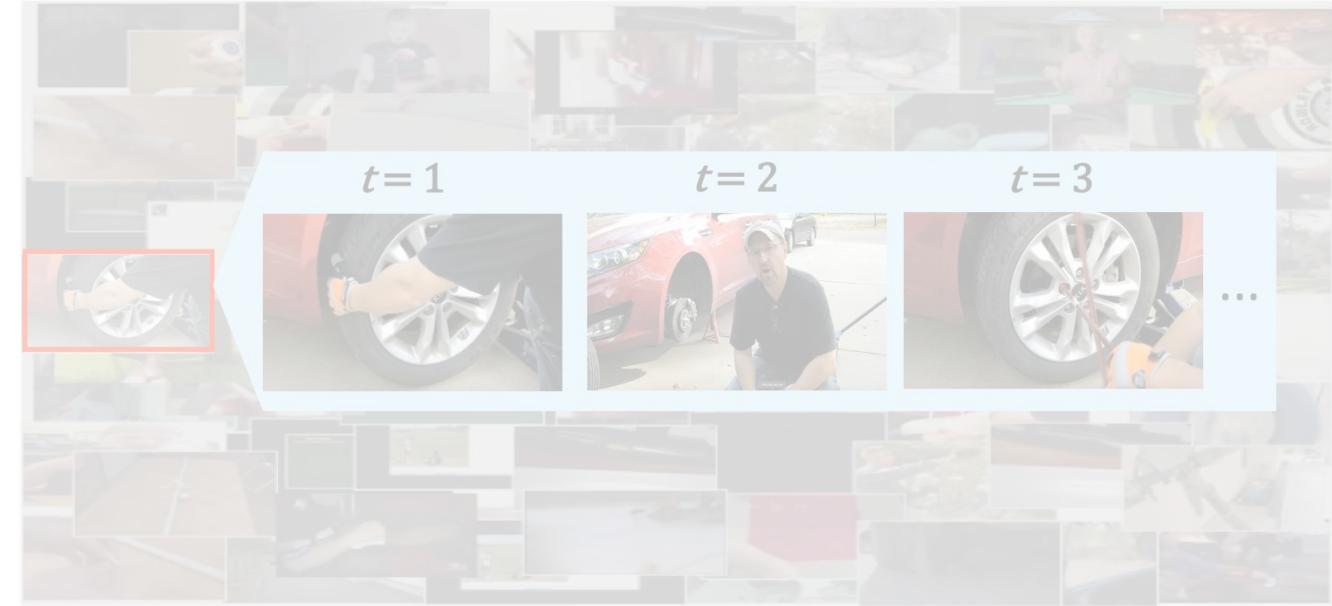
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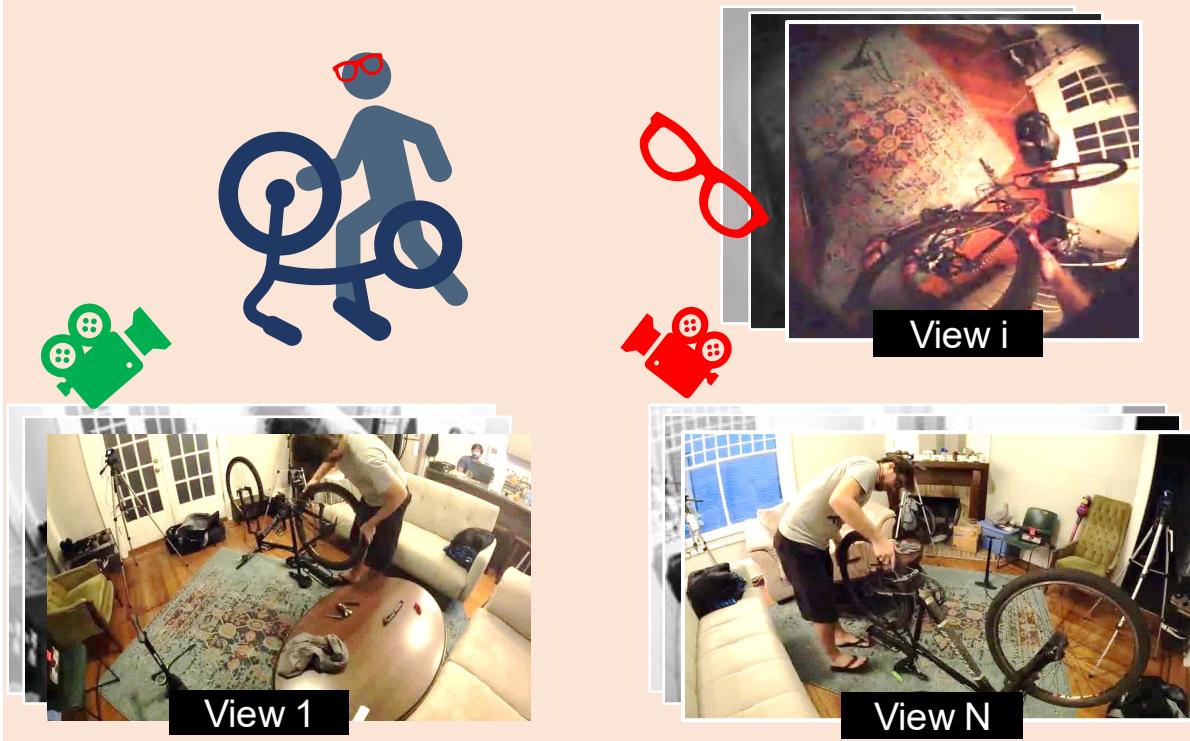


Switch-a-View

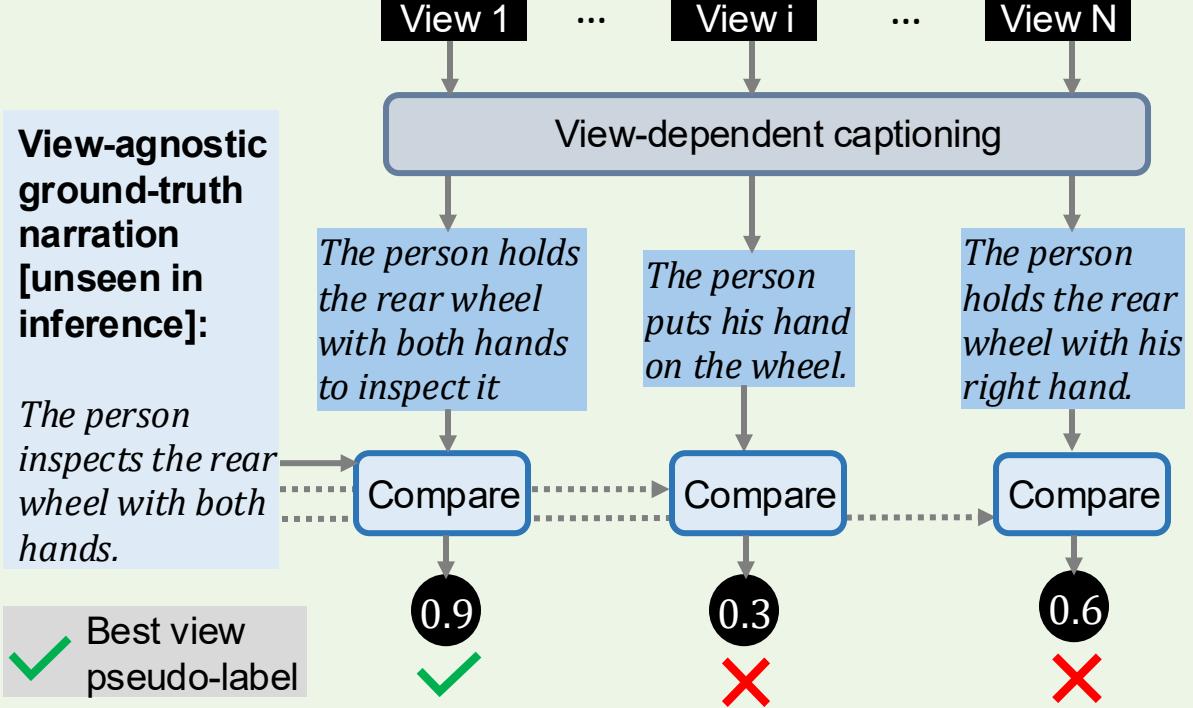
... by learning human view choices from unlabeled but edited in-the-wild how-tos

LangView: weakly supervise via language

Task: select the best view in the absence of labels



Idea: Use language as weak supervision during training



Task: given a multi-view instructional video, learn to select the best view without manual labels

Idea: use video captions (narrations) to provide weak supervision at train time

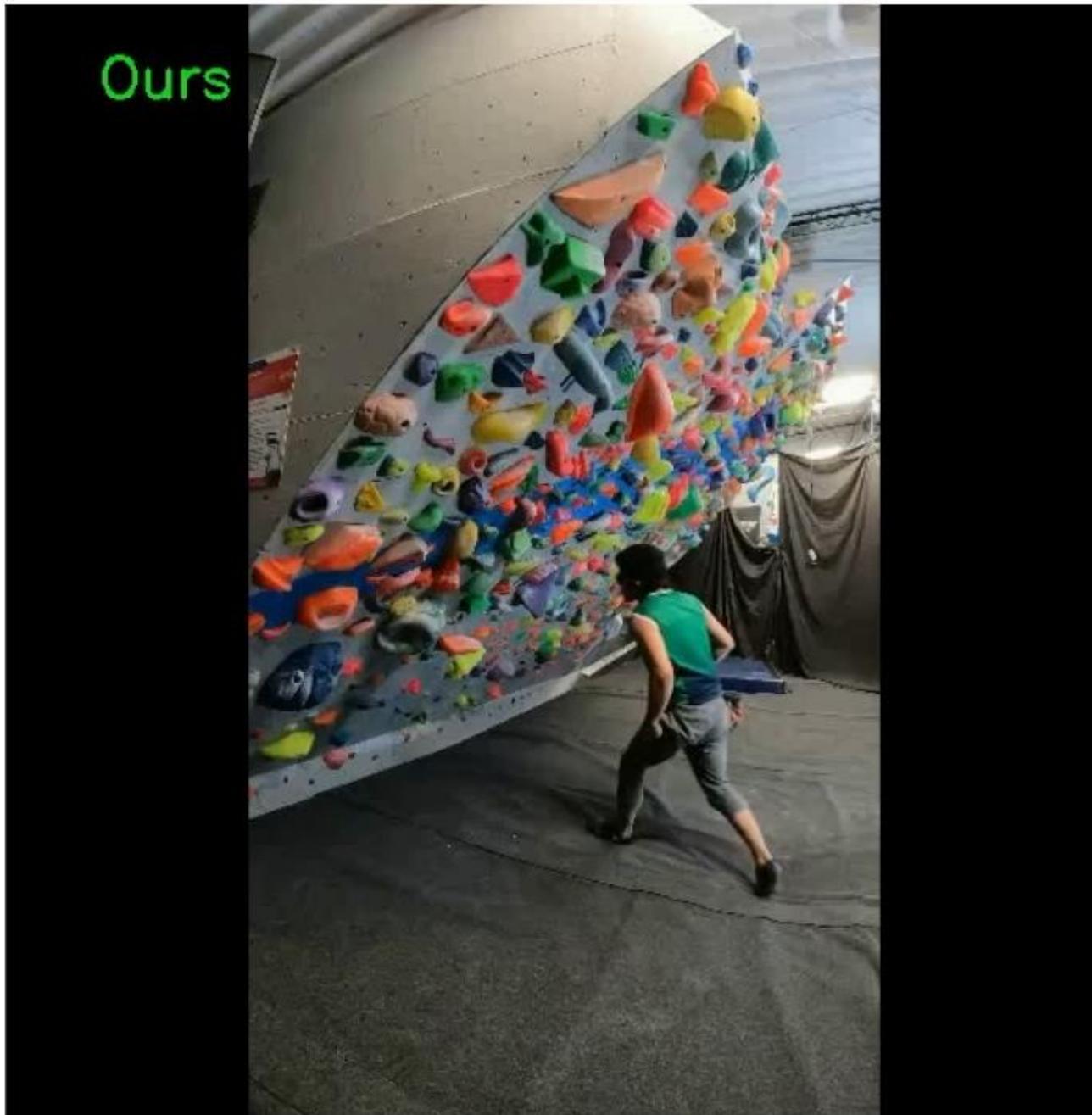
Method: • caption each candidate training view separately

• compare predicted captions with view-agnostic ground-truth caption

• choose the view with the most accurate caption as the best view pseudo-label

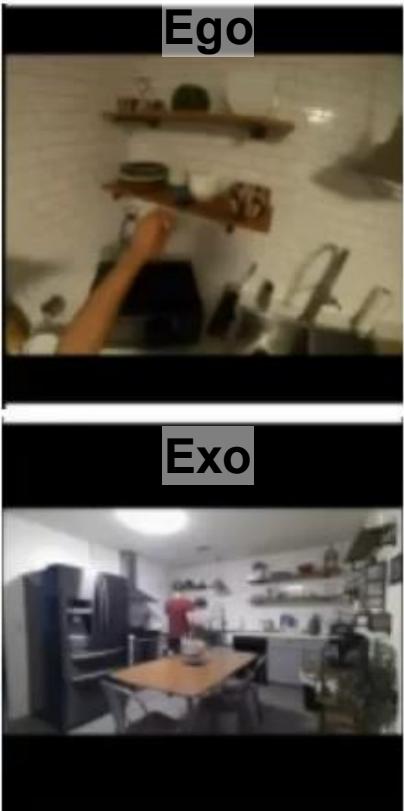
Qualitative results: Ego-Exo4D

All-view panel



Qualitative results: LEMMA

All-view panel



Automatic evaluation results

Model	Ego-Exo4D [1]					LEMMA [2]				
	Captioning		Actions and objects			Captioning		Actions and objects		
	CIDEr	METEOR	V-IoU	N-IoU	NC-IoU	CIDEr	METEOR	V-IoU	N-IoU	NC-IoU
Naive heuristics	Ego-only	12.2	47.2	32.2	36.7	30.6	41.7	71.1	38.2	41.3
	Random	11.5	45.9	30.4	36.6	31.0	30.9	63.1	31.2	33.2
	Random-exo	11.9	46.0	30.5	37.0	30.9	17.7	51.3	21.6	22.4
Hand-object interactions and body visibility	Hand-object	12.6	47.4	33.6	36.7	29.6	40.7	72.7	38.5	41.5
	Body-area	12.9	48.2	32.5	37.2	31.1	42.1	73.8	38.6	41.3
	Joint-count	12.6	46.6	31.5	29.1	27.7	17.8	51.4	21.7	22.4
SOTA	Snap angles [3, 4]	12.2	46.7	30.7	35.8	29.1	38.9	70.6	37.1	40.2
Alternative for using language	Longest-caption	10.7	47.3	30.5	34.6	28.8	32.7	65.4	36.9	37.9
	Ours	13.5	48.4	33.7	39.2	32.9	42.7	74.4	40.1	42.9

Our model outperforms all baselines on both Ego-Exo4D and LEMMA datasets across all metrics

[1] Ego-Exo4D. Grauman et al., CVPR 2024.

[2] LEMMA. Jia et al., ECCV 2020.

[3] Enhanced 360° viewing via automatic guidance. Cha et al., ACM Trans. Graph. 2020.

[4] Snap angle prediction for 360° panoramas. Xiong and Grauman, ECCV 2018.

View selection in label-scarce settings

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LangView

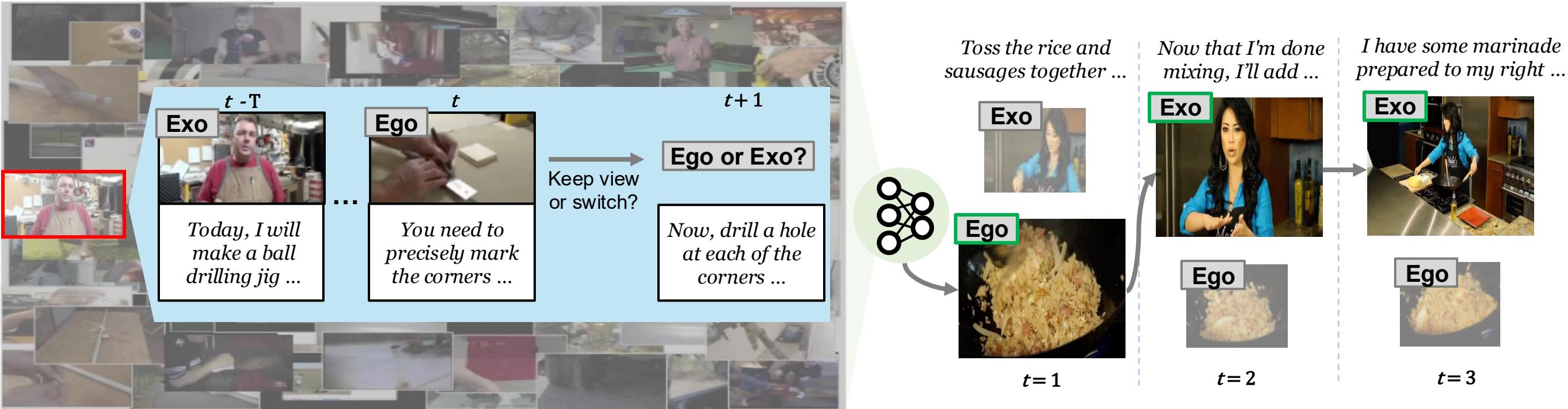
... by using captions for producing best-view pseudo-labels during training



Switch-a-View

... by learning human view choices from unlabeled but edited in-the-wild how-tos

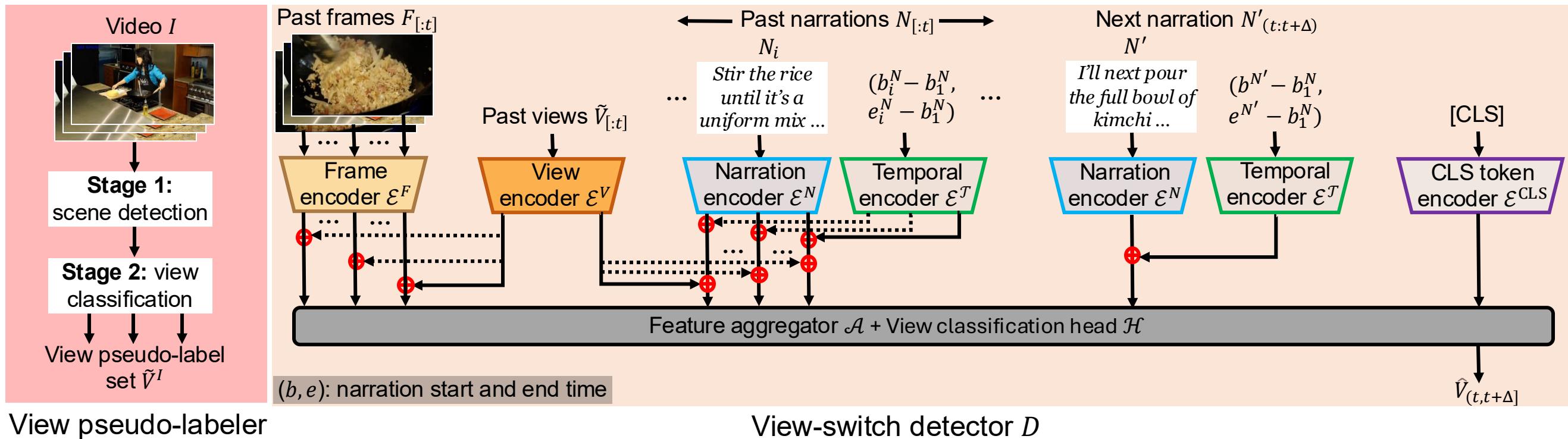
Switch-a-View: View Selection Learned from Unlabeled In-the-wild Videos



Task: Learn view selection in multi-view instructional videos with **limited** labels

- Idea:**
- Learn human view choices from large-scale unlabeled in-the-wild videos by solving a weakly-supervised view-switch detection task
 - Finetune this model for view selection with limited labels

View-switch detection model

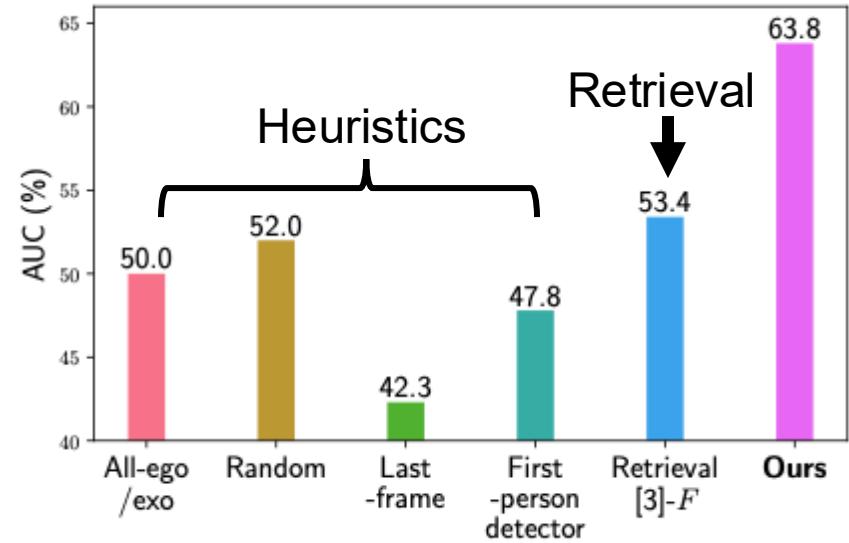


Model components:

1. View pseudo-labeler -- pseudo-labels the dominant view type in a video clip
2. View-switch detector -- given past frames, narrations and view types, and the next narration, predicts the next view type

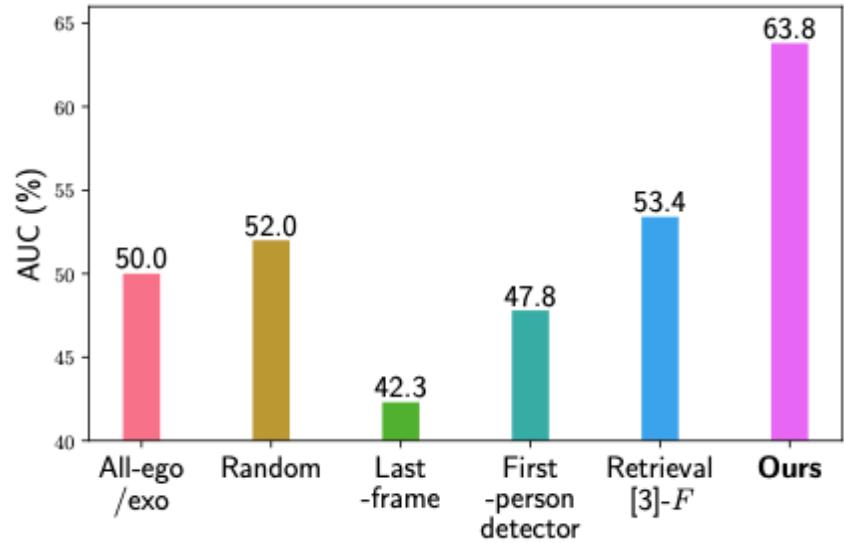
Training loss: $\mathcal{L}^D = \mathcal{L}_{CE}(\hat{V}_{(t,t+\Delta]}, \tilde{V}_{(t,t+\Delta]})$

Quantitative results

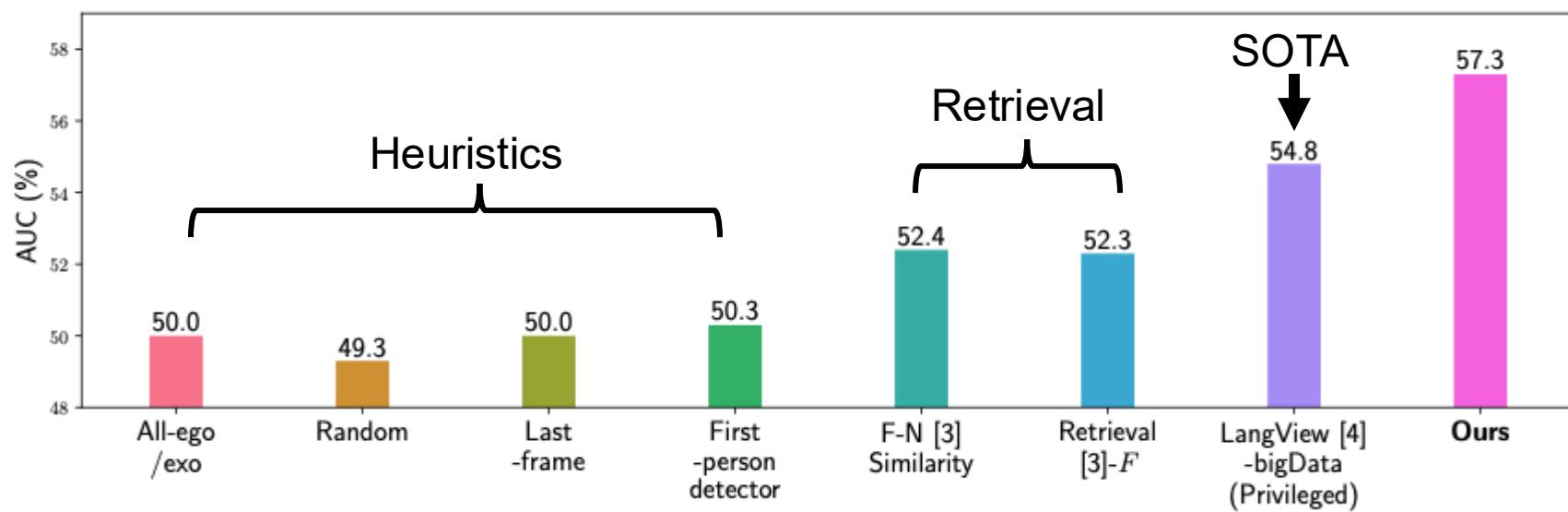


View-switch detection on HT100M

Quantitative results



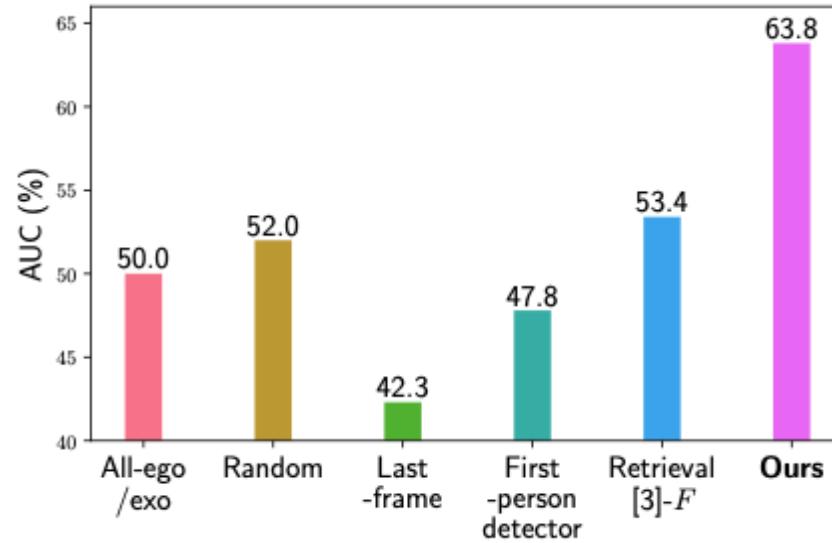
View-switch detection on HT100M



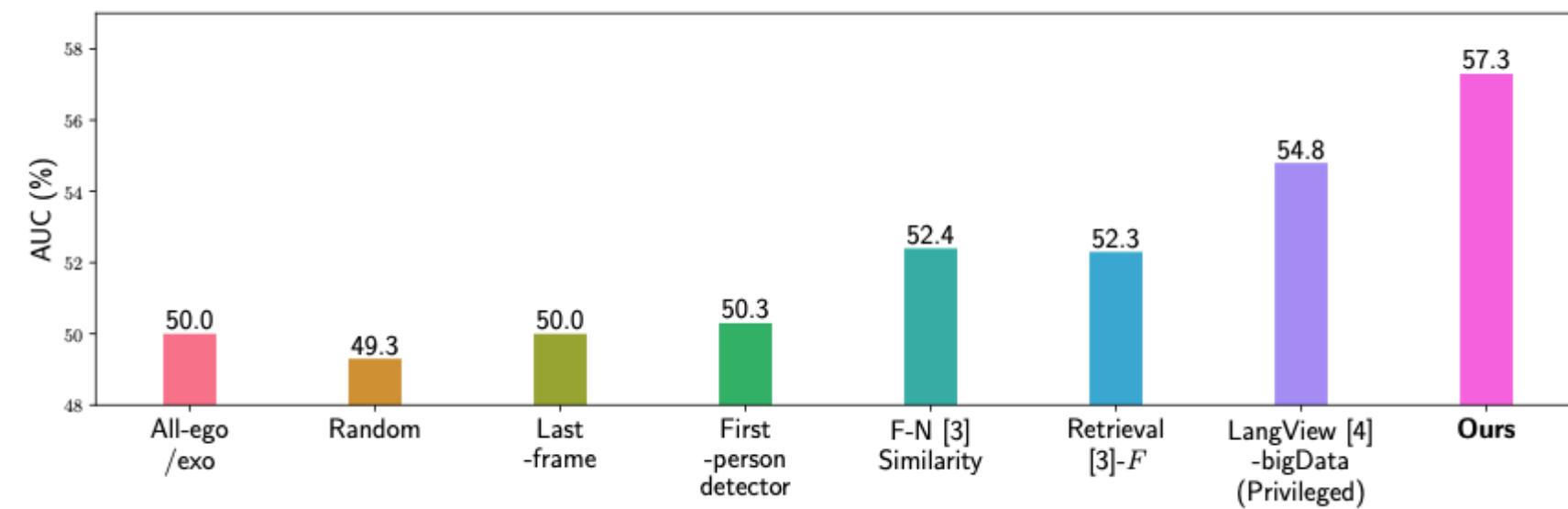
View selection on Ego-Exo4D

- ❖ Our model outperforms all baselines on both HowTo100M and Ego-Exo4D on all metrics

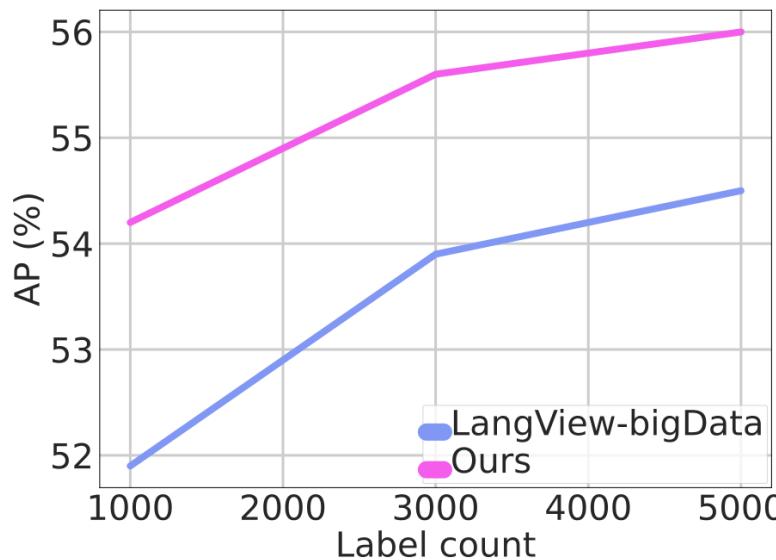
Quantitative results



View-switch detection on HT100M



View selection on Ego-Exo4D



View selection AP vs. label #

- ❖ Our model outperforms all baselines on both HowTo100M and Ego-Exo4D on all metrics
- ❖ The lower the count of best view labels, the higher our margin of improvement is over the baselines

View-switch detection example

Past frames and narrations

Next USEEN frames and SEEN narrations

View selection example

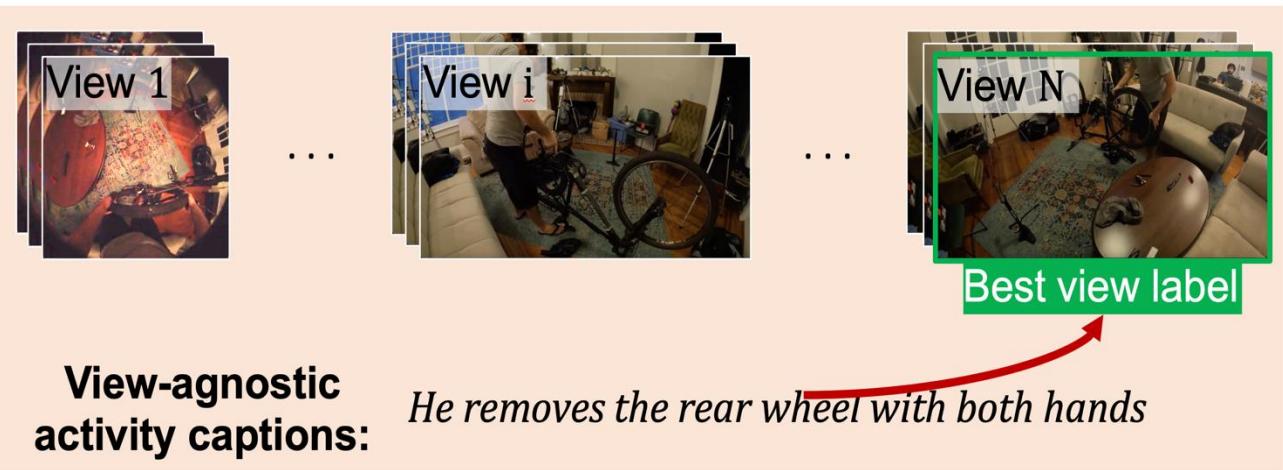
Past frames and narrations

Next narrations and frames from candidate views

Label,
Prediction

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