Adaptive Latent Trajectory Anchoring for Action Segmentation Dataset Condensation

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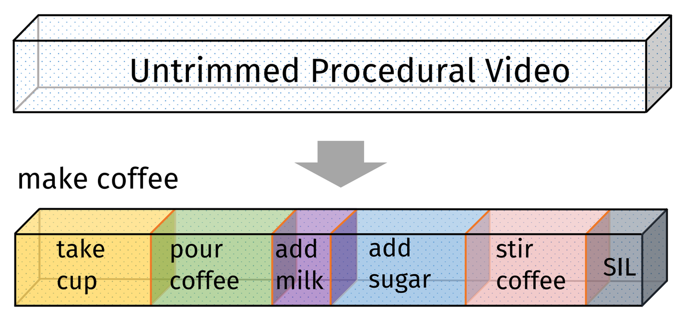
Task & Motivation

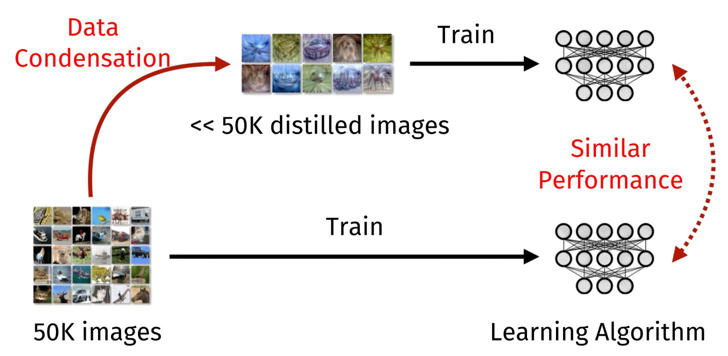
Temporal Action Segmentation

- **Temporally segment** untrimmed procedural videos and assign **frame-wise semantic labels**



Dataset Condensation

- Synthesizes a **small set** that **trains models as effectively as** the **full dataset**



Challenges

- How to *preserve fine-grained temporal dynamics* under aggressive condensation?
- How to *distribute condensation budget* across segments of varying complexity?
- How to *efficiently achieve high-fidelity reconstruction*?

Approach

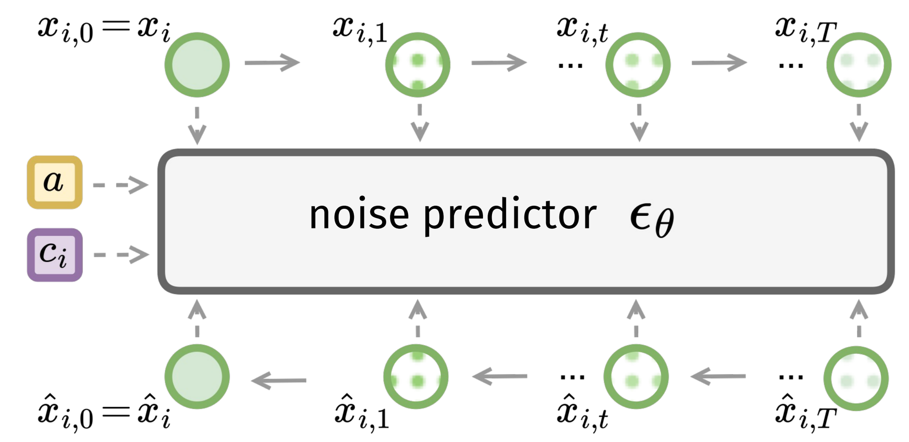
1) Action Modeling with Diffusion Model

Model actions with Diffusion conditioned on:

- action label a
- temporal coherence c_i

$c_i = (i-1)/(\ell-1)$ and $c_i \in [0,1]$

DDIM forward: $\Phi_{0\to T}$



DDIM reverse: $\Phi_{T\to 0}$

Loss function $\mathcal{L}_{\text{act}} = \mathbb{E}_{x_i,a,c_i,\epsilon,t}\left[\left|\epsilon - \epsilon_\theta(x_{i,t},a,c_i,t)\right|^2\right]$

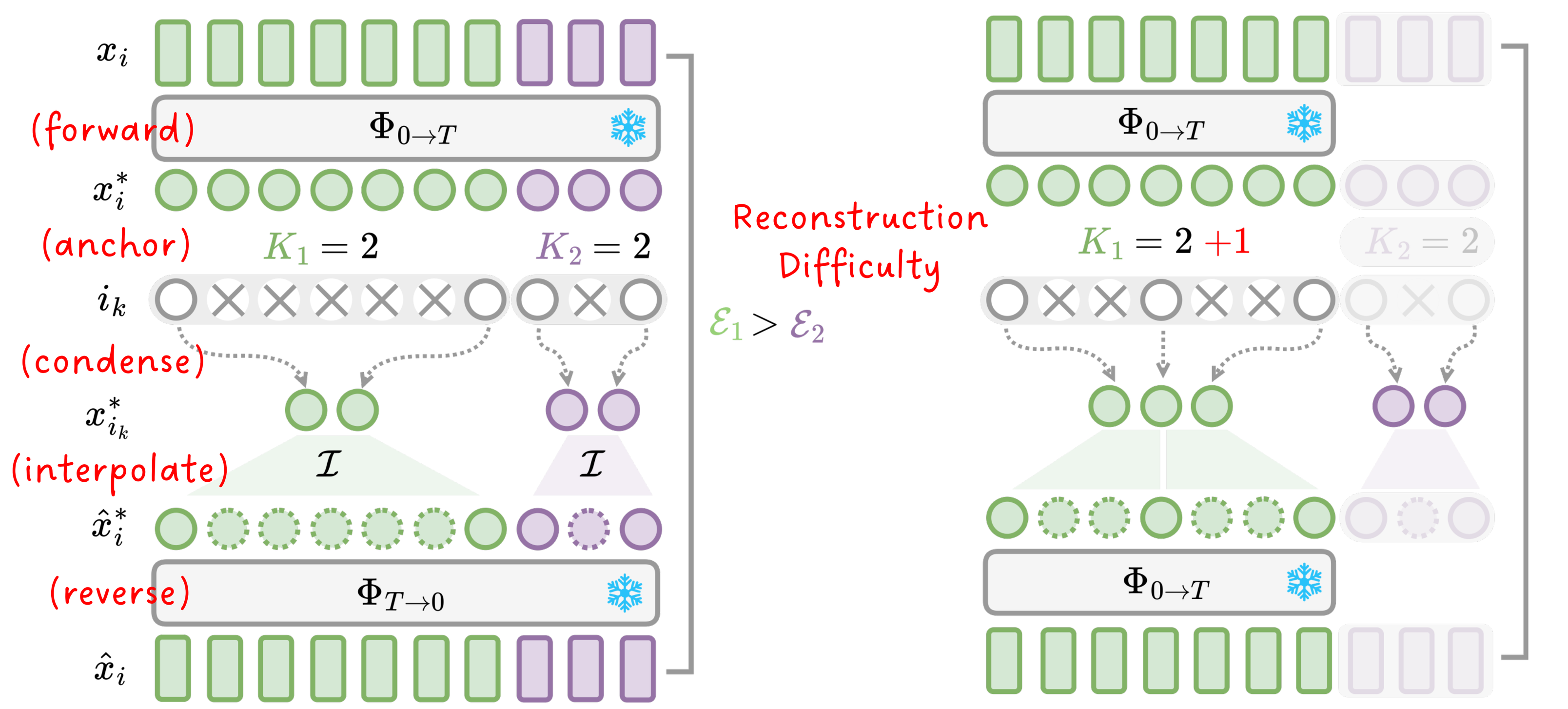
2) Adaptive Latent Trajectory Anchoring

Anchor Initialization:

$$i_k = \lceil 1 + \frac{k-1}{K-1}(\ell-1) \rfloor, \quad k = 1,\ldots,K$$

Adaptive Allocation:

$$\mathcal{E}_n = \mathbb{E}_{x_i \in s_n}[|x_i - \Phi_{T\to 0}(x_i^*, a, c_i)|^2]$$



$$x_j^* = \mathcal{I}(x_{i_k}^*, x_{i_{k+1}}^*; \lambda_j) \quad \lambda_j = \frac{c_j - c_{i_k}}{c_{i_{k+1}} - c_{i_k}}$$

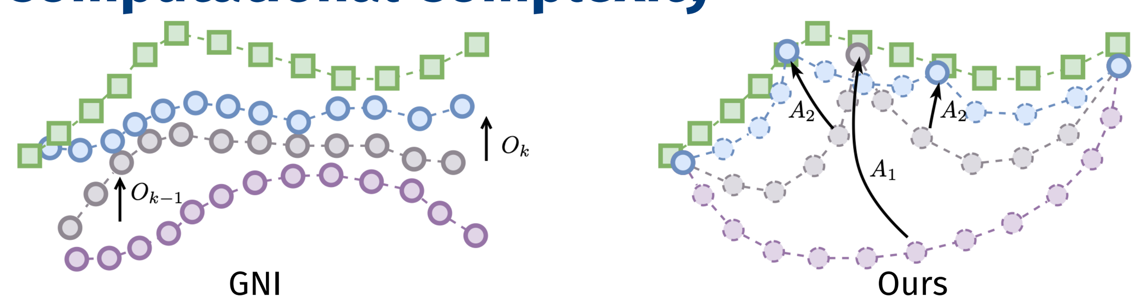
$$n^* = \arg\max_n \mathcal{E}_n, \quad K_{n^*} \leftarrow K_{n^*} + 1$$

3) Decoding & Training

Decoding from latent anchors: $\hat{x}_i = \Phi_{T\to 0}(\mathcal{I}(x_{i_k}^*, x_{i_{k+1}}^*; \lambda_i), a, c_i)$

Identical TAS loss for learning: $\mathcal{L}_{\text{tas}} = \mathcal{L}_{\text{cls}}(\hat{x}, y) + \lambda \mathcal{L}_{\text{sm}}(\hat{x})$

4) Computational Complexity



Method	Complexity	Typical Setting	Operation
GNI	$\mathcal{O}$(NS)	S=10,000	Latent Optimization
Ours†	$\mathcal{O}$(NT)	T=50	DDIM Mapping
Ours	$\mathcal{O}$(NKT)	K=8, T=50	DDIM + Anchor Allocation

N: # segments S: # optimization Step T: # diffusion steps K: # of anchors per segment

More efficient condensation than optimization-based GNI

Results

Performance

	$\bar{K}$	GTEA (256MB) Acc	Edit	F1@10/25/50	50Salads (4.7GB) Acc	Edit	F1@10/25/50	Breakfast (27.4GB) Acc	Edit	F1@10/25/50
MSTCN [10]										
Mean	1	69.4	67.5	72.6/68.6/52.8	70.0	46.7	54.2/49.5/40.2	48.0	33.2	29.6/25.5/17.6
Intp.	2	61.1	69.6	74.6/64.4/46.8	49.9	53.9	54.4/49.6/34.6	33.6	42.9	38.7/31.8/19.3
Coreset	1	60.3	63.4	65.4/59.2/44.2	69.6	62.5	65.7/63.1/56.6	50.2	41.3	36.7/31.6/22.3
GNI [5]	8	66.7	71.9	73.9/68.9/45.9	**73.5**	43.8	49.0/46.6/38.6	37.9	44.5	38.1/33.5/24.7
GNI [5]	64	66.6	66.9	74.2/69.9/48.8	72.8	44.2	49.3/45.0/40.2	47.8	54.0	46.9/41.9/30.9
Ours†	8	71.2	**80.6**	**86.5**/**80.5**/58.6	72.7	**65.1**	**71.9**/**68.6**/**57.9**	54.8	**67.2**	**63.8**/57.6/45.1
Ours	8	**72.1**	79.1	85.9/78.0/**61.4**	70.1	62.3	68.8/65.3/53.5	**63.4**	65.6	**63.8**/**58.4**/**46.1**
Original	ℓ	72.7	73.8	79.9/73.7/59.4	74.6	60.0	66.9/64.7/56.2	67.9	67.9	67.7/61.8/49.5
ASFormer [31]										
Mean	1	70.7	73.3	78.2/76.9/67.3	62.2	40.7	47.9/42.2/33.4	51.8	46.5	44.9/39.8/28.1
Intp.	2	64.1	72.7	76.5/71.9/54.9	54.8	48.2	55.4/49.5/31.9	43.1	48.3	47.3/40.1/25.6
Coreset	1	67.2	69.4	73.6/72.3/55.3	66.8	45.3	53.6/48.4/38.2	49.9	51.0	47.1/41.6/30.2
GNI [5]	8	71.6	76.4	80.8/79.4/63.4	70.5	51.4	61.6/57.6/47.3	62.8	66.3	65.8/59.4/47.2
GNI [5]	64	70.8	73.5	81.2/77.8/62.1	72.1	49.9	59.7/56.1/46.2	61.1	64.6	63.5/58.4/45.9
Ours†	8	**73.7**	**81.5**	84.3/81.5/71.8	**75.1**	**64.9**	**71.7**/**68.8**/**57.6**	65.3	**71.5**	70.1/65.2/48.4
Ours	8	73.4	80.5	**85.2**/**83.1**/**73.9**	71.2	60.7	69.2/64.9/54.4	**68.0**	71.3	**71.4**/**66.3**/**52.9**
Original	ℓ	74.3	77.4	82.9/80.1/73.1	77.1	67.6	77.1/73.1/61.7	70.7	72.0	73.6/69.0/56.1

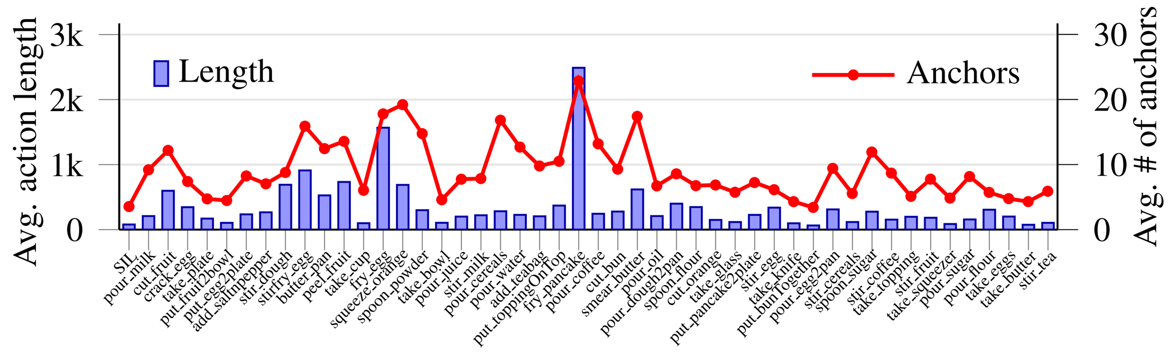
- Significant improvements over baselines
- Close performance to the original features

Anchor Budget

$\bar{K}$	ρ	Ours† Acc	Edit	F1@10/25/50	Ours Acc	Edit	F1@10/25/50
2	0.06	64.4	79.5	78.2/68.4/51.1	-	-	- / - / -
4	0.12	68.6	**81.9**	84.8/76.5/57.6	70.5	78.8	81.4/72.8/59.3
6	0.18	71.2	79.4	85.9/76.3/57.8	72.5	**80.0**	84.8/76.8/58.7
8	0.24	71.2	80.6	**86.5**/**80.5**/58.6	72.1	79.1	**85.9**/**78.0**/61.4
10	0.29	**73.3**	78.4	84.7/78.8/**63.5**	**73.8**	77.2	83.3/75.5/**61.5**
12	0.32	71.5	81.2	82.8/75.5/61.5	71.8	75.5	82.4/76.7/60.2

- Increasing the anchor budget generally improves the performance
- The gains saturate beyond a moderate budget
- Adaptive allocation is more effective than uniform anchoring under smaller budgets

Adaptive Anchor Distribution



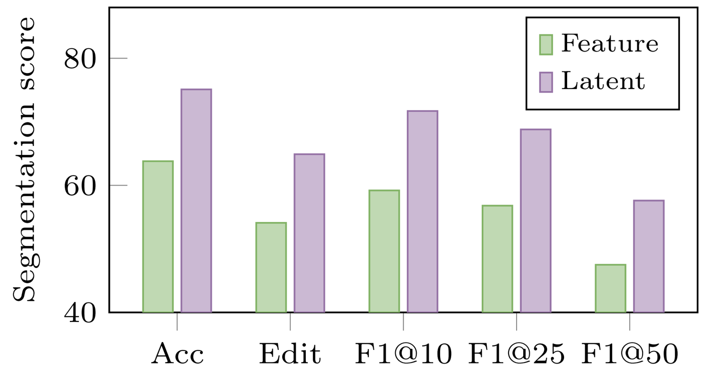
- Adaptive allocation is independent of the action frequency
- Longer actions tend to receive more anchors, reflecting more need for finer grained temporal coverage

Choice of Action Models

	$\bar{K}$	ρ	Acc	Edit	F1@10/25/50
GNI [5]	8	0.03	66.7	71.9	73.9/68.9/45.9
GNI [5]	64	0.24	66.6	66.9	74.2/69.9/48.8
Ours†	8	0.24	71.2	80.6	86.5/80.5/58.6
Ours	8	0.24	72.1	79.1	85.9/78.0/61.4

GNI saturates with more latent codes, indicating an expressiveness bottleneck.

Interpolation Space



Latent-space interpolation consistently outperform feature-space interpolation

Takeaways

Fine-grained Temporal Dynamics

Latent trajectory anchoring preserves fine-grained temporal dynamics through interpolation.

Condensation Budget Allocation

Adaptive anchor allocation distributes capacity according to segment reconstruction difficulty

Efficient High-fidelity Reconstruction

Deterministic DDIM mapping enables high-fidelity reconstruction without iterative optimization.

* Equal Contribution