

# Hierarchical Vector Quantization for Unsupervised Action Segmentation

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Associated institutes

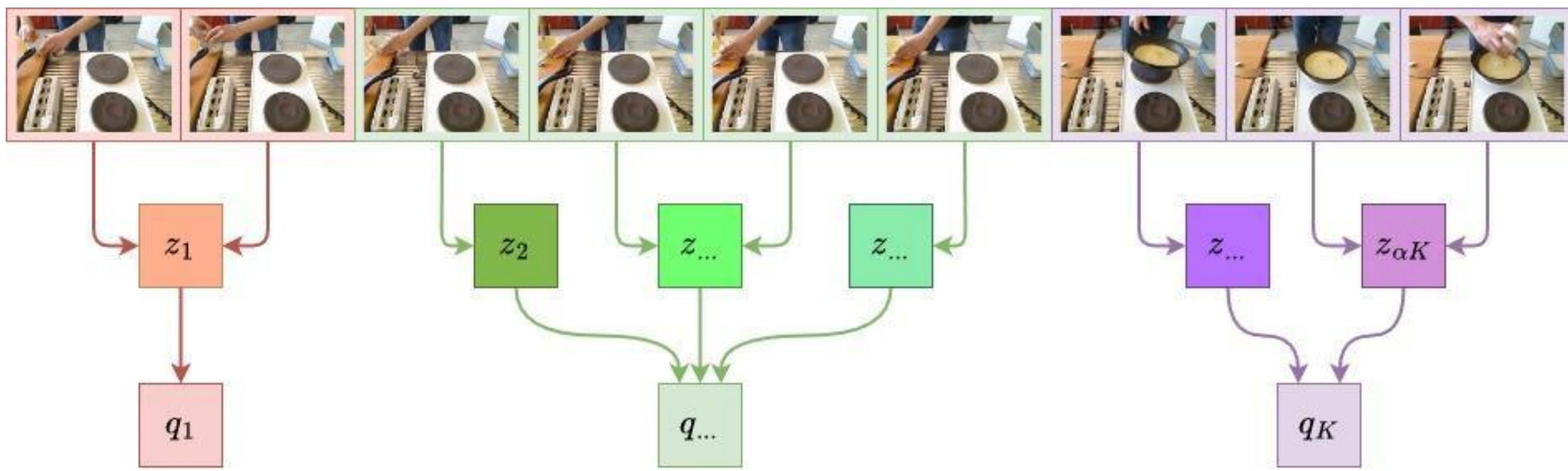
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Link to our code!

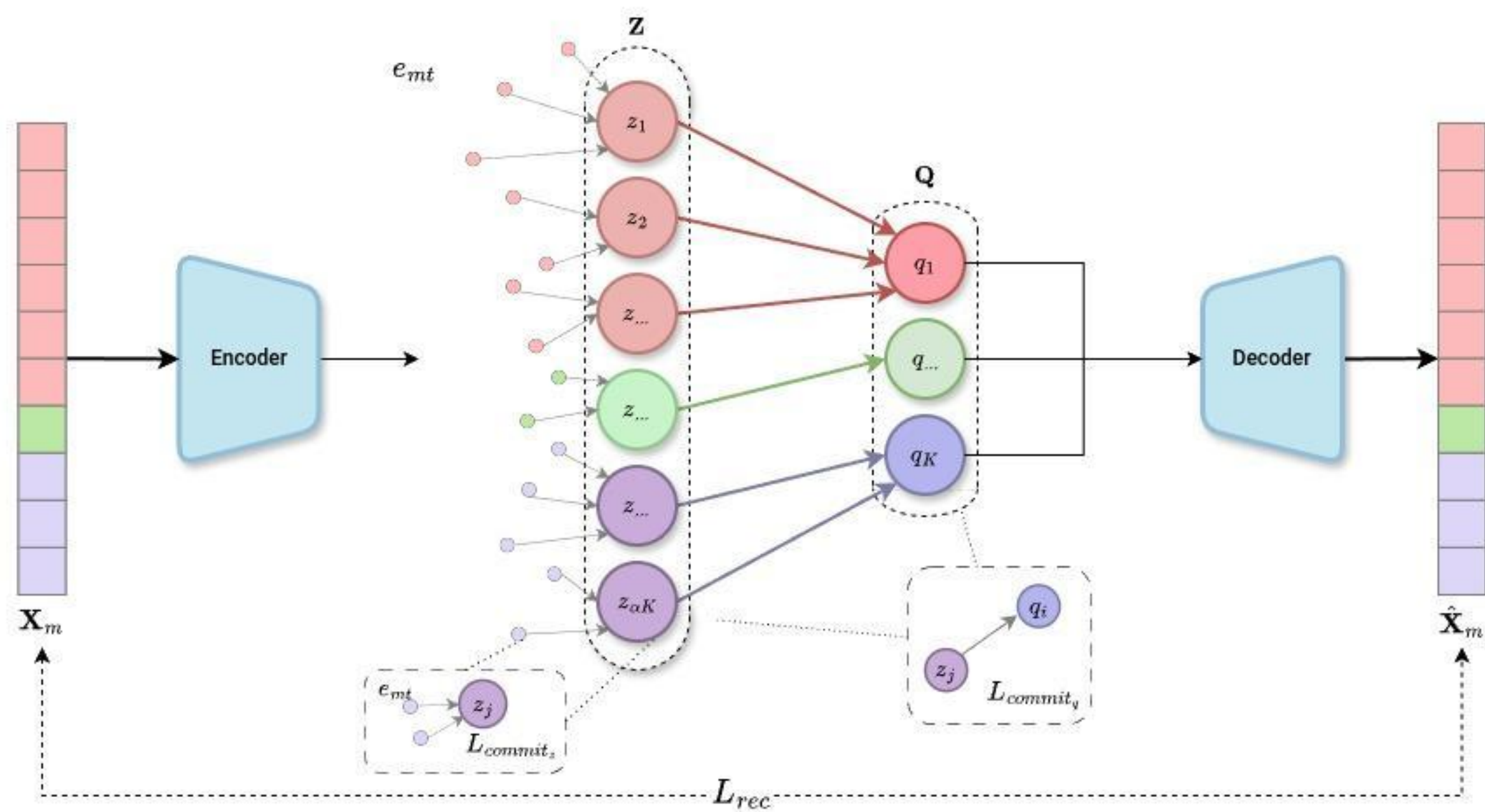
## Introduction

- In this work we deal with the task of **unsupervised action segmentation**, which segments a set of long, untrimmed videos into semantically meaningful segments that are consistent across videos.
- Our **key observation**: human actions are of a compositional nature, i.e. intermediate steps are needed to complete a task. This was not taken into consideration in previous works, where they show good performance, at the expenses of distribution of segment lengths.
- To incorporate this idea, we propose to **hierarchically** model action segments using our novel **Hierarchical Vector Quantization** model. Additionally, to measure the quality of distribution of segment lengths compared to the ground truth, we introduce a new metric based on **Jensen-Shannon Divergence**.
- We show that our model achieves **state-of-the-art** results on 3 datasets: Breakfast, YouTube Instructional and IKEA ASM.



## Hierarchical Vector Quantization

- We model actions using a **fine-to-coarse hierarchical representation**, capturing both **low-level subactions** and **high-level action structures**.
- Our two-levels quantization maps frames to subaction clusters, a **fine-grained representation** of an action, then grouped into coarse action prototypes to form action representation.
- A **commitment loss** enforces consistency between frames and subactions, and between subactions and actions. A **reconstruction loss** ensures meaningful latent representations.
- During inference, each frame is assigned to its **nearest prototype in Q**, and the predictions are refined using **FIFA decoder**.



## JSD Metric

- We notice a **bias in terms of the length of the generated action segments** in prior works. For this reason, we introduced **JSD metric**.
- For each video within same activity, we compute the **histogram of the predicted segment lengths**, and compare it to the ground-truth using the **Jensen-Shannon Distance (JSD)**. The JSD scores are **averaged per activity**, then **weighted by the number of frames** to obtain the final score.

## Quantitative Results

- We evaluated our approach on 3 datasets: Breakfast, YouTube Instructional (YTI) and IKEA ASM. We achieve **state-of-the-art results** in F1-score, recall and JSD.
- We analyze how the **number of levels of quantization** and the **number of prototypes in Z ( $\alpha$ )** affect the predictions.

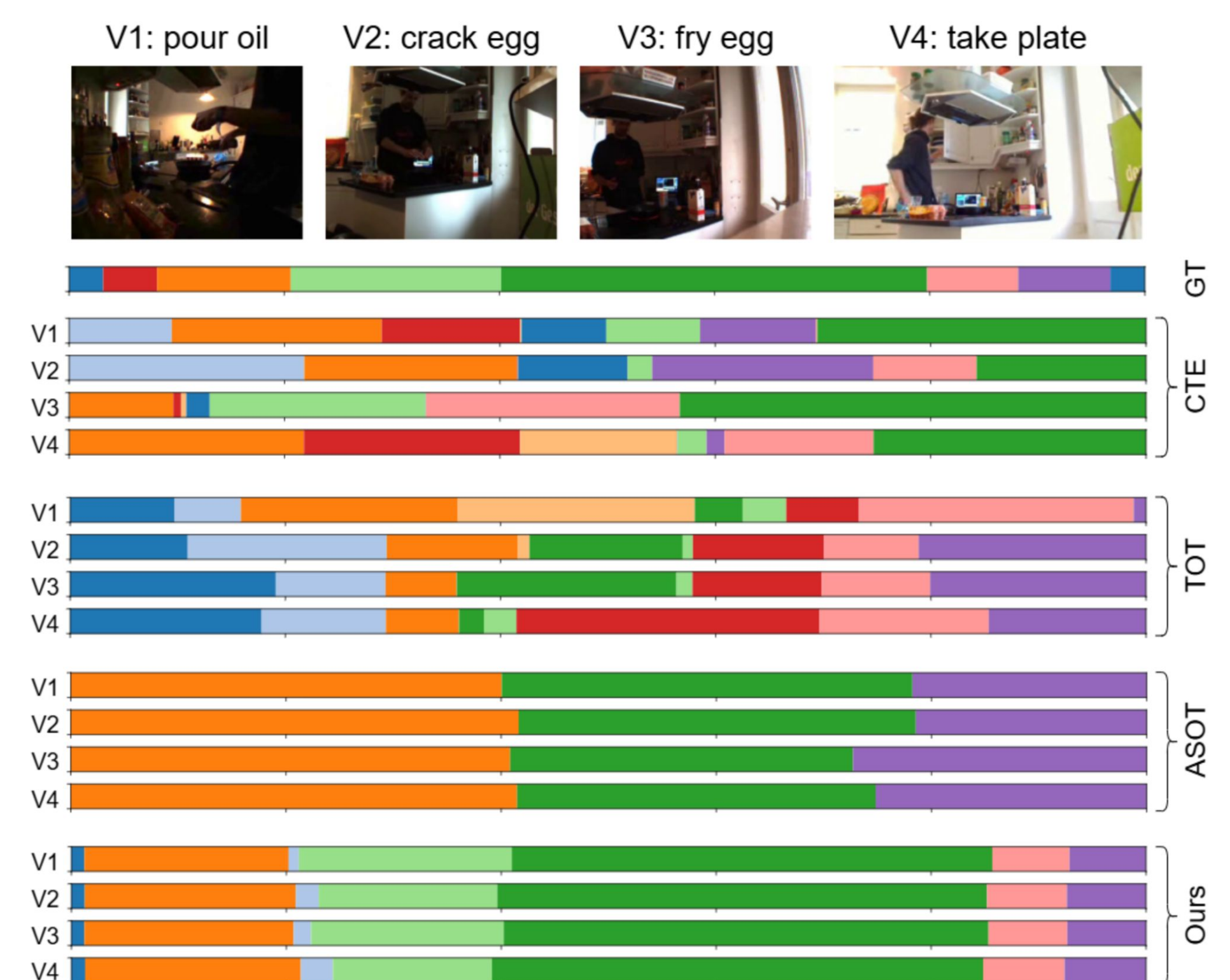
Dataset	Breakfast				YTI			IKEA ASM*			
Method	MOF	F1	Recall*	JSD*↓	MOF	F1	Recall*	MOF*	F1*	Recall*	JSD*↓
CTE	41.8	26.4	27.0	87.4	39.0	28.3	22.1	23.1	22.6	18.9	<u>73.7</u>
ASAL	52.5	37.9	-	-	44.9	32.1	-	-	-	-	-
TOT	47.5	31.0	26.3	90.2	40.6	30.0	<u>31.4</u>	21.0	20.1	17.1	80.0
TOT+TCL	39.0	30.3	36.0	<u>85.6</u>	45.3	<u>32.9</u>	27.9	23.8	20.9	17.7	79.5
UFSA	52.1	38.0	-	-	<u>49.6</u>	32.4	-	-	-	-	-
ASOT	<b>56.1</b>	<u>38.3</u>	<u>40.1</u>	94.9	<b>52.9</b>	<b>35.1</b>	27.8	<u>34.0</u>	<u>27.9</u>	<u>24.0</u>	88.7
Ours (HVQ)	<u>54.4</u>	<b>39.7</b>	<b>44.9</b>	<b>82.5</b>	50.3	<b>35.1</b>	<b>38.7</b>	<b>51.2</b>	<b>30.7</b>	<b>25.9</b>	<b>64.8</b>

	Breakfast			
	$\alpha = 1$	$\alpha = 2$	$\alpha = 3$	$\alpha = 4$
MOF	53.6	<b>54.4</b>	52.7	51.8
F1	38.2	<b>39.7</b>	38.3	38.2
JSD ↓	83.7	82.5	83.0	<b>82.2</b>

Dataset	Metric	Single	Double	Triple
YTI	F1	33.0	<b>35.1</b>	31.9
IKEA ASM	F1	25.8	27.6	<b>30.7</b>
	JSD	81.9	<b>62.2</b>	64.8
Breakfast	F1	37.1	<b>39.7</b>	38.2
	JSD	83.1	<b>82.5</b>	84.1

## Qualitative Results

Segmentation results for a sample of Breakfast. Our approach delivers **highly consistent results** across multiple videos (V1, V2, V3, V4) recorded from different cameras, but with the same ground truth.



## References

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